Spatial modelling and GIS-based decision support tools to evaluate the suitability of sustainable aquaculture development in large catchments

A thesis submitted to the University of Stirling

for the degree of Doctor of Philosophy

by

Lynne Falconer

Institute of Aquaculture

University of Stirling

November 2013

DECLARATION

I declare that this thesis is an original piece of work conducted independently by myself and the work contained here has not been submitted for any other degree. All research material and sources of information have been duly acknowledged and cited.

Signature of Candidate

Lynne Falconer

November 2013

ABSTRACT

Land, water and natural resources are under increasing pressure due to rising demands for food and energy from the rapidly growing global population. Across a catchment there can be multiple stakeholders with conflicting opinions over how space and resources should be used and managed. Consequently, it is important to consider the suitability of a catchment for a particular purpose to optimise use of the area and minimise potential conflicts and impacts on the wider environment. Aquaculture is a significant contributor to world food supply and as fisheries are unlikely to increase it is expected that the industry will continue to grow and expand in the future to help meet food security requirements. As a result, it is essential that the sector aims for sustainable development within the most suitable locations. However, it can be difficult to assess the suitability of multiple large catchments and some issues may not be immediately apparent. This project aimed to show how spatial models could be used as decision support tools to evaluate the suitability of large catchments for sustainable aquaculture.

Four large areas of importance to aquaculture were selected; covering 10,148km^2, 26,225km^2, 48,319km^2 and 66,283km^2 in Bangladesh, China, Thailand and Vietnam respectively. Asia is by far the most dominant aquaculture region in the world and each of the four study areas contribute to local, regional and global food supplies. The study area in Bangladesh was located in Khulna region in the south west of the country and the main species of focus were prawn and shrimp. The Chinese study area was located in the south eastern province of Guangdong and the main species covered were tilapia and shrimp. Similarly, in Thailand, the main species evaluated were tilapia and shrimp whilst the study area extended across the Central region. Finally, the

largest study area was the Mekong Delta in Vietnam and the main species of focus in this area were pangasius catfish and shrimp.

One of the challenges in modelling large catchments is model applicability and data availability. Often, the required data are not available (or accessible) and it would be difficult, time consuming and expensive to collect new information. Furthermore, when assessing multiple areas is it vital that a representative and unbiased approach is used where no one catchment is favoured over the other due to higher quality data. Therefore, this study used data that are available for almost any area in the world; allowing future application of the models and enabling effective and unbiased decision support.

Four modelling stages were employed in this study to evaluate the suitability of large catchments for sustainable aquaculture development. The first stage was the classification of seasonal land use models from satellite imagery. This provides information on what the land is used for and how aquaculture could impact or be impacted by the wider environment. The second step was the development of seasonal models of site suitability using optimal values within a GIS-based multi-stage framework. These models identify which locations are best for culture and can also be used to estimate the availability of areas for food production. The next stage investigated the use of Maxent as a novel approach in site suitability modelling to evaluate the conditions experienced by existing farms. The information from Maxent can be used to identify trends, opportunities and concerns related to sustainable management and farm locations. Finally, qualitative models of non-point source pollution (NPSP) were developed which assess the risk of NPSP within a catchment. NPSP is an issue which can impact both aquaculture and the wider environment. Thus, it is important to understand the areas within a catchment where NPSP risk is higher enabling the establishment of monitoring and/or mitigation procedures.

The models support the ecosystem approach to aquaculture (EAA) and enable objective planning and management strategies to enhance productivity across large catchments without negatively impacting the environment. In order to meet growing food requirements, large areas will need to be used for agriculture and aquaculture; therefore, analysis at a wider catchment level, which complements assessment at a local scale, is required as it allows a holistic view of the situation. The work presented here illustrates the potential use of spatial models across large catchments and considers the suitability of the areas for aquaculture development.

ACKNOWLEDGEMENTS

First, and foremost, I would like to thank my supervisors, Professor Lindsay Ross and Dr Trevor Telfer, for their advice, encouragement, guidance and support. Their doors were always open and I truly appreciate the time they spent with me. Thank you for the opportunity and for believing in me.

This work was funded by the Institute of Aquaculture, University of Stirling and the EU FP7 Food, Agriculture and Fisheries, Biotechnology Programme funded SEAT project (Sustaining Ethical Aquaculture Trade, Grant 222889). I would like to thank Professor Dave Little, Dr Francis Murray and everyone involved with the SEAT project. In particular, I would like to express my gratitude to the Asian SEAT project teams, notably Ripon in Bangladesh, Wenbo in China, Key and Jigsz in Thailand and Lam in Vietnam for their kind hospitality during my visits to each country and for providing information on the areas, species and systems within this study. I would also like to thank the staff and students, past and present, within the Institute who have helped me over the years and Denes Cseh for helping with the IMS.

I must thank Lynn Munro for her advice, chat and banter, without which I would have gone crazy, thank you for being a good friend. I would also like to thank Victor Peredo Alvarez for his help and advice, long chats and a lot of laughs. I thank Neil Handisyde for his technical assistance and for putting up with my inane conversations about anything and everything. I am extremely grateful to the "potential" Long Pham and Supat Khongpuong for translating documents and helping to find data. I would also like to thank my friends outside of the University for their support and understanding.

Finally, I must thank my family; particularly my mum, dad and my brother Gordon. I could not have done this without your support.

CONTENTS

ABSTRACT I

ACKNOWLEDGEMENTS IV

CHAPTER 1

INTRODUCTION 1

CHAPTER 2

STUDY AREAS

2.1. Introduction 10

2.2. Selection of study areas in each country 12

2.3. Bangladesh 15

2.3.1 Bangladeshi aquaculture 17

2.3.2 Bangladeshi study area 19

2.4. China 23

2.4.1. Chinese aquaculture 24

2.4.2. Chinese study area 28

2.5. Thailand 30

2.5.1. Thai aquaculture 32

2.5.2. Thai Study area 36

2.6. Vietnam 39

2.6.1. Vietnamese aquaculture 41

2.6.2 Vietnamese study area 45

CHAPTER 3

DATABASE DEVELOPMENT

3.1. Introduction 49

3.2. Software 50

3.3. Spatial database 50

3.3.1. Spatial database preparation 50

3.3.2. Data 55

3.3.3. Weighting 64
3.4. Seasonality 65
3.5. Scoping and SEAT Farmer Survey 66
3.6. Internet Map Server (IMS) 67
3.7. IDRISI macro models 68

CHAPTER 4

THE DEVELOPMENT OF SPATIAL MODELS OF SEASONAL LAND USE TO EVALUATE THE SUITABILITY OF LARGE CATCHMENTS FOR AQUACULTURE

4.1. Introduction 70
4.2. Methodology 74
4.2.1. Data preparation 74
4.2.2. Ground truth information 76
4.2.3. Image classification 78
4.2.4. Towns/cities, mangroves and forests 81
4.2.5. Seasonal change 82
4.2.6. Accuracy assessment 82
4.3. Results 84
4.3.1 Bangladesh 84
4.3.2 China 87
4.3.3 Thailand 89
4.3.4 Vietnam 91
4.3.5 Accuracy assessment 93
4.4. Discussion 97

CHAPTER 5

MODELLING THE SEASONAL SUITABILITY AND SUSTAINABILITY OF POND AQUACULTURE ACROSS MULTIPLE LARGE CATCHMENTS USING GIS

5.1. Introduction 101
5.2. Study Areas 103
5.3. Methodology 103
5.3.1 Data Processing 103
5.3.2 Model structure 104
5.3.2.1 Pond submodel 106
5.3.2.2 Species submodel 109
5.3.2.3. System submodel 112

5.3.2.4. Access Submodel ... 115
5.3.2.5. Constraints ... 117
5.3.3. Overall model development and farm assessment ... 117
5.4. Results ... 119
5.4.1. Submodel outcomes ... 119
5.4.2. SEAT farm locations and individual submodels ... 122
5.4.3. Overall site suitability models ... 126
5.4.4. Partial validation ... 136
5.5. Potential production ... 140
5.6. Discussion ... 148

CHAPTER 6

ASSESSING THE SUITABILITY OF LARGE CATCHMENTS FOR AQUACULTURE USING EXISTING FARM LOCATIONS AND IDENTIFYING KEY TRENDS AMONGST SELECTED VARIABLES

6.1. Introduction ... 155
6.2. Study area and species ... 159
6.3. Methodology ... 160
6.3.1. Variables ... 160
6.3.2. Farm locations ... 163
6.3.3. Maxent modelling ... 164
6.4. Results ... 165
6.4.1. AUC ... 165
6.4.2. Percent contribution analysis ... 166
6.4.3. Jackknife test of variable importance ... 170
6.4.4. Response curves ... 172
6.4.5. Predicted distribution of farms ... 176
6.5. Discussion ... 181

CHAPTER 7

USING GIS BASED MODELS TO IDENTIFY POTENTIAL RISKS OF NON-POINT SOURCE POLLUTION IN LARGE CATCHMENTS OF IMPORTANCE TO AQUACULTURE

7.1. Introduction ... 186
7.2. Methodology ... 190
7.2.1 Model structure and development ... 190
7.2.2. Nutrient generation submodel and index ... 191

7.2.3 Runoff submodel and index 193
7.2.4 Transport submodel and index 195
7.2.5. Rainfall index 197
7.2.6 Population index 197
7.2.7 Normalisation and final model development 198
7.2.8. Assessment of model results 199
7.3. Results 200
7.3.1. Individual models 200
7.3.2. Assessment of model results 208
7.3.3. Comparison across multiple areas 211
7.4. Discussion 213

CHAPTER 8
DISCUSSION
8.1. Introduction 218
8.2. Seasonal land use 220
8.3 Site suitability models 221
8.4. Analysis using Maxent 223
8.5. Non-point source pollution models 225
8.6. Using spatial models to evaluate the overall suitability of large catchments for aquaculture 226
8.6.1. Bangladesh 226
8.6.2. China 229
8.6.3. Thailand 232
8.6.4. Vietnam 235
8.7. Conclusions 238

REFERENCES 241

APPENDIX A : Error/confusion matrices for the land use models 268
APPENDIX B : IDRISI Macro Models for the Non-point source pollution (NPSP) models 284

LIST OF FIGURES

Figure 1.1: The six components of a GIS outlined by Longley *et al*. (2008) 6

Figure 2.1: Study areas with catchments and surveyed farms highlighted for A) Bangladesh, B) China, C) Thailand, D) Vietnam 13

Figure 2.2: Study areas 14

Figure 2.3: Study area for Vietnam with political boundary 14

Figure 2.4: Map of Bangladesh and the surrounding area (Google, 2013)................. 15

Figure 2.5: Growth of aquaculture In Bangladesh between 1950 and 2011 (FAO, 2013b) 17

Figure 2.6: Study area in Bangladesh and administrative districts within the boundary (Google Earth, 2013)... 20

Figure 2.7: Prawn farms in Bangladesh.. 22

Figure 2.8: Shrimp farms in Bangladesh.. 22

Figure 2.9: Map of China and the surrounding area (Google, 2013) 23

Figure 2.10: Growth of Chinese aquaculture between 1984 and 2011 (FAO, 2013b) . 25

Figure 2.11: Tilapia farms in Maoming, Guangdong province, China.......................... 26

Figure 2.12: Shrimp farms in Zhanjiang, Guangdong province, China 27

Figure 2.13: Study area in China and administrative districts within the boundary (Google Earth, 2013)... 28

Figure 2.14: Map of Thailand and the surrounding area (Google, 2013)..................... 31

Figure 2.15: Aquaculture production in Thailand between 1950 and 2011 (FAO, 2013b) 33

Figure 2.16: Tilapia farms in Chachoengsao, Thailand.. 34

Figure 2.17: Shrimp farms in Chachoengsao, Thailand 36

Figure 2.18: Study area in Thailand and administrative districts within the boundary (Google Earth, 2013)... 37

Figure 2.19: Map of Vietnam and the surrounding area (Google, 2013) 40

Figure 2.20: Aquaculture production in Vietnam between 1950 and 2011 (FAO, 2013b) 41

Figure 2.21: Pangasius farms in Can Tho/An Giang, Vietnam 43

Figure 2.22: Shrimp farms in Soc Trang, Vietnam 44

Figure 2.23: Study area in Vietnam and administrative districts within the boundary (Google Earth, 2013) 46

Figure 3.1: Study areas and UTM zones 52

Figure 3.2: LandScan population data representing the ambient population (average over 24 hours) at a resolution of 30 arc seconds for each study area. Produced by Oak Ridge National Laboratory (2008) using census information, spatial data and high resolution imagery. 56

Figure 3.3: ASTER DEM and highlighted area showing errors 57

Figure 3.4: Temperature data for the study area in China. The original layer shows the missing data near the coast 60

Figure 3.5: Comparison between the rivers layer obtained from the HydroSHEDS database and the layer which was digitised from Google Earth 62

Figure 3.6: Background satellite imagery for each study area during the dry season.. 63

Figure 3.7: Average length of the dry and rainy seasons for each study area 65

Figure 3.8: Members of the SEAT project interviewing a farmer in Maoming, China... 66

Figure 3.9: Screen shot of an early version of the Internet Map Server (IMS) 68

Figure 3.10: Macro for the site suitability model (Bangladesh) 69

Figure 4.1: RGB colour composites of the original Landsat scene compared to the gap-filled Landsat scene 75

Figure 4.2: Examples of cloud cover issues with Landsat imagery 76

Figure 4.3: Examples of ground truth information 77

Figure 4.4: Conceptual design for the land use models 79

Figure 4.5: Results of the land use model and analysis for the study area in Bangladesh 85

Figure 4.6: Photographs showing trees within agricultural areas 86

Figure 4.7: Results of the land use model and analysis for the study area in China.... 88

Figure 4.8: Results of the land use model and analysis for the study area in Thailand .... .90

Figure 4.9: Results of the land use model and analysis for the study area in Vietnam .... .92

Figure 4.10: Errors of commission for each land use model 95

Figure 4.11: Errors of omission for each land use model 96

Figure 5.1: Conceptual design of the multi-tiered site suitability framework 105

Figure 5.2: The sequential process of model development....................................... 118

Figure 5.3: Submodels for Bangladesh (prawn and shrimp) and China (tilapia and shrimp) 120

Figure 5.4: Submodels for Thailand (tilapia and shrimp) and Vietnam (pangasius and shrimp) 121

Figure 5.5: Comparison of the four spatial submodel outcomes for selected freshwater species with SEAT farm locations in the dry season and rainy season..................... 123

Figure 5.6: Comparison of the four spatial submodel outcomes for shrimp with SEAT farm locations in the dry season and rainy season 125

Figure 5.7: Overall site suitability models for Bangladesh (prawn) and China (tilapia) 127

Figure 5.8: Overall site suitability models for Thailand (tilapia) and Vietnam (pangasius) 128

Figure 5.9: Overall site suitability models for shrimp in Bangladesh and China 132

Figure 5.10: Overall site suitability models for shrimp in Thailand and Vietnam......... 133

Figure 5.11: Highly suitable areas for production of prawn and shrimp in Bangladesh 141

Figure 5.12: Highly suitable areas for production of tilapia and shrimp in China 143

Figure 5.13: Highly suitable areas for production of tilapia and shrimp in Thailand... 145

Figure 5.14: Highly suitable areas for production of pangasius and shrimp in Vietnam 147

Figure 6.1: Study areas with the locations of the shrimp farms (white points)........... 164

Figure 6.2: Percentage contribution analysis 168

Figure 6.3: Results of the Jackknife test of variable importance 171

Figure 6.4: Response curves of the top three variables for each model.................... 173

Figure 6.5: Response curves for the water balance variable for the four SEAT models 175

Figure 6.6: Predicted distribution of the SEAT farms using the Maxent model. The higher the Maxent score the higher the suitability of the area for conditions similar to those experienced by the SEAT farms. 177

Figure 6.7: Predicted distribution of the FAO farms using the Maxent model. The higher the Maxent score the higher the suitability of the area for conditions similar to those experienced by the FAO farms. 179

Figure 6.8: Comparison of the Maxent model results for Thailand using the SEAT and FAO data.. 180

Figure 7.1: Model framework 190

Figure 7.2: The risk of NPSP across the study area in Bangladesh.......................... 201

Figure 7.3: The risk of NPSP across the study area in China 203

Figure 7.4: The risk of NPSP across the study area in Thailand 205

Figure 7.5: The risk of NPSP across the study area in Vietnam............................... 207

Figure 7.6: Assessment of the nitrogen NPSP model results using measurements of nitrogen (N) from MRC (2012).. 209

Figure 7.7: Assessment of the phosphorus NPSP model results using measurements of phosphorus (P) from MRC (2012) 210

Figure 7.8: The risk of non-point source pollution across multiple study areas 212

LIST OF TABLES

Table 2.1: Top 10 world aquaculture producers in 2010 (FAO, 2012)........................ 10

Table 2.2: Species studied by the SEAT project in each country 11

Table 2.3: Top five aquaculture species by quantity (tonnes) and value (USD$) in Bangladesh for 2011 (FAO, 2013b).. 18

Table 2.4: Top five aquaculture species by quantity (tonnes) and value (USD$) in China for 2011 (FAO, 2013b) 25

Table 2.5: Top five aquaculture species by quantity and value in Thailand for 2011 (FAO, 2013b) 33

Table 2.6: Top five aquaculture species by quantity and value in Vietnam for 2011 (FAO, 2013b) 42

Table 3.1: Reference parameters that were used in each study area 53

Table 3.2: Parameters for the windowed study area images 54

Table 3.3. Main sources of data 58

Table 4.1: Classes for the image classification 79

Table 4.2: Overall Kappa index for each land use model... 94

Table 5.1: Scoring system for model development 106

Table 5.2: Reclassification values and weightings within the Pond submodel........... 107

Table 5.3: Reclassification values within the Species submodel.............................. 111

Table 5.4: Reclassification values within the System submodel.............................. 113

Table 5.5: Reclassification values and weightings used within the Access submodel..... 116

Table 5.6: Area (km^2) of each suitability category from the overall site suitability models for selected freshwater species 129

Table 5.7: Area (km^2) of each suitability category from the overall site suitability models for shrimp 134

Table 5.8: Comparison of SEAT farms and overall site suitability models for freshwater species 137
Table 5.9: Comparison of SEAT farms and overall site suitability models for shrimp 139

Table 5.10: Potential production scenarios for Prawn and Shrimp in Bangladesh 142

Table 5.11: Potential production scenarios for tilapia and shrimp in China 144

Table 5.12: Potential production scenarios for tilapia and shrimp in Thailand 146

Table 5.13: Potential production scenarios for pangasius and shrimp in Vietnam..... 148

Table 6.1: Variables used within the Maxent model 161

Table 6.2: Percentage contribution values 167

Table 7.1: Export coefficients assigned to each land use category 192

Table 7.2: Curve numbers (CN_2) for the different land use categories and hydrological soil groups 194

CHAPTER 1
INTRODUCTION

Over the next few decades, driven mainly by increasing demands for energy and food, competition for land (and water) will intensify (Harvey and Pilgrim, 2011). As a result, there is a need to develop land use strategies which have socio-economic benefits and minimal detrimental environmental impacts across multiple scales (Foley *et al*., 2005). One of the biggest challenges facing the world is food security as there is a need to feed the poorest populations, whilst also meeting the demands and changing palates of affluent countries (Godfray *et al*., 2010). Although it is necessary to increase food production, there is also a need to minimise conflict with competing activities and maintain biodiversity (Ericksen *et al*., 2009; Godfray *et al*., 2010; Foley *et al*., 2011; Rice and Garcia, 2011; Tscharntke *et al*., 2012; McClanahan *et al*., 2013). Therefore, in order to maintain current supplies and meet growing demands with minimal adverse impacts, it is important to identify suitable areas for food production and employ sustainable management practices.

Natural resources are already under heavy pressure from existing users and transitions from one activity to another are impacting current and future stakeholders (Foley *et al*., 2005). Consequently, further development should aim to prevent additional pressure through careful planning and management strategies. Moreover, as noted by Verburg *et al*. (2013), research is needed to assess the availability of land (and water) which considers production potential as well as trade-offs and limitations. Not all land can be used for food production and some areas are more suitable than others. Rapid urbanization has resulted in the loss of agricultural land and soil degradation; decreasing the overall availability of land to produce food (Chen, 2007) and moving farming systems to areas that were previously considered unsuitable or used for other purposes. Furthermore, throughout the world, there is increasing adoption of biofuels to meet energy requirements which has led to many farmers switching from farming for food to farming for energy (Koh and Ghazoul, 2008; Rathmann *et al*., 2010). This puts additional pressure on land, soil and water (Phalan, 2009) and can reduce the availability of resources for other purposes.

Aquatic products are rich in protein, essential fatty acids, vitamins and minerals; consequently they can help to meet nutritional requirements throughout the world (Williams, 1997; Subasinghe *et al*., 2009). Fisheries have long been overexploited (Jackson *et al*., 2001; King, 2007; Allsopp *et al*., 2009; Worm *et al*., 2009) and aquaculture is seen as a way to meet some of the demand for aquatic products (Subasinghe *et al*., 2009; Smith *et al*., 2010; Merino *et al*., 2012; Tacon and Metian, 2013). Aquaculture is also a valuable industry for many regions and it is often a vital livelihood for rural populations as it provides a source of income which can help individual households and communities (Subasinghe *et al*., 2009). However, there are many negative impacts associated with the sector, such as the use of fish meal and fish oil in aquafeeds, use of wild seed to stock ponds, introduction of exotic organisms, habitat modification and effluent discharge (Naylor *et al*., 2000; Naylor *et al*., 2009). Furthermore, aquaculture is a controversial sector and often has a public image problem, particularly within developed countries, due to such negative impacts (Kumar and Cripps, 2012). Accordingly, it is important that the industry aims for sustainable production to try and minimise potential impacts and gain the support of consumers throughout the world.

The Food and Agriculture Organization of the United Nations (FAO) has adopted the ecosystem approach as a key strategy to unite food security and environmental conservation through their programmes for agriculture, forestry, fisheries and aquaculture (FAO, 2013a). The ecosystem approach to aquaculture (EAA) is defined by Soto *et al.* (2008) as "*a strategic approach to development and management of the* *sector aiming to integrate aquaculture within the wider ecosystem such that it promotes sustainability of interlinked social-ecological systems*". This approach can be considered a framework for sustainable aquaculture development and there are three key principles outlined by Soto *et al*. (2008):

1. *" Aquaculture development and management should take account of the full range of ecosystem functions and services, and should not threaten the sustained delivery of these to society".*
2. *"Aquaculture should improve human well-being and equity for all relevant stakeholders".*
3. *"Aquaculture should be developed in the context of other sectors, policies and goals".*

The advantage of the EAA is that it combines many relevant ideas associated with sustainable development and integrated natural resource management under one strategy. However, the implementation of the EAA is not always straightforward as there are multiple scales and issues to be considered. Aquaculture is not a constant process and consequently there are temporal scales which should be addressed. Seasonal environmental issues can affect reproduction, animal health and water quality (Cowan *et al*., 1999; Pankhurst and Porter, 2003; Bowden *et al*., 2007), whilst seasonal land management practices can influence non-point source pollution (Carpenter *et al*., 1997) and potentially impact the aquaculture system and the surrounding environment. Therefore the suitability of an area should take into account the changing conditions across the year. This is highlighted by Ross *et al*. (2011) who found significant differences in the availability of suitable areas for fish culture between two seasons.

Additionally, one of the most important decisions with regard to adopting the EAA is deciding which spatial scale to apply the framework to. Soto *et al*. (2008) suggest three spatial scales; farm, watershed/aquaculture zone and global. As noted by Shepherd (2008) "*the sustainable interaction of people and biodiversity can only be developed in a larger ecosystem area, and the ecosystem approach encourages both a larger version on the ground and an exploration of interconnections*". In order to achieve a sustainable system the farm should minimise impact on both the occupied area and the surrounding region. Inadequate management of all components within an ecosystem threatens the viability of that ecosystem (Frankic and Hershner, 2003) and the activities taking place. Therefore, to assess the suitability of an area for aquaculture, issues beyond farm level should be monitored and assessed; as promoted by the EAA.

Assessment of an area requires suitable boundaries which should allow a representative evaluation of the wider environmental issues associated with inland and coastal culture. The catchment, which can be considered the natural management unit (Chandler, 1994), provides a focus for understanding systems in a holistic manner (Ferrier and Jenkins, 2010). Across a catchment there are many challenges in trying to achieve long term environmental sustainability. Land (and water) use conflicts, environmental degradation and depletion of biodiversity are all negative consequences experienced in the wider environment and often associated with aquaculture (Boyd and Tucker, 1998). Generally, the detrimental environmental impacts credited to aquaculture have resulted from several factors including poor planning, inappropriate site selection and inadequate management procedures (Kumar and Cripps, 2012). Management procedures are often down to individual farmers (sometimes supported by policy and legislation), whilst the identification of suitable areas for expansion and development can be conducted at a broader catchment level. This is particularly important with regard to food security as regional planners and governments can estimate the potential for further food production, assess risks which may affect supply and identify potential sources of conflict with other industries.

However, large catchments can be challenging to assess manually due to the wide range of environmental conditions and multiple issues which should be considered within suitability studies. Therefore it is essential to use available technology such as Geographic Information Systems (GIS) which can process large amounts of data (often in different formats), produce multiple scenarios and present spatial information in a visual format which is easier for stakeholders with little or no scientific background to understand (Corbin and Young, 1997; Longley *et al*., 2005). A GIS is a combination of six components, outlined by Longley *et al*. (2005) and presented in Fig. 1.1, and it enables the development of spatial models which can be used to understand the characteristics, relationships and interactions of the factor/scenario being studied (Haining, 2003). As noted by Mulligan and Wainwright (2005), models are a simplification of reality and an abstraction of a real system which takes influence from both the existent reality and the modeller's perception of the system. Modelling is not an alternative to observation, however, in many circumstances it is a powerful tool in understanding observations and developing and testing theory (Mulligan and Wainwright, 2005). Spatial models developed using GIS and remote sensing tools can be used to provide information on previous, current, future and even alternative scenarios that could be difficult or dangerous to simulate in the real world.

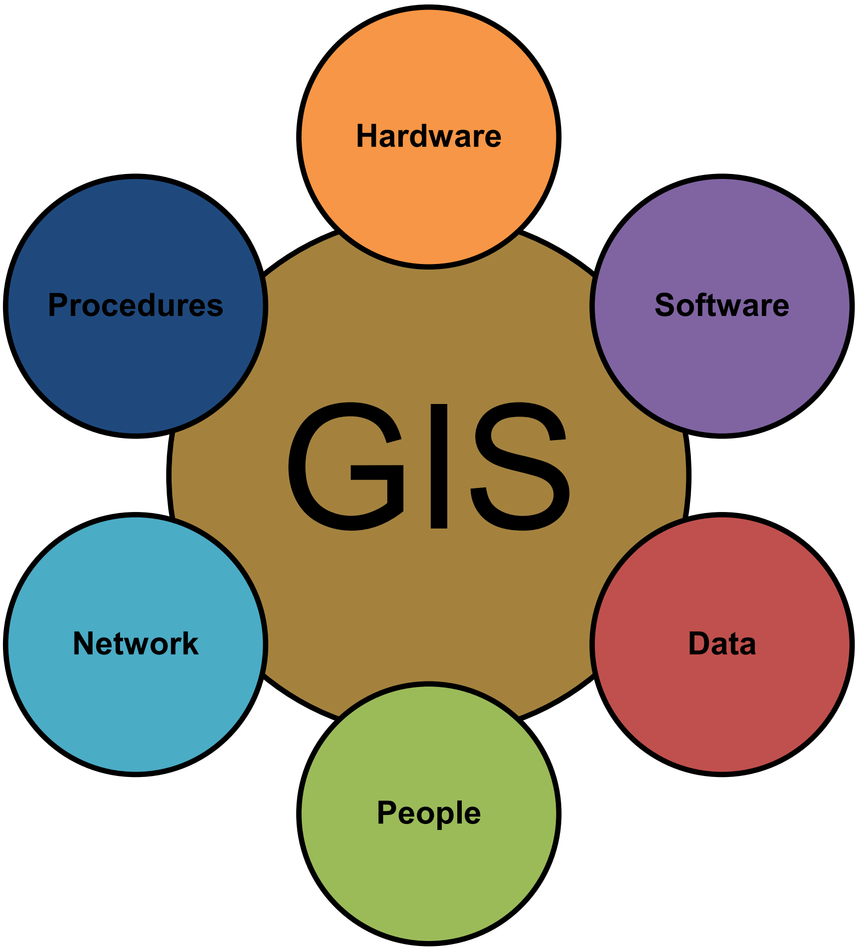


Figure 1.1: The six components of a GIS outlined by Longley *et al*. (2008)

GIS and remote sensing tools have been widely used in aquaculture studies, particularly as a method of site selection; covering many species, systems and study areas throughout the world (Ross *et al*. 2009; Ross *et al*. 2013). Some recent examples of the vast range of species and areas studied include shrimp in Vietnam (Giap *et al*. 2005), tilapia in Mexico (Ross *et al*. 2011), kelp in Japan (Radiarta *et al*. 2011) and oyster farms in Korea (Cho *et al*. 2012). Additional applications have included using spatial modelling to assess the impact of aquaculture on the benthic environment (Shih *et al*., 2009); identify suitable habitats and estimate potential commercial yields (Vincenzi *et al*., 2006); highlight environmental vulnerability of marine aquaculture (Navas *et al*. 2011); predict waste distribution from fish cages

(Corner *et al*., 2006) and evaluate the visual impact of coastal aquaculture (Falconer *et al*., 2013).

The potential use of spatial planning tools for the EAA has already been highlighted by Aguilar-Manjarrez *et al*. (2010). One key area where models can be used is decision analysis. Decision making is a complex process which involves value judgements, analysis of a vast array of information and a choice between two or more alternatives (National Academy of Sciences, 2002; Sugumaran and DeGroote, 2011). A lack of information for one choice may result in bias towards another and uncertainty can undermine the overall decision; potentially leading to further conflict between different stakeholders. Decision support systems and tools can be used to help in this process, providing additional information or alternative analysis. Although a computer model is a common component of decision support, a model is not automatically a decision support tool as a tool needs to provide the information in terms of a decision variable as discussed by Sullivan (2002).

The use of decision support in ecosystem and environmental management is becoming increasingly more important as it can help to address complex issues such as site suitability which involves multiple factors. However, the integration of science with decision making is difficult as tools often fail to meet the challenge of real-world problems (Giupponi, 2007; Liu *et al*. 2008). It is essential that a balance is achieved and a tool is easy to use whilst also remaining scientifically complex enough to address the selected issue.

Evaluating the suitability of a catchment for aquaculture is important as many farms are already located in areas which are under pressure from competing activities. Asia is responsible for almost 90% of global aquaculture production (FAO, 2012) and as a result it is a particularly important area to focus on with respect to site suitability and sustainable development. Over 50% of available land in Asia is already used for agriculture (Zhao *et al*. 2006) and consequently future development must be carefully managed. The intensification of agriculture, urbanization and deforestation have led to significant habitat modifications which, combined with forest fires and overexploitation of wildlife, has led to serious ecological concerns (Sodhi *et al*. 2004; Zhao *et al*. 2006); Sodhi *et al*. (2004) suggested that Southeast Asia in particular is at risk from an imminent biodiversity disaster. As a result, it has never been more important to evaluate the suitability of significant aquaculture regions and identify potential issues associated with the development and/or production.

The Sustaining Ethical Aquaculture Trade (SEAT) project is a large-scale multi-disciplinary collaborative research project which was established under the EU 7th Framework Programme (FP7) to explore the sustainability of trade in aquaculture products from Asia (www.seatglobal.eu). The project ran from 2009 - 2013 and involved a consortium of 14 international institutions and organisations across Europe and Asia. Four countries of importance to aquaculture production were used in the project; Bangladesh, China, Thailand and Vietnam and four key species were also considered; pangasius catfish, prawn (*Macrobrachium rosenbergii*), tilapia and shrimps (*Penaeus* spp.). The work in this PhD project formed part of Work Package 4 (Environmental Models).

The overall aim of this work was to develop spatial models which could be used to assess the suitability of aquaculture across large catchments. The main focus is on pond aquaculture; however, some of the work could be applied to other systems. The specific objectives were:

1. To summarise the characteristics of each study area.

2. To construct a spatial database suitable for each of the four study areas using data which is available for the rest of the world.

3. To derive seasonal land use models from Landsat ETM+ satellite imagery.

4. To produce models of site suitability which identify potential areas for aquaculture production.

5. To use Maxent, a predictive species distribution and habitat modelling software, to analyse selected variables associated with farm location and assess the suitability of the study areas for aquaculture.

6. To develop spatial models which can be used to estimate the risk of seasonal non-point source pollution from the wider environment to aquaculture across large catchments.

7. To propose how these spatial tools and models can be exploited in objective decision support to evaluate the suitability of large catchments for aquaculture.

The following chapters aim to address the aforementioned objectives. Chapter 2 contains general information on each of the four study areas. Chapter 3 describes the spatial database and associated components. It also includes challenges encountered and other relevant issues. Chapter 4 focuses on the development of land use models from Landsat satellite imagery which assess seasonal patterns of land use between the dry and rainy season. Chapter 5 discusses the development of a multi-stage spatial model to assess site suitability with regard to optimal conditions for culture. Chapter 6 explains the use of Maxent modelling techniques to analyse the spatial distribution of farms used in this study. Maxent is a software primarily used for species distribution modelling and this chapter evaluates its potential use as a site selection tool for aquaculture. Chapter 7 concentrates on the use of spatial modelling as a decision support tool to help assess the risk of non-point source pollution from the wider environment to aquaculture across each study area and help identify areas in need of further assessment. The work concludes with Chapter 8 which is a general discussion collating the main points from the preceding chapters into a single chapter and highlights how the models and tools can be used in objective decision support.

CHAPTER 2
STUDY AREAS

2.1. Introduction

In terms of global aquaculture, Asia is the dominant region; supplying over 85% of world production by volume in 2010 (FAO, 2012). Consequently, Asia is a significant contributor to seafood supplies both domestically and internationally. Four Asian countries which are significant suppliers to global aquaculture production were selected by the SEAT project to focus on; Bangladesh, China, Thailand and Vietnam which are ranked first, third, fifth and sixth in the world, respectively, in terms of world food fish production by quantity (Table 2.1). Within each country the SEAT project focussed on two of the four major aquaculture species (Table 2.2).

Table 2.1: Top 10 world aquaculture producers in 2010 (FAO, 2012)
Note: Data exclude aquatic plants and non-food products. Data for 2010 for some countries are provisional and subject to revisions.

	Tonnes	Percent
China	**36,700,000**	**61.4**
India	4,650,000	7.8
Vietnam	**2,670,000**	**4.5**
Indonesia	2,300,000	3.8
Bangladesh	**1,310,000**	**2.2**
Thailand	**1,290,000**	**2.2**
Norway	1,000,000	1.7
Egypt	900,000	1.5
Myanmar	850,000	1.4
Philippines	750,000	1.3
Other	7,400,000	12.4
Total	59,800,000	100

Table 2.2: Species studied by the SEAT project in each country

	Pangasius	Prawn	Shrimp	Tilapia
Bangladesh	**No**	**Yes**	**Yes**	**No**
China	**No**	**No**	**Yes**	**Yes**
Thailand	**No**	**No**	**Yes**	**Yes**
Vietnam	**Yes**	**No**	**Yes**	**No**

The names pangasius, prawn, shrimp and tilapia can refer to different things depending on who is using the term. Within the context of this study the terms refer to the following:

- Pangasius - *Pangasius hypothalmus* (also known as river catfish, striped catfish and in Vietnam it is referred to as tra) and *Pangasius bocourti* (also known as basa in Vietnam).
- Prawn - *Macrobrachium rosenbergii* (also known as the giant freshwater river prawn)
- Tilapia - Oreochromis sp. (particularly *Oreochromis niloticus*, also known as the Nile tilapia)
- Shrimp - Penaeid shrimp (particularly *Litopenaeus vannamei*, formerly, *Penaeus vannamei*, also known as the whiteleg shrimp and *Penaeus monodon*, also known as the giant tiger prawn).

2.2. Selection of study areas in each country

Study areas were selected following scoping trips to each of the countries in October/November 2010, in addition to information provided by a field survey conducted by SEAT in-country partners (Murray et al., 2011). For the present study, one area was selected per country which included as much of the areas surveyed during the farmer survey as possible.

As geographical features such as rivers and waterbodies do not adhere to political boundaries the study areas were selected and defined within a geographical context using catchments to set boundaries for the study areas in each country. Catchments are often considered the natural management unit (Chandler, 1994) and are the spatial unit for an integrated management approach in many sustainable plans for all sectors. Furthermore, defining a study area using a catchment or watershed allows the ecosystem approach to be applied at that level.

Drainage basin vector files were downloaded from the Hydro 1K dataset (USGS, 2011) and the boundary for each study area was then identified. Hydro 1K is a geographic dataset that was developed by the US Geological Survey (USGS) to provide a set of comprehensive and consistent data at a global scale using topographically derived data sets derived from the GTOPO 30 (a global raster Digital Elevation Model (DEM)) (USGS, 2011). The drainage basins are sub-catchments of larger systems and the study areas were delineated based on where the SEAT survey farms were located (Fig. 2.1). Unfortunately not all of the surveyed areas could be included within the spatial study areas due to the large distances between surveyed sites; Cox's Bazaar in Bangladesh, Hainan in China and Surat Thani in Thailand were all excluded.

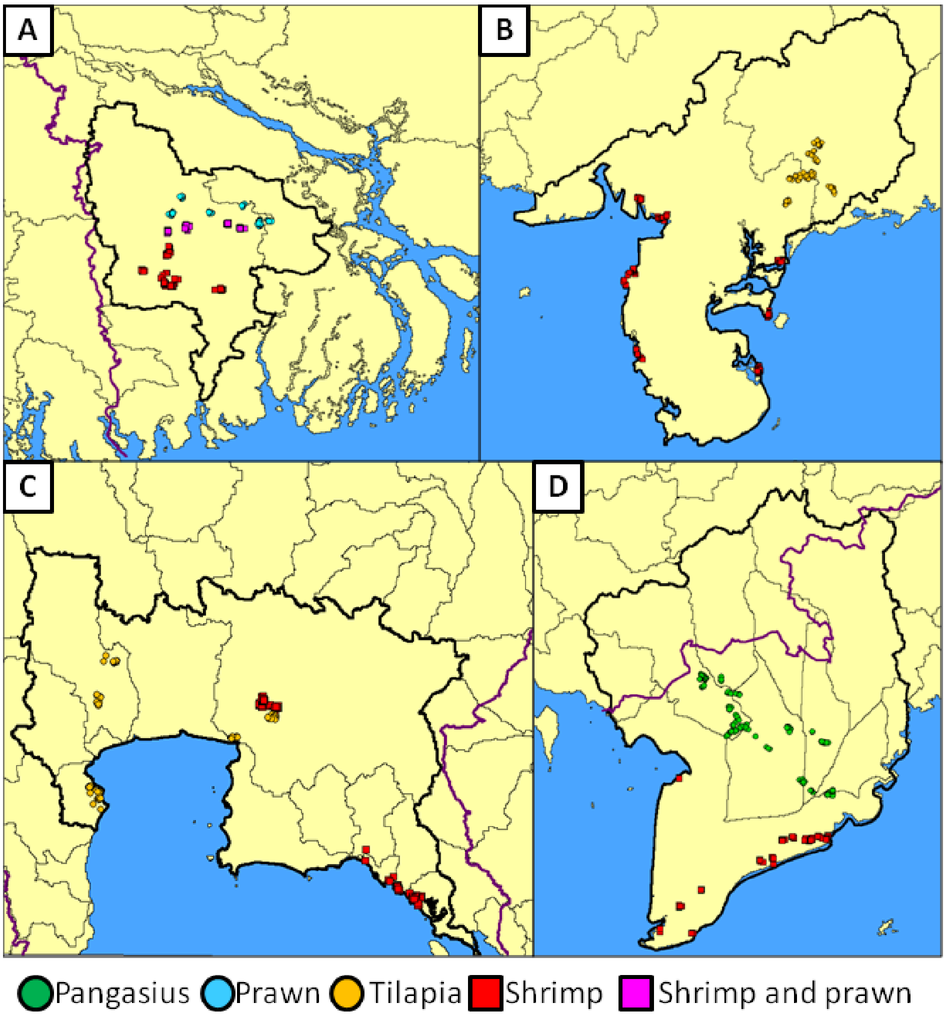


Figure 2.1: Study areas with catchments and surveyed farms highlighted for A) Bangladesh, B) China, C) Thailand, D) Vietnam

Note - Purple line indicates border between countries.

The four study areas vary in size, however they are all relatively large; 10,148km^2, 26,225km^2, 48,319km^2 and 66,283km^2 in Bangladesh, China, Thailand and Vietnam respectively (Fig. 2.2). Due to the topographical features of the Mekong basin, the study area in Vietnam extends into eastern Cambodia. As resources would not be shared between countries, the chapters which evaluated site suitability and individual sites (Chapters 5 and 6) used the political boundary for Vietnam (Fig 2.3).

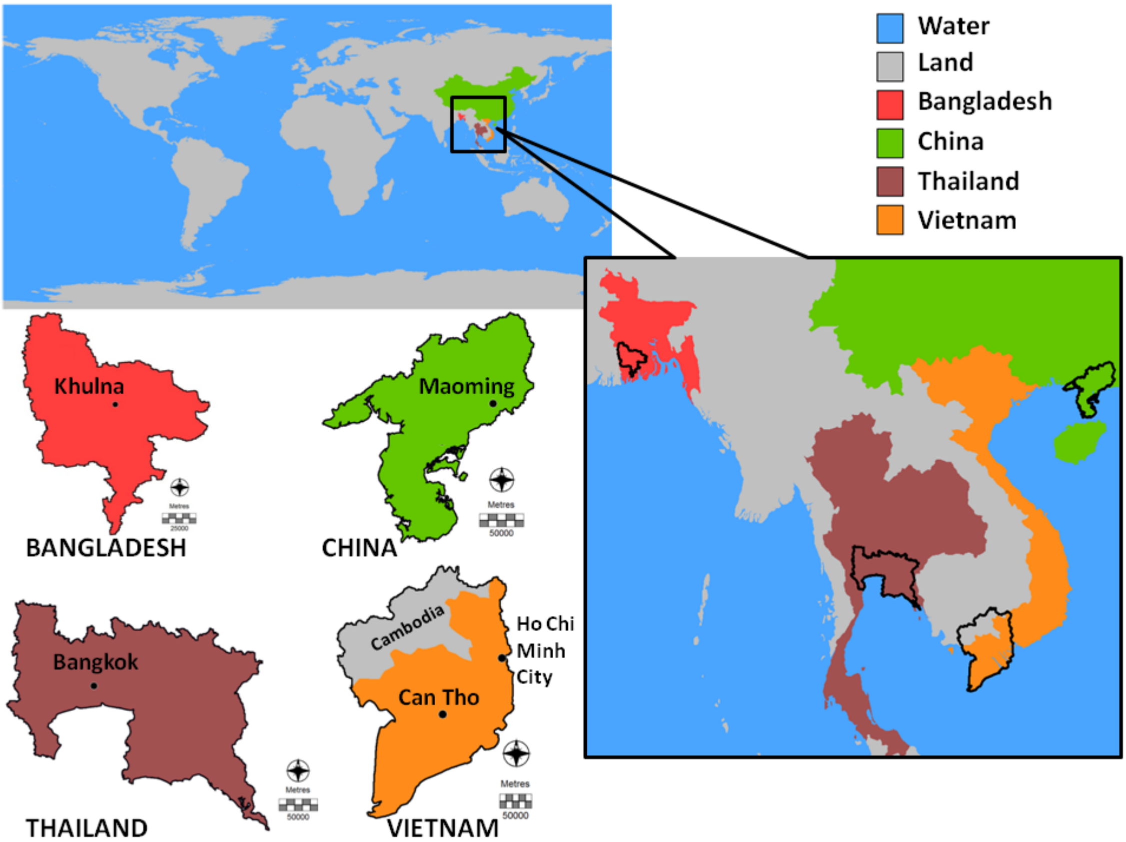


Figure 2.2: Study areas

Figure 2.3: Study area for Vietnam with political boundary

2.3. Bangladesh

Bangladesh (Fig. 2.4) covers an area of 147,570km^2 and shares borders with India and Myanmar (Burma) (UN, 2013). It is one of the most densely populated countries in the world with an estimated population density of 1019.8 people per km^2 in 2011 and a total population of over 150 million people (UN, 2013). Due to overcrowding, environmental issues and natural disasters, poverty is an issue throughout the country in both urban and rural areas. One of the key food security challenges for Bangladesh is to enhance food production whilst minimising the impact on land and water resources which are already constrained (Yu *et al*. 2010). This is further complicated by risks of climate change and seasonal variability from existing issues and unpredictable future impacts (Faisal and Parveen, 2004; Yu *et al*. 2010).

Figure 2.4: Map of Bangladesh and the surrounding area (Google, 2013)

The country is a vast delta leading to the Bay of Bengal in the south; much of the landmass is flood plain and 93% of the land area is less than 10m above sea level (Dey *et al.*, 2008). There are approximately 250 perennial rivers, 56 of which originate outside of the country and the three main rivers are the Ganges, the Brahmaputra and the Meghna (Alexander, 1993). Generally, Bangladesh experiences four seasons which are dictated by the Southwest and Northeast monsoons; dry winter season (December to February), a transitional "pre-monsoon" season (March to May), monsoon season (June to September) and a transitional "post-monsoon" season (October to November) (Salam, 2000). However these seasons can be further placed into two more general categories; a rainy season/monsoon period from June to October and a dry season from November to May (Faruque and Ali, 2005).

Bangladesh is prone to devastating natural disasters and climatic events such as droughts, cyclones, tornadoes, storms and floods (Penna and Rivers, 2013). As noted by Alexander (1993) floods can be seasonal (normal for the season) and contingent (unexpected and generally damaging). There are four types of contingent floods; flash floods due to heavy monsoon/pre-monsoon rains, river floods which occur in response to specific rainfall events, rainfall floods due to localised precipitation and cyclonic (sea) flooding when cyclones make landfall in Bangladesh from the Bay of Bengal resulting in a storm surge inland of sea water (Alexander, 1993). It has been predicted that the impact of cyclonic storm surge floods will increase in the future due to climate change and sea-level rise (Karim and Mimura, 2008). In addition to the natural characteristics of the area, which make Bangladesh susceptible to natural disasters, the overall vulnerability is increased due to widespread poverty and overcrowding which means the death toll from disasters is often very high (Penning-Rowsell *et al.* 2013); both from the actual event and in the following weeks (or months) due to the spread of disease (Penna and Rivers, 2013).

2.3.1 Bangladeshi aquaculture

Aquaculture is an extremely important industry in Bangladesh with aquatic resources providing a vital source of nutrition, income, employment and international trade (Azad *et al*., 2009; Dey *et al*. 2010). Fish are the second most valuable agricultural crop and account for more than 60% of animal source food within the Bangladeshi diet (Belton *et al*. 2011b). Bangladeshi aquaculture has grown significantly over the period between 1950 and 2011 (Fig. 2.5) and the top five species produced by quantity are all freshwater fish and four out of the five species are carps (Table 2.3). As shown in Table 2.3, three species of carp are also amongst the top five produced species by value in addition to giant river prawn (*M. rosenbergii*) and giant tiger prawn (*P. mondon*).

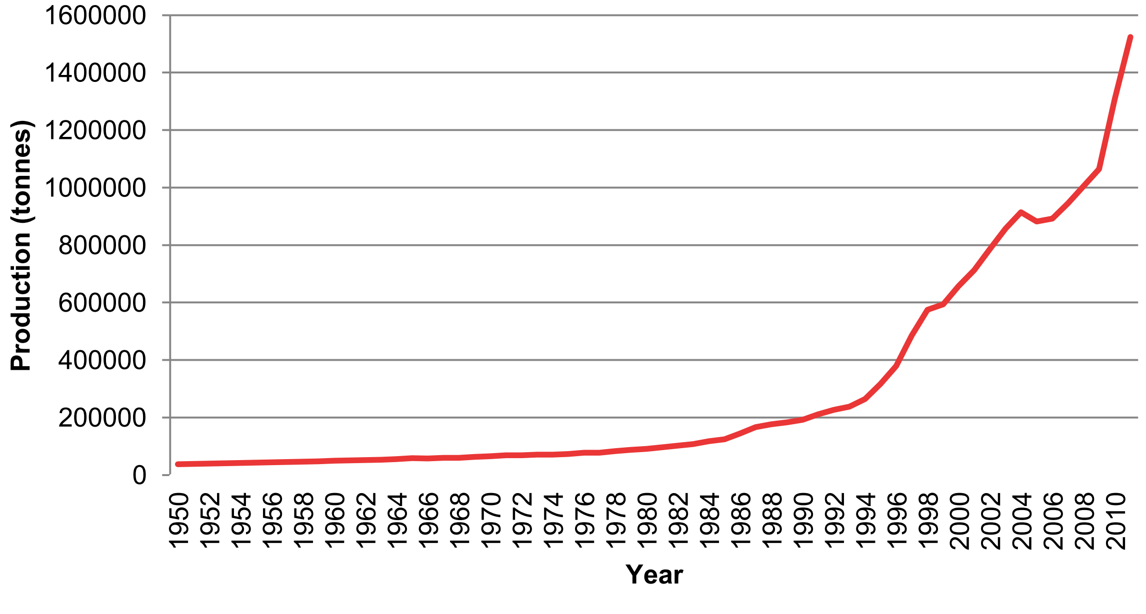


Figure 2.5: Growth of aquaculture In Bangladesh between 1950 and 2011 (FAO, 2013b)

Table 2.3: Top five aquaculture species by quantity (tonnes) and value (USD$) in Bangladesh for 2011 (FAO, 2013b)

Quantity	Tonnes	%	Value	000' USD$	%
Rohu (*Labeo rohita*)	277,000	18	Rohu (*L. rohita*)	661,000	17
Catla (*Catla catla*)	215,000	14	Catla (*C.catla*)	450,000	12
Mrigal carp (*Cirrhinus mrigala*)	158,000	10	Giant tiger prawn (*P. monodon*)	389,000	10
Striped catfish (*P. hypopthalmus*)	156,000	10	Giant river prawn (*M. rosenbergii*)	296,000	8
Silver carp (*Hypopthalmicthys molitrix*)	139,000	9	Mrigal carp (*C. mrigala*)	267,000	7
Total (all species)	1,520,000	100	Total (all species)	3,800,000	100

Shrimp (*P. monodon*) and prawn (*M. rosenbergii*) are the second highest value export commodities after readymade garments, generating US$412 million in 2009/2010 (Belton *et al*. 2011b). In 2011 the estimated production of giant tiger prawn and giant river prawn was approximately 57,000 and 40,000 tonnes respectively (FAO, 2013b). However, as discussed by Ahmed (2013), there are environmental issues which increasingly threaten the sustainability of prawn and shrimp farming such as land transformation and climate change. The future of the industry is dependent on economic growth, social justice and environmental sustainability which can all be promoted within the EAA (Ahmed, 2013).

The expansion of the shrimp aquaculture industry began in 1971. However it was not until the 1980s, when brackish water shrimp farming began to attract urban-based outside investors, that the industry began to take off and shrimp exports have been rising since then (Azad *et al.*, 2009; Ito, 2004). Currently coastal shrimp farming in Bangladesh is attempting to increase production and gain the subsequent expected economic benefits by moving from the traditional extensive farming methods to semi-intensive culture systems (Siddique and Volpe, 2009). Likewise, in the past two decades the culture of freshwater prawn (*M. rosenbergii*) has attracted significant attention due to its export potential and it is now one of the most important sectors for the national economy (Ahmed *et al.*, 2008c).

2.3.2 Bangladeshi study area

The study area in Bangladesh lies just below the Tropic of Cancer, covering an area of 10,148km^2 between E88°54' and E90°18', N23°30' and 21°54' (Fig. 2.6). Most of the study area is located within Khulna division; however the eastern part of the study area does expand into the Dhaka and Barisal divisions. Furthermore, due to the topographical features of the study area, and the natural catchment, the western boundary of the study area encroaches slightly into India in a few instances. The study area also includes part of the Sundarbans; one of the world's largest mangrove forests. The forest covers 6,017km^2 of the coastal zone in Bangladesh, is rich in biodiversity and supports many livelihoods in the area (Iftekhar and Saenger, 2008).

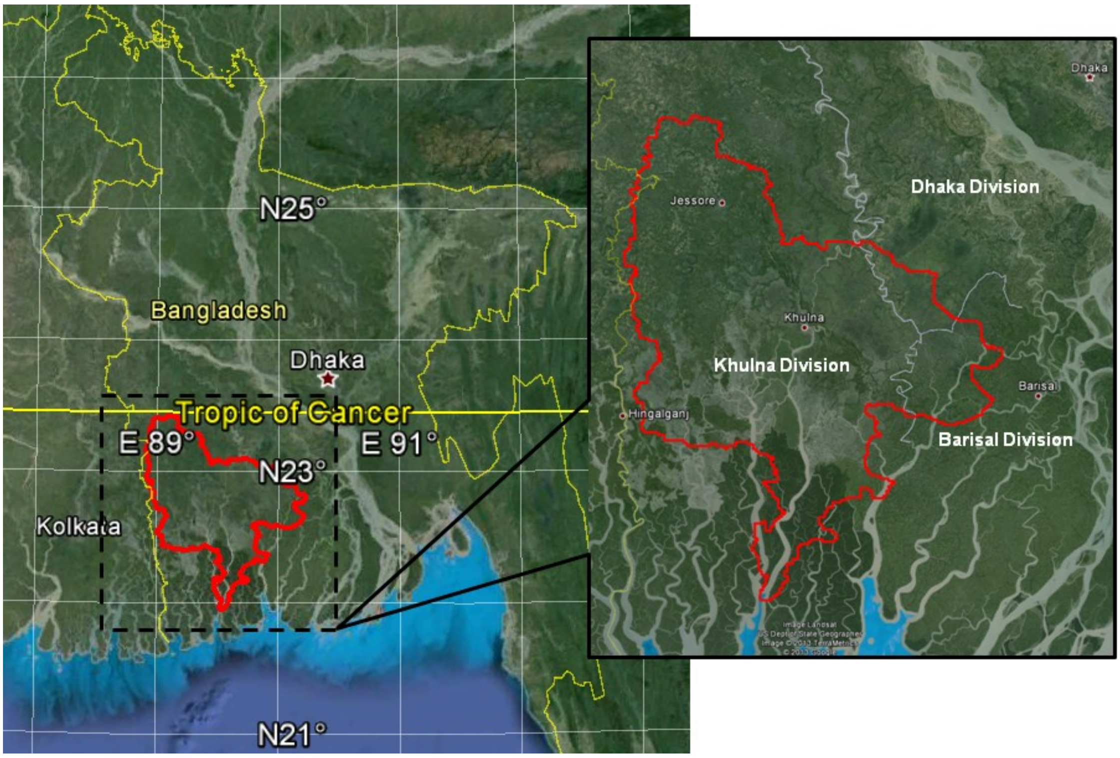


Figure 2.6: Study area in Bangladesh and administrative districts within the boundary (Google Earth, 2013)

There are several key towns and cities located in the study area, of which Khulna, located on the banks of the Rupsa and Bhariab rivers, is the largest with a population of almost 1.4 million making it the third largest city in Bangladesh (Whyte and Lin, 2009). Khulna is an industrial city which was once a major exporter of jute; however, the introduction of artificial fibres led to the decline of the sector and the city now relies on the export of frozen shrimp and port activities (Ahmed, 2003). The port of Mongla, 50km from Khulna in the south of the study area, is also an important export centre where prawn and shrimp are exported to markets in the USA, Japan and Europe (Ahmed, 2003). Other crops that are grown throughout the region include rice and fish, which are often grown together with prawns in ghers (Ahmed, 2013). Prawn monoculture is uncommon, with most farmers opting for prawn and fish polyculture with rice (Wahab *et al*. 2012).

The culture of black tiger shrimp (*P. monodon*), known locally as bagda, and giant freshwater prawn (*M. Rosenbergii*), which the locals refer to as golda, is widespread throughout the southwest of the country (Belton *et al*., 2011b). The south-western coastal region, where the study area is located, is responsible for a major share of total shrimp produced in Bangladesh and the region is popularly referred to as the “shrimp zone” of the country (Datta *et al*. 2010). The highest concentration of shrimp and prawn farms is in the greater Khulna region and the districts of Khulna, Satkhira and Bagerhat (Belton *et al*., 2011b). Most of the shrimp farms in the coastal region are extensive systems which rely on natural productivity and little or no additional fertilization or feeding (Belton *et al*., 2011b). Improved extensive systems follow the same method of farming but use slightly higher stocking densities which result in higher yields, while semi-intensive systems include heavy feeding, waste removal, aeration and higher stocking densities (Belton *et al*., 2011b).

Although prawn and shrimp aquaculture is a vital livelihood for many, and a significant contributor to the economy, the development and expansion of farms in the south west has had significant negative impacts. Ghers are low-lying rice fields which are used for freshwater prawn culture (New and Kutty, 2010) and their construction has often occurred in an unplanned manner (Azad *et al*. 2009). As noted by Azad *et al*. (2009), to save labour costs famers often shared dikes rather than build their own which resulted in poor drainage and insufficient irrigation systems, whilst blocking canals and making the farms reliant on rainfall. Furthermore, the expansion of shrimp farming in the south west has had significant detrimental impacts on the surrounding land, water and local communities as discussed by Deb (1998). As a result, any future development should be carefully planned and managed to ensure potential negative impacts are minimised. Figs 2.7 and 2.8 show examples of prawn and shrimp farms in the study area.

Figure 2.7: Prawn farms in Bangladesh

Figure 2.8: Shrimp farms in Bangladesh

2.4. China

China is the world's most populous country, with an estimated population of almost 1.3 billion people in 2011 (UN, 2013). It is also the second largest country; extending across much of Eastern Asia (Fig. 2.9), covering over 9,500,000 km^2 (UN, 2013). Consequently, China is a vast country with an exceptionally diverse physical environment which covers almost every type of terrestrial biome (Veeck *et al*. 2011). However, high demands for space, resources and increasing urbanization has led to significant environmental issues and many ecosystems such as forests are now fragile and degraded, requiring rehabilitation and protection to develop a sustainable environment (Yin, 1998). In recent years the government has invested billions of dollars to try and protect the environment through environmental programs. However, these have had varying success (Liu and Diamond, 2008).

Figure 2.9: Map of China and the surrounding area (Google, 2013)

The northern and western regions of China are semi-arid and arid, whilst the southern regions are humid, extending to Hainan Island, a subtropical island in the south east (McBeath and McBeath, 2010). There is a high degree of natural climatic variability due to changes in precipitation from south to north, atmospheric oscillations and the East Asian monsoon (Fu *et al*. 2008; McBeath and McBeath, 2010). During the rainy season, strong monsoons bring heavy precipitation to the North China Plain and the humid areas in the south also experience heavy precipitation during these months, although there can also be drought conditions due to the El Niño Southern Oscillation (McBeath and McBeath, 2010; Veeck *et al*. 2011). Southeast China is also highly susceptible to typhoons, particularly during the period from May to October (Fu *et al*. 2008).

2.4.1. Chinese aquaculture

Although China has 22% of the global population it contains just 7% of the world's arable land and therefore food security is a key issue for the country (McBeath and McBeath, 2010). The aquaculture industry continues to grow with over 50,000,000 tonnes produced in 2011 (Fig. 2.10). Kelp, carp and shellfish are the top aquaculture species by quantity, however in terms of value, Whiteleg shrimp (*L. vannamei*) was the top species; representing 9% of the total value of all farmed species (Table 2.4). Although production (quantity) is dominated by carps and aquatic plants, Nile tilapia (*O. niloticus*) and Whiteleg shrimp (*L.vannamei*) are also commonly farmed; in 2011 production was estimated at 1,080,000 and 1,330,000 tonnes for tilapia and shrimp (FAO, 2013b). As a result, China is the top producer for both species worldwide.

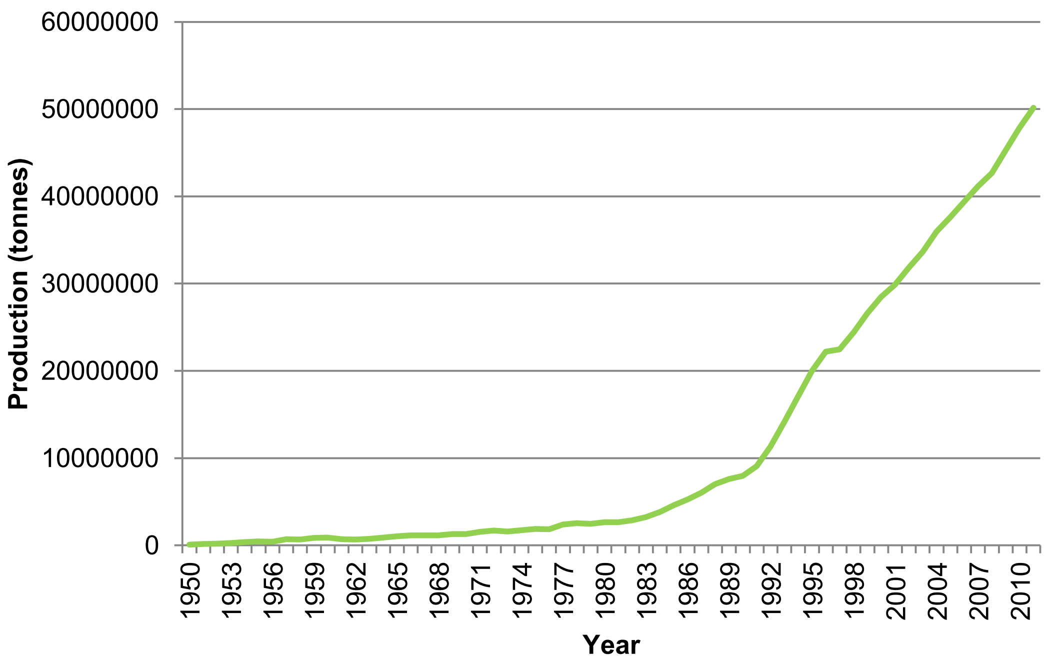


Figure 2.10: Growth of Chinese aquaculture between 1984 and 2011 (FAO, 2013b)

Table 2.4: Top five aquaculture species by quantity (tonnes) and value (USD$) in China for 2011 (FAO, 2013b)

Quantity	**Tonnes**	**%**	**Value**	**'000 USD$**	**%**
Japanese kelp (*Laminaria japonica*)	4,540,000	9	Whiteleg shrimp (*P. vannamei*)	5,820,000	9
Grass carp (*Ctenopharyngodon idellus*)	4,440,000	9	Grass carp (*C. idellu*)	5,600,000	9
Cupped oysters (*Crassostrea* spp.)	3,760,000	7	Silver carp (*H. molitrix*)	4,680,000	7
Silver carp (*Hypophthalmichthys molitrix*)	3,710,000	7	Chinese mitten crab (*Eriocheir sinensis*)	4,520,000	7
Japanese carpet shell (*Ruditapes philippinarum*)	3,610,000	7	Bighead carp (*Hypophthalmicthys nobilis*)	3,420,000	5
Total (all species)	50,200,000	100	Total (all species)	64,300,000	100

Tilapia was one of the first exotic species introduced to China and is often considered the only alien finfish species that is aquaculturally important to the country (De Silva *et al.*, 2006; Liu and Li, 2010). Production of tilapia increased slowly between 1950 and 1988; during this time China produced less tilapia than other Asian countries such as Taiwan, Indonesia and the Philippines (El-Sayed, 2006). From 1989 onwards there was a boom in Chinese tilapia production where the average annual growth rate was over 20% (El-Sayed, 2006). This rapid expansion was significant for the industry and China has now been the dominant producer and exporter of tilapia for over a decade (Liu and Li, 2010). Although the industry continues to grow, one of the biggest constraints is low temperatures which restrict the areas where tilapia can be cultured (Sifa et al. 2002). Figure 2.11 shows some examples of tilapia farms in China.

Figure 2.11: Tilapia farms in Maoming, Guangdong province, China

Low yield, extensive shrimp farming for household consumption and the local market began in the late 1970's along the eastern coast of China (Biao & Kaijin, 2007). In the early 1990’s, along with other major shrimp producers in the region, the Chinese shrimp industry suffered major losses due to the outbreak of viral diseases (Miao and Yuan, 2007). The industry gradually recovered by changing culture systems and techniques as well as the introduction of an exotic species (Miao and Yuan, 2007). *P.vannamei* was first introduced to China in 1988 and by 1994 hatchery techniques were established which led to the commercial culture of the species in the late 1990s (Liu and Li, 2010). The shrimp industry has developed rapidly ever since; contributing to the national and rural economy and increasing the supply of shrimp to the domestic and export markets (Miao and Yuan, 2007). Figure 2.12 shows some examples of shrimp farms in China.

Figure 2.12: Shrimp farms in Zhanjiang, Guangdong province, China

2.4.2. Chinese study area

The study area is located in the south east of the country in Guangdong province, although due to the topographical delineation of the catchment the western side of the study area extends into Guangxi province. It lies below the Tropic of Cancer between E109°and E111°, N20° and N23° (Fig. 2.13) and covers 26,225km^2; making it the second smallest area included in this study. The area is located approximately 200 km from the major city of Guangzhou, which is about 170 km from Hong Kong, and the large island of Hainan is also to the south. Both Hainan and Guangdong generally experience a dry season from November to April and a rainy season from May to October (Seto *et al*., 2004).

Figure 2.13: Study area in China and administrative districts within the boundary (Google Earth, 2013)

The southern section of the study area is relatively low elevation whilst the northern section is mountainous with steep slopes which are covered in trees and vegetation. Guangdong province is the most populous province in China (Guo, 2013) and the area is rich in mineral, aquatic and plant resources (Eng, 2005) which allows a wide range of industries to operate within the region. The province has the third highest GRP per capita amongst all provinces of mainland China; however large rural areas still remain relatively poor in comparison (Guo, 2013). Zhanjiang is an economic centre in southwest Guangdong and the port has played a key role in the development of the industry of the area which includes chemicals, textiles, paper, machinery, shipbuilding and sugar refining (Eng, 2005). Rice, vegetables and fruit are grown throughout Guangdong and are an important livelihood for many people. Over 200 varieties of fruit are grown in the province, including pineapples, bananas and lychees, and production is mainly located around Maoming (Guo, 2013). Other major agricultural crops include sugarcane, rice, silkworms, peanuts, subtropical fruits, timber, animals and fish (Eng, 2005). Forests cover 57.5% of the province and there is an extensive network of interconnected waterways with many reservoirs, lakes and fish ponds (Guo, 2013).

In 2010 Guangdong was responsible for almost 47% of tilapia production in China (Matala *et al*., 2013), with much of the production in the area around Maoming. Tilapia production is seen as a source of income for the rural population and some farmers have moved to tilapia production from traditional fish species such as carp (Bean and Xinping, 2006). However in recent years extreme weather events have detrimentally impacted tilapia production; high temperatures have resulted in disease and low temperatures directly reduced output by 25% between 2007 and 2008 (Liu *et al*. 2012). Additionally, tilapia ponds were also damaged by typhoons in 2010 which led to outbreaks of disease and the escape of hundreds of thousands of broodstock and millions of growout crop (Liu *et al*. 2012). Guangdong province is also the largest contributor to the production of *P. vannamei* in China (Sulit *et al*. 2005). The area around Zhanjiang is the centre of shrimp production as it has a well-developed processing industry and a major port for export in addition to favourable geographic environments (Zhang *et al*. 2011).

2.5. Thailand

Thailand extends across 513,120km^2 with borders to Myanmar (Burma) in the west and Laos and Cambodia in the east (UN, 2013) (Fig. 2.14). In 2011 it was estimated that the population was over 69 million, with an estimated population density of 135.5 people per km^2 (UN, 2013). Although they have not been defined formally, Thailand has four distinctive regions that each have unique geographic and cultural characteristics; Northeastern (Pahk Easahn), Northern (Pahk Neuah), Central (Pahk Glahng) and Southern (Pahk Dai) (Hoare, 2004). Almost one third of the area and approximately one third of the population of the country is located within the Northeastern region (UN, 2008). However, compared to the rest of Thailand, the Northeastern region has the lowest per capita income and the farming villages are relatively impoverished as a result of very low levels of productivity due to erratic rainfall, poorer soils and low levels of irrigation (Hori, 2000; UN, 2008).

Figure 2.14: Map of Thailand and the surrounding area (Google, 2013)

The Northern region is mountainous, and most of the population within this area are distributed in the narrow alluvial valleys along the four north-south flowing rivers which join in the northern central plain to form the Chao Phraya river (UN, 2008). The basin of the Chao Phraya, located in the Central region of Thailand, contains the most fertile and extensive agricultural land in the country and is often known as the "rice bowl" (Tingting and Chuang, 2010). Furthermore, the central region is also home to the capital city, Bangkok, through which the Chao Phraya flows until it reaches the Gulf of Thailand. In recent years, rapid population growth, urbanization and industrialization have led to a decline in environmental quality and resource degradation within the Gulf of Thailand (Cheevaporn and Menasveta, 2003).

The Southern region is on the Malay Peninsula where forests cover approximately 28% of the area and farmland covers almost 40%; the area is also rich in rubber and tin (Nijkamp and Vreeker, 2000). The Southern region in Thailand was one of the areas worst affected (after Indonesia, Sri Lanka and India) by the series of deadly tsunamis triggered by the 9.2 magnitude earthquake which occurred off the coast of Northern Sumatra on the 26th December 2004 (Hutanuwatr *et al*. 2013). The impacts were widespread; towns and villages were destroyed, livelihoods ruined and thousands of people were displaced affecting both the areas that were hit by the wave and beyond (Rigg *et al*. 2005; Hutanuwatr *et al*. 2013).

2.5.1. Thai aquaculture

Aquaculture is a significant contributor to the Thai economy and supports many local and rural livelihoods. In terms of quantity, Thailand is ranked sixth in the world with regard to aquaculture production (FAO, 2012) and Fig. 2.15 shows the growth in aquaculture production from 1950 to 2011. There was a significant increase between the 1980's and 2000's; however, there have also been some serious disease outbreaks affecting shrimp which have significantly impacted production. Due to disease issues many farmers switched from farming *P. monodon* to *L. vannamei* as it is less susceptible and there are other benefits (Lebel *et al*., 2010). Lebel *et al.* (2010) assessed the culture of *L. vannamei* and *P. monodon* in Thailand and found that *P. vannamei* requires substantially fewer resources and produces less waste than *P. monodon*. According to the assessment by Lebel *et al.* (2010) *P. monodon* required 9 times more land and 3 times the volume of water than *L. vannamei.* Furthermore, the feed formulae for *L. vannamei* requires less fish meal and production is more efficient converting feed into shrimp meat. Table 2.5 shows that whiteleg shrimp (*L. vannamei*) accounted for over 50% of production by quantity and over 70% of production by value in 2011. Table 2.5 highlights the importance of shrimp to Thailand. However the shrimp market is unstable and fluctuations with price and disease outbreaks can significantly impact production. The Thai government is now promoting sustainability in the industry rather than just expansion (Hishamunda *et al*. 2009).

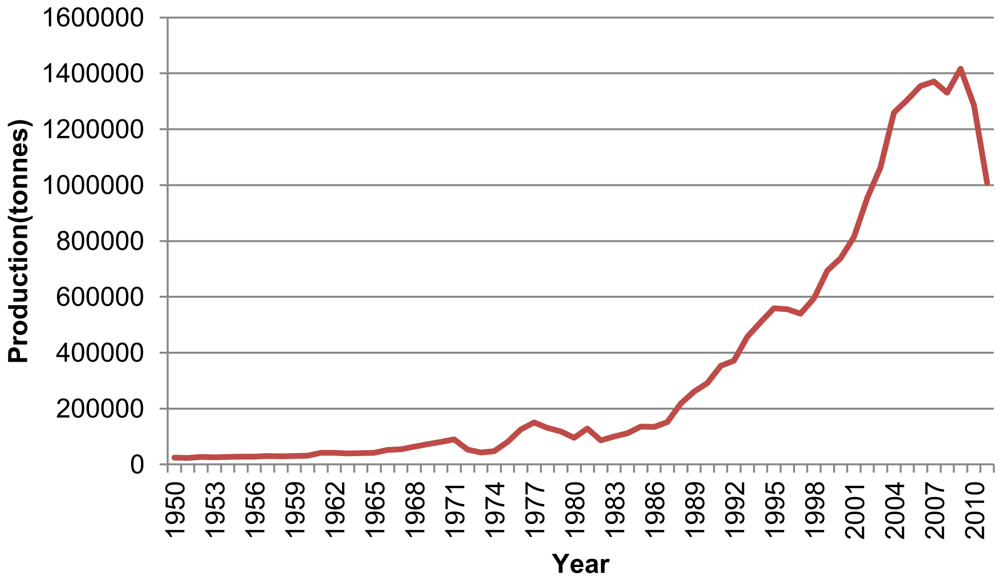


Figure 2.15: Aquaculture production in Thailand between 1950 and 2011 (FAO, 2013b)

Table 2.5: Top five aquaculture species by quantity and value in Thailand for 2011 (FAO, 2013b)

Quantity	**Tonnes**	**%**	**Value**	**'000 USD$**	**%**
Whiteleg shrimp (*P. vannamei*)	511,000	51	Whiteleg shrimp (*P. vannamei*)	1,840,000	72
Nile tilapia (*O. niloticus*)	139,000	14	Nile tilapia (*O. niloticus*)	197,000	8
Catfish, hybrid (*Clarias gariepinus x Clarius macrocephalus*)	95,400	9	Catfish, hybrid (*C. gariepinus x C. macrocephalus*)	139,000	5
Green mussel (*Perna viridis*)	84,700	8	Giant river prawn (*M. rosenbergii*)	95,200	4
Blood cockle (*Anadara granosa*)	40,500	4	Barramundi (*Lates calcarifer*)	61,600	2
Total (all species)	1,010,000	100	Total (all species)	2,560,000	100

Although shrimp is by far the most important aquaculture species in Thailand, the second most important species is Nile tilapia which accounts for approximately 14% and 8% of aquaculture production by quantity and value respectively (Table 2.5). Belton and Little (2008) suggest that the tilapia industry has emerged in the central region of Thailand due to the increased demand for aquaculture products from the relatively affluent consumers occurring as a result of urbanization and industrialization. Tilapia are commonly farmed in polyculture systems where tilapia are grown with assorted carp species which fill ecological niches in the pond and help maintain water quality (Belton *et al*. 2009). Cage culture of tilapia also occurs in Thailand, however, studies have found that cages are riskier than ponds and more cage farms fail to break even due to poor performances as a result of mortalities relating to industrial, agricultural or municipal pollution (Belton *et al*. 2010). Belton *et al*. (2009) suggest that more farmers will move from cage culture in multi-use waterbodies to intensive cage based culture in aerated ponds as this method is less vulnerable to wider environmental pressures. Fig. 2.16 shows Tilapia ponds in the Chachoengsao province.

Figure 2.16: Tilapia farms in Chachoengsao, Thailand

Shrimp farming in Thailand began in traditional extensive systems, farming banana shrimp (*P. Merguiensis*) and school shrimp (*Metapenaeus sp*.), along the coastline of the inner Gulf of Thailand as a by-product of the salt pens (Aksornkoae and Tokrisna, 2004). The area was ideally suited for shrimp farming due to the nutrient rich water and abundance of wild seed (Tokrisna, 2006). In the late 1960's the number of shrimp farms increased due to better economic value from shrimp over salt (Aksornkoae and Tokrisna, 2004). During the 1980's to the early 1990's there was rapid development in the industry; largely due to the adoption of intensive farming techniques from Taiwan and the success of hatcheries (Tokrisna, 2006). However, this rapid expansion came at a cost as mangrove forests were destroyed and replaced with shrimp ponds (Barbier and Cox, 2004). There are other detrimental environmental issues associated with the exponential rise in shrimp culture such as salinization of land and freshwater supplies, land subsidence, poor water quality and abandoned shrimp ponds in addition to social consequences such as displacement and loss of livelihood (Flaherty and Karnjanakesorn, 1995; Dierberg and Kiattisimkul, 1996). With a lack of available space in coastal environments and increasing negative attention focusing on coastal shrimp farming the industry looked for alternative solutions to meet the growing demand for shrimp (Flaherty and Vandergeest, 1998). One of the major developments was low salinity culture which allowed the use of inland areas for culture (Roy *et al*. 2010) and therefore increased the potential for shrimp production. Fig. 2.17 shows inland shrimp farms in central Thailand.

Figure 2.17: Shrimp farms in Chachoengsao, Thailand

2.5.2. Thai Study area

The study area is located in the Central region of Thailand between E99° and E103°, N12° and N15° (Fig. 2.18) covering an area of 48,319km^2 which includes the city of Bangkok. Central Thailand generally has a rainy season from May to October and a dry season from November to April (Szuster, 2006). During the rainy season of 2011 Thailand experienced its worst flood in 50 years when 65 out of the 77 provinces were inundated with flood waters, killing 756 people and impacting the lives of a further 14 million people (Rakwatin *et al*. 2013). The river at the centre of the flood was the Chao Phraya River which runs through the middle of Bangkok and the catchment of the river covers approximately 160,000km^2, which is 30% of the total area of Thailand (Komori *et al*. 2012). The study area covers a sub catchment of the lower reaches of the river. This area has low elevations which make it susceptible to flooding and although there are mitigation methods in place to prevent flooding, such as dams and reservoirs, high seasonal rainfall, such as the levels experienced in 2011, can result in widespread damage (Komori *et al*. 2012). Furthermore, during the dry season, saltwater can intrude up to 175km inland in the central region due to low gradients and stream flows (Szuster, 2006). This can have an impact for all users, particularly the agricultural sector.

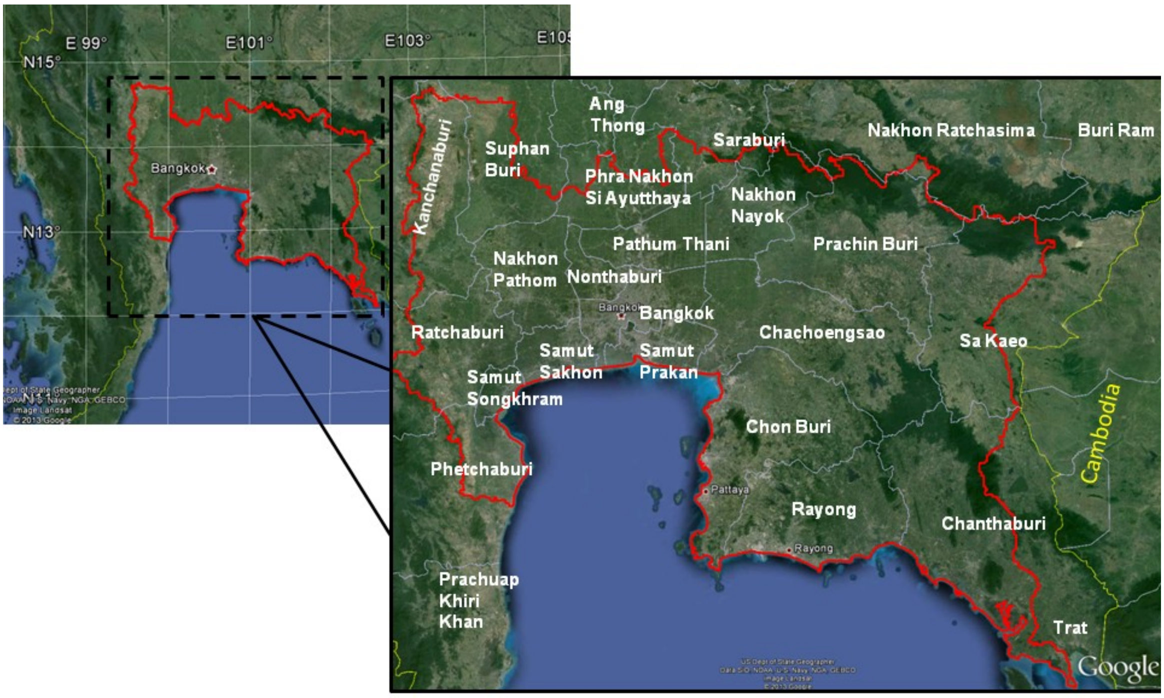


Figure 2.18: Study area in Thailand and administrative districts within the boundary (Google Earth, 2013)

Many major towns and cities are located in the study area with the capital city Bangkok in the middle. Bangkok and other regional cities in Thailand have grown rapidly in the last two decades and as a result there are issues associated with overcrowding, water pollution, congestion and air pollution in many areas (Nitivattananon and Noonin, 2008). Rapid industrialisation is occurring in the peri-urban areas around Bangkok where major firms are setting up businesses in industrial estates (Webster, 2004).

Consequently, the landscape around Bangkok is a mosaic with green fields, factories and settlements crossed by freeways, arterial roads and rail lines (Webster, 2004).

Although today Thailand is a rapidly industrialising country, only twenty years ago rice was the mainstay of the economy (Krairapanond and Atkinson, 1998), particularly in the area where the study area is located. After the Second World War, Thailand increased production and export of rice to help meet the global food shortage and, in turn, stimulate trade (Belton and Little, 2008). These rice exports provided the foundation of Thailand's economic development and were the precursor to the country joining the global economy (Flaherty *et al*. 1999). However, the development and improvement of irrigation schemes during the 1950's in the Central region which allowed agricultural intensification also resulted in widespread destruction of wetland habitat and a decline in the productivity of the inland fishery (Belton and Little, 2008). By the 1980's it was apparent that there was a severe water management crisis in Thailand and wider resource management was required (Krairapanond and Atkinson, 1998). In the mid 1980's the Thai government started to define and develop strategies, policies and plans for river basin management (Krairapanond and Atkinson, 1998) and the stabilization of water supplies, in addition to the diminished wild fish stocks, led to widespread aquaculture development in the region (Belton and Little, 2008).

The consequences of rapid development of the shrimp industry have already been discussed and farms are located in coastal areas in the study area; particularly in Chanthaburi province. The development of low-salinity methods for shrimp farming allowed expansion further inland with some of the most extensive development in the province of Chachoengsao in Thailand's Central Plain (Braaten & Flaherty, 2000). As discussed by Flaherty and Vandergeest, (1998) the Central region was ideal for development as irrigation networks were already available throughout the area. Additionally, the Central region had low land prices compared to the coast and a lack of institutional control and regulation allowed rapid development across the area

(Flaherty and Vandergeest, 1998). However, due to the elevation of salts in the surrounding environment, the Thai Government has placed a moratorium on inland marine shrimp farms in areas designated as freshwater ecosystems by provincial governments (Roy *et al*. 2010). Although shrimp is the dominant species in the area, farmers also took advantage of existing irrigation networks to establish tilapia culture across the Central region, as discussed by Belton and Little (2008).

2.6. Vietnam

Vietnam is located in South East Asia and covers an area of 330,957km^2, has an estimated population of over 88 million and a population density of 268.3 per km^2 (UN, 2013). It has a long coastline which extends from the Gulf of Thailand and the South China Sea to the Gulf of Tonkin, and the country borders Cambodia and Laos in the west and China in the north (Fig. 2.19). Within Vietnam the terrain is highly varied from the low, flat land of the deltas (Mekong and Red rivers) to the hilly and mountainous regions of the northeast and northwest. Approximately 28% of total land cover is agriculture, which is mainly concentrated in the southeast, central highlands, northeast, north central coast regions, Mekong and Red River delta regions (Ha *et al*. 2004).

Figure 2.19: Map of Vietnam and the surrounding area (Google, 2013)

The climate varies significantly across the country. The north experiences a temperate to subtropical climate and is affected by the northeast monsoon wind which makes the climate hot and rainy from May to October and cold and sunny from November to April (Ha *et al*. 2004). While the south generally has a dry season from December to April and a rainy season from May to November (Sakamoto *et al*. 2009).

2.6.1. Vietnamese aquaculture

There has been rapid growth in the Vietnamese aquaculture sector since it began in the early 1960s, largely due to the diversification of systems and techniques, in addition to the intensification of the culture of highly important species such as pangasius catfish over the past two decades (Phuong & Oanh, 2010). Fig. 2.20 shows the increase in production from 1950 to 2011 and it highlights the recent rapid growth, beginning in the 1990's, which coincides with the rise of the pangasius sector (Belton *et al*. 2011a). Pangasius is the most produced species; representing approximately 38% and 30% in terms of both quantity and value of all of Vietnams farmed species, respectively (Table 2.6). Whiteleg shrimp is also an important species accounting for approximately 6% and 13% of total production by quantity and value (Table 2.6).

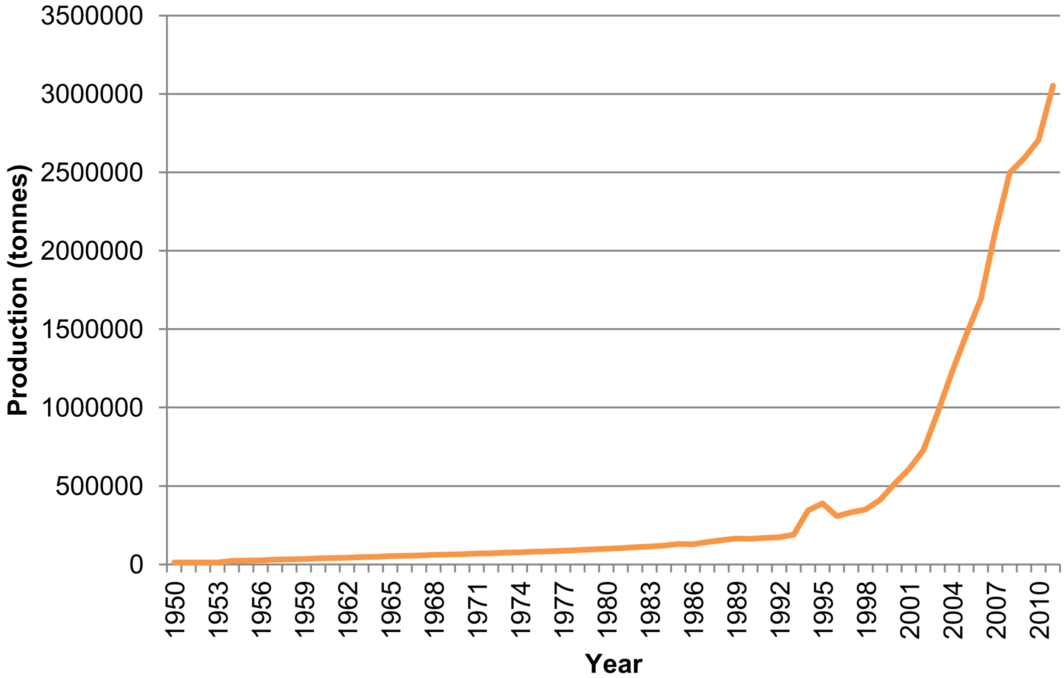


Figure 2.20: Aquaculture production in Vietnam between 1950 and 2011 (FAO, 2013b)

Table 2.6: Top five aquaculture species by quantity and value in Vietnam for 2011 (FAO, 2013b)

Quantity	Tonnes	%	Value	'000 USD$	%
Pangas catfishes (*Pangasius* spp.)	1,150,000	38	Pangas catfishes (*Pangasius* spp.)	1,730,000	30
Cyprinids (Cyprinidae)	490,000	16	Giant tiger prawn (*P. monodon*)	1,200,000	21
Giant tiger prawn (*P. monodon*)	300,000	10	Whiteleg shrimp (*P. vannamei*)	748,000	13
Whiteleg shrimp (*P. vannamei*)	187,000	6	Cyprinids (Cyprinidae)	735,000	13
Marine molluscs (Mollusca)	180,000	6	Common carp (*Cyprinus carpio*)	225,000	4
Total (all species)	3,050,000	100	Total (all species)	5,700,000	100

P. bocourti (also known as basa) and *P. hypophthalmus* (also known as tra) have been cultured in Vietnam since the 1960's when they were produced for local domestic consumption (Belton 2011a,c). Pangasius catfish are favourable species for aquaculture as they grow quickly, tolerate low dissolved oxygen conditions, are relatively disease free, can be fed inexpensive diets and can be ongrown in simple systems such as floating net cages, fenced enclosures and earthen ponds (Lucas, 2012). Market liberalisation in the 1980's and the development of artificial propagation techniques in the late 1990's were significant steps for the Vietnamese pangasius industry and production has increased significantly since then (Belton *et al*. 2011a). As noted by Belton *et al*. (2011c) no development of any agricultural export crop in any location has been comparable to the rise of intensive export orientated pangasius catfish production in Vietnam with regard to speed and scale. However, the rapid growth of pangasius production and subsequent international trade has drawn criticism from many areas as discussed by Bush and Duijf (2011) and Little *et al*. (2012). Phuong and Oanh (2010) recommend that urgent steps are taken to develop sustainable production systems using best management practices (BMP). Fig. 2.21 shows some examples of pangasius farms in the Mekong Delta of Vietnam.

Figure 2.21: Pangasius farms in Can Tho/An Giang, Vietnam

Modern shrimp farming in Vietnam began in the 1980s after the country launched the economic reform (Doi Moi) and the government actively encouraged and supported the development of shrimp farming (Nhuong *et al*., 2002; Raux *et al*. 2006). Between 1987 and 1988 controlled stocking of hatchery-produced postlarvae (PL) was introduced and in 1987 a governmental decree officially promoted shrimp culture for export (Raux *et al.*, 2006). Another major step in the sector occured in 2000 when the government issued a resolution allowing farmers to transform coastal saline rice fields into shrimp farms (Nhuong *et al.*, 2002). *Penaeus merguiensis* and *Penaeus indicus* are the dominant endemic shrimp species in the Mekong delta. However, progress made by hatcheries moved farms towards the culture of *P. monodon* and to a lesser extent *P. merguiensis* (Raux *et al.*, 2006). *P. monodon* was favoured over *P. merguiensis* due to its higher commercial value and shorter time required to reach a marketable size, however, although *P. mondon* can grow in very low salinity, in order to achieve a rate of growth that is both satisfying and lucrative for the commercial market it requires relatively high salinity and temperature conditions (Raux *et al*., 2006). Consequently, many areas in the Mekong delta are not suitable environments for the culture of *P. Monodon* in the rainy season due to low salinity. Uncertainties including disease, high investment costs and volatile markets are a risk for shrimp farmers and many are moving from *P. mondon* culture to *L. vannamei* (Ha *et al*. 2013). As previously mentioned, this practice already occurred in the Thai shrimp industry between 2002 and 2006 as *L. vannamei* requires fewer resources, food production is more efficient and there are fewer problems with disease (Lebel *et al*. 2010). Fig. 2.22 shows some shrimp farms in Vietnam.

Figure 2.22: Shrimp farms in Soc Trang, Vietnam

2.6.2 Vietnamese study area

The study area is located in the Mekong Delta in southern Vietnam, extending slightly into Cambodia due to the natural characteristics of the catchment and covers an area of 66,283km^2 (Fig. 2.23). The delta has a network of canals, scattered settlements, roads on levees, rice in swampy depressions, depleted forests and mangroves (Campbell, 2009). Anthropogenic modifications are visible throughout the delta and include the many man-made channels that have significantly altered the natural landscape and hydrodynamic conditions (Campbell, 2009; Hung *et al.*, 2012).The study area includes part of the capital city Ho Chi Minh City (formally Saigon) and other major cities and towns including Can Tho, Soc Trang, Ca Mau and Rach Gia and Gia and extends almost to Cambodia's capital, Phnom Penh (Fig. 2.23). Ho Chi Minh City is the most important national economic centre with regards to industry and in the Mekong Delta industrial production is highly concentrated within the three provinces of Can Tho, Long An and Kien Giang (Garschagen *et al*. 2012). In recent years there has been rapid growth in industry within the Mekong Delta along with an increase in foreign investment and trade, urban development, agriculture and fisheries (Fabres, 2011). The most important industrial sector is food-related industry, particularly food processing, production of agricultural and aquacultural products (feeds, seeds, pesticides etc), equipment and machinery (for aquaculture and agriculture) in addition to textile and building material production (Garschagen *et al*. 2012).

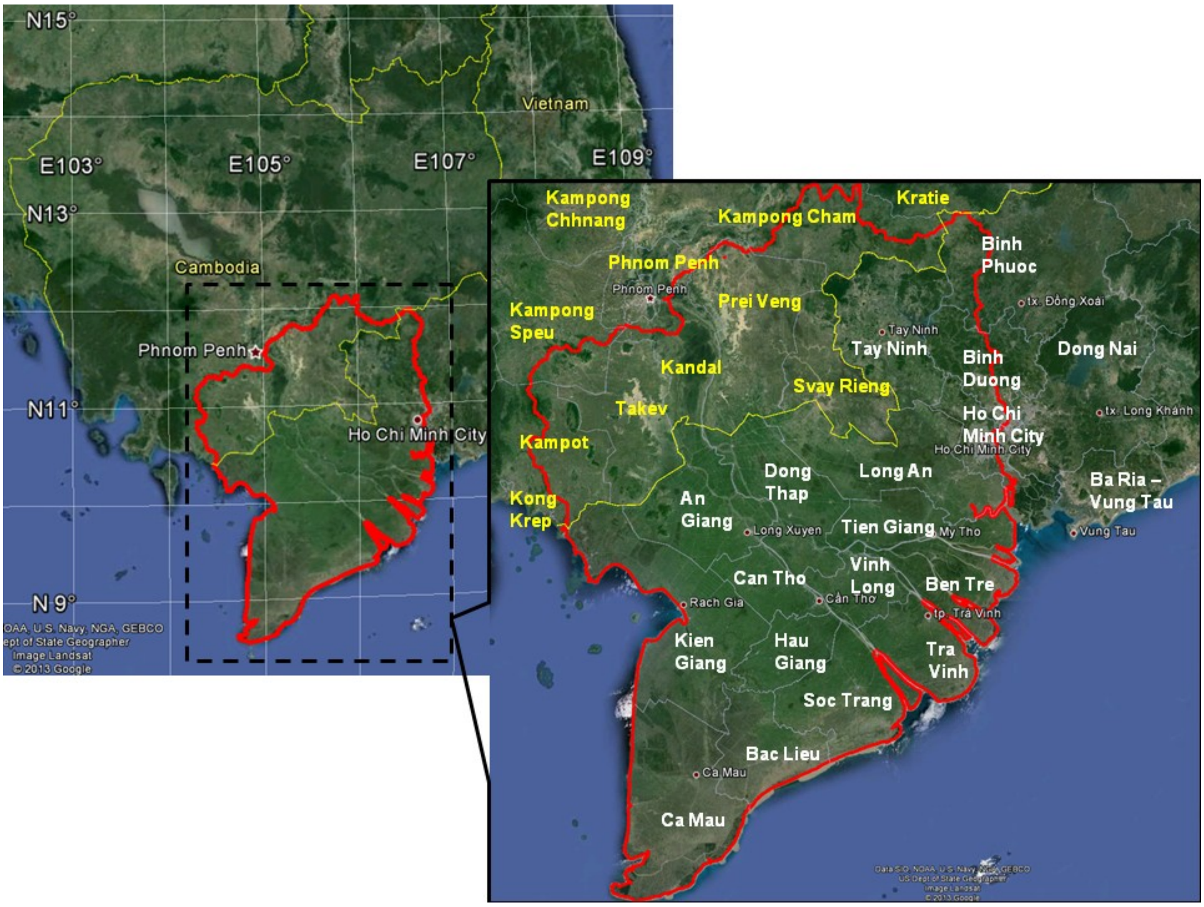


Figure 2.23: Study area in Vietnam and administrative districts within the boundary (Google Earth, 2013)

The Mekong is the 12th longest river in the world, stretching 4880km from China, flowing through Burma (Myanmar), Thailand, Laos, Cambodia and Vietnam until it reaches the South China Sea (Gupta and Liew, 2007). The Mekong Delta starts in Cambodia, near Phnom Penh, where, approximately 330km from the sea, the Bassac (the first distributary) leaves the main channel and runs parallel to the Mekong for about 200km before the first interconnecting channel appears (Gupta and Liew, 2007). The largest part of the delta, approximately 39,000km^2, is located in Southern Vietnam where the river drains into the South China Sea (Hung *et al.*, 2012). In the rainy season, large freshwater flows feed the delta's rice crops, however, during the dry season, the river flows are so low that sea water intrudes into the lower reaches of the river, producing brackish water conditions that are unsuitable for rice growth (Douglas, 2005). Saltwater intrusion is a natural phenomenon and commonly occurs in deltaic environments in seasonal patterns that are principally determined by the topography of the area and flow of the river (Miller, 2007).

As noted by Fabres (2011) the delta is the most biodiverse section of the Mekong in terms of fish species with 73 families and 481 species. It is also one of the most productive agricultural areas in the world and approximately 25% of the area is under rice cultivation (Stewart and Coclanis, 2011). However, pollution loads into the Mekong Delta are significant with a mixture of agriculture and aquaculture wastes in addition to urban and industrial effluents (Fabres, 2011). Furthermore, due to the size and scale of the Mekong there are transnational issues which can affect the delta. One of the most controversial issues in the whole of the Mekong river is the development of dams. Approximately 153 major dams are in various stages of development throughout the basin (and different countries) and each of these dams will alter the hydrology, sediment load and water quality of the river and have significant impacts on the delta (Fabres, 2011). The Mekong River Commission (MRC) has been established to work directly with the governments of China, Thailand, Laos and Vietnam on the joint management and sustainable development of the Mekong (MRC, 2013).

The natural geography of the Mekong delta, combined with a strong tradition of fish consumption and rapidly depleting natural resources, means there is high potential for aquaculture in this area (Sinh, 2007). This is confirmed by Raux *et al*. (2006) who note that the Mekong Delta is the biggest aquaculture production area in Vietnam and has a key role in Vietnamese fishing exports. Many of the current aquaculture systems are dependent on the irrigation/drainage network that was developed between the 1980’s and 1990’s for agriculture or were constructed and upgraded by small scale farmers (Sinh, 2007). Agricultural farmers in the Mekong Delta have had to adapt their practices in response to the natural dry season saline intrusion (Brennan *et al*. 2006). As discussed by Brennan *et al*. (2006) one of the adaptations is to develop a rice-shrimp farming system where rice is cultured in the rainy season and shrimp is cultured in the dry season. This has allowed farmers to recoup some of the lost revenue they were previously experiencing and improve livelihoods (Brennan *et al*. 2006). However it is essential that aquaculture development within the catchment is suitably managed as there are environmental issues associated with both the farming of pangasius (Sinh, 2007) and shrimp (Lebel *et al*. 2002) and it is vital that both sectors aim for a sustainable industry.

CHAPTER 3
DATABASE DEVELOPMENT

3.1. Introduction

Geographic Information Systems (GIS) and the associated technology have been available since the 1960's. However the industry only started to develop in the 1980's when computers with the required capabilities became affordable in the commercial environment (Heywood et al. 2002). GIS is described by Davis (2001) as "*a computer-based technology and methodology for collecting, managing, analysing, modelling and presenting geographic data for a wide range of applications*". A more detailed analysis of the structure of a GIS is provided by Longley *et al*. (2005) who separate a GIS into six main components; people, hardware, software, procedures, network and the data. Often the "people" component is overlooked when discussing GIS however users and developers are fundamental to any GIS project as they plan and organise the structure in addition to making decisions on operations and output (Heywood *et al*. 2002).

The database is a primary component of all GIS projects; without it very little analysis can be performed and GIS would simply be a cartographic exercise in drawing maps rather than a powerful analytical tool (Davis, 2001). Despite the necessity of the database there is no uniform method for its construction and as a result a database can be structured differently for alternative projects (Rodriguez-Bachiller and Wood, 2009). As noted by Rodriguez-Bachiller and Wood (2009) it is important to recognise that the development of a GIS database can also be costly, both in terms of time and money.

3.2. Software

The primary GIS software used for analysis was IDRISI Selva [Clarks Lab, Massachusetts, USA]; an integrated GIS and image processing software. Additional GIS procedures were conducted using Manifold 8 [Manifold, Hong Kong] and ArcGIS 10 (ESRI, Redlands, California, USA). These were mainly involved in tasks where the original data files were incompatible with IDRISI. Google Earth [Google, California] was used for background information, digitising layers, identification of key features and for verification purposes. Microsoft Access 2007 [Microsoft, Redmond, Washington, USA] was used for management of attribute data.

3.3. Spatial database

3.3.1. Spatial database preparation

Prior to using geographical data in GIS analysis all data must be in a common georeference system. Georeferencing is the term given to the action of assigning locations to information (Longley *et al*. 2005). There are many different systems available and no one reference system is suitable for all purposes. One of the most commonly used reference systems is the Universal Transverse Mercator (UTM) projection (Samama, 2008), which is a grid consisting of many projections side by side in "zones" rather than one single projection (Aitchison, 2009). The grid extends between 80° North and 80° South latitude and comprises of 60 zones, each of which are 6° wide with adjacent zones overlapping by approximately 30 minutes (Gopi, 2005; Longley *et al*., 2005). The zones are numbered 1 - 60 and a suffix of either N or S is added depending on whether the zone is in the Northern or Southern hemisphere (Aitchison, 2009). The advantages of the UTM system are that it is often used in datasets with global or national coverage (Longley *et al*. 2005), is decimal based and is measured in metres. Consequently the UTM reference system was selected as the system for use in this study.

The study areas in both Vietnam and China were located within one UTM zone (UTM-48N and UTM-49N respectively); however, in Bangladesh and Thailand the study areas were on the boundary between two zones (Fig. 3.1). The UTM system can be used for areas that cross UTM zones. However study areas that extend past the central meridian of the adjacent zone to the selected UTM reference system should be avoided (Spencer *et al*., 2003). Furthermore, extending a zone to cover a particular study area can result in larger distortions than usual and another way of overcoming the hurdle of two zones is to define a special zone with its own central meridian (Herzfeld, 2004; Johnson, 2004; Longley *et al*., 2005). Therefore for Bangladesh and Thailand new reference files were created in IDRISI (bangladesh.ref and thailand.ref respectively) and the details of these reference files and those of China and Vietnam are shown in Table 3.1. Additionally, a resolution of 30m was selected for this study as that is the resolution of Landsat ETM+ satellite imagery which was a major source of data. The dimensions of the windowed area for each of the four countries are shown in Table 3.2.

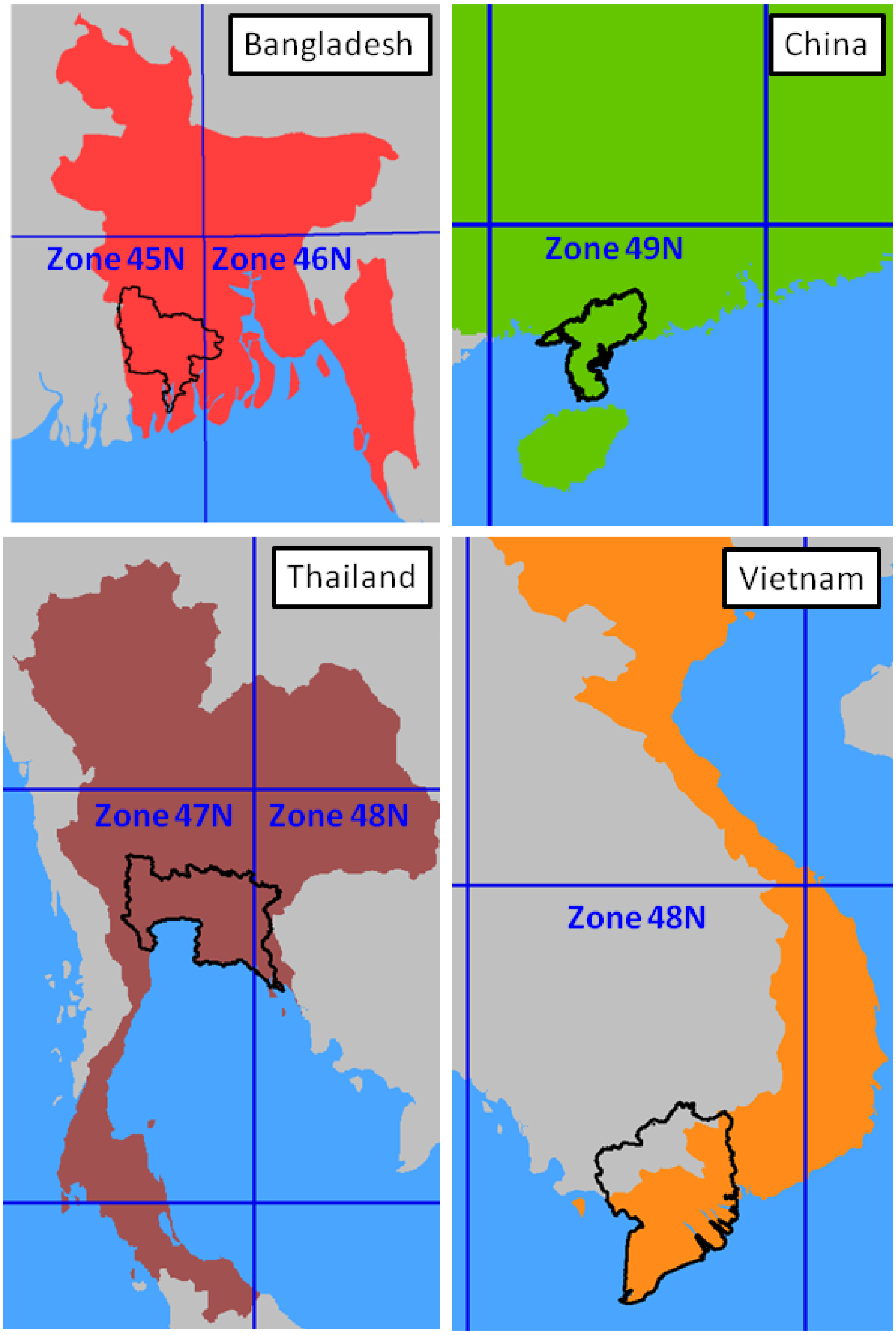


Figure 3.1: Study areas and UTM zones

Table 3.1: Reference parameters that were used in each study area

	Bangladesh	China	Thailand	Vietnam
Ref system	Bangladesh	UTM-49N	Thailand	UTM-48N
Projection	Transverse Mercator	Transverse Mercator	Transverse Mercator	Transverse Mercator
Datum	WGS 84	WGS 84	WGS 84	WGS 84
Delta WGS84	0 0 0	0 0 0	0 0 0	0 0 0
Major s-ax	6378137	6378137	6378137	6378137
Minor s-ax	6356752.314	6356752.314	6356752.314	6356752.314
Origin longitude	89	111	101	105
Origin latitude	0	0	0	0
Origin X	500000	500000	500000	500000
Origin Y	0	0	0	0
Scale factor	0.9996	0.9996	0.9996	0.9996
Units	m	m	m	m
Parameters	0	0	0	0

Table 3.2: Parameters for the windowed study area images

	Bangladesh	China	Thailand	Vietnam
Number of columns	5632	10137	11776	11065
Number of rows	6790	9752	10189	14515
Min. X	472739.4687500	283388.5601903	326575.1875000	396284.0000000
Max. X	641692.7500000	587496.3933469	679836.7500000	728234.0000000
Min. Y	2405323.5000000	2227174.7276798	1328989.2500000	925365.0000000
Max. Y	2609027.0000000	2519721.2542163	1634668.7500000	1360815.0000000
Y Resolution	30.000515	29.998618	30.000932	30
X Resolution	29.998807	29.999786	30.000982	30

3.3.2. Data

One of the main aims of this study was to develop models that could be applied to each of the four study areas and other areas beyond the scope of the project. In this way future applicability of the models was placed at the forefront of the decision making process when selecting data and effort was made to use data that could be obtained freely for almost any study area in the world. Although all of the data were freely available at the time of database development there is no guarantee that this will always be the case as the data comes from many different providers with varying policies. One such example is the use of LandScan population datasets (Fig. 3.2) which were free at the time of model development; however, the data provider has since introduced a subscription fee for data access (Oak Ridge National Laboratory, 2013). This highlights one of the challenges when using spatial data as providers can change the terms and conditions when they wish and other users may not be able to access the information as easily at a later date.

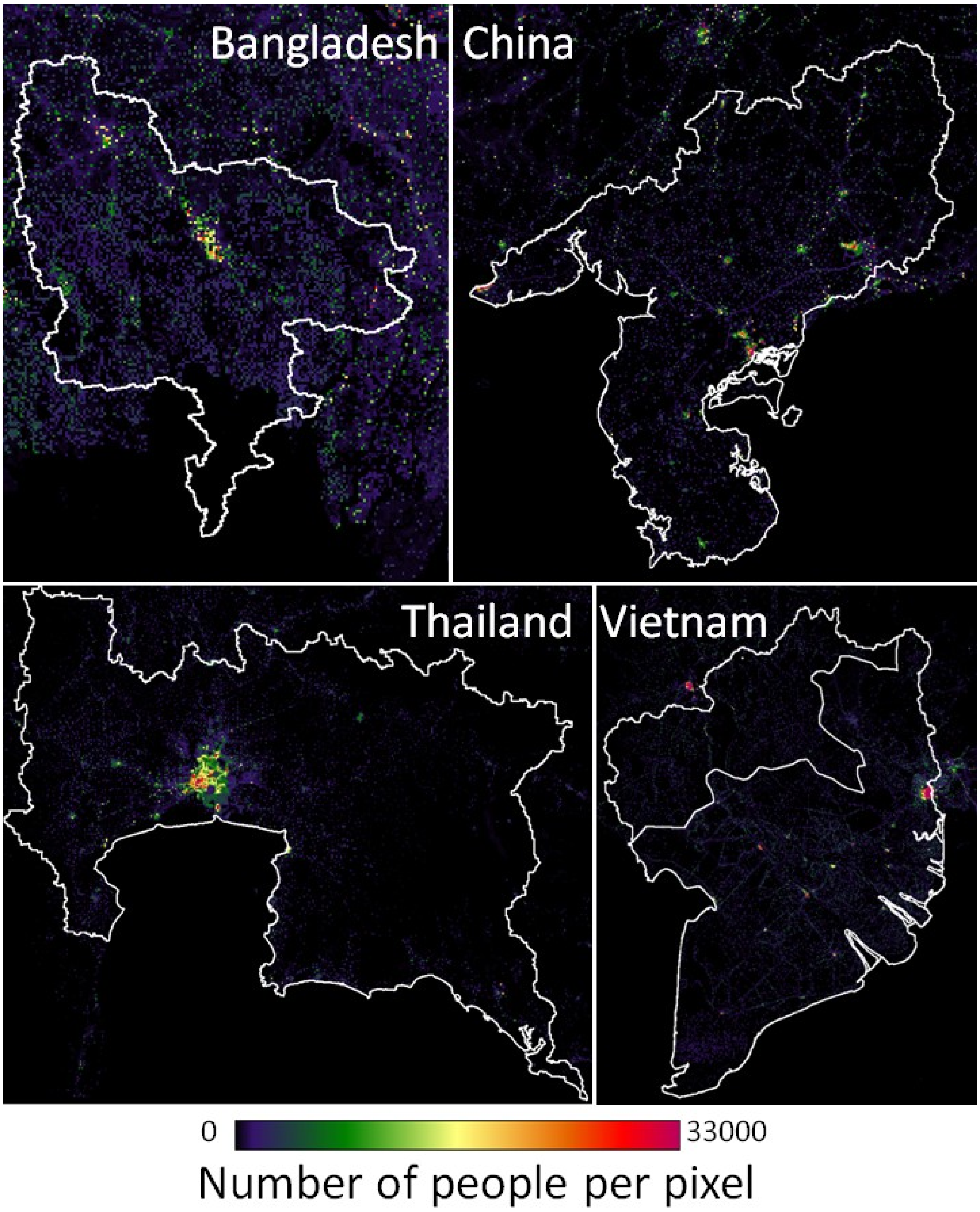


Figure 3.2: LandScan population data representing the ambient population (average over 24 hours) at a resolution of 30 arc seconds for each study area. Produced by Oak Ridge National Laboratory (2008) using census information, spatial data and high resolution imagery.

Selecting, collecting and organising data was time consuming as there are multiple data sources available for many of the parameters and these needed to be screened to find the most appropriate dataset to use. Prior to incorporation within the database each source was evaluated with regard to overall suitability and representativeness for each study area and literature reviews were conducted to identify any potential issues. Some data sources proved to be suitable for one area but unsuitable for another; therefore there was an element of trade off when selecting the data to ensure it was as suitable as possible for all study areas. Fig. 3.3 shows an example of a problem identified during data evaluation; the ASTER Global Digital Elevation Model (DEM) (NASA, 2011) has a resolution of 30m and could have been useful for this study. However, detailed examination revealed significant errors in the Vietnamese study area where large areas had unusual "tiled" patterns and higher values of elevation than would be expected (Fig. 3.3). Therefore the ASTER DEM was not used in this study as it was not suitable for all study areas. Table 3.3 outlines the main sources of data.

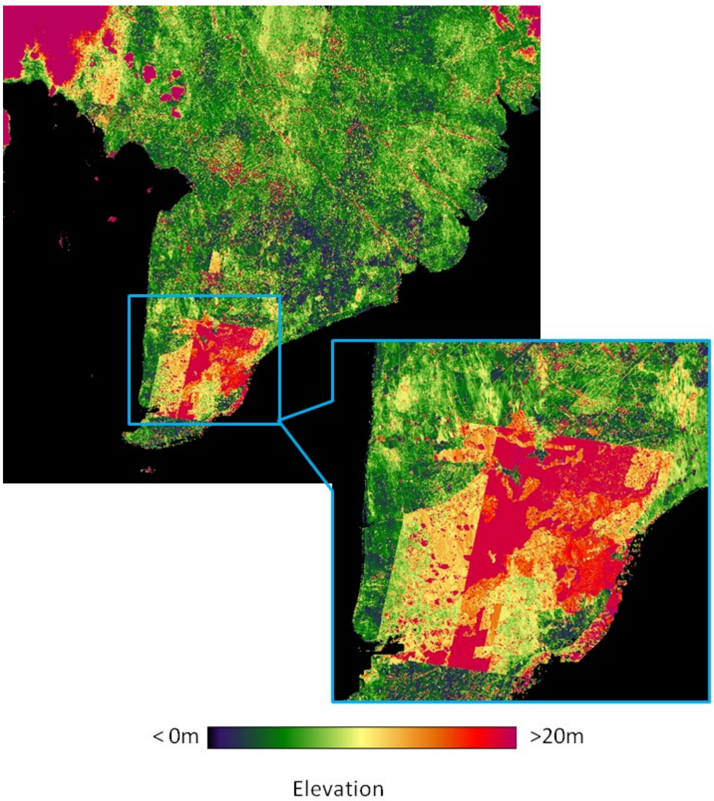


Figure 3.3: ASTER DEM and highlighted area showing errors

Table 3.3. Main sources of data

Name of Layer	Description	Modified using Google Earth	Original Projection	Original Resolution	Source
Catchments / Drainage Basins	Polygon Vector	No	Lambert Azimuthal Equal Area	1km	USGS HYDRO 1K (USGS, 2011)
Coastline	Raster	No	LatLong	90 m	Classified from SRTM DEM (NASA, 2009)
Elevation	Raster	No	LatLong	90 m	SRTM DEM (NASA, 2009)
Evapotranspiration	Raster	No	Latlong	30 arc seconds	CGIAR (Trabucco and Zomer, 2009)
Land use	Raster	No	UTM	30m	Classified from Landsat 7 ETM+ satellite imagery (USGS, 2013)
Population	Raster	No	LatLong	30 arc seconds	Landscan 2008 dataset (Oak Ridge National Laboratory, 2008)
Precipitation	Raster	No	LatLong	30 arc seconds	WorldClim (Hijmans *et al*. 2005)
Protected areas/areas of national importance	Polygon Vector	Yes	LatLong	n/a	Protected planet (IUCN and UNEP-WCMC, 2012)

Rivers	Line Vector	Yes	LatLong	n/a	HYDROsheds (USGS, 2010) and digitised from Google Earth (Google Earth, 2013)
Roads	Line Vector	Yes	LatlLong	n/a	Digitsed from Google Earth (Google Earth, 2013)
SEAT farm locations	Point Vector	Yes	Latlong	n/a	SEAT project primary survey (Murray *et al*. 2011)
Slope	Raster	No	LatLong	90 m	Calculated from SRTM DEM (NASA, 2009)
Soil clay content	Polygon Vector	No	LatLong	30 arc seconds	HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Soil drainage groups	Polygon Vector	No	LatLong	30 arc seconds	HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Soil pH	Polygon Vector	No	LatLong	30 arc seconds	HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Temperature	Raster	No	LatLong	30 arc seconds	WorldClim (Hijmans *et al*. 2005)
Urban Areas	Text	Yes	n/a	n/a	citypopulation.de (Brinkhoff, 2011)
Water bodies	Polgon Vector	Yes	LatLong	n/a	USGS SRTM Water Body Data (SWBD) (NASA, 2009)

There were a few issues with some of the global datasets (such as temperature and precipitation) where there were missing data near the coast where the edge and coastline did not fully coincide. A maximum filter was applied multiple times to the original layer to extend the values outwards and to force an extension to the original layer so that the final layer had real values in areas which previously had missing data (Fig. 3.4). Whilst this situation is not truly representative of the actual conditions it was more appropriate than leaving some pixels with no values as that would result in inaccurate results in the subsequent models.

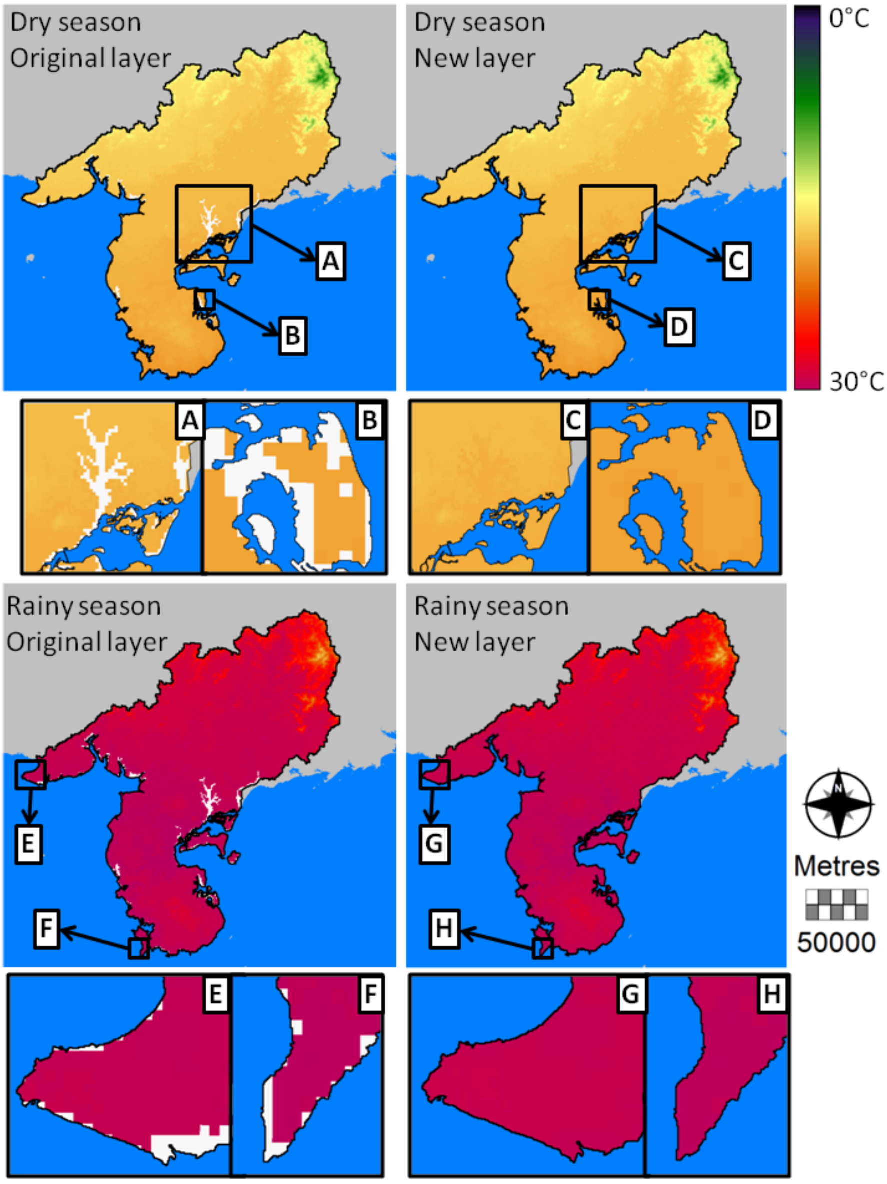


Figure 3.4: Temperature data for the study area in China. The original layer shows the missing data near the coast

Google Earth is one of a number of “virtual globes” that have been established over recent years as a way of representing the world in a 3D environment (Yu and Gong, (2012). The use of such virtual globes, particularly Google Earth, is increasing significantly as both experts and non-experts are able to visualize and share data quickly and efficiently (Sheppard and Cizek, 2009). Potential applications of Google Earth in research projects can include visualization, data collection, data exploration, data integration, modelling and simulation, validation, communication/dissemination of research results and decision support (Goodchild, 2008; Yu and Gong, 2012). However, as discussed by Yu and Gong (2012), caution must be applied when using Google Earth (as with any virtual globe) in a research project as there is inconsistent image quality, infrequent updates for some areas, inadequate capability for quantitative measurements, a lack of analytical tools and there are issues associated with the co-ordinate system. The risks of both experts and non-experts using virtual globes are discussed in detail by Sheppard and Cizek (2009). Currently, Google Earth cannot be used as a replacement for more “traditional” desktop based GIS systems. However it does serve a valuable role as a supplementary data tool.

In this study Google Earth was used to visualise farm locations, digitise some of the required layers and assist with land use classification and verification. One of the layers that was digitised from Google Earth was the layer representing rivers. Originally, data on rivers was downloaded from the USGS HydroSHEDS database (USGS, 2010) which uses the SRTM DEM to produce a vector layer of the global river network. As the HydroSHEDS layer is based on the topography of the region it does not take into account anthropogenic modifications such as the extensive irrigation network in Vietnam, Therefore, satellite imagery and Google Earth were used to digitise a new layer which was representative of the actual main rivers and canals within the study area. The differences between the HydroSHEDS layer and the digitised layer are shown in Fig. 3.5. There were some issues with Google Earth due to inconsistent data quality; with poor resolution and infrequently updated images being the primary cause. Therefore Google Earth data was cross-checked with Bing maps [Microsoft, Washington, USA] and satellite imagery to ensure results were representative.

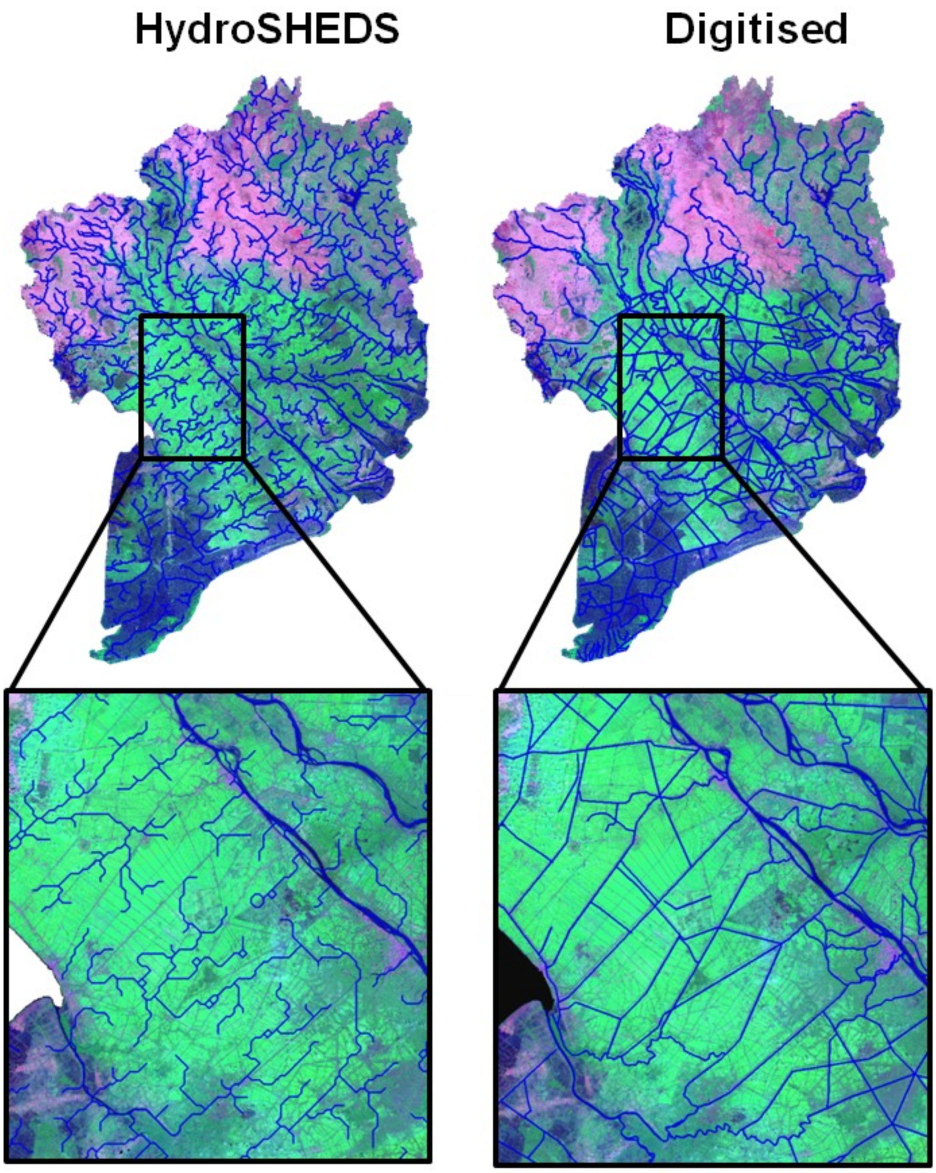


Figure 3.5: Comparison between the rivers layer obtained from the HydroSHEDS database and the layer which was digitised from Google Earth

Note: Vector layer of rivers is displayed in blue and superimposed on Landsat ETM+ colour composite for the study area in Vietnam.

Background satellite imagery (Fig 3.6) was obtained from Landsat 7 and was also used to produce the land use models. Landsat data has a resolution of 30m which is considered moderate resolution compared to some alternative satellite data which may have a high resolution of 4m or less (Lillesand *et al.*, 2008). High resolution data can be expensive whereas Landsat data it is available at no cost and, as noted by Coe (2010), it can be useful for regional studies as it covers large areas with fewer scenes/tiles.

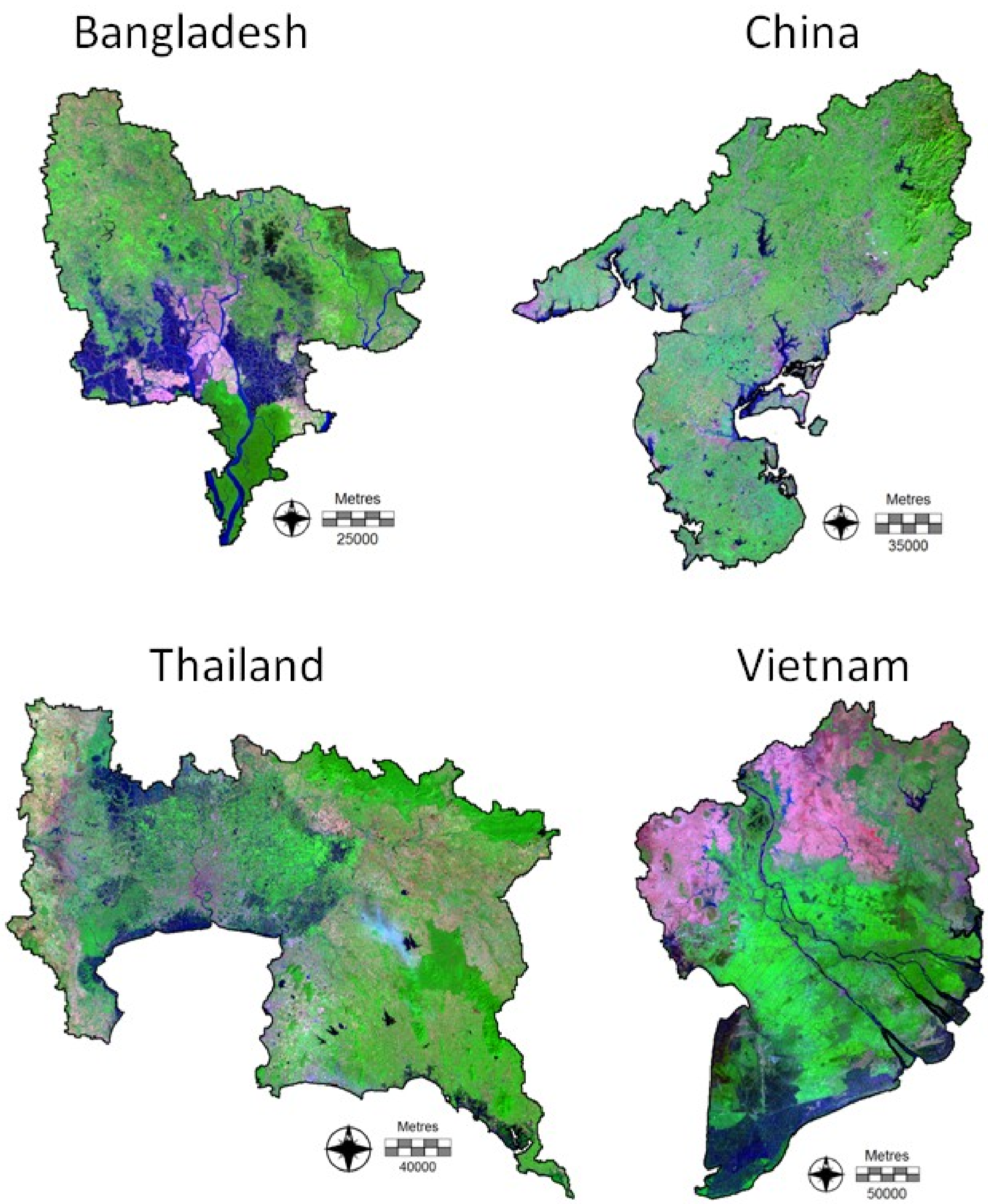


Figure 3.6: Background satellite imagery for each study area during the dry season

3.3.3. Weighting

Within model development and decision making there are often variables and factors which have different levels of importance (Nath *et al.,* 2000). Weights can be applied to variables to specify the importance of the factors relative to others included in the assessment (Carver, 1991). As discussed by Nath *et al.* (2000) weighting can be subjective and GIS analysts need to ensure that weights have been assigned in an objective manner. The use of expert opinion to help assign weights can be an advantage but it must also be noted that experts with different backgrounds and agendas may have differing views on the weights (Nath *et al.,* 2000).

To establish weights for the site suitability models a group of 10 aquaculture experts from Asia and Europe were consulted. A pairwise comparison matrix was used to guide this process for submodels and models containing three or more factors. The pairwise comparison matrix uses the logic developed by Saaty (1977) under the analytical hierarchy process (AHP) where variables are rated on a continuous 9 point scale from extremely less important (1/9) to extremely more important (9) and 1 indicates the variables are of equal importance (Eastman, 2012). The AHP process is designed to evaluate the relative importance of variables and can be used in analysis where absolute measures do not exist (Millet and Wedley, 2002; Saaty and Vargas, 2012) such as combining many variables within site suitability assessment. Judgemental uncertainty can occur due to the emotional state of the expert (Paulson and Zahir, 1995), to account for this the experts were contacted after two months and asked if they agreed with the weights. The overall weights did not change with the results from the second consultation. The consistency ratio of the matrix indicates the probability that the values were randomly assigned (Eastman, 2012). All of the consistency ratios had a value below 0.1 which indicated good consistency.

Five experts in hydrology and the environment were consulted to establish the weights for the non-point source pollution (NPSP) models. This involved a group discussion regarding the individual indices and then a scaling factor (weight) was assigned based upon how influential each index would be with regard to generating non-point source pollution. After the weights had been established two previous NPSP studies were consulted to compare the results. Although the models use slightly different methodologies and include different numbers of indices/submodels (three in Munafo et al., 2005, four in Zhang and Huang, 2011 and five in this study, Chapter 7) the final weights were similar in their order of importance.

3.4. Seasonality

The average length and timing of the seasons varies across the individual countries and regions considered in this project (Fig. 3.7). Within this study the terms dry season and rainy season refer to slightly different time periods in each country; in Bangladesh the rainy season lasts from June to October with a dry season from November to May (Faruque and Ali, 2005), in Guangdong, South East China the rainy season is usually from May to October with the dry season from November to April (Seto *et al*., 2004), Central Thailand has a rainy season from May to October and a dry season from November to April (Szuster, 2006), and in Vietnam the dry season is from December to April and a rainy season from May to November (Sakamoto *et al*., 2009).

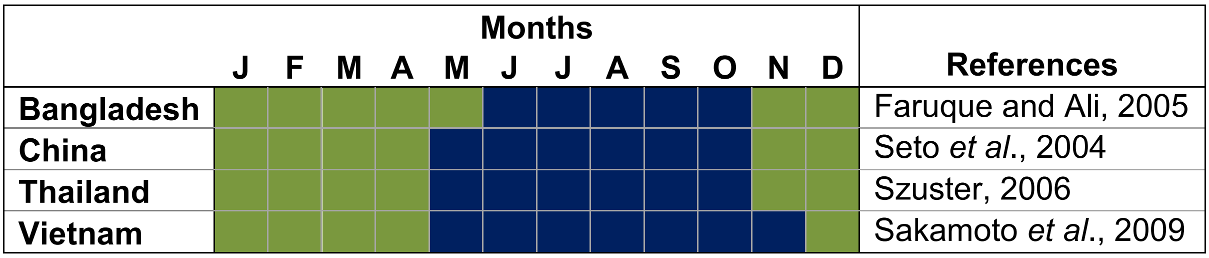


Figure 3.7: Average length of the dry and rainy seasons for each study area

3.5. Scoping and SEAT Farmer Survey

Initial scoping work was undertaken in all four study areas during October/November 2010 which provided valuable information about the areas, species and systems involved in the study. This period also involved piloting a survey developed by the SEAT project which used questions from all work packages to evaluate sustainable and ethical issues associated with the culture of the two key species for each country (Fig. 3.8). Over 200 farmers were interviewed for each species in each country by the SEAT project teams led by Bangladesh Agricultural University in Bangladesh, Shanghai Ocean University in China, Kasetsart University in Thailand and Can Tho University in Vietnam. The surveys were conducted between November 2010 and March 2011 and the results were translated into English and uploaded to Access databases for interrogation and analysis by SEAT project partners. Further details are available in Murray *et al*. (2011).

Figure 3.8: Members of the SEAT project interviewing a farmer in Maoming, China

The site selection process for the SEAT farmer survey followed a multi-stage procedure which involved the exclusion of areas with low concentrations of farms, selecting administrative units based on factors such as production and then the identification of "clusters" of farms in one or more adjoining villages where a random selection of farmers were then targeted (Murray *et al*., 2011). Although this approach may be useful for social/economic analysis it was not truly random with respect to spatial issues and therefore the usefulness of the SEAT farmer survey for geographic analysis was limited. However, the information in the survey did provide some background information and the farm locations were used to partially verify the site suitability models (Chapter 5) and as input to the Maxent models (Chapter 6).

3.6. Internet Map Server (IMS)

The internet allows wider dissemination of spatial information and the results from GIS analysis, enhancing the use of models beyond the traditional desktop approach (Peng and Tsou, 2003). An Internet Map Server (IMS) is a valuable way of sharing models and their outcomes amongst developers, decision makers and stakeholders. However, establishing a fully functioning IMS can take time and money; even when using software such as Manifold which has an IMS function built into it. An IMS is not an end product and needs to be hosted on a server which can be accessed and updated frequently. As a demonstration, a simple IMS was established on a local network for the models in this study (Fig. 3.9). However the quantity of data associated with the models and the size of the files was a significant issue which resulted in long loading times and delays in displaying the data, rendering the IMS unusable. This is an issue that would be aggravated by deploying the IMS to the wider internet as, although many countries have access to the internet, the bandwidth of their connection may be limited and might not fully support the use of an IMS. Future work could involve further investigation into the use of an IMS; however it would be more useful for a smaller scale project with files of a more manageable size.

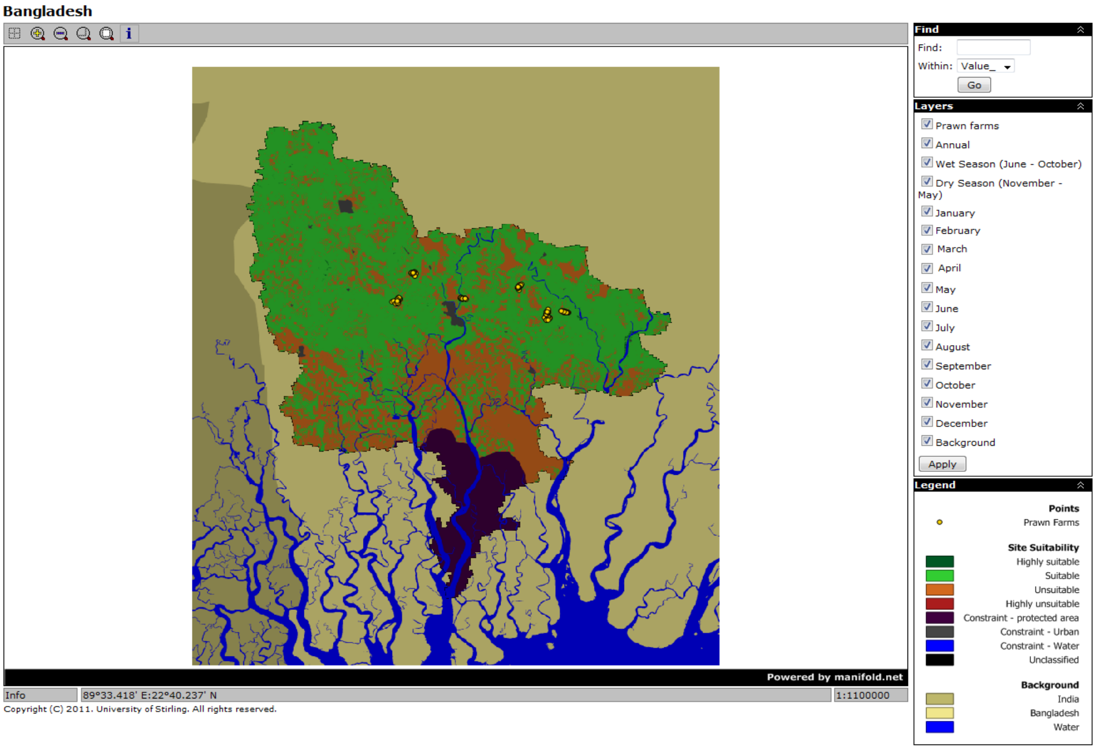


Figure 3.9: Screen shot of an early version of the Internet Map Server (IMS)

3.7. IDRISI macro models

The Macro Modeler within IDRISI provides a graphical environment in which multi-step models can be established and executed (Eastman, 2012). A macro model can be an individual model or a multi-tiered framework with submodels and have the advantage of being easily updated, re-parameterised and re-run, depending upon project requirements or as circumstances change. Extensive use was made of macro models in this study and macro models were developed for site suitability (Chapter 5), shown in Fig. 3.10, and non-point source pollution (Chapter 7) which are located in Appendix B. This approach also enables future application of the models to new study areas beyond the scope of the current project.

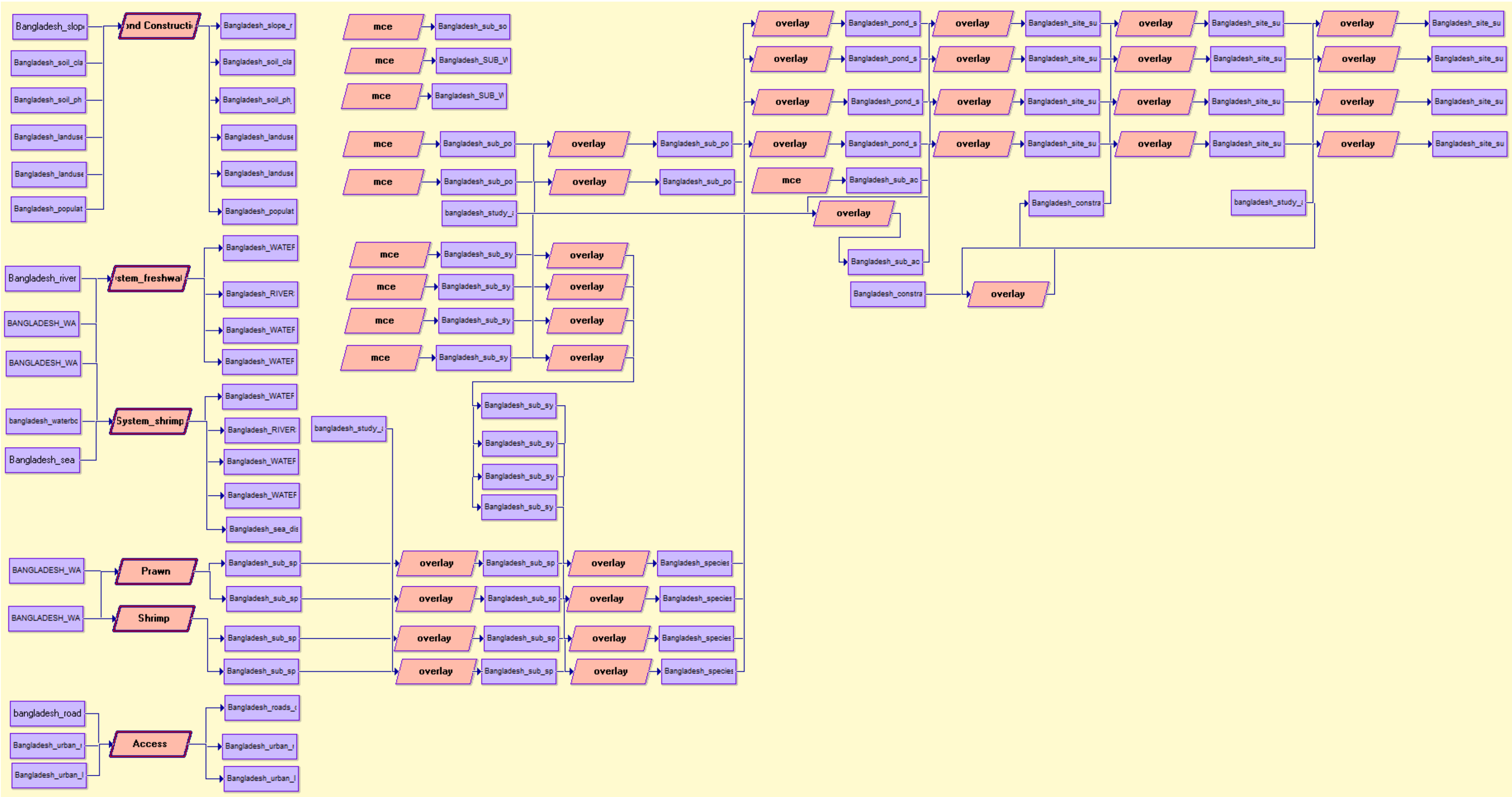


Figure 3.10: Macro for the site suitability model (Bangladesh)

CHAPTER 4

THE DEVELOPMENT OF SPATIAL MODELS OF SEASONAL LAND USE TO EVALUATE THE SUITABILITY OF LARGE CATCHMENTS FOR AQUACULTURE

4.1. Introduction

Aquaculture is highly dependent on land and water; directly for the area occupied by the facility and indirectly to provide support and service functions such as feed production, waste treatment, access and storage (Beveridge *et al*., 1997; Boyd *et al*., 2007). Due to the growing global population, and subsequent increased demand for land, water and natural resources, aquaculture must ensure that it is being managed and developed in a fair and sustainable way. Frankic and Hershner (2003) suggest that the first step for a successful management plan should be an inventory of natural resources. This is a logical step as decision makers need to know what is in the area.

Free global datasets of land cover are available from a variety of sources. However, the quality and resolution can vary significantly. Until recently, GlobCover (ESA, 2011) was the highest resolution dataset at 300m. However, the FROM-GLC (Finer Resolution Observation and Monitoring of Global Land Cover) (Gong *et al*., 2013) is now available at 30m. Although the FROM-GLC dataset has a resolution of 30m, in some areas it has poor accuracy and many areas suffer from significant cloud cover and/or classification issues where the scenes overlap. Furthermore, global datasets of land use/land cover are usually only available for one point in time and do not take into account seasonal variations. Land regularly experiences seasonality which can have significant implications for catchment wide issues such as non-point source pollution

(Carpenter *et al.*, 1998). Therefore, it is imperative that suitability studies take into account seasonal land use and the potential implications to and from aquaculture.

Monitoring and mapping land use, especially at a regional or national level, can be costly and time taking. Remote sensing tools, GIS software and image classification techniques can be used to develop land use models from satellite imagery. Individual land use types reflect, transmit or absorb electromagnetic energy differently and this interaction varies from one wavelength to the next, known as the spectral response pattern (Eastman, 2012). Spectral signatures refer to the spectral response pattern that is characteristic of a type of land use (e.g. water) and these signatures are used as the basis of image classification. The resulting land use models can be used to highlight potential conflicts, issues and opportunities within the selected area. Decision makers can identify areas which could be susceptible to urbanisation and the spread of towns and cities, assess potential areas where one activity could impact another or highlight unproductive bare land which could be used for development.

Land use models can also be used as an indicator of land use change; which is considered to be one of the major negative impacts of aquaculture with much of the attention focussing on the destruction of mangroves to build shrimp ponds (Diana, 2009; De Silva, 2012). Mangroves play a significant role in nutrient cycling, serve as important breeding and nursery grounds for many species of fish and shellfish and they also protect coastal areas from wind, waves and coastal erosion (Boyd and Tucker, 1998). The impact of aquaculture on mangroves has been well documented (Páez-Osuna, 2001; Diana, 2009) and it is estimated that in the past few decades, development of culture ponds for shrimp and fish accounts for the destruction of around 20-50% of mangroves worldwide (Primavera, 1997). However, although aquaculture contributes to mangrove destruction, other activities such as agriculture, logging, urban expansion, industrial development and tourism are also responsible (Neiland *et al.*, 2001; Guimarães *et al.*, 2010). Therefore it is difficult to establish a direct link between mangrove destruction and aquaculture development using land use maps and models unless there is substantial evidence and information.

Although much of the controversy associated with land use and aquaculture focuses on the destruction of mangroves, many areas of agriculture, residential land, forests and even burial grounds have also been transformed to ponds (Primavera, 1997) resulting in significant changes to the landscape and impacting other stakeholders and their livelihoods. Neiland *et al*. (2001) note concern regarding the long term future of agricultural land converted to shrimp ponds where ponds are abandoned after a few years and the land is unable to support any natural or agricultural productivity. Changes which occur due to pond construction are not necessarily irreversible. However it takes time and money to revert the land back to its original state (Pillay, 2004). Land use should be monitored on a continual basis to ensure that important areas and endangered habitats such as wetlands and mangroves are protected from new and existing developments. It is vital that the industry learns from the past and focuses on the issues of the present day; ensuring that action is taken to minimise potential negative impacts in the future.

The impacts beyond the actual farm should also be considered as many aquaculture systems have adversely impacted surrounding land use and disrupted livelihoods. An example of this is the seepage of brackish water from shrimp ponds into groundwater supplies and adjacent agricultural land which resulted in economic loss (Flaherty and Karnkankesorn, 1995; Ali, 2006). The risk of elevated salt levels in the surrounding environment has led to some governments restricting the development of inland shrimp culture (Roy *et al*., 2010). Furthermore, Muňoz *et al*. (2013) recommend the consideration of the combined impact of land use change from other sectors and the impact from aquaculture. The study by Muňoz *et al*. (2013) found that a change in land use from forest to crops resulted in increased diffuse nutrients loads which, combined with wastes from existing fish cages, resulted in changes to the sediment and water quality.This highlights the importance of considering not only the affect aquaculture has on the area occupied by the facility but also the wider impacts to and from other land use; confirming the need to understand what activities occur throughout a catchment and how the land is used across the year.

Whilst some consequences of land use and change are easily visualised, such as the destruction of mangroves for ponds, the socio-economic issues associated with a change in activity are not always apparent until after the transition has taken place. Although aquaculture is generally considered to be a beneficial activity for many regions, providing direct and indirect livelihoods to millions and contributing to food security and poverty alleviation (De Silva and Davy, 2010), there can be negative impacts on local communities as a result of changing the land to aquaculture. During the shrimp farming boom many multiple-use areas, with numerous stakeholders, were converted to single-purpose industries which dispossessed people of their traditional resource use rights (Deb, 1998). Additionally, in some cases, aquaculture development has occurred as a result of corruption and land grabbing, where politicians and bureaucrats have allocated areas for culture to themselves or associates rather than the local communities (Deb, 1998; Azad *et al*., 2009). It is important to understand where different types of land cover and land use are located to ensure there is fair access for all stakeholders and any change in use or development of new activities, such as aquaculture, would not adversely impact the livelihoods of existing users.

Often the short-term changes which occur throughout the year are ignored and whilst the seasonality of land use is an obvious factor, few studies take it into account. In order to assess the overall suitability of catchments for sustainable aquaculture it is essential that decision makers understand what land use types are present within an area and where and when they occur. Therefore, this study aimed to develop seasonal land use models for large catchments using freely available Landsat ETM+ satellite imagery and image classification techniques within a GIS environment. Qualitative and quantitative analysis was performed on each study area to identify the type of land use and the extent of land covered.

4.2. Methodology

4.2.1. Data preparation

There are numerous options for satellite imagery, all of which have advantages and disadvantages to their use. For the purpose of this study, Landsat 7 ETM+ satellite imagery was used as it is easily accessible, available at no cost and is updated regularly. Within each study area (Fig. 2.2) multiple Landsat scenes were needed to cover the area and these were selected from similar dates and times of year to account for the phenological changes throughout the growing season which result in highly variable signatures from vegetation types even within seasons (Eastman, 2012). The average length and timing of the seasons varies slightly between the study areas and is shown in Fig. 3.7.

Unfortunately the Landsat 7 Scan Line Corrector failed in May 2003 and all of the subsequent images contain data gaps along the eastern and western sides of the images (Lillesand *et al*., 2008). In order to fill these gaps a freeware program, Frame and Fill [NASA, Washington D.C., USA], was used to replace the missing data with information from other images (Fig. 4.1). Initial work showed that using pre-SLC failure images to fill the gaps produced better final images than using scenes post-SLC failure as there was less striping. Cloud cover can also be a major issue for satellite imagery (Fig. 4.2). Unfortunately 100% cloud free scenes were not available for some of the study areas. Thus, for each scene where there were clouds a cloud mask was developed and then another image from a similar time of year was used to fill the gaps. After each scene had been gap-filled the relevant new images were combined to create an overall image for each study area and season using the Mosaic function in IDRISI Selva [Clarks Lab, Worcester, MA, USA] which spatially overlaps the scenes and balances the numeric characteristics of the images using the overlapping areas (Eastman, 2012). This produced eight sets of satellite imagery which were then used in image classification; Bangladesh dry season, Bangladesh rainy season, China dry season, China rainy season, Thailand dry season, Thailand rainy season, Vietnam dry season and Vietnam rainy season.

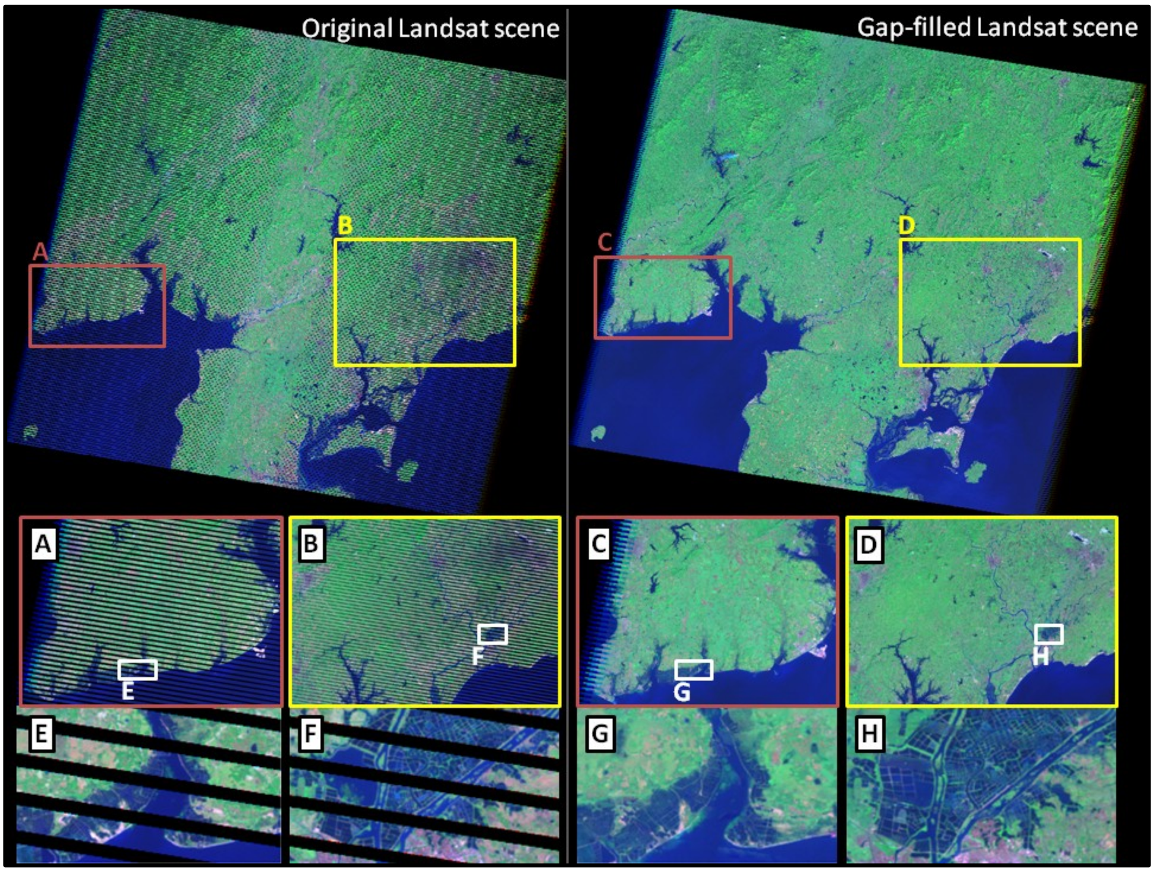


Figure 4.1: RGB colour composites of the original Landsat scene compared to the gap-filled Landsat scene

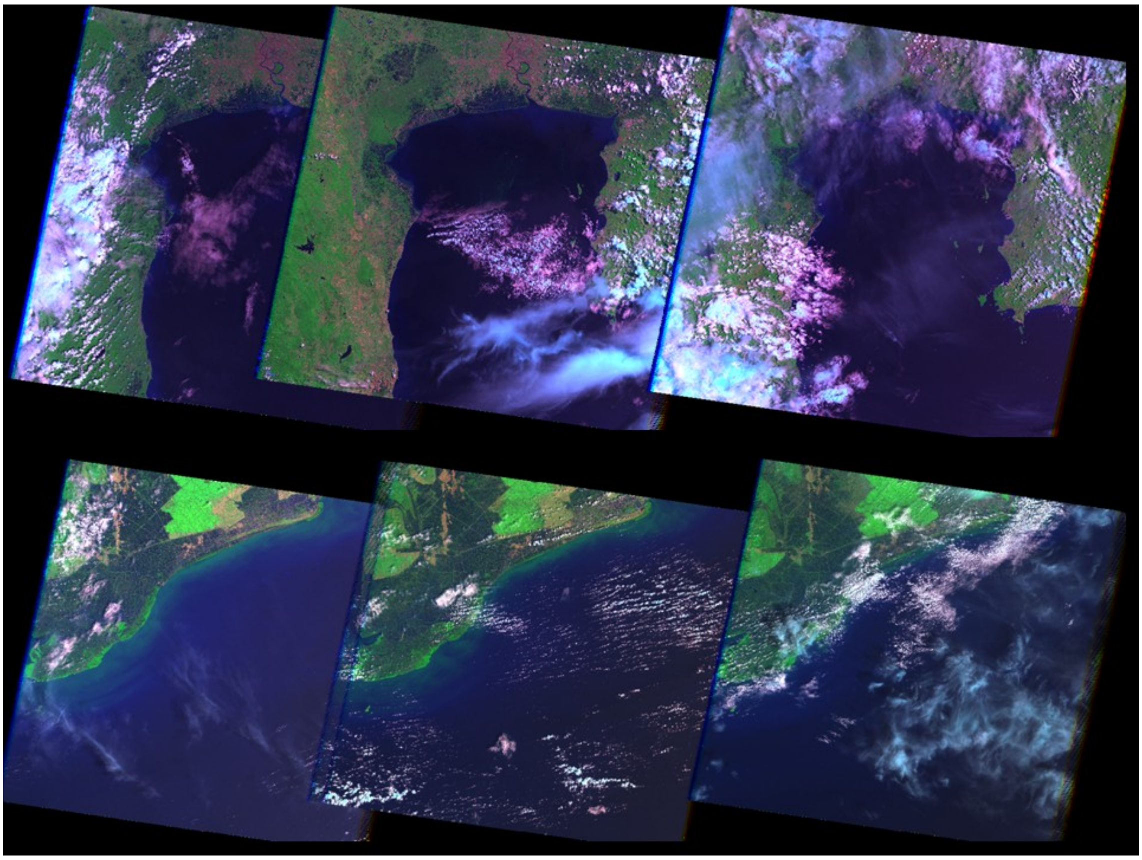


Figure 4.2: Examples of cloud cover issues with Landsat imagery

4.2.2. Ground truth information

Ground truth information, in the form of georeferenced photographs and notes, was collected during field visits to each of the four study areas and was used together with local knowledge, existing information and Google Earth data within model development. Fig. 4.3 shows examples of ground truth data in the form of georeferenced photographs and Google Earth images for the study area in Bangladesh. As noted by Congalton and Green (1999) simple classification schemes which include a few general classes can often be reliably assessed from interpretation of aerial photography. Therefore virtual globes such as Google Earth are a valuable source of information and can supplement field work. This is particularly useful over large catchments, such as those evaluated in this study, where it would be expensive and time consuming to conduct a full ground truth campaign. The ground truth information was used for two stages of model development; training sites for image classification and points for accuracy assessment and validation. The training sites were independent of the accuracy assessment points.

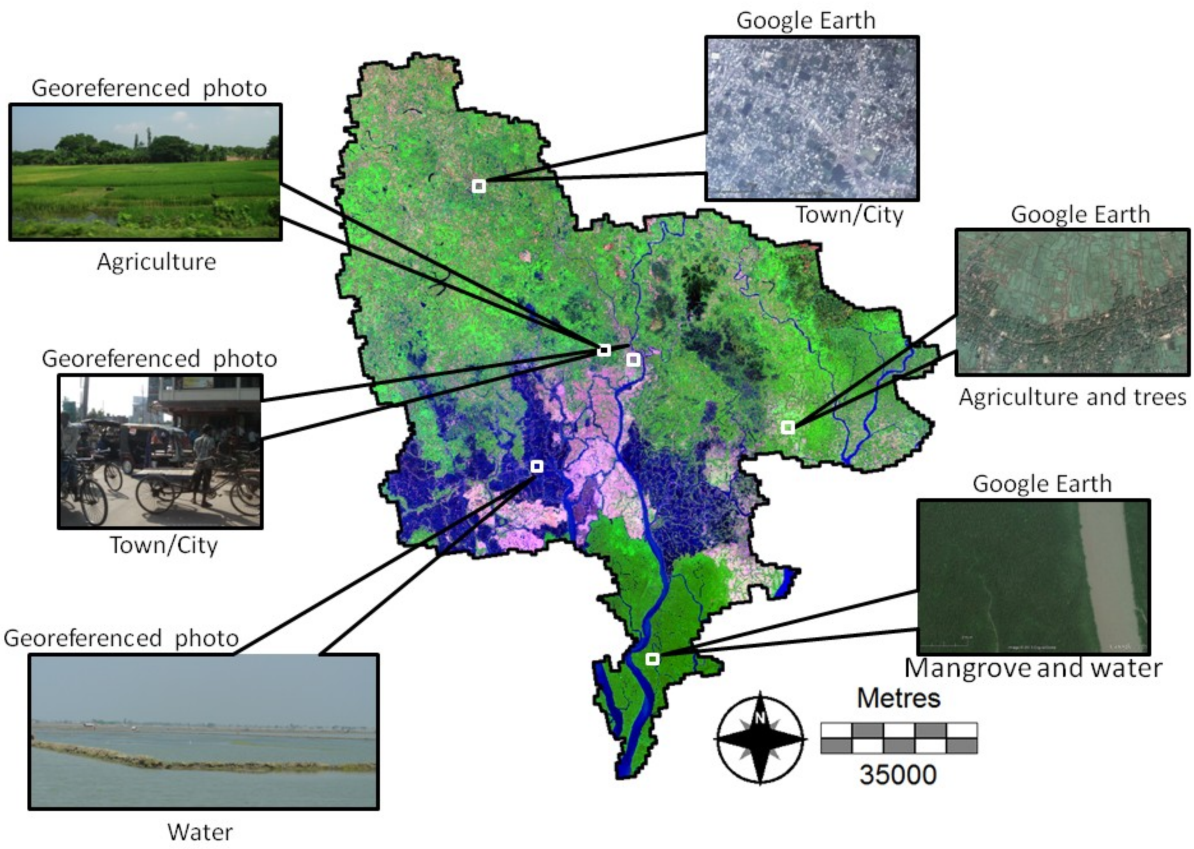


Figure 4.3: Examples of ground truth information

4.2.3. Image classification

There are two basic approaches to image classification; supervised and unsupervised. Supervised classification requires significant input by the user prior to the classification who must identify areas within the image that are known to belong to specific classes (training sites), whereas unsupervised classification can occur with minimal input from the user and the programme searches for natural groups of pixels within the image (Campbell, 2007). Either method can be used to classify an image or they can be used together in a hybrid approach; where an unsupervised classification is performed initially and the result is interpreted by ground truth information followed by a supervised classification of the original image using the statistics of the unsupervised classification as training knowledge (Liu and Mason, 2009).

This study used a hybrid approach, outlined in Fig. 4.4, and an unsupervised image was produced using an iterative self-organising unsupervised classifier (Isoclust) to inform of the potential classes which was then used together with prior knowledge and ground truth information to help develop the final classes (Table 4.1). Sub-classes were used to help with the classification as sometimes the same type of land cover/use within an image can have different spectral signatures and there could be misclassification if this is not taken into account. This is a particular issue when using an image consisting of several Landsat scenes. Therefore in order to try to mitigate against this the classes were split further, e.g. water was actually split into shallow water and deep water for the purpose of the analysis and then was reclassified to the main class after the supervised classification had taken place.

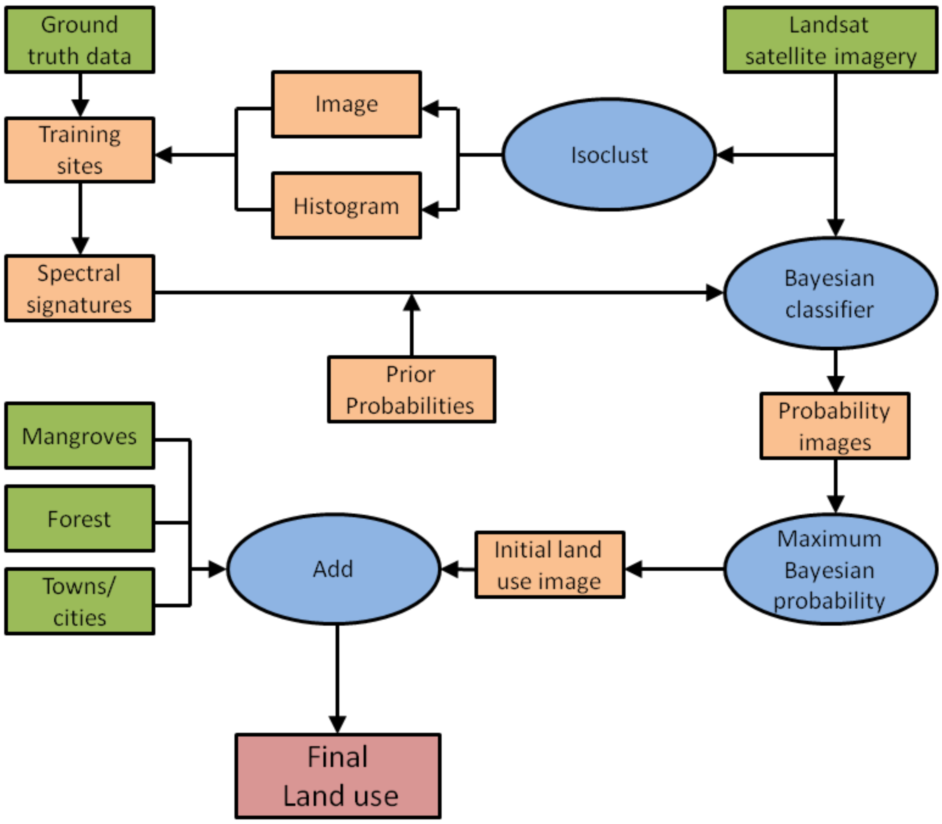


Figure 4.4: Conceptual design for the land use models

Table 4.1: Classes for the image classification

Class	Initial	Examples
Water	W	Rivers, lakes, aquaculture ponds
Forest	F	Dense forests
Trees / heavy vegetation	T	Orchards, trees, dense vegetation
Grassland / shrubland	G	Grassland, shrubland
Bare ground	B	Rocks, land with no vegetation
Agriculture	A	Cropland
Soil / light vegetation	S	Fallow fields, newly planted crops
Mangroves	M	Mangroves
Town/city	TC	Towns, cities, buildings

There are numerous methods for supervised classification; however preliminary analysis using different approaches found that the Bayesian classifier was most suitable for this study as the results were more representative. The application of Bayes's theorem is particularly effective in supervised classification when the classes are indistinct or overlap in spectral data space (Campbell, 2007); therefore it is a good method to use in large catchments which cover multiple Landsat scenes. The Bayesian classifier is a soft classifier which is based on a probabilistic method where pixels are assigned the probability of membership of the various classes that have been specified by the user (de Smith *et al.*, 2009). Ground truth information collected during field visits to each of the study areas was used to define training sites which were then used within the analysis and layers were produced for each class that indicated the posterior probability of each individual pixel belonging to the selected class; calculated using Equation 4.1 (Eastman, 2012).

$$p(h|e) = \frac{p(e|h)*p(h)}{\sum_i p(e|h_i)*p(h_i)} \qquad \text{[Equation 4.1]}$$

Where:

p(h|e) = the probability of the hypothesis being true given the evidence (posterior probability)

p(e|h) = the probability of finding that evidence given the hypothesis being true (derived from training site data)

p(h) = the probability of the hypothesis being true regardless of the evidence (prior probability).

In the analysis the user must input the "prior probability" or expected occurrence of each class, which requires some knowledge of the study area. Campbell (2007) noted that if the classes have been sensibly chosen, along with representative training data, then this method of classification should be as effective as any other classification method that can be applied. However if classes are poorly defined and the training data is not representative then the results are no better than those of other classifiers applied in similar circumstances (Campbell, 2007). Images of probability were developed for each land use category and combined to create the final supervised classification layer.

4.2.4. Towns/cities, mangroves and forests

Initial analysis revealed an issue where towns/cities were misclassified as bare land and *vice versa* because of the similarity in the spectral signatures of the two land use classes. This is a particular issue for large areas which overlap several Landsat scenes. Urban areas and towns do not change significantly between seasons and therefore they can be easily identified using the satellite imagery, ground truth information and Google Earth. A mask layer was established using Google Earth and Landsat imagery which indicated where the urban layers were located. This mask layer was then applied to the satellite data which was reclassified to produce a layer representing towns and cities.

There are many methods used to delineate mangroves from other vegetation using remote sensing tools (Green *et al.*, 1998). The method employed in this study used visual identification, supplemented by literature and ground truth information, to create a mask layer showing the probable location of mangroves. The mask was then applied to a Normalized Difference Vegetation Index (NDVI) image which had been developed from the Landsat bands 3 and 4 and the resulting image was then reclassified to produce a layer representing mangroves. The same methodology was used to develop a layer representing forests. The resulting layers for towns/cities, mangroves and forests were then added to the results of the Bayesian classifier to produce the land use model.

4.2.5. Seasonal change

The seasonal change between the output images for each country was analysed using the Land Change Modeller in IDRISI. A map of persistence was created which highlighted pixels which remain the same between the seasons. Quantitative analysis for each individual season and the map of persistence was performed by calculating the areas within each land use category.

4.2.6. Accuracy assessment

Accuracy assessment is a critical element of land use mapping or modelling. However, there are no definitive protocols or universally adopted guidelines for assessing the accuracy of a land use map, particularly within large areas or regions (Foody 2002; Wulder *et al*., 2006). There are generally two types of accuracy assessment; non-site specific accuracy and site specific accuracy. The former compares two maps and assesses the overall accuracy of the category but does not consider miscalculations between categories, whereas the latter is more detailed and assesses the agreement of two maps, or a map and ground truth points, at specific locations (Campbell, 2007). The most popular method of site specific accuracy assessment, and the one used in this study is the use of an error matrix (also known as a confusion matrix) which identifies overall errors for each category in addition to misclassifications between categories (Campbell, 2007).

It is essential that accuracy assessment uses an appropriate number of sample points otherwise the results could be skewed. Congalton and Green (1999) recommend that a minimum of 50 ground truth points are used for each land use category within the error matrix. However if the area is large then either 75 or 100 points should be used. The number of sample points used in this study was adapted so that land use categories that covered an area of less than 5% of the total study area had 50 ground truth points and categories covering over 5% of the study area had 100 points. A sample size of 100 will ensure the proportion of correct classifications can be estimated with a standard error of no greater than 0.05, regardless of the size of the study area, as described by Stehman (2001).

The degree of agreement between the ground truth data and the map is indicated by the KAPPA index of agreement (KIA),also known as KHAT or KAPPA coefficient of agreement, and is calculated for the overall image and each individual category (Eastman, 2012). Although an overall accuracy above 85%, originally outlined by Anderson *et al.* (1976), is often cited as the acceptable level of accuracy (Foody, 2002) some studies have questioned the value and its legitimacy as a target and suggest that the acceptable level of accuracy is dependent on the intended application of the map (Wulder *et al*., 2006) or data layer. Regardless of the selected accuracy target it is important to use a transparent accuracy assessment protocol which will provide information on the nature and limitations of the accuracy of the product (Wulder *et al*., 2006), as this provides potential users with the knowledge needed to make a judgement on the acceptable use of the product.

4.3. Results

4.3.1 Bangladesh

With a total area of 10148 km^2, the study area in Bangladesh is the smallest area in this study. The results in Fig 4.5 show that in the rainy season the dominant land type is water covering 3262km^2 (32.1% of the study area) and in the dry season the dominant land type is trees/heavy vegetation covering 3019km^2 (29.8%). In the dry season water covers 1934km^2 (19.1%). The increase during the rainy season is due to flooded land, irrigated fields and the use of ghers (a rice-prawn farming system). Some of the persistent water that is present all year round (1604km^2, 15.8%) represents rivers and standing waterbodies. However most of the large areas of water in the south of the study area are shrimp ponds. In the southern section of the study area, covering 754km^2 (7.4%), is part of one of the World's largest continuous mangrove forests, the Sunderbans. The mangroves are a valuable coastal resource and play a significant role in the economy with over 3.5 million people directly or indirectly relying on the Sunderbans for their livelihood, however, overfishing and over-exploitation of the natural resources is resulting in extreme pressure on the fragile ecosystem (Islam and Haque, 2004).

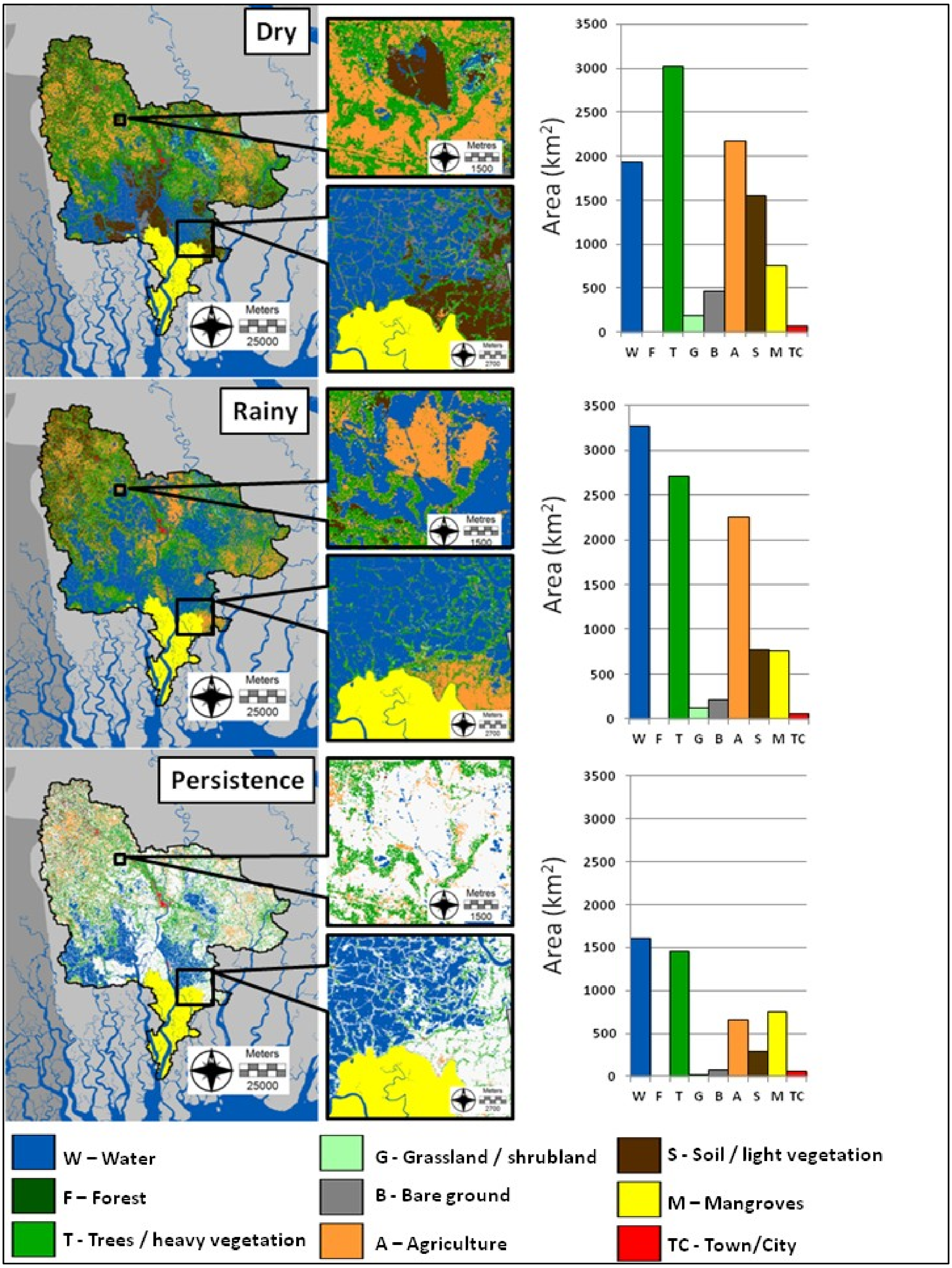


Figure 4.5: Results of the land use model and analysis for the study area in Bangladesh

Agricultural land has a large presence during both the dry (2175km^2, 21.4%) and the rainy season (2255km^2, 22.2%). However 659km^2 (6.5% of the study area) of the areas identified as agriculture are persistent throughout the year (Fig. 4.5). Although some of this could be due to classification error it could also be changing land use priorities and differences in the growing cycles of certain crops. This is important to aquaculture systems and other user groups as it could have significant land management issues with some areas being used for different purposes throughout the year. It must also be noted that the image classification is dependent on the dominant spectral signatures and, as shown in Fig. 4.6, many areas with crops also have trees/heavy vegetation surrounding them which could result in misclassification where trees/heavy vegetation are identified as the dominant land use rather than crops. Therefore consideration should be given to potential misclassification when using the model outputs.

Figure 4.6: Photographs showing trees within agricultural areas

4.3.2 China

The study area in China covers an area of 26225 km^2. The results in Fig. 4.7 show that in the dry season the most dominant land type is soil/light vegetation (6923km^2, 26.4% of the study area) whereas in the rainy season the most dominant land type is agriculture (9547km^2, 36.4%). This is due to the seasonal growing pattern of crops; in the dry season, temperatures are lower and fields are either fallow or freshly planted therefore only bare soil is detected. There is a slight increase in the number of pixels classified as water between the dry (836km^2, 3.2%) and rainy season (1483km^2, 5.7%). However this is not as significant as it is in the other three study areas. This is due to the topography of the area in China, as there are fewer low lying areas where water is likely to accumulate in the rainy season. Additionally, 761km^2 (2.9%) classified as water is present throughout the year representing rivers, lakes and other standing waterbodies. Analysis of where and how much water there is in an area also allows for identification of potential areas for either seasonal or all-year round production.

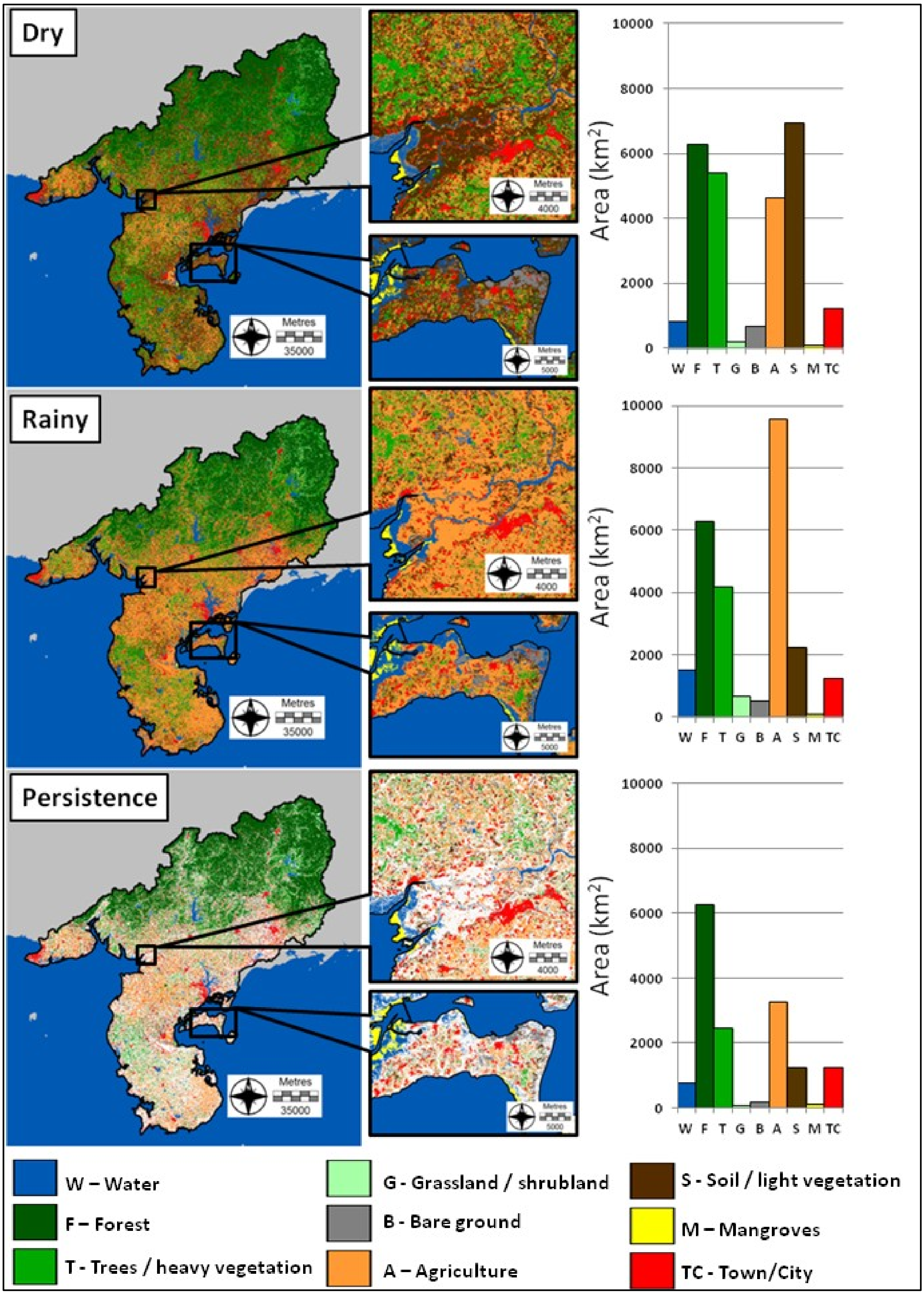


Figure 4.7: Results of the land use model and analysis for the study area in China

Approximately 6261 km^2 (23.9%) of the area is classified as forest (Fig 4.7). This land cover type is generally located in areas with steep slopes and is unsuitable for urban areas, agriculture or aquaculture; however runoff from this land could have significant nutrient inputs into aquatic systems. Furthermore, almost 5% of the study area (1231 km^2) is classified as town/city; this land use type is distributed throughout the area and consists of many rural towns and several dense cities such as Zhanjiang. Urbanisation, untreated domestic wastewater and street runoff are all contributors to decreasing surface water quality (Yin *et al*., 2005). Thus, there could be significant implications for aquaculture systems if they are located in or adjacent to such areas.

4.3.3 Thailand

Extending across central Thailand the study area covers 48319 km^2. Fig 4.8 shows the area of land covered by water almost doubles in the rainy season from 3339km^2 (6.9%) to 6058km^2 (12.5%) due to areas being flooded and also because of irrigated crops such as rice paddies. Some of the area classified as trees/heavy vegetation represents orchards and fruit trees, such as Durian, which are valuable to the local and national economy. Approximately 4.3% (2077km^2) of the area is town/cities, much of this is Bangkok and it is important that aquaculture developers understand the potential spatial spread of the city and the possible conflicts with additional stakeholders. New developments will have to take into account changing user groups and/or different pressures on the land and resources from permanent citizens, seasonal residents and short term tourists.

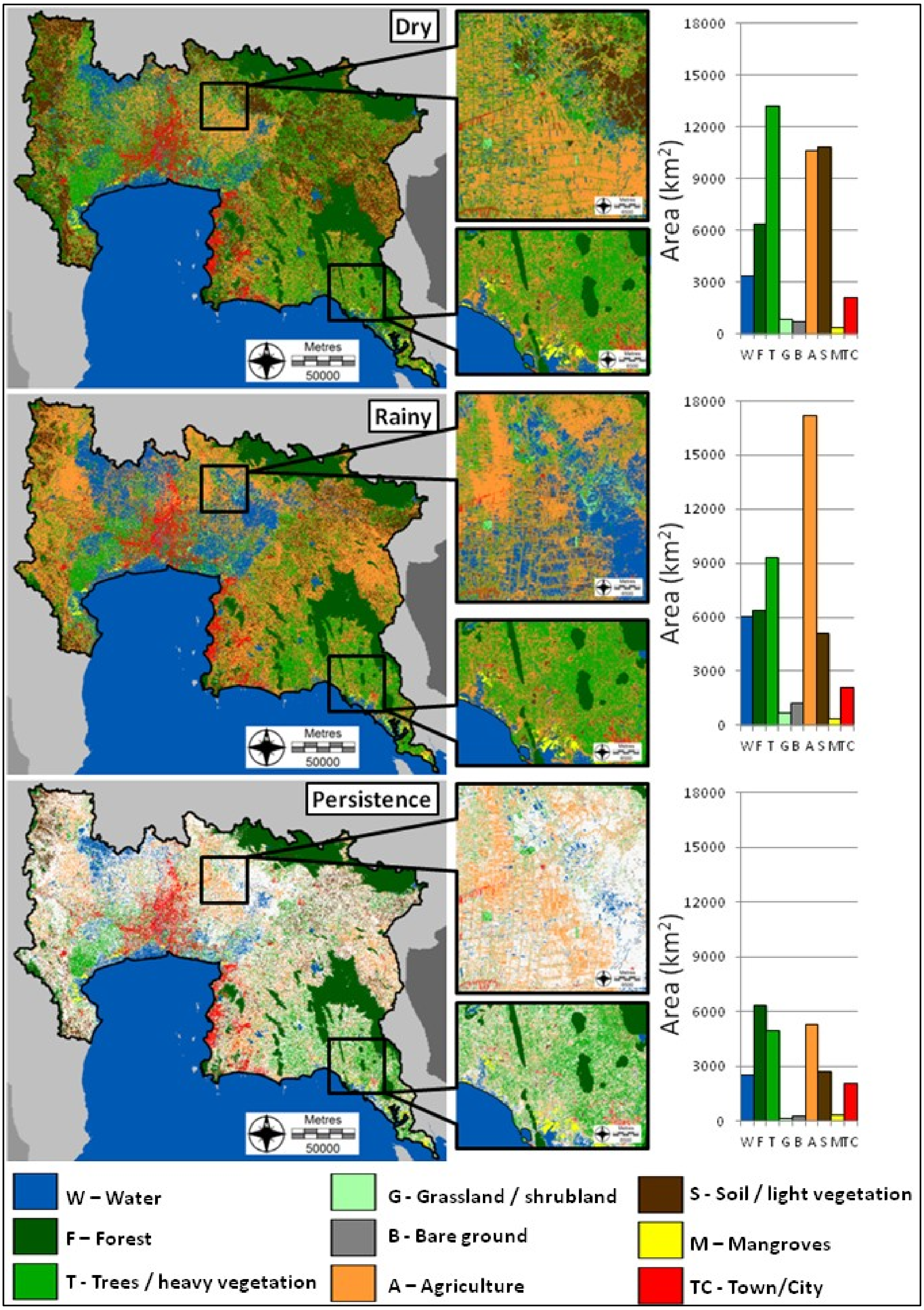


Figure 4.8: Results of the land use model and analysis for the study area in Thailand

As shown in Fig. 4.8 forests cover 6352km^2 (13.1%) and are mainly located in protected areas such as the Khao Yai National Park in the northeast of the study area (National Park Office, 2006; IUCN and UNEP-WCMC, 2012). Similar to the forests in China, they generally cover areas of higher elevation and steeper slope and would be unsuitable for development. However, the potential risk of runoff from the land into aquatic systems should be evaluated if considering sites nearby. Only 349 km^2 (0.7%) of the area is classified as mangroves; mangrove destruction in this area has been well documented (Spalding *et al.,* 2010). Hence it is vital that planners and regulators know where the surviving areas of mangrove are in relation to existing and proposed aquaculture developments.

4.3.4 Vietnam

The study area in Vietnam covers 66283km^2 and encompasses the lower Mekong Delta. Fig. 4.9 shows the dominant land classification in the rainy season is water (25198km^2, 38%) which is an increase from 10144km^2 (15.3%) in the dry season. This is due to a large section of the low-lying Mekong Delta being flooded and also flooded rice fields. The overall area of land classed as agriculture decreases from the dry season (19231km^2, 29%) to the rainy season (13720km^2, 20.7%). However, some of this could be due to rice paddies being classified as water. Rice yields are generally better when grown in a flooded environment (Dowling *et al*., 1997); unfortunately this makes it difficult to distinguish actual rice paddies from flooded areas. The map of persistence indicates that there is approximately 7982km^2 (12%) water that is present all year round; these are larger rivers and canals in addition to shrimp ponds.

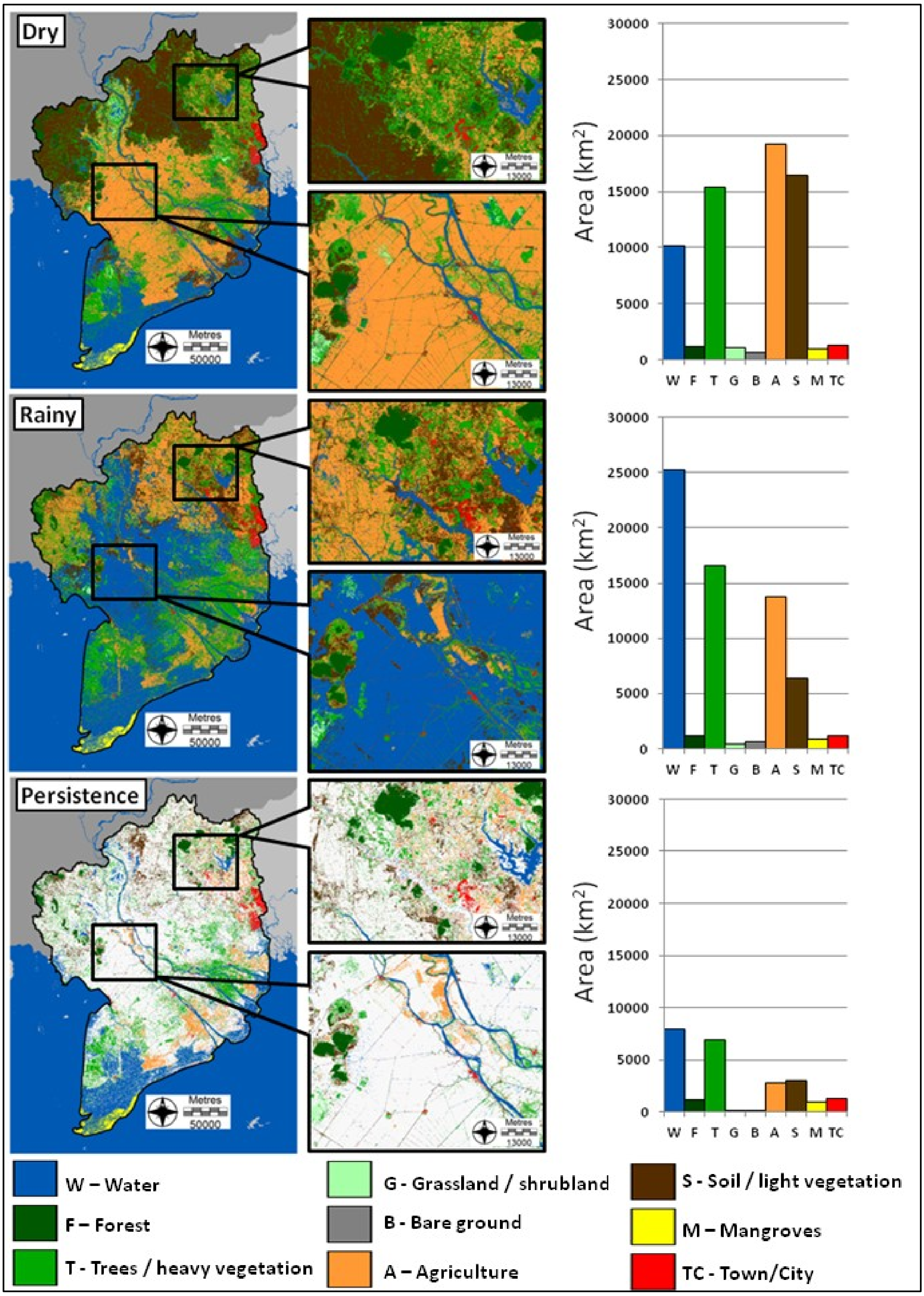


Figure 4.9: Results of the land use model and analysis for the study area in Vietnam

There are small areas of forest (1214km^2, 1.8%), which are generally protected areas and/or wildlife sanctuaries (IUCN and UNEP-WCMC, 2012), and approximately 901km^2 (1.4%) of the area is classified as mangroves (Fig. 4.9). All types of forest in Vietnam have experienced dramatic deforestation in the last century due to the war and the need for space and resources. One of the major consequences of this deforestation is the increased frequency and severity of floods (Danh and Mushtaq, 2011), particularly during the rainy season which can be seen in Fig. 4.9.

4.3.5 Accuracy assessment

The overall kappa index of agreement for each model indicates that the models are representative with kappa values above the recommended limit of 0.85 (85%) (Table 4.2). Each land use category was assessed further within error matrices which indicate errors of commission and errors of omission for each land use type. Errors of commission occur when an area is included in an incorrect category, whereas errors of omission occur when an area is excluded from the category to which it belongs (Congalton and Green, 1999). Summaries of the results from the error matrices (Appendix B) are shown in Fig. 4.10 which highlights the errors of commission for each land use model and Fig. 4.11 which highlights the errors of omission. Fig. 4.10 and 4.11 both show that although each model had an overall kappa index above 0.85 there were some individual categories for both omission and commission that had error levels of below 0.85. This indicates that some land use types were more distinguishable than others. Water tends to have the lowest level of classification error signifying that it was easily distinguishable from other land use classes, whereas, there was a high degree of misclassification between trees/heavy vegetation and agricultural land. These areas tend to be located near each other, such as trees lining a field or an orchard surrounded by agricultural land (Fig. 4.6) and therefore some confusion with the classification could be expected. It could also be a consequence of the spatial resolution of the Landsat ETM+ imagery not being high enough to clearly distinguish land classes.

Table 4.2: Overall Kappa index for each land use model

	Overall Kappa
Bangladesh dry season	0.8744
Bangladesh rainy season	0.8604
China dry season	0.8515
China rainy season	0.8713
Thailand dry season	0.8777
Thailand rainy season	0.8680
Vietnam dry season	0.8857
Vietnam rainy season	0.8785

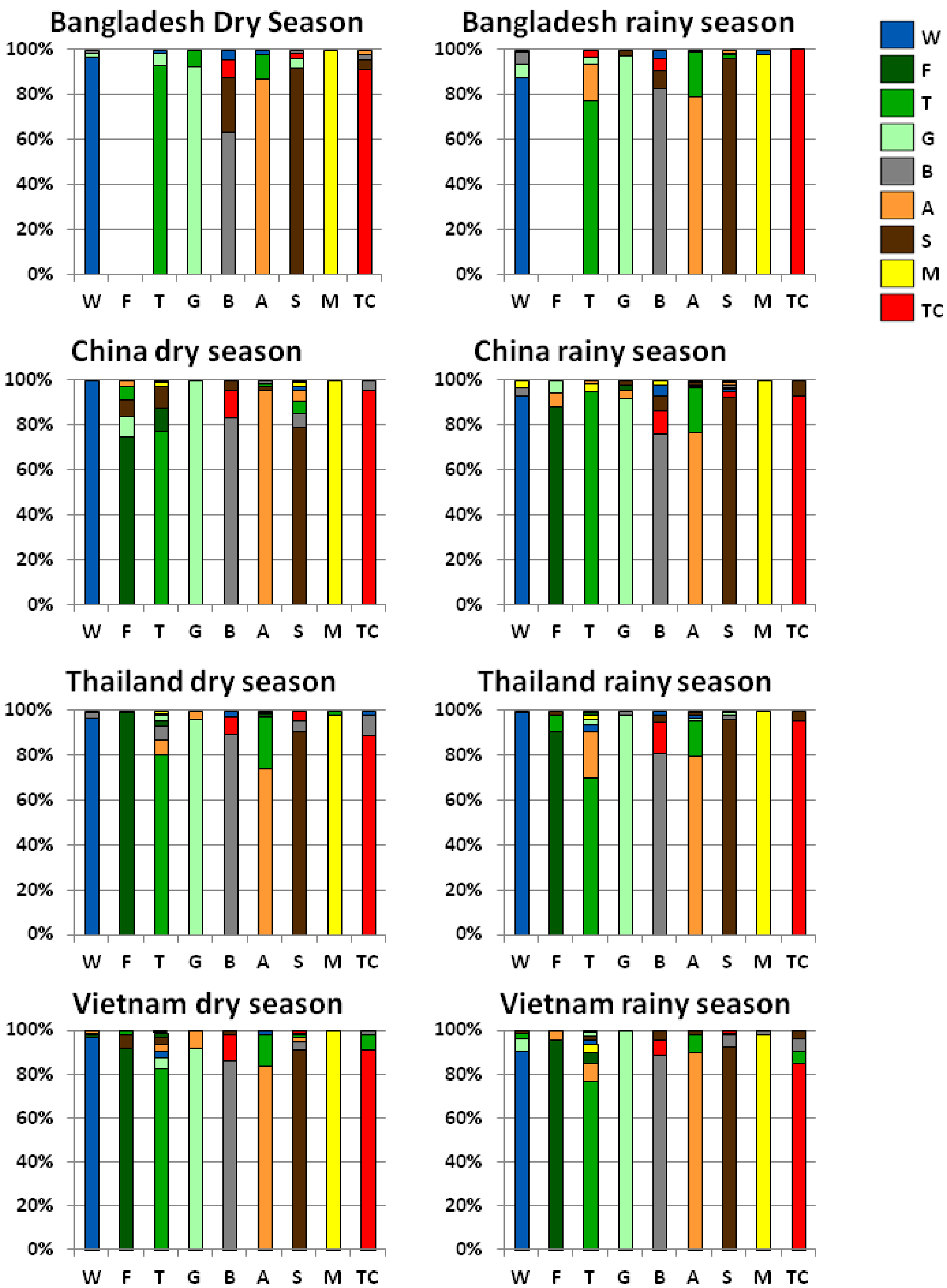


Figure 4.10: Errors of commission for each land use model

Note: This represents the information which is mistakenly included in a particular class, where points on the map are found to be something different using ground truth information (Eastman, 2013). The bars show the misclassification between the model and the ground truth points (e.g. for approx 5% of the sampled map points for Vietnam rainy season that should have been forest the ground truth data indicated it was agriculture).

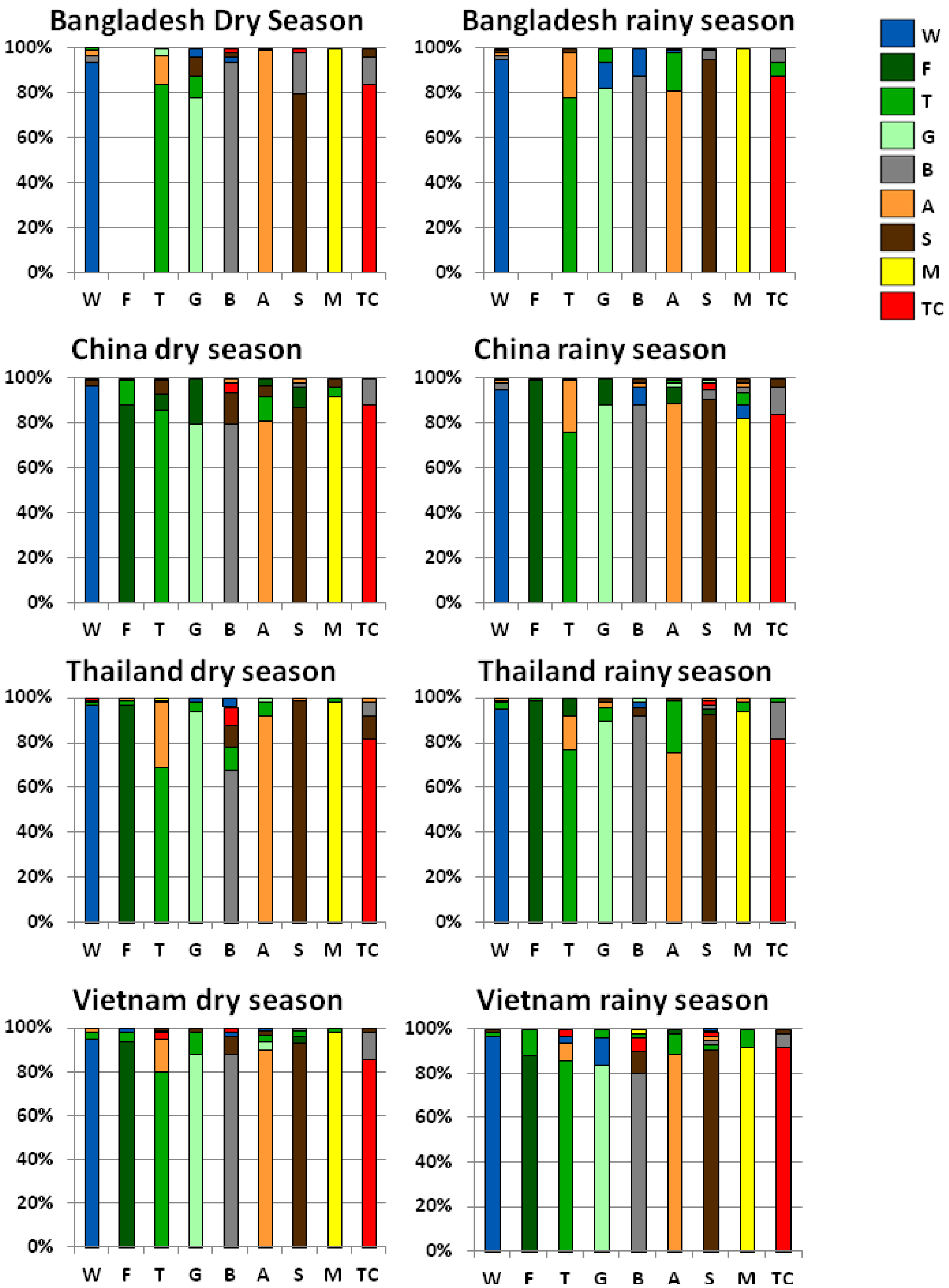


Figure 4.11: Errors of omission for each land use model

Note: This represents the information which is mistakenly excluded in a particular class, where ground truth points are something different on the land use model (Eastman, 2013). The bars show the misclassification between what the model and what the ground truth points (e.g. for approx 10% of the ground truth points for Vietnam rainy season that should have been forest the map indicated it was trees/heavy vegetation).

4.4. Discussion

Access to and use of land is a contentious issue particularly when different stakeholders and user groups are involved. The EAA aims to ensure that aquaculture is developed sustainably whilst taking into account the full range of ecosystem functions and services with respect to all relevant stakeholders (Soto *et al.*, 2008). Consequently it is essential that the aquaculture industry considers the wider environment and interactions with surrounding land use. Spatial models of land use and cover can be used to indicate potential areas for development, identify areas that should be protected and isolate areas that have many stakeholders and require detailed land management practices. Furthermore, if the models are updated regularly they can be also used as an indicator of land use change and inform of the potential impact of an activity.

However, a cautionary approach must be adopted when making conclusions from land use maps and models as they are essentially snapshots in time and can vary significantly over the years; therefore it is important that land use maps and models are updated frequently. Moreover, often studies that include land use maps and models utilize datasets that have only been developed for one particular time and do not take into account seasonal variability. The results from this study have shown there are significant seasonal differences in land use which should be considered within aquaculture development and environmental management, especially in view of the EAA.

Naturally occurring seasonal events such as flooding and excess rainfall can have a significant impact on the land as shown in Bangladesh and Vietnam where the largest increase between dry season and rainy season is water (Figs 4.5 and 4.9). Both study areas have low elevation and naturally experience seasonal flooding. As a result, people may use the land differently throughout the year, rotating crops, harvesting and managing seasonal flooding for rice paddies. The extent of water coverage is difficult to assess without the use of spatial models which extend across the entire catchment. Flooding may significantly impact production as stock is often lost and/or supply chains and transport links damaged (Tran *et al*., 2008) potentially impacting local and regional food security. Decision makers can use the spatial models to identify areas that may be susceptible to flooding and put in mitigation methods such as barriers to protect farms. On the other hand, with suitable containment systems, flooded areas may also present an opportunity for aquaculture where other agriculture crops cannot be grown (Kumar, 2011). This could provide a valuable adaptation to environmental conditions and a source of income and food for local communities.

The agricultural cycle can also be visualised, such as the change from soil / light vegetation to agriculture in China and Thailand which is largely due to the growing season (Figs. 4.7 and 4.8). If an area is dominated by agriculture then a seasonal approach might not be sufficient and monthly models may be required to account for more complex crop management issues, such as areas in Bangladesh where triple crops are produced per year. Knowing the areas where aquaculture and agriculture coexist is important as there may be extra demands for water resources at certain times of the culture cycle. Furthermore some aquaculture systems, such as shrimp farming, can have adverse impacts on agriculture (Flaherty and Karnkankesorn, 1995; Ali, 2006), whilst runoff from agriculture systems can result in water quality issues (Sebesvari *et al*., 2012; Muňoz *et al*., 2013). Understanding potential areas of conflict and/or concern (such as poor water quality) allows regulators to restrict development such as the initiative shown by the Thai government where a moratorium was placed on inland marine shrimp farms in areas designated as freshwater ecosystems due to concerns over elevation of salts (Roy *et al*., 2010).

Large regional models, such as those presented in this study, have some limitations. It is expensive, in terms of time, resources and money, to conduct detailed ground truth work. Therefore, this study adopted a general classification scheme (Table 4.1) which covered the major uses of land but does not detail individual crop classes or farming systems. A more detailed classification using the same methodology and a larger number of more specific classes could be applied to smaller study areas if representative ground truth information is available. However, this is not always achievable at a large watershed/regional scale as some areas are used for multiple purposes such as integrated rice-shrimp farming in Vietnam (Brennan *et al*., 2006) and rice-prawn farming within ghers in Bangladesh (Ahmed *et al*., 2008a). The image classification may identify rice as the dominant land use but could miss the additional uses such as shrimp and prawn culture which cannot be detected in the Landsat ETM+ satellite imagery. Mixed pixels can be used where clear clusters are not apparent. However this can complicate issues when land use is used in subsequent analysis and may be more appropriate for smaller areas.

It is also important to note there may be misclassification between classes as shown in Figs. 4.10 and 4.11. More training sites could be used; however, the main challenge is modelling across multiple Landsat ETM+ scenes where the spectral responses of the same land cover are different even after the scenes have been mosaiced into a larger image. Consequently, obtaining distinct training sites and spectral signatures can be complicated. Modelling is an iterative process and as such models should be continually updated and refined. Regional land use models should be used along with local level studies to provide a holistic view of the situation and enable effective decision support.

The advantage of modelling a large catchment is that it provides decision makers an overview of potential issues within an area which would not be apparent at a local or farm specific scale. As noted by Soto *et al*. (2008) when aquaculture activities are poorly planned and regulated there can be increased inequality within the watershed scale. Whilst efforts should be made to ensure that no stakeholders are impacted adversely, this could be an unintentional consequence if they are not included within an overall assessment that is only conducted at a local level. There could be a scenario where upstream stakeholders benefit from a system whilst downstream stakeholders are negatively impacted and this would be against the key principles of the EAA where all stakeholders should be treated equally (Soto *et al.*, 2008). Furthermore, even across large regions and catchments individual areas may be subject to different issues, such as urbanisation and flooding, the extent of which can only be identified using models across large spatial areas. Such models can be used as decision support tools allowing an informed decision of where attention and support is needed whether that is a result of areas at risk, resources being under pressure or conflict between users.

Whilst land use can be monitored easily and efficiently at a very local level, it can be difficult, costly and time consuming to repeat this process across a large catchment. As this study has shown, spatial models of land use classified from satellite imagery are a valuable source of information at a catchment/regional level and they can be a useful tool for regional planners, policy makers and regulators. Many studies employ land use maps and models that have been developed for one time of year. However, to truly fulfil the requirements of the EAA and develop the industry in a sustainable manner a singular land map or model is not sufficient and land use should be monitored at least on a seasonal basis.

CHAPTER 5

MODELLING THE SEASONAL SUITABILITY AND SUSTAINABILITY OF POND AQUACULTURE ACROSS MULTIPLE LARGE CATCHMENTS USING GIS

5.1. Introduction

Population growth, intensification of agriculture, industrialisation and urbanisation all compete with aquaculture, particularly intensive systems, over access to and consumption of the same environmental goods and services (Beveridge et al. 1997). With increasing competition, and pressure from countless users on all aspects of the environment, aquaculture must aim for sustainable production whilst achieving a balance between the demand for aquaculture development and the need to conserve natural resources (Frankic and Hershner, 2003).

Within the EAA one of the key issues where GIS can be employed is aquaculture development; identification of suitable sites, zoning and allocation of space and planning (Aguillar-Manjarrez et al. 2010). GIS is advantageous to aquaculture planning and site selection as it provides the capability to process, analyse and present large amounts of data more efficiently and effectively than if the same assessment was conducted manually (Corbin & Young, 1997). The use of GIS for aquaculture site selection has been well documented (Ross et al. 2009; Ross et al., 2013) and studies cover many different species, systems and study areas (McLeod et al. 2002; Giap et al. 2005; Salam et al. 2005; Ross et al. 2011).

The success and sustainability of an aquaculture system can be strongly influenced by seasonal aspects of the environment (particularly factors such as temperature, rainfall and photoperiod) which can have significant implications for fish reproduction (Pankhurst and Porter, 2003), animal health (Bowden et al., 2007) water quality (Cowan et al., 1999) and wild seed supply (Parker, 2012). There are also other non-environmental seasonal issues, such as labour supply, finance and trade (Engle, 2011; Parker, 2012), which are important considerations for the aquaculture industry. Seasonal issues should be considered within aquaculture planning and farm management plans. Temporal data can be easily incorporated into spatial models and some studies have used seasonal measurements within their analysis (Longdill et al. 2008; Silva et al., 2011). The seasonal variability of site suitability is further highlighted in a study by Ross et al. (2011) which found significant differences of water availability in a reservoir in Mexico due to a large drop in water level between the wet and dry season. Consequently there were significant seasonal differences for both the availability and suitability of areas for cage culture (Ross et al. 2011). If the model used one single output then this seasonal variation could have been missed and the final model output would over estimate or under estimate the availability of suitable sites in the dry and wet season respectively. This stresses the importance of incorporating seasonal measurements, where possible, into site suitability studies.

Most site suitability and site selection studies focus on potential areas for new developments or expansion of aquaculture. However, site suitability models can also be applied to farms retrospectively to assess whether they are in the most suitable location. In extreme cases farms could be moved to a more suitable area. However, it also provides valuable information for decision makers and stakeholders in identifying individual farms or areas which may need assistance in the future, whether that is financial support, infrastructure development or even mitigation against potential climatic events. Aquaculture has developed rapidly in the past few decades and sites may have been selected for financial reasons to capitalise on the demand for products rather than what is best for aquaculture and the surrounding environment.

The aim of this study was to develop a model which could be used to assess the seasonal variations and suitability of sites for pond culture of several key aquaculture species in four areas of importance to global aquaculture production. Often models are developed for one specific area or system and wider applicability to other areas is an afterthought. Therefore in order to enable the application of the same model to different study areas and species a multi-stage framework was developed which can be adapted to new areas and scenarios. The framework also uses global datasets that are freely available allowing the model to be applied to almost any study area in the world.

5.2. Study Areas

Each of the four study areas are regions which farm selected species of commercial importance (Fig. 2.2); Penaeid shrimp (*L. vannamei* or *P. monodon)* in all four countries, Nile tilapia (*O. niloticus*) in China and Thailand, Giant river prawn (*M. rosenbergii)* in Bangladesh and pangasius (*P. hypophthalmus)*, also known as Striped catfish or Tra in Vietnam. The study area in Vietnam originally extended into Cambodia due to topographical features, however, as resources are unlikely to be shared between countries the political boundary was used to retain the study area within Vietnam (Fig. 2.3).

5.3. Methodology

5.3.1 Data Processing

The input data layers were selected as a result of field visits to each of the four study areas, visiting different farming systems and communicating with stakeholders to understand the parameters involved in farming the selected species. In order to produce models that could be used not only in the study areas but also other areas, an effort was made to use global datasets rather than data that is only available for one country. All data layers were processed so that they were in the UTM reference system for the study area with a spatial resolution of 30m.

5.3.2 Model structure

The model is structured in a multi-layered framework which gives users more flexibility as they can use the individual submodels and the combined final output within the decision making process. Fig. 5.1 shows the model structure, where the outcomes of four major submodels (Pond, Species, System and Access) are added together, along with a constraints layer, to produce the final output; the overall site suitability model. The model follows a tiered approach which represents the decision making process when evaluating an area for an aquaculture pond; where is the best place for a pond? What species can be farmed where? What system could be established and how easily accessible is that farm from transport networks and urban centres? This sequential process was established after discussions with aquaculture experts from both Europe and Asia.

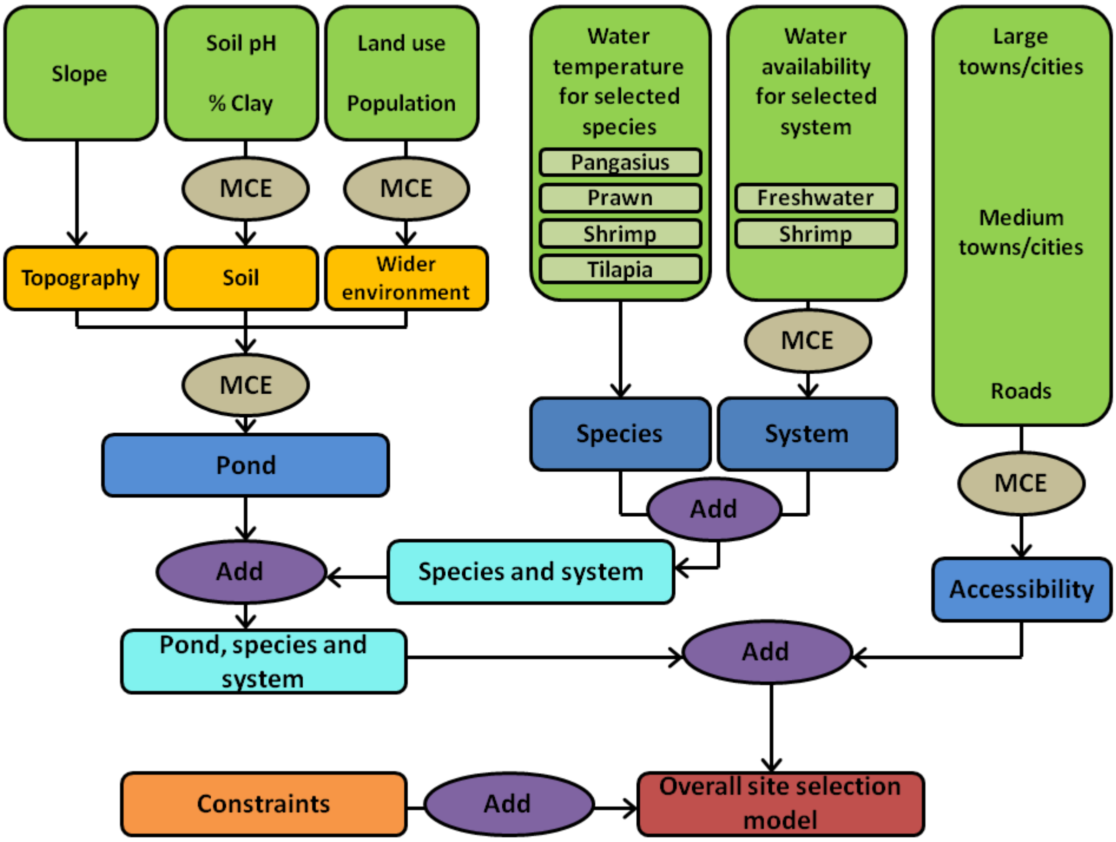


Figure 5.1: Conceptual design of the multi-tiered site suitability framework

Each submodel was developed using layers which are relevant to the overall factor being evaluated. All layers were standardised to a common numeric range of 1 to 4 prior to integration within a submodel, based upon a thorough literature review to derive scores which represented how suitable the factor was in terms of aquaculture, sustainability and environmental impact (Table 5.1).

Table 5.1: Scoring system for model development

Score	Descriptor	Description
1	Highly unsuitable /unsustainable	Area would require too much time and money to develop a sustainable system and/or would result in significant long-term damage to the environment.
2	Unsuitable /unsustainable	Area would require a significant and continued investment of time and money to develop and manage sustainable pond aquaculture, and/or there would be long-term damage to the environment.
3	Suitable /sustainable	Area would require some investment (time and money) to develop sustainable pond aquaculture and/or there could be some impact on the environment which could be mitigated against.
4	Highly suitable /sustainable	Area would require minimal investment (time and money) to develop sustainable pond aquaculture and there would be minimal impact to the environment.

5.3.2.1 Pond submodel

The Pond submodel indicates suitable areas for ponds regardless of water availability and aquaculture requirements. This is the most complex submodel as it includes three minor submodels; wider environment, topography and soil which were then combined using a weighted linear multi-criteria evaluation (MCE) as outlined in Table 5.2.

Table 5.2: Reclassification values and weightings within the Pond submodel

Submodel	Layer	Site suitability Score				
		Highly Suitable 4	Suitable 3	Unsuitable 2	Highly Unsuitable 1	References
Topography Weight: 0.2970	**Slope**	0.5 - 2 %	0 - 0.5 % 2 -5 %	5 -10%	> 10%	Modified from: FAO, 1995; Hajek & Boyd, 1994; Mittlemark & Landkammer, 1990
Soil	**Soil pH** Weight: 0.55	6 - 9	4.5 -6	3.5 - 4.5 >9	0 -3.5	Adapted from: Bose *et al.*, 1991; Boyd, 1995; Hajek & Boyd, 1994;
Weight: 0.1634	**Clay content** Weight: 0.45	25-35%	35-60%	15-25%	<15% >60%	Adapted from: Boyd *et al.*, 2002; Hajek & Boyd, 1994; Tucker, *et al.*, 2008;
Wider Environment	**Land use** Weight: 0.60	Water	Agricultural land, bare soil/light vegetation	Grassland/shrubbery, Orchard/trees/heavy vegetation,	Forest, Mangroves, Towns/cities	Adapted from: Boyd & Tucker, 1998; Dudgeon, 2000; Boyd & Shmittou, 1999; Zhao *et al.*, 2006
Weight: 0.5396	**Population** Weight: 0.40	Rural low density (<100 people per km^2)	Rural high density (100-500 people per km^2)	Peri-urban (500-5000 people per km^2)	Urban (>5000 people per km^2)	Adapted from: van Brakel & Ross, 2011

Topography

The topography of an area can have significant implications for the sustainability of an operation. If the land around the pond is flat then the pond will not be able to drain entirely without pumping as there may not be a nearby area where the ground level is lower than the bottom of the pond (Mittlemark and Landkammer, 1990). On the other hand if a slope is too steep then pond construction becomes difficult and costly (Mittlemark and Landkammer, 1990; Hajek and Boyd, 1994), and could also significantly alter the natural landscape. Slope was calculated from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) (NASA, 2009) and reclassified as noted in Table 5.2 to become the topography submodel.

Soil

Soils are an important factor in aquaculture as they influence both production and water quality (Boyd, 1995). In recent years the recommendations regarding the clay content of soils have been updated (Boyd *et al*., 2002). Previously, it was suggested that soils for pond construction should have a clay content greater than 35% (Hajeck & Boyd, 1994). However, soils with a high clay content are highly plastic and cohesive which can result in difficulties using machinery, therefore a slightly lower clay content is now preferred when constructing ponds and soils with a clay content as low as 5 - 10% can be used for the construction of embankments providing that they are well graded (Tucker & Hargreaves, 2008). It is also important to ensure that soils are not too acidic or too alkaline in order to ensure animal growth and good health. Mitigation methods can be employed where the soil is unsuitable such as the use of pond liners for water retention and using lime to increase the alkalinity of water in areas which are too acidic. The soil data in this study was obtained from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012), reclassified and combined as shown in Table 5.2 to produce the soil submodel.

Wider environment

One of the main principles of the EAA is that aquaculture should be developed in the context of other sectors and the surrounding natural and social environments should be considered (Soto *et al*., 2008). Land use and population density were used as indicators of current use and pressure on the natural resources and the layers were combined to produce the wider environment submodel. A supervised classification technique was used to classify Landsat ETM+ satellite imagery to produce two land use layers for each country; one for the rainy season and one for the dry season (Chapter 4). This was then reclassified as outlined in Table 5.2 to represent the suitability and sustainability of aquaculture within different types of land use. Due to the multitude of activities that can occur on river networks it can be assumed that higher population levels will lead to more pressure on the water resources, stakeholder conflict and a higher potential for pollution. Population density was used as a proxy in this model to represent human pressure on the water resources and the potential impact on water quality. If population level is high then there will be more pressure from human communities with greater amounts of water being extracted so there will be less for aquaculture. There is also a greater risk of contamination from pollutants from other water users and so areas with a higher population level are unsuitable for aquaculture development. Population density was calculated from ambient population data obtained from the LandScan 2008 dataset (Oak Ridge National Laboratory, 2008) and reclassified and combined with the Land use layer as shown in Table 5.2.

5.3.2.2 Species submodel

The Species submodel is comprised of one layer representing the suitable temperature for growth of a selected species. As noted by Boyd and Tucker (1998) water temperature is possibly the most important factor affecting aquaculture production as it affects the natural productivity of aquatic ecosystems, and all other water quality variables. In addition, water temperature also plays a significant role in the physiology, health and welfare of the farmed species (Brett and Groves, 1979; Boyd and Tucker, 1998). The four species used in this study are *M.rosenbergii* (prawn) in Bangladesh, *O.niloticus* (tilapia) in China and Thailand, *P. hypophthalmus* (pangasius) in Vietnam and or *Penaeus sp.* (shrimp) in all four study areas. Each of these species have different temperature ranges and tolerances therefore they must be treated individually. Monthly air temperature, obtained from the Worldclim database (Hijmans et al., 2005), was converted to water temperature using Equation 5.1 (Kapetsky, 1994). The resulting layers were then reclassified using suitable values extracted from the literature (Table 5.3). It must be noted that there have been few studies on the environmental requirements for pangasius; particularly with regards to optimum temperature. Many reports cite a temperature range of 22 - 26°C from Riehl and Baensch (1996). However, this is inaccurate as the authors are referring to suitable temperatures for aquariums rather than aquaculture. Le (1994) and Giang et al. (2008) report temperature ranges that are more representative of the natural conditions of the Mekong where pangasius thrives and these were therefore used in this study (Table 5.3).

$$Water\ temperature = -6.35 + 1.3 * Air\ temperature \quad \text{[Equation 5.1]}$$

Table 5.3: Reclassification values within the Species submodel

Layer	Highly Suitable	Suitable	Unsuitable	Highly Unsuitable	References
	Site suitability				
	4	**3**	**2**	**1**	
Tilapia (*O. niloticus*)	27 - 30	24 - 27 30 -35	20 - 24	<20 >35	Adapted from: El-Sayed, 2006; Ross, 2000
Pangasius (*P. hypophthalmus*)	27.5 -30	25 - 27.5 30 - 34	20 - 25 34- 35	<20 >35	Adapted from: Le 1994; Giang *et al*., 2008;
Prawn (*M. rosenbergii*)	28 - 31°C	25 - 28	19 -25 31 - 33	<19 > 33	Adapted from: New, 2002
Shrimp (*Penaeus sp.*)	27 - 30	23 - 27	15 - 23 30 - 33	< 15 > 33	Adapted from: Briggs *et al*., 2005

5.3.2.3. System submodel

The System submodel represents the availability of water and therefore the type of system that could be sustained within an area, assuming minimal climate change. If a farm is situated in an area with no access to rivers or lakes and is solely dependent on rainfall then there could be issues with water supply in dry seasons and it could be difficult to establish a sustainable system. Furthermore, during a period of drought farms that are reliant on a single water source could suffer from water shortages and it is more suitable to have multiple options for water supply. There are two separate System submodels; one for freshwater which is comprised of three layers (distance to rivers, distance to waterbodies and water balance) and one for shrimp which has four layers (distance to the sea, distance to rivers, distance to waterbodies and water balance) as shown in Table 5.4.

Table 5.4: Reclassification values within the System submodel

Submodel	Layer	Site suitability Highly Suitable 4	Suitable 3	Unsuitable 2	Highly Unsuitable 1	References
Freshwater aquaculture	**Water balance** Weight: 0.2098	>0mm	-1 to -500mm	-500 to -1000mm	<-1000mm	Adapted from: Aguilar-Manjarrez & Nath, 1998
	Distance to rivers Weight: 0.5499	0 to 500m	500 to 1000m	1000 to 2000m	>2000m	Adapted from: McLeod *et al*., 2002; Salam *et al*., 2005
	Distance to waterbodies Weight: 0.2402	0 to 500m	500 to 1000m	1000 to 2000m	>2000m	Adapted from: McLeod *et al*., 2002; Salam *et al*., 2005
Shrimp culture	**Water balance** Weight: 0.1087	>0mm	-1 to -500mm	-500 to -1000mm	<-1000mm	Adapted from: Aguilar-Manjarrez & Nath, 1998
	Distance to rivers Weight: 0.3339	0 to 500m	500 to 1000m	1000 to 2000m	>2000m	Adapted from: McLeod *et al*., 2002; Salam *et al*., 2005
	Distance to water bodies Weight: 0.1362	0 to 500m	500 to 1000m	1000 to 2000m	>2000m	Adapted from: McLeod *et al*., 2002; Salam *et al*., 2005
	Distance to Sea Weight: 0.4212	0 to 1000m	1000 to 2000m	2000 to 4000m	>4000m	Adapted from: Giap *et al*., 2005

Data on rivers was downloaded from the USGS HydroSHEDS database (USGS, 2010) which uses the SRTM DEM to produce a vector layer of the global river network. Subsequent assessment using satellite imagery found the data was not representative for low lying areas, particularly the deltaic regions of Bangladesh and Vietnam. Furthermore, as it uses the topography of the region to calculate the river network it does not take into account anthropogenic alterations. Consequently the data omits the many man-made channels and dike systems that have significantly altered the natural landscape and hydrodynamic conditions in Vietnam (Hung *et al*., 2011). The HydroSHEDS layer was used for China as many of the rivers follow the contours of the land; however, some rivers that were absent were digitised from Google Earth and added to the layer. For Bangladesh, Thailand and Vietnam three river layers were digitised within IDRISI using Landsat ETM+ satellite imagery, Google Earth and ground truth information. Dry season Landsat ETM+ imagery was used to provide an indication of rivers that are present all year round as seasonal rivers can be common in Asian countries such as Bangladesh (Chowdhury, 2010).

Layers representing waterbodies were downloaded from the USGS SRTM Water Body Data (SWBD) database (NASA, 2009). Landsat satellite imagery, Google Earth and IDRISI were used to verify and update the images as required. Only standing bodies of water such as lakes and reservoirs were used within this layer as rivers and the sea were included within other layers. The sea layer was obtained by reclassifying the SRTM DEM. Finally the water balance for pond aquaculture, which represents the balance of inputs from precipitation against losses due to evaporation and seepage from ponds, was calculated using Equation 5.2 (Aguilar-Manjarrez and Nath, 1998). Monthly precipitation was obtained from the worldclim database (Hijmans, 2005), monthly evapotranspiration data was obtained from Trabucco and Zomer (2009) and the model included a seepage rate of 8cm/month as had been used previously in the same equation for Africa (Aguilar-Manjarrez and Nath, 1998) and Latin America

(Kapetsky and Nath, 1997). All of the layers were reclassified as described and combined within weighted linear MCEs as described in Table 5.4.

$$WaterBalance = [(Precipitation\ (mm) * 1.1) - (Evapotranspiration * 1.3) - (Seepage)]$$

[Equation 5.2]

5.3.2.4. Access Submodel

Accessibility of a site can be a critical factor for an aquaculture venture and could influence the success or failure of an operation. This submodel was considered to be the final stage in the modelling process as accessibility does not influence the actual ability to farm products however it does have issues for labour, markets and trade. Layers were digitised within IDRISI representing the major roads in each of the study areas using satellite imagery, Google Earth and ground truth data. Information on all towns and cities in each study area with a population above 20,000 was obtained from Brinkhoff (2011). Google Earth was used to digitise polygons around each town/city and this information was then imported into IDRISI; cities and towns with a population of less than 100,000 were classified as a medium urban area and cities and towns with a population of more than 100,000 were classified as a large urban area. Although close proximity to urban areas is an advantage there should also be a buffer zone around the urban area where aquaculture is not developed to allow for further expansion of the town/city and to reduce potential pollution impacts. The layers were reclassified and combined within a weighted linear MCE to produce the Access submodel as shown in Table 5.5.

Table 5.5: Reclassification values and weightings used within the Access submodel

Layer	Site suitability Highly Suitable 4	 Suitable 3	 Unsuitable 2	 Highly Unsuitable 1	References
Distance to roads Weight: 0.5499	0-500m	500-1500m	1500-4000m	>4000m	Adapted from: Salam *et al.*, 2005; Giap *et al.*, 2005
Distance to large sized urban area (population>100,000) Weight: 0.2402	2 - 7km	7-10km	10-15km	0-2km >15km	Adapted from: Salam *et al.*, 2005
Distance to medium sized urban area (20,000 - 100,000 population) Weight: 0.2098	1 - 5km	5-7km	7-10km	0-1km >10km	Adapted from: Salam *et al.*, 2005

5.3.2.5. Constraints

Three categories were considered to be constraints to pond aquaculture. These are areas where ponds could not or should not be developed; areas of biodiversity and national importance, urban areas and large water bodies such as lakes and reservoirs. The urban areas included within the Access submodel were used within the constraints layer as were the large water bodies from the System submodel. Areas of biodiversity and national importance were obtained from IUCN and UNEP-WCMC (2012), cross referenced with national and regional information and then refined in Google Earth and IDRISI, if necessary, to ensure the layer was representative of the national parks and protected areas of the study areas. The three layers were then added together to create a mask containing all constraints.

5.3.3. Overall model development and farm assessment

Following development of the four submodels (Pond, Species, System and Access) there was a sequence of intermediate submodels (Species and system and Pond, Species and System) as the individual submodels were added together to produce the final output as shown in Fig. 5.2. This transparent tiered approach assists decision makers as it allows a detailed understanding of how the individual submodels contribute to the overall result.

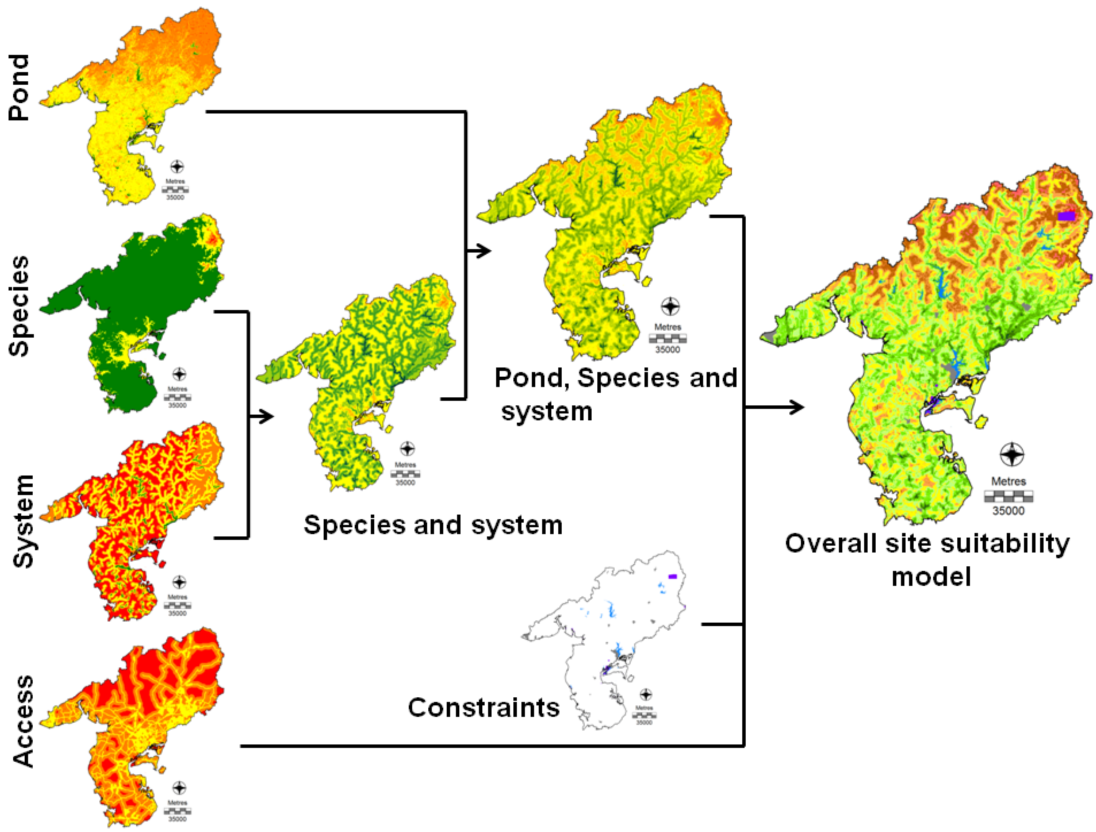


Figure 5.2: The sequential process of model development

(Example – Tilapia in the dry season, China)

GPS locations of existing farms in the four study areas were obtained from a farmer survey conducted by the SEAT project (Murray et al. 2011). Whilst the SEAT farmer survey covered a number of areas across each country this study only used farms that were located within the catchments selected for spatial modelling and hence the numbers of farms varied; however there were at least 100 farms per species for each study area. The location of each farm was assessed within the outputs of the individual submodels to evaluate the suitability of sites.

Suitability models are difficult to validate as they are often based on a combination of features which cannot be evaluated outwith a modelled environment. However it is important to assess if they are representative; therefore partial verification can take place using the GPS co-ordinates of existing farms and cross-referencing them with the model output. This study compared the locations of the SEAT farms with the overall site suitability models to assess how representative the model results are and partially validate the model. This is an accepted method for validating site suitability models and has been used previously by many studies including Hossain and Das (2010), Radiarta *et al*. (2008) and Salam *et al.* (2005).

5.4. Results

5.4.1. Submodel outcomes

The results of the submodels for Bangladesh (prawn and shrimp) and China (tilapia and shrimp) are shown in Fig. 5.3 and the results for Thailand (tilapia and shrimp) and Vietnam (pangasius and shrimp) are shown in Fig. 5.4. It should be noted that there are two submodels for Pond (dry season and rainy season), four submodels each for Species, four submodels for System and one submodel for Access. Most of the areas are suitable or highly suitable with regard to the Pond submodel; however some areas in China (Fig. 5.3) are classed as unsuitable due to steep slopes which would prevent pond construction. The results indicate that the submodel with the most significant seasonal change is the Species submodel with three of the four study areas (Bangladesh, China, Thailand) experiencing differences in suitability for both species due to temperatures outwith optimal ranges (Fig. 5.3, Fig. 5.4). The System submodel indicates seasonal variability for prawn in Bangladesh (Fig. 5.3) and pangasius in Vietnam (Fig. 5.4) due to seasonal changes in water balance. The results from the Access submodel show there are extensive transport networks throughout each study area which would be advantageous for aquaculture and suitable for site selection. However, there are also many areas which are highly unsuitable, allowing decision makers to identify areas which may need support or help to establish transport links if aquaculture was to be developed there.

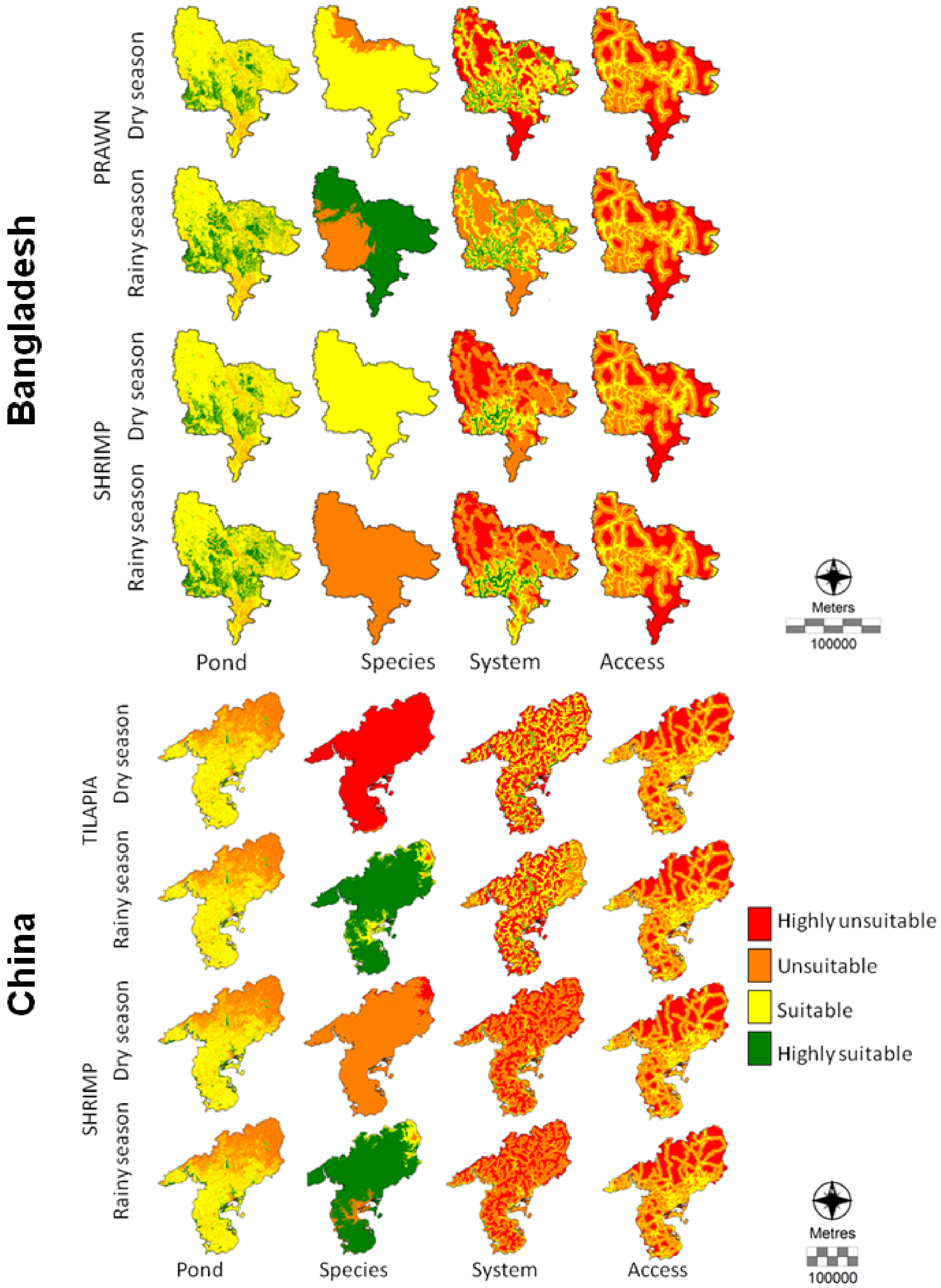


Figure 5.3: Submodels for Bangladesh (prawn and shrimp) and China (tilapia and shrimp)

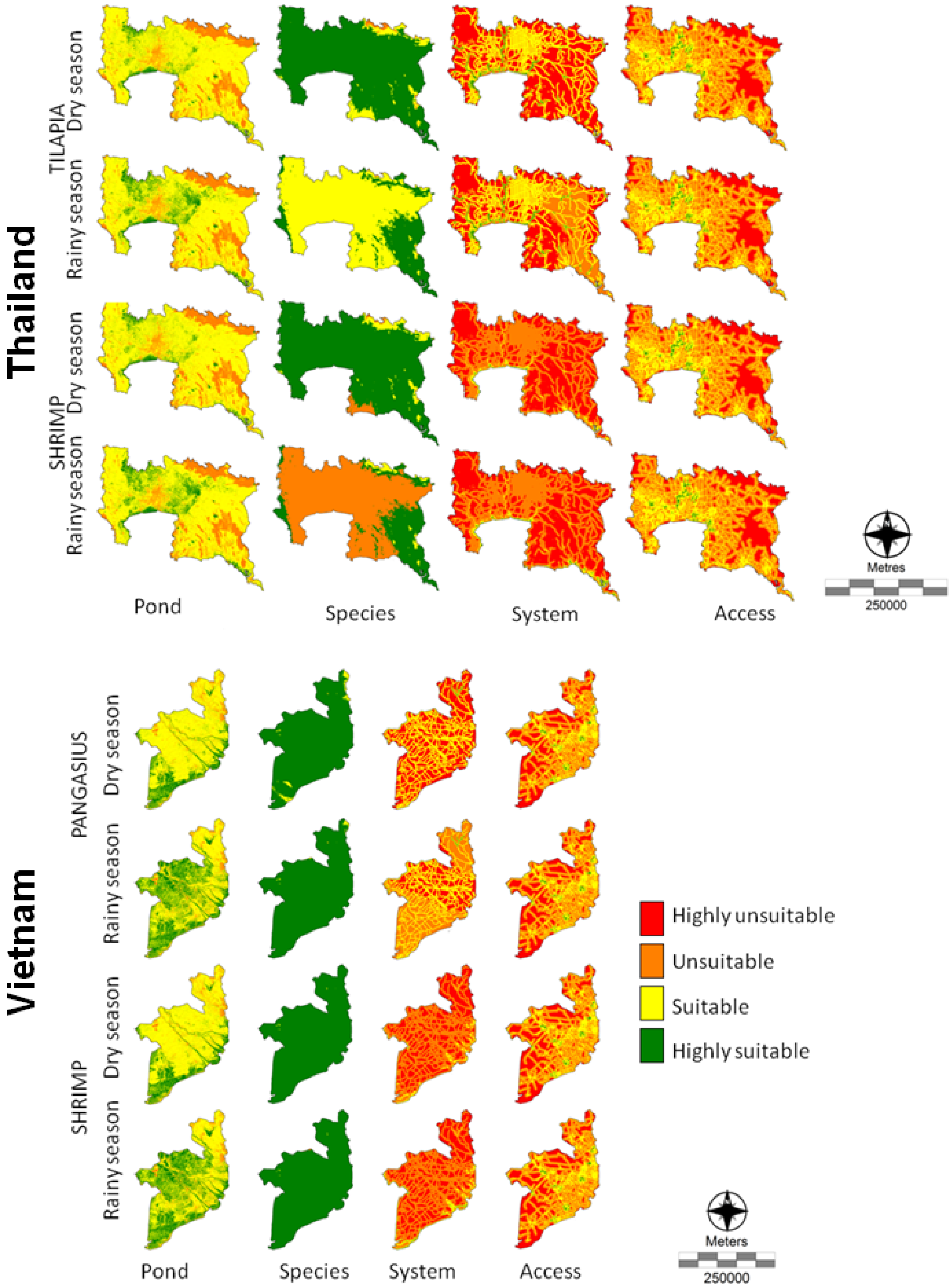


Figure 5.4: Submodels for Thailand (tilapia and shrimp) and Vietnam (pangasius and shrimp)

The Vietnamese Species submodel (Fig. 5.4) shows little seasonal variation for pangasius and shrimp culture due to temperatures remaining within the optimal range throughout the year which highlights the potential for year round culture. However, the Vietnamese System submodel for pangaisus indicates that there are fewer suitable areas for culture in the dry season than in the rainy season which may prevent expansion to some areas. This highlights the benefit of using a transparent multi-tiered approach as decision makers can identify the individual submodels which contribute to a result rather than just the final outcome.

5.4.2. SEAT farm locations and individual submodels

The results of the analysis of freshwater farm locations and the individual submodels are shown in Fig. 5.5. Most of the farms in each study area are located in areas considered to be either suitable or highly suitable with regard to the Pond submodel. Most of the surveyed farms in all of the countries, apart from Vietnam (where temperatures are within the optimal range throughout the year), experienced a seasonal change in suitability with regard to the Species submodel. In Bangladesh all of the farms are located in suitable areas during the dry season but in the rainy season approximately 30% are in areas that are classified as unsuitable due to high temperatures. The Chinese farms are located in areas where the temperature is highly unsuitable for tilapia culture during the dry season. However, in the rainy season, all of the farms are located in highly suitable areas; illustrating the change in suitability between seasons and the need for farmers in such areas to adjust their farming practices to fit in with the seasonal water temperatures. In Thailand, all of the farms are located in highly suitable areas in the dry season and suitable areas in the rainy season as although temperatures increase in the rainy season outwith the optimal range for tilapia this would not inhibit culture.

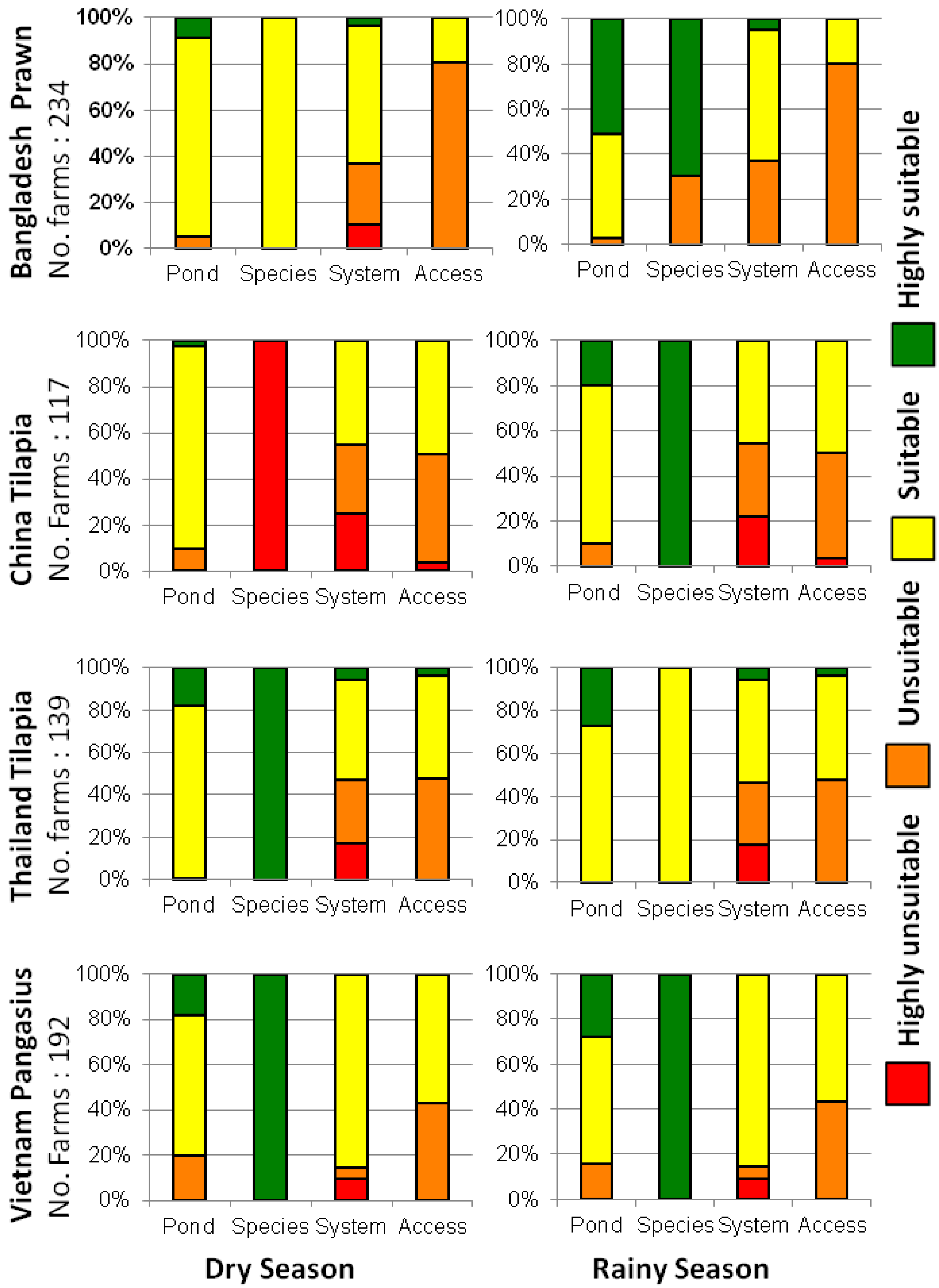


Figure 5.5: Comparison of the four spatial submodel outcomes for selected freshwater species with SEAT farm locations in the dry season and rainy season

Fig. 5.5 shows there is little seasonal variation with regard to the System submodel. In Bangladesh almost 40% of the surveyed farms are considered to be in unsuitable or highly unsuitable areas in both seasons. This indicates that these farms could have water supply issues if there is a sustained drought; an issue that could be particularly serious in the dry season. Approximately 55% and 46% (varying slightly between seasons) of the farms in China and Thailand, respectively, are located in unsuitable or highly unsuitable areas according to the System submodel. It must be noted that some of these farms may rely on smaller channels and rivers which were not evident from the satellite imagery; however the smaller channels and rivers may also be at risk from lower flows during the dry season making them less suitable as a source of water. In Vietnam less than 20% of the farms are found to be in unsuitable or highly unsuitable areas. This is because most of the surveyed pangasius farms were located along the Mekong river and secondary canals; therefore, they are not solely reliant upon rainfall to fill the ponds. Analysis of the Access submodel indicates that many of the farms in each study area are located in areas that are unsuitable. This is because many of the surveyed farms were in rural communities that were away from major roads and cities.

The results of the analysis of shrimp farm locations and the individual submodels are shown in Fig. 5.6. As with the results from the freshwater farms, almost all of the shrimp farms in each study area are located in areas which are either suitable or highly suitable with regards to the Pond submodel. Likewise there are similar seasonal issues with the shrimp farms as there are with the freshwater species. All of the farms in Bangladesh and China are considered suitable and highly suitable respectively during the dry season and all of the farms in Bangladesh and approximately 60% of the farms in Thailand are in areas considered unsuitable locations in the rainy season due to high temperatures. In China, farms are in unsuitable locations during the dry season as a result of the cold temperatures, while Vietnam experiences temperatures within the optimal range for shrimp culture in both seasons.

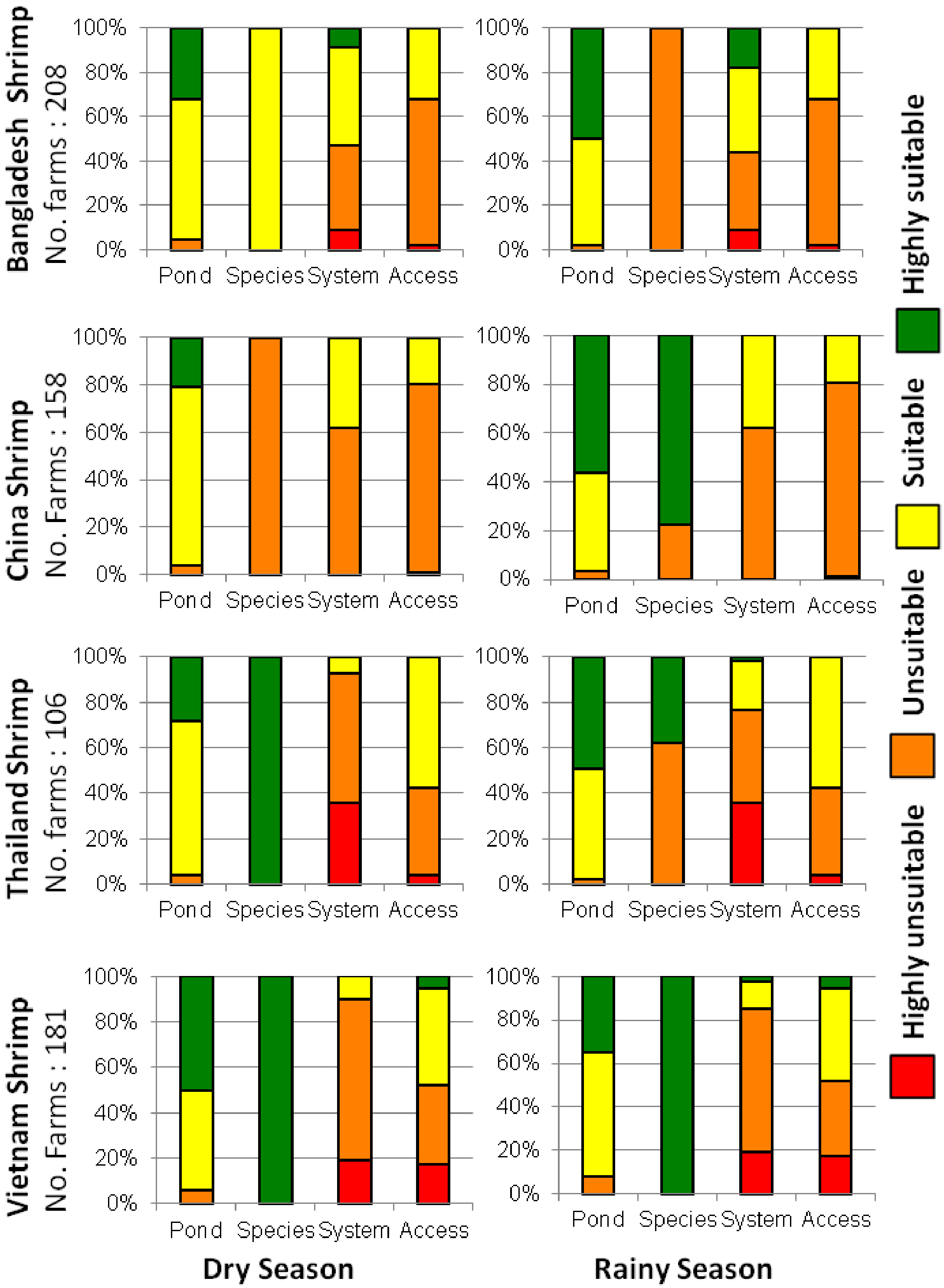


Figure 5.6: Comparison of the four spatial submodel outcomes for shrimp with SEAT farm locations in the dry season and rainy season

Fig. 5.6 shows that many of the shrimp farms are located in areas which are considered to be unsuitable or highly unsuitable with regard to the System submodel. This is due to shrimp culture moving further inland into more marginal areas away from the sea, which was the highest weighted layer in the System submodel for shrimp. Whilst inland culture has developed in recent years it can lead to contamination of freshwater supplies and some governments have restricted the development of inland shrimp farms in certain areas (Roy *et al*., 2010). Therefore, not all inland areas are suitable for culture of shrimp and local regulations should also be consulted prior to site selection. The comparative analysis of shrimp farm locations and the Access submodel shows similar results to the freshwater species. Again, this is due to farms being located in rural areas further away from major transport networks and urban centres. Although these farms can function successfully, they may require extra time to travel to and from the site which may have higher transport costs. Additionally, the farms may also be at higher risk from isolation if a disaster, such as flooding, occurs and damages links to the wider community; decreasing the overall suitability of the site.

5.4.3. Overall site suitability models

The overall site suitability models for the selected freshwater species are shown in Fig. 5.7 and Fig. 5.8 whilst Table 5.6 shows the area of each suitability category. The overall suitability model has a range which was developed from addition; therefore, the original 1 to 4 scale applied to the submodels is not relevant. To make the results easier to interpret the overall site sutiability models were divided into similar categories with a new category, moderate, added to describe areas which were neither suitable nor unsuitable

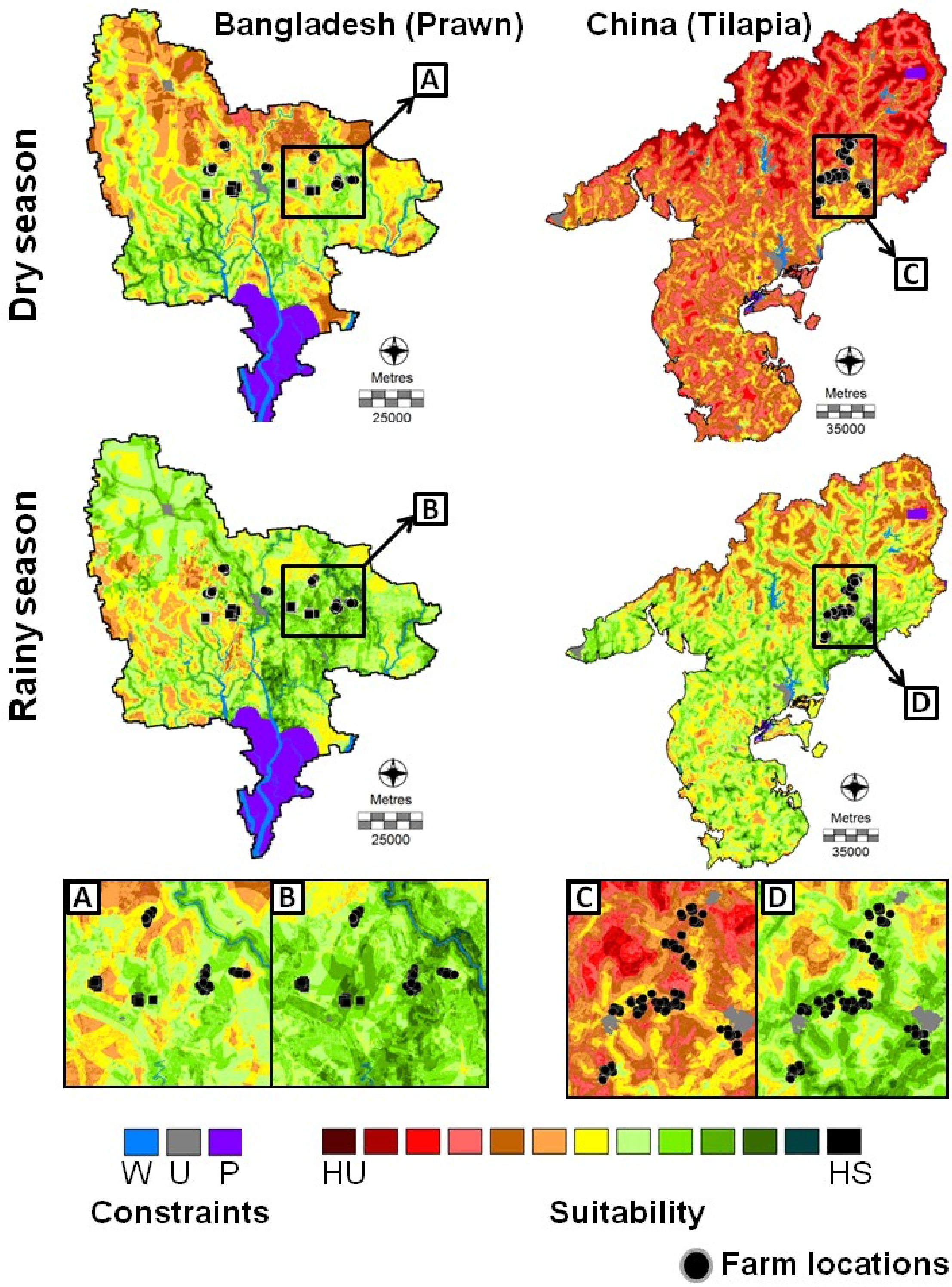


Figure 5.7: Overall site suitability models for Bangladesh (prawn) and China (tilapia)

W = Water, U = Urban areas, P = Protected areas,

HU = Highly Unsuitable, HS = Highly suitable.

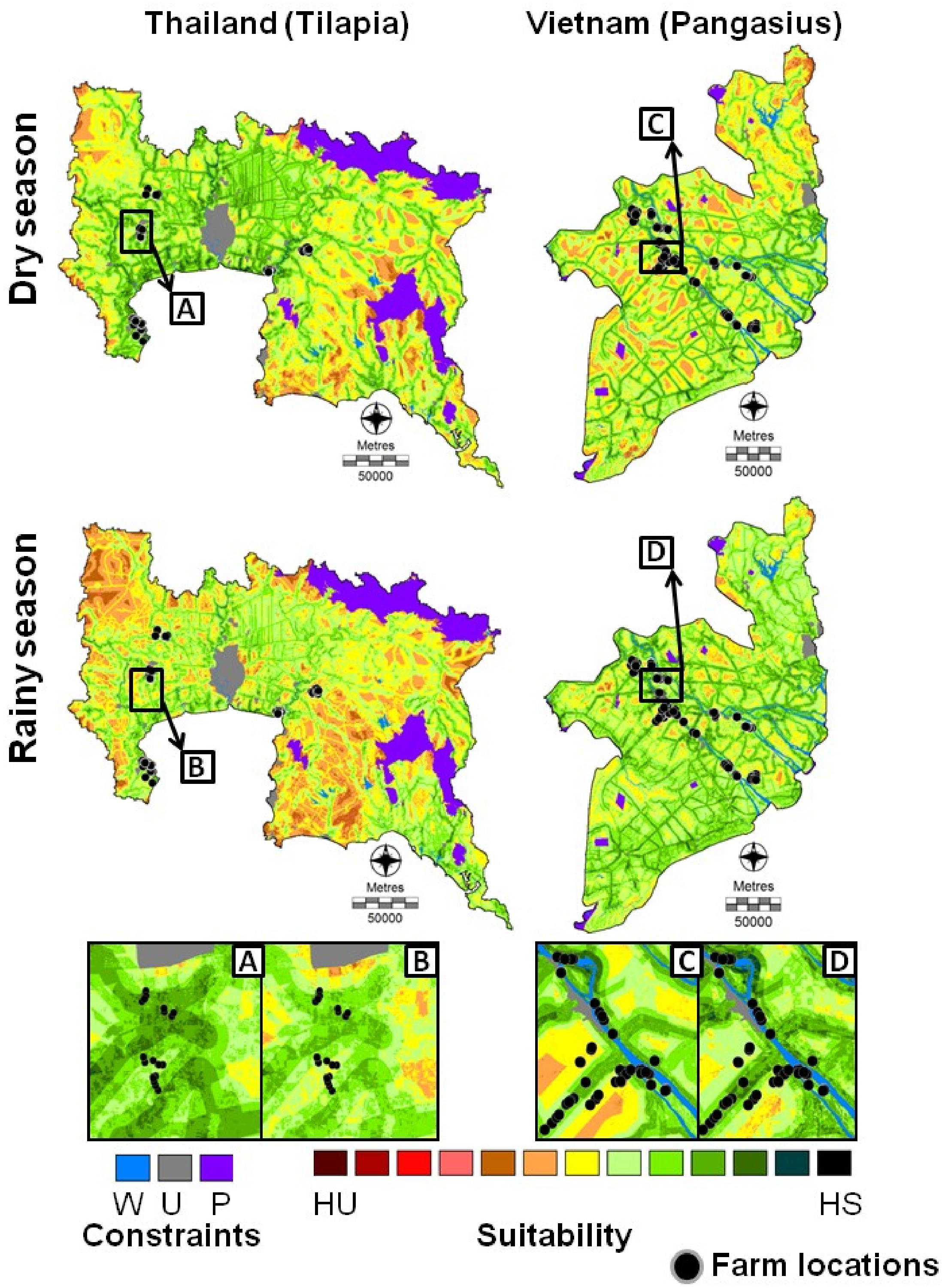


Figure 5.8: Overall site suitability models for Thailand (tilapia) and Vietnam (pangasius)

W = Water, U = Urban areas, P = Protected areas,

HU = Highly Unsuitable, HS = Highly suitable.

Table 5.6: Area (km^2) of each suitability category from the overall site suitability models for selected freshwater species

Score	Descriptor	Bangladesh (Prawn)		China (Tilapia)		Thailand (Tilapia)		Vietnam (Pangasius)	
		Dry	Rainy	Dry	Rainy	Dry	Rainy	Dry	Rainy
n/a	**Constraints**	1182	1182	626	626	6086	6086	2497	2497
4	**Highly unsuitable**	0	0	25	0	0	0	0	0
5	**Highly unsuitable**	0	0	2161	0	0	0	0	0
6	**Highly unsuitable**	9	0	3860	15	1	0	0	0
7	**Unsuitable**	145	8	6570	350	70	110	35	0
8	**Unsuitable**	896	137	6610	2189	866	1793	372	77
9	**Unsuitable**	1929	799	4612	3747	4158	8047	4689	1216
10	**Moderate**	2462	1954	1553	6422	10837	11942	11976	7170
11	**Suitable**	2032	2940	193	6608	10603	11606	12604	15327
12	**Suitable**	1135	2019	14	4519	9632	7039	9465	13143
13	**Suitable**	289	894	0	1534	5152	1561	5187	6791
14	**Highly suitable**	68	197	0	195	829	129	672	1261
15	**Highly suitable**	0	18	0	19	83	6	16	31
16	**Highly suitable**	0	0	0	0	2	0	0	0
Total	**Constraints**	**1182** (11.6%)	**1182** (11.6%)	**626** (2.3%)	**626** (2.3%)	**6086** (12.6%)	**6086** (12.6%)	**2497** (5.3%)	**2497** (5.3%)
Total	**Highly unsuitable**	**9** (0.1%)	**0** (0%)	**6047** (23%)	**15** (0.1%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)
Total	**Unsuitable**	**2971** (29.3%)	**944** (9.3%)	**17792** (67.8%)	**6287** (23.4%)	**5094** (10.5%)	**9950** (20.6%)	**5096** (10.7%)	**1293** (2.7%)
Total	**Moderate**	**2462** (24.3%)	**1954** (19.3%)	**1553** (6%)	**6422** (24%)	**10837** (22.4%)	**11942** (24.7%)	**11976** (25.2%)	**7170** (15%)
Total	**Suitable**	**3455** (34%)	**5852** (57.7%)	**208** (0.8%)	**12661** (48.2%)	**25387** (52.5%)	**20206** (41.8%)	**27256** (57.3%)	**35261** (74.2%)
Total	**Highly suitable**	**68** (0.7%)	**215** (2.1%)	**0** (0%)	**214** (0.8%)	**914** (1.9%)	**135** (0.3%)	**688** (1.4%)	**1292** (2.7%)

The results show there are a wide range of suitability scores across each catchment for the selected species. However, there is also the potential for future development in many areas, with at least 45% of each study area classified as suitable or highly suitable for at least one season. In Bangladesh the availability of suitable and highly suitable areas is higher in the rainy season (5852 and 215km^2) than in the dry season (3455 and 68km^2) (Table 5.6). This difference is largely due to temperatures outwith the optimal range during the dry season in addition to a slightly negative water balance where more water would be leaving the pond than entering it. The change in suitability is also apparent in Fig 5.7A and 5.7B which shows some of the SEAT farms in the east of the study area; the east also has more potential for development, particularly in the rainy season, as it has large areas of suitable/highly suitable land.

The study area in China experiences the most significant change of all the study areas (Fig. 5.7). Over 90% of the area is unsuitable or highly unsuitable (17,792 and 6047km^2) for tilapia culture in the dry season (Table 5.6). This is due to the cold temperatures which mean that the area is unsuitable for culture during some of the dry season. Areas which remain unsuitable in the rainy season generally have steep slopes, limited water resources and are difficult to access making it difficult to establish a sustainable aquaculture system. Areas with the highest suitability are found in the eastern side of the study area where farms are already located (Fig. 5.7D).

In Thailand the suitability of most areas decreases in the rainy season from approximately 54% highly suitable/suitable in the rainy season to 42% in the dry season (Table 5.6), largely due to higher temperatures which are outwith the optimal range for tilapia production. Many areas where tilapia is already grown (including those highlighted in Figs. 5.8A and 5.8B) are suitable for culture in both seasons. A large amount of suitable area is located in the middle of the study area where there may be conflict over land use as this area has a significant agriculture industry. Therefore further socio-economic analysis would be required to meet the requirements of the EAA and develop sustainable aquaculture without impacting other users.

In the Vietnamese study area approximately 58% and 76% of the area is suitable or highly suitable for pangasius culture in the dry and rainy season respectively (Table 5.6). Most of the current production occurs along the Mekong in the middle of the study area. However, the results from the site suitability model (Fig 5.8) show there are further areas throughout the delta where pangasius culture could be established. The model indicates that, due to temperatures within the required range for pangasius throughout the year, the suitable areas in Vietnam could potentially be used for year round production, as is already current practice for many farms in Vietnam (Sinh *et al.*, 2007).

The overall site suitability models for shrimp are shown in Figs 5.9 and 5.10 and Table 5.7 shows the area contained within each suitability category. Fig 5.9 shows that most of the suitable areas for shrimp culture in Bangladesh are located in the south west of the study area; many of the SEAT farms were also located in this area (Figs. 5.97A, 5.9B). Over 25% of the area is considered suitable or highly suitable during the dry season for shrimp culture, whilst less than 12% is suitable or highly suitable in the rainy season due to temperatures outwith optimal ranges.

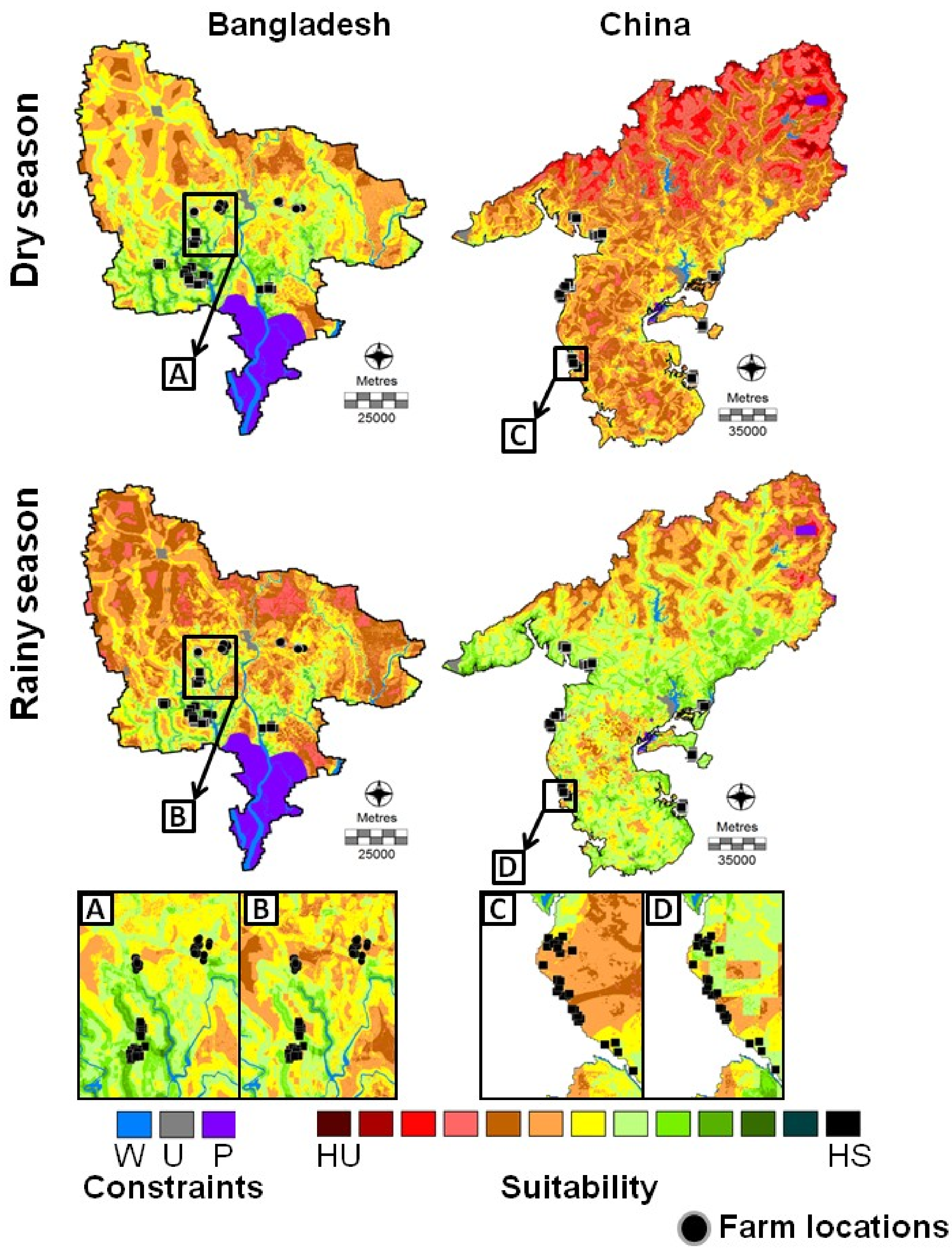


Figure 5.9: Overall site suitability models for shrimp in Bangladesh and China

W = Water, U = Urban areas, P = Protected areas,

HU = Highly Unsuitable, HS = Highly suitable.

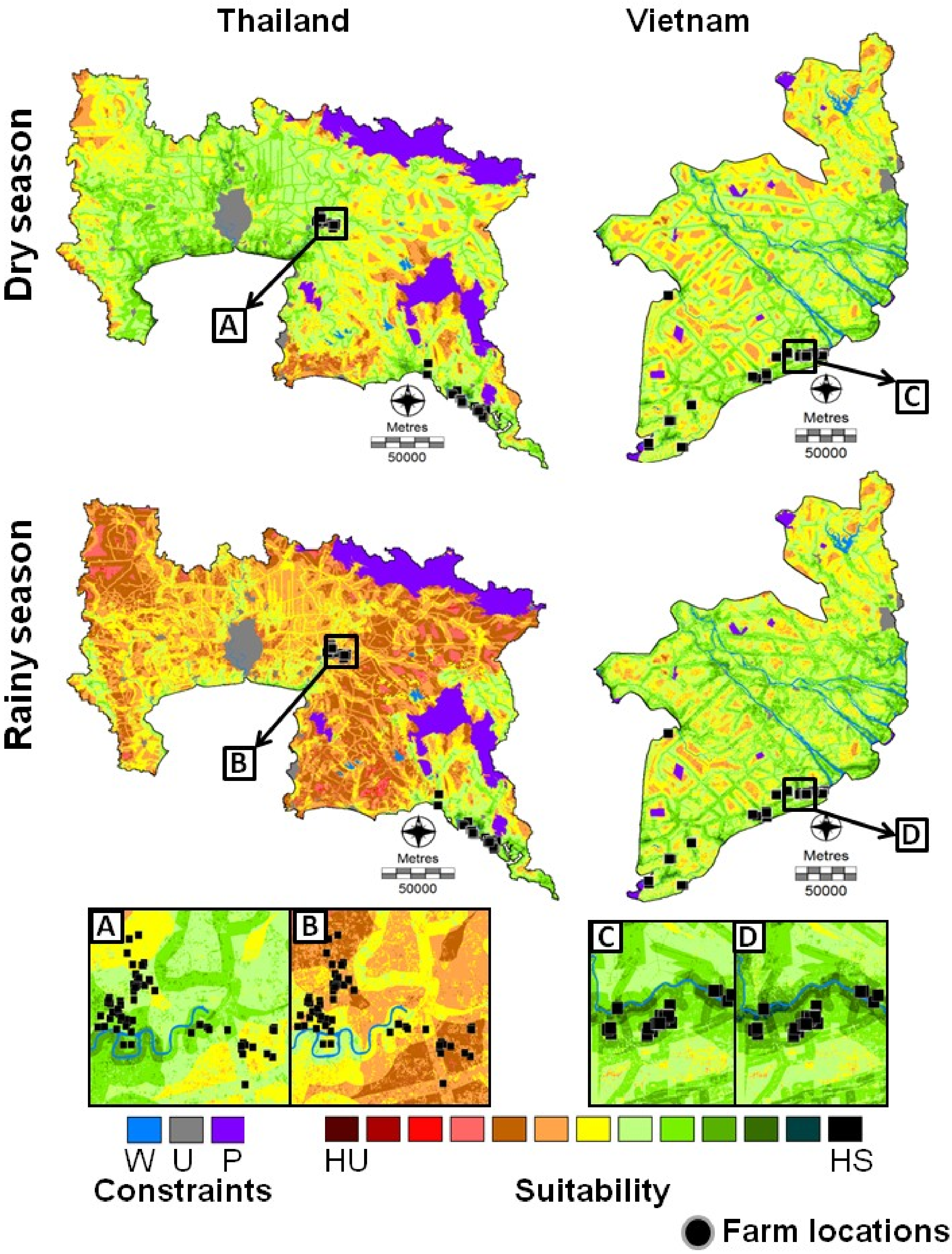


Figure 5.10: Overall site suitability models for shrimp in Thailand and Vietnam

W = Water, U = Urban areas, P = Protected areas,

HU = Highly Unsuitable, HS = Highly suitable.

Table 5.7: Area (km^2) of each suitability category from the overall site suitability models for shrimp

Score	Descriptor	Bangladesh Shrimp Dry	Bangladesh Shrimp Rainy	China Shrimp Dry	China Shrimp Rainy	Thailand Shrimp Dry	Thailand Shrimp Rainy	Vietnam Shrimp Dry	Vietnam Shrimp Rainy
n/a	**Constraints**	1182	1182	626	626	6086	6086	2497	2497
4	**Highly unsuitable**	0	0	5	0	0	0	0	0
5	**Highly unsuitable**	0	0	423	0	0	0	0	0
6	**Highly unsuitable**	0	36	2423	66	0	128	0	0
7	**Unsuitable**	47	656	4382	694	142	2042	1	4
8	**Unsuitable**	743	2316	6700	2620	1125	9652	186	186
9	**Unsuitable**	2623	2831	7700	4739	4323	14409	4339	3116
10	**Moderate**	2936	1933	3434	6619	11827	10555	13819	11629
11	**Suitable**	1765	839	485	7148	15143	4008	15844	15935
12	**Suitable**	623	299	46	3147	8162	1151	8976	11146
13	**Suitable**	195	56	1	500	1313	249	1674	2716
14	**Highly suitable**	35	0	0	63	177	36	178	270
15	**Highly suitable**	0	0	0	2	21	3	0	16
16	**Highly suitable**	0	0	0	0	0	0	0	0
Total	**Constraints**	**1182** (11.6%)	**1182** (11.6%)	**626** (2.4%)	**626** (2.4%)	**6086** (12.6%)	**6086** (12.6%)	**2497** (5.3%)	**2497** (5.3%)
Total	**Highly unsuitable**	**0** (0%)	**36** (0.4%)	**2851** (10.9%)	**67** (0.3%)	**0** (0%)	**128** (0.3%)	**0** (0%)	**0** (0%)
Total	**Unsuitable**	**3413** (33.6%)	**5803** (57.2%)	**18781** (71.6%)	**8053** (30.7%)	**5591** (11.6%)	**26104** (54.0%)	**4526** (9.5%)	**3305** (7.0%)
Total	**Moderate**	**2936** (28.9%)	**1933** (19.0%)	**3434** (13.1%)	**6619** (25.2%)	**11827** (24.5%)	**10555** (21.8%)	**13819** (29.1%)	**11629** (24.5%)
Total	**Suitable**	**2582** (25.4%)	**1194** 11.8%)	**533** (2.0%)	**10795** (41.2%)	**24617** (50.9%)	**5408** (11.2%)	**26494** (55.8%)	**29797** (62.7%)
Total	**Highly suitable**	**35** (0.3%)	**0** (0%)	**0** (0%)	**65** (0.2%)	**198** (0.4%)	**39** (0.1%)	**178** (0.4%)	**286** (0.6%)

Only 2% of the study area in China is considered suitable for shrimp culture in the dry season compared to the rainy season where over 40% of the area is suitable (Table 5.7). As with tilapia culture (Fig. 5.7), the main reason for the decrease in suitable areas for shrimp culture (Fig. 5.9) is due to low temperatures outwith the optimal range for culture. Areas in the north and west of the study area remain unsuitable throughout the year due to the steep slopes which would make pond construction difficult. The most suitable areas within the Chinese study area for development of shrimp farms are located in the low lying coastal areas where shrimp culture is already present.

In Thailand there is a decrease in the availability of suitable or highly suitable areas for shrimp culture from over 50% in the dry season to 11.2% in the rainy season (Table 5.7). The coastal area in the south east of the study area remains suitable in both seasons, whereas the inland area where SEAT farms are located (Figs 5.10A, 5.10B) is suitable in the dry season but unsuitable in the rainy season. As mentioned previously, although inland areas such as those shown in Figs 5.10A and 5.10B are used for shrimp culture, the local regulations would have to be consulted prior to additional development in other inland areas identified as suitable for production as the Thai government has placed a moratorium on shrimp farming in many locations (Roy *et al*., 2010).

The study area in Vietnam has the largest percentage of suitable areas for shrimp culture with approximately 56% of the area in the dry season and 63% in the rainy season identified as suitable or highly suitable for development (Table 5.7). Whilst most of the remaining areas are considered to be moderate suitability where it is neither suitable or unsuitable for culture. Coastal areas along the eastern side of the study area have the highest levels of suitability and these are areas where shrimp farming is already well established (Fig. 5.10C, 5.10D). As with Thailand, although the model indicates the area would be suitable for inland shrimp culture the local and national regulations would have to be consulted before development and mitigation methods would be required to prevent salination of water resources and damage to adjacent agricultural land.

5.4.4. Partial validation

Table 5.8 shows the comparison between existing farm locations and the results of the overall suitability model for the freshwater farms. The results can be used to partially validate the overall site suitability model for the freshwater species as, with the exception of China, most of the farms are found in suitable areas for both seasons. Although no Chinese farms are located in suitable areas during the dry season the results show that 89.7% and 3.4% are classified as suitable and highly suitable in the rainy season which is the period when most culture takes place.

Table 5.8: Comparison of SEAT farms and overall site suitability models for freshwater species

Score	Descriptor	Bangladesh Prawn		China Tilapia		Thailand Tilapia		Vietnam Pangasius	
		Dry	Rainy	Dry	Rainy	Dry	Rainy	Dry	Rainy
n/a	Constraints	0	0	0	0	0	0	0	0
4	Highly unsuitable	0	0	0	0	0	0	0	0
5	Highly unsuitable	0	0	0	0	0	0	0	0
6	Highly unsuitable	0	0	5	0	0	0	0	0
7	Unsuitable	0	0	7	0	0	0	0	0
8	Unsuitable	1	0	37	0	0	0	0	0
9	Unsuitable	21	11	49	5	0	8	3	2
10	Moderate	61	17	19	3	11	30	12	10
11	Suitable	95	71	0	34	30	38	18	18
12	Suitable	56	64	0	49	40	48	67	59
13	Suitable	0	65	0	22	46	12	73	76
14	Highly suitable	0	6	0	4	9	3	19	27
15	Highly suitable	0	0	0	0	3	0	0	0
16	Highly suitable	0	0	0	0	0	0	0	0
Total	Highly unsuitable	**0** (0%)	**0** (0%)	**5** (4.3%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)
Total	Unsuitable	**22** (9.4%)	**11** (4.7%)	**93** (79.5%)	**5** (4.3%)	**0** (0%)	**8** (5.8%)	**3** (1.6%)	**2** (1.0%)
Total	Moderate	**61** (26.1%)	**17** (7.3%)	**19** (16.2%)	**3** (2.6%)	**11** (7.9%)	**30** (21.6%)	**12** (6.3%)	**10** (5.2%)
Total	Suitable	**151** (64.5%)	**200** (85.5%)	**0** (0%)	**105** (89.7%)	**116** (83.5%)	**98** (70.5%)	**158** (82.3%)	**153** (79.7%)
Total	Highly suitable	**0** (0%)	**6** (2.6%)	**0** (0%)	**4** (3.4%)	**12** (8.6%)	**3** (2.2%)	**19** (9.9%)	**27** (14.1%)

The results of the comparison between existing farms and the overall suitability model for shrimp are shown in Table 5.9. One SEAT shrimp farm in China was located in an area which was classified as a constraint (water). This is due to the farms being very close to the sea and the model has classified the sea as a constraint to pond development. Additionally, thirteen SEAT shrimp farms in Vietnam were located in areas classified as constraints (protected areas). These farms are located in an area within the Dat Mui (Nam Can) nature reserve (IUCN and UNEP-WCMC, 2012) and therefore were classified as a constraint. The results partially validate the models as most of the farms are located in suitable areas for at least one season. However, the results also show seasonal suitability of many of the farm locations, particularly for Bangladesh China and Thailand which is again due to temperature variations throughout the year.

Table 5.9: Comparison of SEAT farms and overall site suitability models for shrimp

Score	Descriptor	Bangladesh		China		Thailand		Vietnam	
		Dry	Rainy	Dry	Rainy	Dry	Rainy	Dry	Rainy
n/a	**Constraints**	0	0	1*	1*	0	0	13**	13**
4	**Highly unsuitable**	0	0	0	0	0	0	0	0
5	**Highly unsuitable**	0	0	0	0	0	0	0	0
6	**Highly unsuitable**	0	0	0	0	0	0	0	0
7	**Unsuitable**	0	0	0	0	0	0	0	0
8	**Unsuitable**	0	11	1	0	0	8	0	0
9	**Unsuitable**	18	24	66	8	0	24	1	1
10	**Moderate**	39	76	65	21	15	24	27	35
11	**Suitable**	74	73	23	37	43	16	40	41
12	**Suitable**	61	11	2	42	29	14	50	40
13	**Suitable**	12	13	0	49	18	14	39	42
14	**Highly suitable**	4	0	0	0	1	6	11	9
15	**Highly suitable**	0	0	0	0	0	0	0	0
16	**Highly suitable**	0	0	0	0	0	0	0	0
Total	**Constraints**	**0** (0%)	**0** (0%)	**1*** (0.6%)	**1*** (0.6%)	**0** (0%)	**0** (0%)	**13**** (7.2%)	**13**** (7.2%)
Total	**Highly unsuitable**	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)	**0** (0%)
Total	**Unsuitable**	**18** (8.7%)	**35** (16.8%)	**67** (42.7%)	**8** (5.1%)	**0** (0%)	**32** (30.2%)	**1** (0.5%)	**1** (0.5%)
Total	**Moderate**	**39** (18.8%)	**76** (36.5%)	**65** (41.4%)	**21** (13.4%)	**15** (14.2%)	**24** (22.6%)	**27** (14.9%)	**35** (19.3%)
Total	**Suitable**	**147** (70.7%)	**97** (46.6%)	**25** (15.9%)	**128** (81.5%)	**90** (84.9%)	**44** (41.5%)	**129** (71.3%)	**123** (68.0%)
Total	**Highly suitable**	**4** (1.9%)	**0** (0%)	**0** (0%)	**0** (0%)	**1** (0.9%)	**6** (5.7%)	**11** (6.1%)	**9** (5.0%)

* Located in area classified as constraint (water) ** Located in areas classified as constraint (protected area)

5.5. Potential production

The results can be developed to illustrate potential production scenarios. Decision makers need to ensure that aquaculture occurs in the best possible location. Although many of the areas were classified as suitable it is recommended that the highly suitable locations are investigated first. The final overall suitability models were reclassified to show the areas which had a highly suitable score (14, 15 or 16) in the dry season, rainy season or both seasons. Some simple production statistics were then applied to illustrate how planners could use the results assuming 5% of the area classified as highly suitable (a conservative estimate) was available for pond development.

5.5.1. Bangladesh

The results show there are many areas available for the development of prawn culture across the study area, particularly in the west during the dry season (Fig. 5.11A) and the east during the rainy season (Fig. 5.11B). Approximately 793 ha of the study area is suitable for culture throughout the year. If 5% of this area was used for prawn culture then 172 ghers could be established (Table 5.10), assuming an average size of 0.23ha for a gher (Ahmed et al. 2008a). However, as most prawn culture lasts for 9 months, with the majority of production occurring in the rainy season (Ahmed et al. 2008a), there is the opportunity to use areas which are highly suitable during the rainy season and perhaps a lower suitability in the dry season. Table 5.10 shows that if 5% of that area was used for culture then approximately 447 tonnes could be produced.

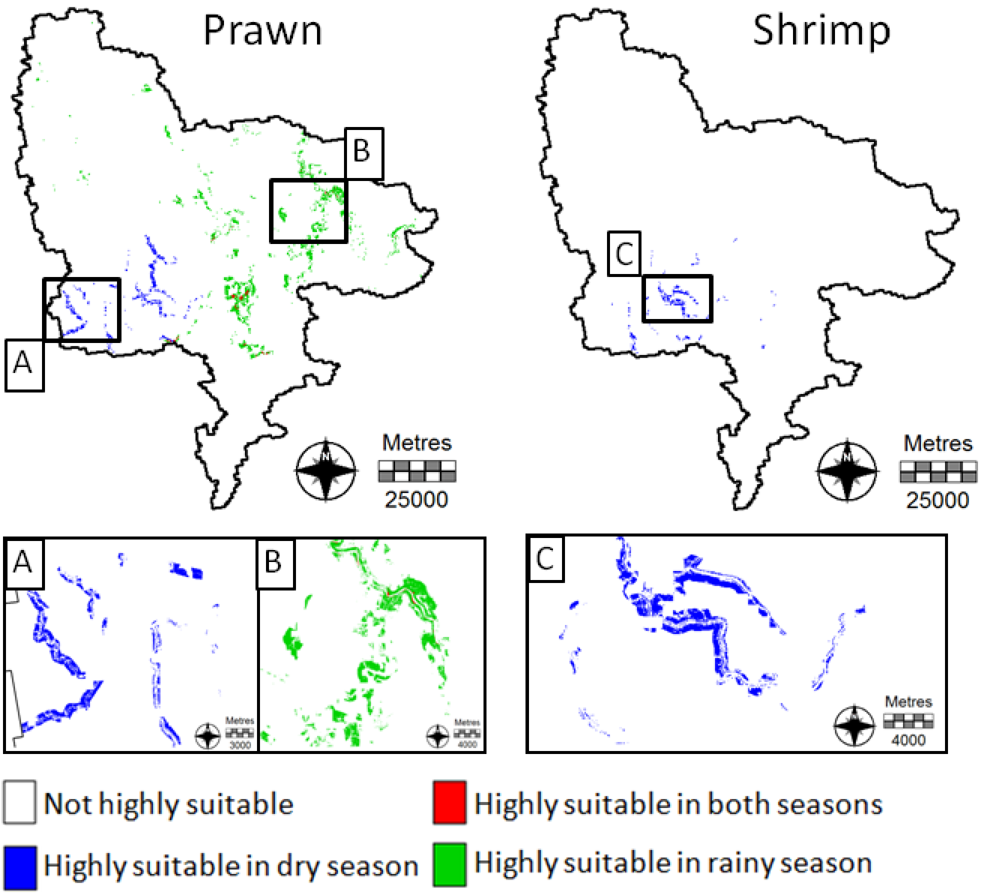


Figure 5.11: Highly suitable areas for production of prawn and shrimp in Bangladesh

The results also show there are fewer highly suitable areas available for shrimp farming within the study area. Most of the highly suitable areas are located in the south west of the study area (Fig. 5.11C). However these areas are only highly suitable within the dry season. Table 5.10 shows that 14 ponds (12ha each) could be established if 5% of the area is available for culture which would allow approximately 108 tonnes to shrimp to be produced per cycle. On the other hand, if smaller sizes were used then 83 ponds could be constructed assuming an average size of 2.1ha (Belton et al. 2011b).

Table 5.10: Potential production scenarios for Prawn and Shrimp in Bangladesh

Prawn (Production data from Ahmed et al. (2008a))	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	6025	20712	793
5% area of high suitability (ha)	301	1036	4
Productivity (kg/ha/year)	432	432	432
Productivity (t/ha/year)	0.432	0.432	0.432
Potential productivity in 5% area (kg)	130,140	447,379	17,129
Potential productivity in 5% area (t)	130	447	17
Potential no. ghers (size 0.23ha)	1309	4502	172
Shrimp (Production data from Islam et al. (2004))	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	3515	0	0
5% area of high suitability (ha)	176	0	0
Productivity (kg/ha/cycle)	615	615	615
Productivity (t/ha/cycle)	0.6145	0.6145	0.6145
Potential productivity in 5% area (kg)	107,998	0	0
Potential productivity in 5% area (t)	108	0	0
Potential no. ponds (size 12ha)	14	0	0

5.5.2. China

The only highly suitable areas for both tilapia and shrimp are in the rainy season (Fig. 5.12). However, the results show there is significant potential for development in the study area even if only 5% of the highly suitable area is available for ponds. The highly suitable areas for tilapia are located throughout the study area with the most extensive areas in the south and east (Figs. 5.12A and 5.12B), whereas, the highly suitable areas for shrimp tend to be located very close to the coast as shown in Fig. 5.12C. There is the potential to yield approximately 6281 tonnes of tilapia and 1166 tonnes of shrimp within the area, with the construction of 1071 tilapia farms and 651 shrimp ponds (Table 5.11).

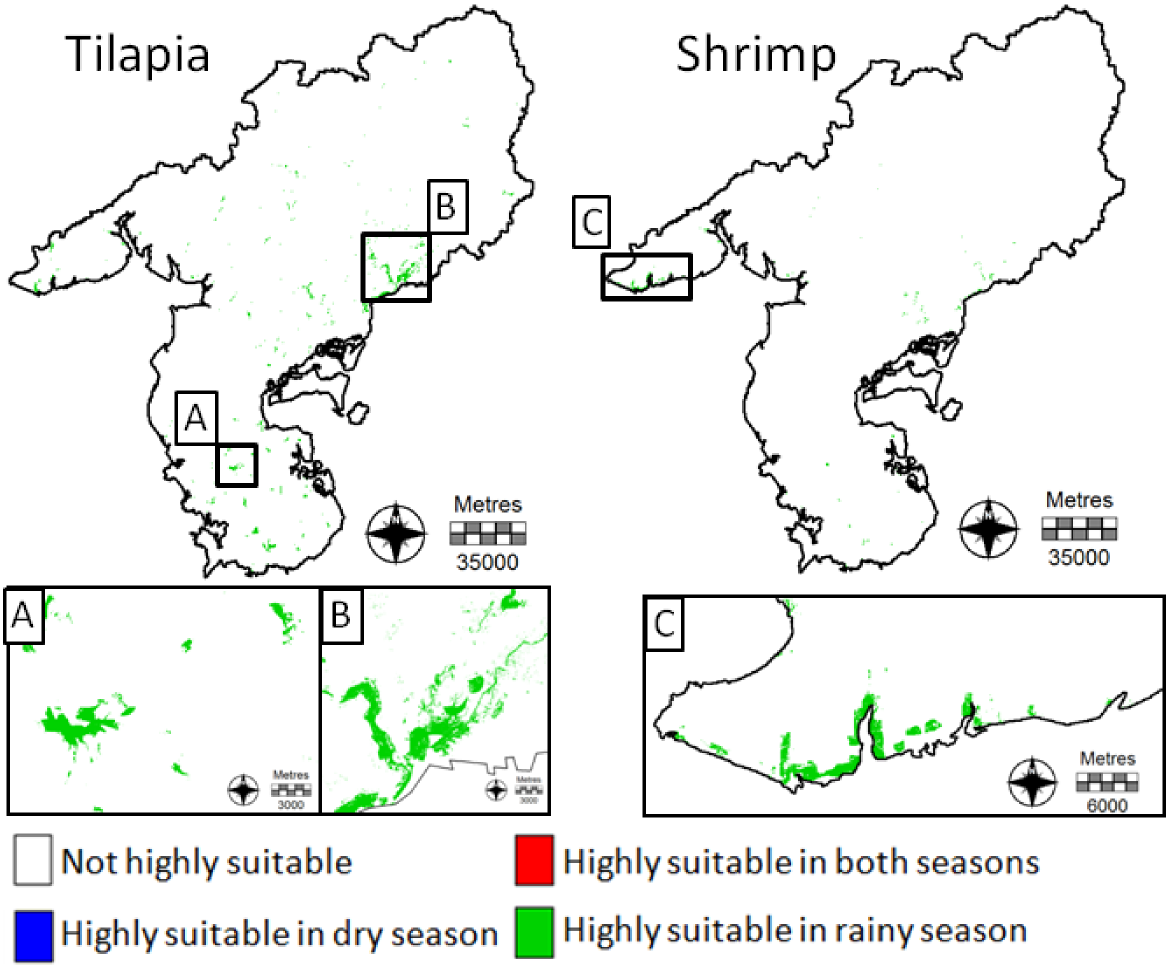


Figure 5.12: Highly suitable areas for production of tilapia and shrimp in China

Table 5.11: Potential production scenarios for tilapia and shrimp in China

Tilapia (Production data from De Silva et al. (2004))	Dry	Rainy	Annual
Area of high suitability (ha)	0	21436	0
5% area of high suitability (ha)	0	1072	0
Productivity (kg/ha/year)	5860	5860	5860
Productivity (t/ha/year)	5.86	5.86	5.86
Potential productivity in 5% area(kg)	0	6,280,748	0
Potential productivity in 5% area(t)	0	6281	0
Potential no. ponds (size 1 ha)	0	1071	0
Shrimp (Production data from Yuan et al. (2006))	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	0	6510	0
5% area of high suitability (ha)	0	326	0
Productivity (kg/ha/year)	3582	3582	3582
Productivity (t/ha/year)	3.582	3.582	3.582
Potential productivity in 5% area(kg)	0	1165941	0
Potential productivity in 5% area(t)	0	1166	0
Potential no. ponds (size 0.5 ha)	0	651	0

5.5.3. Thailand

Fig. 5.13 shows there is significantly more potential for the development of tilapia than shrimp using areas that are highly suitable for culture. More area is available during the dry season (79,387 ha and 18,647 ha for tilapia and shrimp) which could be used for 1459 tilapia ponds and 2274 shrimp ponds if only 5% of land was used for aquaculture development (Table 5.12). Most of the available area for tilapia culture is in the middle and west of the study area (Fig. 5.13A), whilst areas available for shrimp culture during the dry season are located along the coast of the gulf of Thailand (Fig. 5.13B) and in the rainy season are in the east of the study area (Fig. 5.13C). Some areas near Chanthaburi in the east of Thailand are also suitable for year round culture of shrimp (Fig. 5.13C). This is an area where there is already a significant shrimp industry.

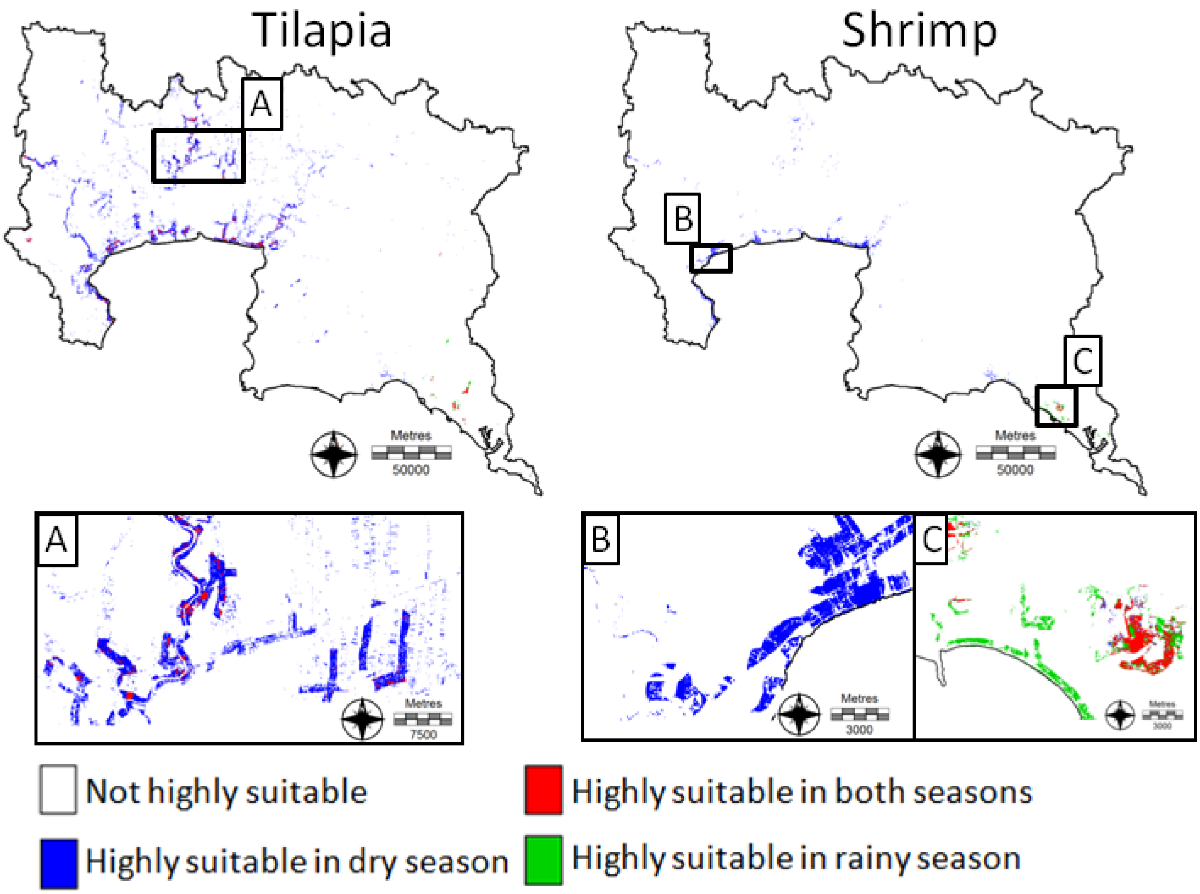


Figure 5.13: Highly suitable areas for production of tilapia and shrimp in Thailand

Table 5.12: Potential production scenarios for tilapia and shrimp in Thailand

Tilapia (Production data from Thunjai et al. 2004)	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	79,387	1530	11,964
5% area of high suitability (ha)	3969	77	598
Productivity (kg/ha/year)	5000	5000	5000
Productivity (t/ha/year)	5	5	5
Potential productivity in 5% area(kg)	19,846,750	382,500	2,991,000
Potential productivity in 5% area(t)	19847	383	2991
Potential no. ponds (size 2.72 ha)	1459	28	219
Shrimp (Production data from Piumsombun et al. 2005)	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	18647	2736	1139
5% area of high suitability (ha)	932	137	57
Productivity (kg/ha/year)	4530	4530	4530
Productivity (t/ha/year)	4.53	4.53	4.53
Potential productivity in 5% area (kg)	4,223,546	619,704	257,984
Potential productivity in 5% area (t)	4224	620	258
Potential no. ponds (size 0.41ha)	2274	333	138

5.5.4. Vietnam

Throughout the Mekong Delta there is significant potential for the development of pangasius ponds (Fig. 5.14) and over 145,000 ha of the study area in Vietnam is highly suitable for culture of pangasius with over 50,000 ha classified as highly suitable for year round production (Table 5.13). Using just 5% of this available area would enable the development of approximately 2568 pangasius ponds. Comparing the results for pangasius and shrimp in Fig. 5.14 shows that there is far less area available for shrimp culture with 33,125 ha in total and 13,221 ha available for year round production (Table 5.13). However, this would still allow the development of approximately 330 ponds and almost 1200 tonnes of shrimp (assuming 5% of the area could be used for culture).

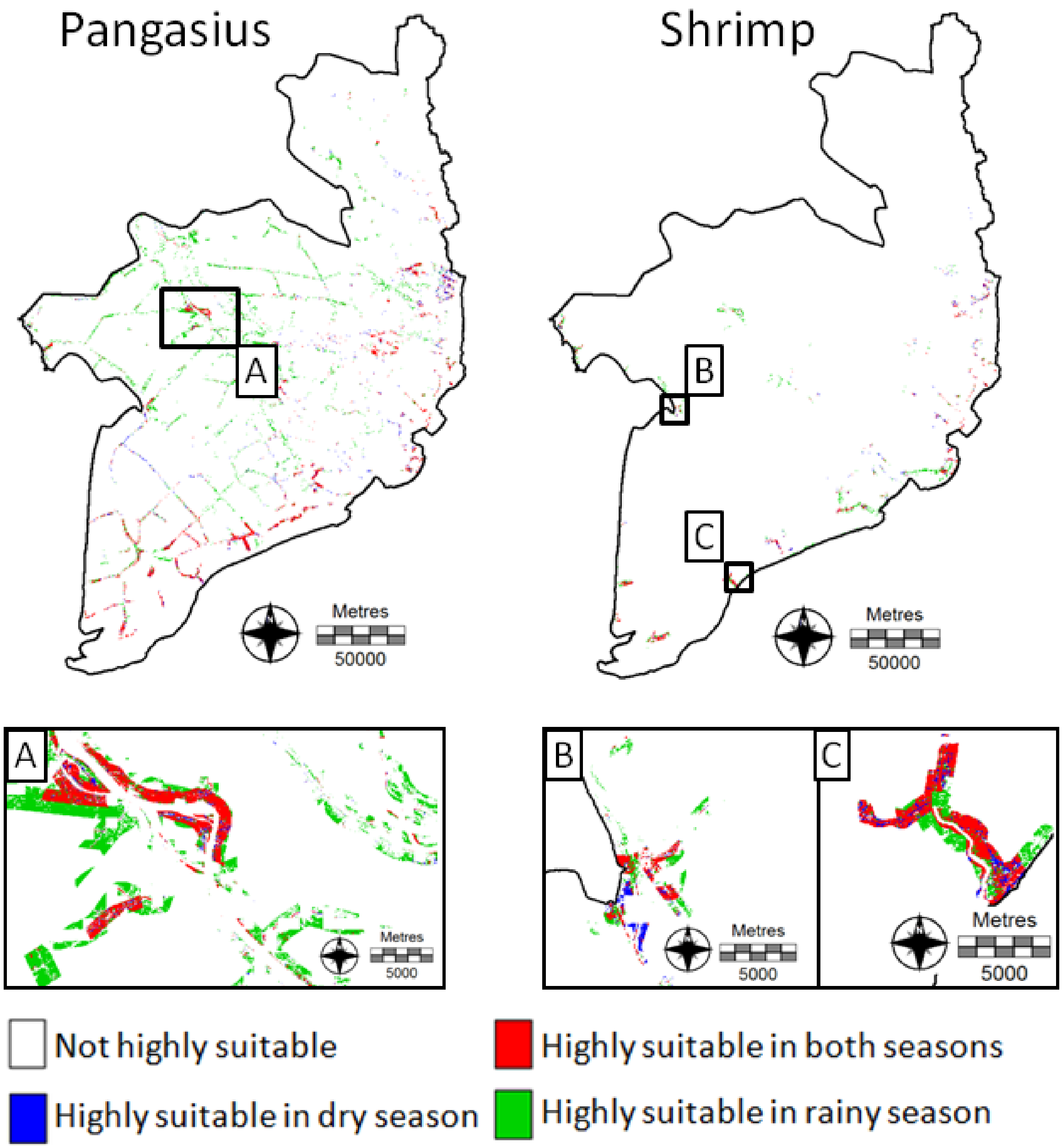


Figure 5.14: Highly suitable areas for production of pangasius and shrimp in Vietnam

Table 5.13: Potential production scenarios for pangasius and shrimp in Vietnam.

Pangasius (Production data from Anh et al. (2010b))	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	17,390	77,872	51,376
5% area of high suitability (ha)	870	3894	2569
Productivity (kg/ha/crop)	240,000	240,000	240,000
Productivity (t/ha/crop)	240	240	240
Potential productivity in 5% area(kg/ha/crop)	208,680,000	934,464,000	616,512,000
Potential productivity in 5% area(t/ha/crop)	208,680	934,464	616,512
Potential no. ponds (size 1 ha)	869	3893	2568
Shrimp (Production data from Anh et al. (2010a))	**Dry**	**Rainy**	**Annual**
Area of high suitability (ha)	4552	15352	13221
5% area of high suitability (ha)	228	768	661
Productivity (kg/ha/crop)	1800	1800	1800
Productivity (t/ha/crop)	1.8	1.8	1.8
Potential productivity in 5% area(kg/ha/crop)	409,680	1,381,680	1,189,890
Potential productivity in 5% area(t/ha/crop)	410	1382	1190
Potential no. ponds (size 0.5 ha)	455	1535	1322

5.6. Discussion

Poor planning and inappropriate site selection are amongst the main causes of negative environmental impacts associated with aquaculture (Kumar and Cripps, 2012). Spatial models are ideally suited for site suitability assessment as multiple criteria can be evaluated which enables the identification of many sites (Valvanis, 2002). Although GIS and remote sensing tools are commonly used for aquaculture site selection (Ross *et al*., 2009; Aguilar-Manjarrez *et al*., 2010; Ross *et al*., 2013) often models are only developed for one particular species, system and area with little thought given to applicability to other scenarios. The models developed in this study aim to support decision making across large regions with regard to existing farms and new developments. The models can be used to identify suitable areas which can then be explored using more site specific analysis; saving time and money as costly, detailed surveys can be carried out on several pre-identified suitable sites rather than many random locations.

The results from the overall site suitability models show there is potential for further development of aquaculture in each of the study areas (Figs 5.7, 5.8, 5.9 and 5.10). In Bangladesh there are suitable areas for prawn culture in the east of the study area, particularly during the rainy season, whilst the south west of the study area has higher suitability for shrimp culture during the dry season. In China the suitable areas for both tilapia and shrimp are mainly in the rainy season due to seasonal temperature changes whilst in Vietnam there are high levels of suitability for both species throughout both seasons as temperature remains within highly suitable ranges for culture throughout the year. The advantage of assessing the suitability of multiple areas using the same model is that it highlights how regions can experience different seasonal issues and how the suitability for a particular species can vary throughout the year, allowing some areas to capitalise on the potential for longer growing periods or year round production when other areas may not be suitable for aquaculture. This allows farmers to identify opportunities for production and/or risks of competition from other areas, whilst processors and buyers can evaluate the capability of several areas to establish where the most appropriate area is to source their desired product.

The models for Thailand show there are suitable areas for tilapia culture, particularly in the middle of the study area (Fig 5.8). However, this area is often referred to as the “rice bowl” as it contains the most extensive agricultural land in the country (Tingting and Chuang, 2010). Therefore although the model indicates that this area is suitable for aquaculture production, further site specific socioeconomic analysis would have to be conducted to ensure that no other stakeholders are negatively impacted prior to development. It is important to note that the model is not an end result and should be used to support decisions along with further analysis to ensure the best possible result for all stakeholders. This is also relevant for shrimp farming in Thailand, where the model indicates that some inland areas would be suitable for culture during the dry season (Fig. 5.10). However, due to potential negative impacts from inland shrimp culture the Thai government has placed restrictions in many areas on future developments (Roy *et al*., 2010). Consequently, local and national regulations would have to be consulted before a particular site was chosen to ensure the proposed development would be allowed.

The models show multiple levels of suitability and it is recommended that decision makers investigate the potential of the highest scoring sites first. However, although some areas may not be highly suitable for year round production, it does not mean that they should be disregarded as a potential site. Most prawn culture in Bangladesh occurs in gher systems and the culture cycle lasts approximately 9 months throughout the rainy season until the pond is harvested in the dry season (Ahmed *et al*., 2008a). Therefore, there is the potential to use areas which are highly suitable during the rainy season but perhaps less optimal during the dry season. If 5% of the areas identified as highly suitable during the rainy season were used for pond construction during the rainy season then approximately 4502 ghers could be constructed (Table 5.10), which would provide a vital source of income for local communities in addition to providing more food to the region or as export products. Although the overall suitability may be lower during the dry season it may not significantly impair production and there may be more benefits of the site during the rainy season when most growth occurs; therefore decision makers could identify such sites as potential areas for development.

Many of these species have short growing periods and can provide a valuable source of income during those seasons when the temperature is suitable and there is sufficient water supply. Farms which rely on a single source of water are vulnerable as pollution and climatic events could impact the water quality and subsequently production. Moreover, in the future there could be increased conflicts over water use and consumption with the increasing population, along with increasing intensification of agriculture and aquaculture (Beveridge *et al.* 1997). There is a need for farm developers to look beyond the farm level and ensure that potential conflicts over water and impacts on water are minimised at a wider scale whilst following the principles of the ecosystem approach to aquaculture. The models shown in this study are designed to assist with this assessment as the System submodel can highlight areas potentially at risk such as areas with many farms and few sources of water.

It must be noted that groundwater was not included as a potential source of water due to the lack of freely available spatial data. However, there are further environmental and health issues from using groundwater, particularly in Bangladesh where contamination of groundwater by Arsenic has resulted in serious health issues for the population (Chakraborti *et al*., 2010). Consequently, site specific monitoring should take place before considering using groundwater for aquaculture. This highlights an issue when modelling across multiple countries/study areas, as some parameters may pose no problems for one country but can have serious consequences for another. The model needs to be representative for all areas and therefore it is important to use a transparent approach where users can highlight potential issues easily.

Often it is not possible or advantageous to use a single output from a model as it does not tell the whole story. This is particularly relevant for aquaculture which can be affected by seasonal environmental issues. As shown by Ross *et al*. (2011) there can be significant differences in both the availability and suitability of sites within a year which can have considerable impacts for site selection and aquaculture development. The results from this study have shown that in terms of seasonality the Species submodel is the most limiting factor with regards to site suitability. This submodel represents the suitability of the area with respect to water temperature tolerance for each of the selected species. The study area in China is most affected by the seasonal temperature change; in the dry season temperatures are well below the suitable level for tilapia growth. This is an issue common to most of China where the industry is restricted by low temperatures (Sifa *et al*., 2002). However, there has been a lot of work recently developing strains of tilapia that are tolerant to cold climates such as those described by Sifa *et al*. (2002). The model could be easily adapted to take this into account and model the temperature ranges of the cold tolerant strains or other species which might be more suitable to colder climates.

Within large catchments and regions, such as those evaluated in this study, it can be difficult to identify areas which need assistance either at present or in the future. In addition to identifying new areas for development the models presented here can also be used to assess the suitability of existing sites and the potential for remedial work or relocation. The transparent multi-stage framework developed enables the user to make a robust decision as it gives a clearer understanding of the processes involved. This is particularly important when assessing the suitability of a site retrospectively as potential issues within the submodels are often hidden in the overall site suitability model. Figs 5.5 and 5.6 show that many of the existing farms are in areas that are unsuitable with respect to the Access submodel. If farms are further from transport networks and urban populations then there is greater risk that they could be isolated if a natural disaster or civil unrest issue occurs. This is particularly relevant to coastal communities which are often fragile environments and vulnerable to natural hazards such as floods and cyclones (Adger *et al*., 2005; Pomeroy *et al*., 2006). Whilst such hazards are difficult to predict it is nevertheless important to be aware of farms and areas that are further afield that may potentially need assistance. As shown in this study, the Access submodel (Figs. 5.3, 5.4, 5.5 and 5.6) can highlight individual farms or groups of farms that are located in unsuitable areas so that stakeholders can then put in mitigation methods to increase the adaptive capacity of the industry and communities in these areas if necessary. Mitigation methods can be physical ones such as the development of new infrastructure or may be socio-economic involving subsidies, governmental policies and increasing social awareness (Adger *et al*., 2005;

Pomeroy *et al*., 2006), all of which can help to enhance the long term sustainability of aquaculture in regions which are unpredictable and vulnerable to wider issues.

The models were specifically designed using global datasets and data that can be obtained for almost any study area. Arguably one of the biggest challenges facing spatial modelling for aquaculture (and other industries) is data availability and access (Meaden, 2010). Salinity is a major parameter which can impact the ability to farm certain species (Boyd and Tucker, 1998). However, it was not included in the modelling process as there are no freely available global datasets and the availability and quality of salinity data within countries and regions varies greatly. It is acknowledged that salinity should perhaps be included as a variable within the Species submodel. However, this would severely limit the potential application of the model to areas which already have sufficient salinity data. During model development efforts were made to source salinity data for each of the study areas however it was not possible to get sufficient representative information for each location. Furthermore, many species such as tilapia are able to tolerate a wide range of saline conditions (El-Sayed, 2006) so it might not be necessary to include it when evaluating every study area and species. Therefore, salinity was not included within the model framework; allowing applicability to multiple study areas. However, if sufficient salinity data is available for the desired study areas then it should be incorporated into the Species submodel or used as a constraints layer.

The results have shown that it is possible to use a single model framework for site sutiability and apply it to study areas in different countries. Using global datasets allows the model to be applied to most, if not all, desired study areas worldwide. It also enables a comparison between study areas without bias towards certain areas or countries with better or more detailed spatial data resources. The use of global datasets does mean that the final model output may not be as sensitive to local issues. However, following initial use of this model to identify areas of interest, the model can be run again using more detailed datasets if they are available for that area. The transparent approach also allows the model to be applied retrospectively to existing sites, highlighting potential issues and giving regulators and decision makers extra information. When aiming for a sustainable system it is important to acknowledge the wider environment and the area beyond the local scale. Tools such as those developed in this study are valuable sources of information as they allow decision makers a comprehensive view of the large regional issues that can be difficult to understand at a local level. This is an important step in the ecosystem approach to aquaculture as it provides a valuable link between aquaculture and the wider environment and can be used to help new developments and existing farms aim for a long-term sustainable system which can contribute effectively to local, regional and global food security.

CHAPTER 6

ASSESSING THE SUITABILITY OF LARGE CATCHMENTS FOR AQUACULTURE USING EXISTING FARM LOCATIONS AND IDENTIFYING KEY TRENDS AMONGST SELECTED VARIABLES

6.1. Introduction

The desire for profit and the need to compete effectively in the marketplace are the principle drivers for commercial aquaculture (Bostock, 2011), and Paul and Vogl (2011) state that financial risk is associated with the intensity of the culture system and is influenced by planning, design, management capacity and market fluctuations. Kumar and Cripps (2012) also note that poor planning and inappropriate site selection are amongst the main causes of negative environmental impacts associated with aquaculture. Therefore, assessing the suitability of an area is an important factor which can influence the success and sustainability of a farm. As aquaculture production increases to meet food security requirements it is important to understand the variables which potentially influence the distribution of existing farms. This allows decision makers to identify areas of concern, conflict and/or opportunity.

Aquaculture is the fastest growing food production sector in the world and is a valuable livelihood for millions of people (Subasinghe *et al.*, 2009; De Silva and Davy, 2010). As the industry continues to grow it is essential that development is planned and managed to prevent conflict and ensure minimal environmental impacts. One of the most controversial, and often criticised, aspects of aquaculture development is related to shrimp farming, particularly the boom during the 1980's and 1990's where there were many negative impacts as a result of rapid expansion. One of the most notable detrimental environmental impacts was the destruction of mangroves, where valuable wetland ecosystems were converted to shrimp ponds (Naylor *et al*., 2000; Diana, 2009; De Silva, 2012). Agricultural, residential and forest lands were also transformed (Primavera, 1997) and the landscape of many areas changed significantly. In addition to direct land use change and habitat destruction, there were also detrimental impacts on water quality, and the surrounding environment, where brackish water from ponds seeped into groundwater supplies and adjacent agricultural land which has resulted in economic loss, destroyed livelihoods and forced migration (Flaherty and Karnjanakesorn, 1995). Often areas which had been used for multiple resources (with numerous stakeholders) were converted to single-purpose use industries which deprived local communities of their traditional resource use rights (Deb, 1998) and changed the way of life for many people. Although shrimp farming is now a significant economic activity (Lem, 2006) uncontrolled development has resulted in serious detrimental consequences to the wider environment and other users in many areas. As a result it is important to understand the variables which are associated with shrimp farm location and any trends which may exist across multiple areas to identify potential issues for existing and new farms.

Rapid expansion and poor site selection have also resulted in the emergence and spread of disease throughout the shrimp industry (Walker and Mohan, 2009). Between 1990 and 2005 the estimated global loss of production to disease was approximately US$15 billion and about 80% occurred in Asia (Flegel *et al*., 2008; Flegel, 2012). As noted by Flegel *et al.* (2008) the industry was transformed after 2003 with the widespread use of specific pathogen free (SPF) stocks and the use of *Litopenaeus vannamei*; which has replaced *Penaeus monodon* as the main farmed shrimp species worldwide. Although the impact of disease has been reduced, the industry must continue to employ mitigation methods to prevent further serious outbreaks of new or undiscovered diseases. Kautsky *et al*. (2000) suggest the underlying ecological principles should be fully acknowledged to try and understand some of the disease problems within the industry. Walker and Mohan (2009) also recommend that effective management of existing and future diseases requires governments and industry to develop appropriate policies and practices in addition to investment in training and infrastructure development. Suitable site selection is a crucial factor and should be considered within disease management practices. This is highlighted by Leung and Tran (2000) who found that farms which conduct careful site selection along with other management practices have a lower risk of disease outbreaks.

It is evident there are negative consequences of poor site selection for the aquaculture industry, the wider environment, other industries and the associated communities. As noted by Boyd (2008) it is better to avoid building a shrimp pond than to build one that is destined to fail and this includes farms with negative environmental or social consequences. Successful site selection requires assessment of existing conditions as well as the potential trends in environmental, economic and social factors to ensure sustainability (Frankic and Hershner, 2003). Spatial modelling has been used to identify suitable sites for many different species and systems throughout the world (Ross *et al*., 2013) and shrimp farming is no exception (McLeod *et al*., 2002; Salam *et al*., 2003; Giap *et al*., 2005). Most models are developed using a range of parameters which are then reclassified to a common scale and combined within a Geographic Information System (GIS) environment as described by Nath *et al*. (2000) and Ross *et al*. (2009). The models are often developed using weightings and classifications that have been determined by a group of experts and are usually based on optimal ranges for the given species (Nath *et al*. 2000). Whilst this might be a useful method to decide on new developments or assess the suitability of existing developments it does not provide insight on the reasons behind the location and distribution of existing farms.

As discussed by Kautsky *et al*., (1997) in order to evaluate aquaculture in an ecological context the perspective and analysis must be expanded far beyond the local scale. Within the industry, there is growing adoption of integrated management strategies such as the EAA, which promotes sustainable development and consideration of wider influences and impacts. To understand the role aquaculture plays and its links with the wider environment across catchments it is important to understand why farms are located in certain areas. This is particularly important across large regions as it allows regulators to identify factors or areas which may need further assistance. Such information would also help decision makers understand the parameters which contribute to successful and sustainable aquaculture systems and these parameters could be used in future site selection.

Maxent is a popular tool for ecologists which uses presence-only species data to model species distributions (Phillips *et al*., 2006; Phillips and Dudik, 2008; Elith *et al*., 2011). The software is easy to use, which is one of the factors in its success (Merow *et al*., 2009), and it also typically outperforms other predictive methods (Elith *et al*., 2006; Kumar *et al*., 2009; Merow *et al*., 2013). The program was made available in 2004 and has been used extensively to map existing distributions, find correlates of species occurrence and predict movement over time and to new areas (Elith *et al*., 2011). Maxent uses the principle of maximum entropy to estimate suitability and works well with sparse or incomplete datasets (Phillips *et al*., 2006). The principle of maximum entropy aims to find a marginal suitability function for each variable that matches the input data, is maximally uninformative elsewhere and has a mean equal to that from the input data (Warren and Seifert, 2011). The output of Maxent has a natural probabilistic interpretation where there is a smooth gradient from most to least suitable conditions (Phillips *et al*., 2004).

Although Maxent is primarily used for species distribution, in the last few years applications of Maxent have become more diverse; estimating the location of ancient agricultural terraces in Cyprus (Galletti *et al*., 2013), identifying the risk of wildfire in eastern USA (Peters *et al.,* 2013), analysing landslides in Italy (Convertino *et al.,* 2013), assessing the risk of disease in Bolivia (Mischler, 2012), evaluating the environmental conditions associated with bat white-nose syndrome mortality in the north-eastern united states (Flory *et al*., 2012) and predicting the risk of bat fatalities at wind farms (Santos *et al.,* 2013). Evans *et al*. (2010) also note that species distribution models such as Maxent show promise as a method to assess the suitability of geographic regions for agriculture.

The aim of this study was to utilise Maxent to assess the suitability of large catchments for aquaculture using existing shrimp farm locations. One of the advantages of using Maxent is the ability to analyse the variables which contribute to the final output. This provides information about which variables can be used to explain the distribution of points and how important that variable is to overall model development (Baldwin, 2009). Using individual farms to assess the suitability of areas and analyse important variables in a spatial environment will allow stakeholders to identify trends, opportunities and potential conflicts. The information can then be use in planning and management strategies aimed at meeting food security requirements through the sustainable development and management of aquaculture across large catchments.

6.2. Study area and species

Although the SEAT project surveyed two species per country, shrimp was the only common species amongst all four study areas (Fig 2.2). To allow for a representative comparison between the Maxent results it was decided to only use shrimp culture within the Maxent analysis. Shrimp is one of the most important aquaculture products worldwide (Lem, 2006) and two species dominate production; *L. vannamei* (Whiteleg shrimp) and *P. monodon* (Giant tiger prawn). *P. monodon* used to be the main farmed species but problems with disease led to many farmers switching to *L. vannamei* which has fewer issues and also uses fewer resources (Lebel *et al*., 2010). In 2011 production of *L. vannamei* and *P. monodon* accounted for 988,000 and 66,000 tonnes respectively (FAO, 2013b). The value of production was estimated at 12 billion U.S. dollars for *L. vannamei* and 3.5 billion U.S. dollars for *P. monodon* which represented almost 9% and 2.5% of global aquaculture production by value (FAO, 2013b). Although the catchment in Vietnam extends into Cambodia, individual sites would not be selected using the resources or environmental conditions of another country therefore the political boundary was used to ensure the model only considered variables which would be relevant to farm location (Fig 2.3).

6.3. Methodology

6.3.1. Variables

Field visits to each of the countries, stakeholder discussions and literature reviews were used to identify the key parameters involved in farming shrimp. The data were selected from globally available data sources allowing the same datasets to be applied to all study areas; preventing bias towards any data set or country. Table 6.1 outlines the data used within the study. For three variables (land use, water balance and water temperatures) two separate layers were produced; one for the dry season and one for the rainy season. Additionally, two layers were developed for urban areas; one for medium sized areas (20,000 - 100,000 people) and another for large areas (>100,000). Therefore 17 variables were used in total. Each data layer was processed so that it had a spatial resolution of 30m and was georeferenced using the UTM reference system for the selected study area.

Table 6.1: Variables used within the Maxent model

Variable	Description and relevance to aquaculture	Source
Rivers	The distance to rivers can be important as they are often a source of water.	Google Earth (2013) and USGS HYDROsheds (USGS, 2010b)
Roads	The distance to roads represents access to a transport network.	Google Earth (2013)
Urban Areas	Distance to urban areas is important as they are a source of supplies, labour and could also be valuable markets for trade. Two layers were used: medium and large areas.	Brinkhoff (2011) and Google Earth (2013)
Water bodies	The distance to water bodies (lakes and reservoirs) is important as they can be a source of water.	USGS SRTM Water Body Data (SWBD) (NASA, 2009)
Elevation	The elevation of an area can influence pond construction and drainage.	SRTM DEM (NASA, 2009)
Land use	Surrounding land use can impact water quality. Two layers were used: dry and rainy season.	Classified from satellite imagery (Chapter 4)
Population	People represent a market source and opportunity to sell products. Population can also put more pressure on water resources, lead to conflict and increase potential water quality issues.	Landscan 2008 dataset (Oak Ridge National Laboratory, 2008)

Sea	The distance to the sea can be important for shrimp farming as it is a source of water and even seed for some systems such as those in Bangladesh.	Classified from SRTM (NASA, 2009)
Slope	The slope of an area can influence pond construction and drainage.	Calculated from SRTM (NASA, 2009)
Soil - clay content	The clay content of a soil determines the porosity and the potential for water to leak from the pond.	Harmonized World Soil database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Soil – pH	Soil pH can impact the health and growth of animals and pH should not be too acidic or too alkaline.	Harmonized World Soil database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Water balance	The balance of inputs from precipitation against losses due to evaporation and seepage from ponds. Calculated using the methodology from Aguilar-Manjarrez and Nath (1998). Two layers were used: dry and rainy season.	Calculated from rainfall (Hijmans *et al*., 2005) and evapotranspiration (Trabucco and Zomer, 2009)
Water temperature	Water temperature plays a significant role in the health and welfare of animals in addition to affecting the natural productivity of aquatic ecosystems, water quality (Boyd and Tucker, 1998). Water temperature was calculated from air temperature using the methodology from Kapetsky (1994).Two layers were used: dry season and rainy season.	Calculated from air temperature obtained from WorldClim (Hijmans *et al*., 2005).

6.3.2. Farm locations

Between autumn 2010 and spring 2011 the SEAT project interviewed over 200 shrimp farmers in each of the four countries (Murray *et al*., 2011). Surveyed farms which were located within the boundary of the individual study areas were used in the Maxent model; 208 in Bangladesh (*P. monodon*), 158 in China (mostly *L. vannamei*, some *P. monodon*), 106 in Thailand (mostly *L. vannamei*, some *P. monodon*) and 181 in Vietnam (*P. monodon*). Although farms cultured different species there was no clear separation in the areas where *L.vannamei* and *P.monodon* were cultured and they were farmed in the same clusters, therefore it was decided to use both species in Thailand and China to ensure as many points were included in the model as possible. It is also important to note that the results of the models refer to the SEAT farms and should not be extrapolated more widely as the clusters are not spatially representative of the distribution of all farms across the catchments.

To enable the development of a generalised model, additional data was downloaded from the FAO National Aquaculture Sector Overview (NASO) maps (FAO, 2013c) which are datasets indicating where aquaculture is taking place (Aguilar-Manjarrez and Crespi, 2013). Unfortunately the FAO data do not have information for every country and species; therefore, the dataset for *P. vannamei* in Thailand was used as it was the most comprehensive out of all of the studied areas. There were 74 points within the study area. However, it is important to note that the FAO points refer to general areas where aquaculture occurs rather than actual farms. The locations of the points used in this study are shown in Fig. 6.1.

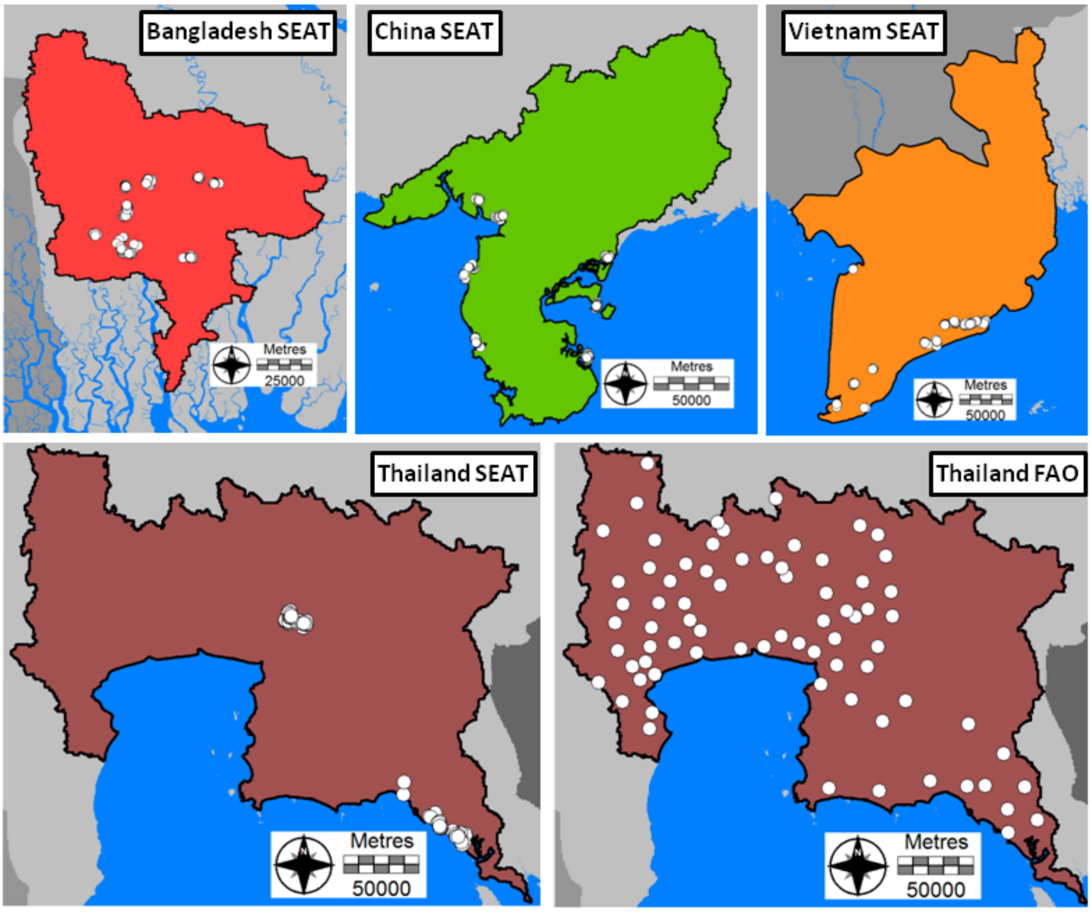


Figure 6.1: Study areas with the locations of the shrimp farms (white points)

6.3.3. Maxent modelling

IDRISI Selva [Clarks Lab, USA] was used as a modelling environment and the version of Maxent used in this study was 3.3.3K which is available to download from www.cs.princeton.edu/~schapire/maxent/. For each model 75% of the data was used for training and the remaining 25% was used for testing through all 100 bootstrap replicate runs.

Maxent tends to overfit the results and often the predicted distributions are clustered around points. The regularization setting can be used to constrain the estimated distribution which enables the average value of the sampled variable to approximate the empirical average and not equal it (Baldwin, 2009). This is an area which needs more work within the wider Maxent community. For example, Phillips and Dudik (2008) recommend using the default settings. However, recent studies by Warren and Seifert (2011) and Merow *et al*. (2013) suggest some settings might need to be adjusted and a range of coefficients should be explored. This study used the standard setting as recommended by Phillips and Dudik (2008) and regularization was kept at 1.

The accuracy of the modelling approach was assessed using the area under the receiver operating characteristic (ROC) curve (AUC) (Fielding and Bell, 1997). The main advantage of ROC analysis is that it provides a single measure of model performance which is independent of any particular choice of threshold (Phillips *et al*., 2006). AUC is on a linear scale where values closer to 1.0 indicate better results and 0.5 or less represents a model with random predictions (Flory *et al*., 2012). The importance of each variable was measured using the percent contribution values and the jackknife estimation in each study area. Response curves were also analysed to assess the relationship between the variables and shrimp farm presence. Finally the visual output of each of the models is analysed as a method of predicting further areas for shrimp farms and assessing the suitability of the area for development.

6.4. Results

6.4.1. AUC

The average training AUC across the 100 replicate runs was very high for the four study areas; Bangladesh (0.988 and the standard deviation was 0.001), China (0.994 and the standard deviation was 0), Thailand (0.995 and the standard deviation was 0) and Vietnam (0.991 and the standard deviation was 0.001). The high AUC values obtained for the four individual study areas are likely due to the distribution of farms. Phillips (2006) explains that AUC values tend to be higher for points with narrow ranges relative to the study area included in the variables. The model developed using the shrimp data from FAO had an AUC of 0.870 and a standard deviation of 0.018 across 100 replicate runs. The lower AUC is probably due to the location of the points as the FAO data is distributed across the entire study area rather than the clusters that were obtained from the SEAT project.

6.4.2. Percent contribution analysis

As the Maxent model is being trained it records which environmental variables are contributing to fitting the model (Phillips, 2006). Each step of the Maxent algorithm increases the gain of the model by modifying the coefficient for a single feature and the program then assigns the increase in the gain to the variable on which that feature depends (Phillips, 2006). It is important to note that strong collinearity can influence results by indicating more importance for one or two highly correlated variables and therefore caution must be applied when interpreting the results (Baldwin, 2009). Table 6.2 shows the percentage contribution for each of the models. Each value is an average over the 100 replicated runs and the top three variables are highlighted in red. The trends in percentage contribution between all models are also visualised in Fig. 6.2.

Table 6.2: Percentage contribution values

	Bangladesh (SEAT)	China (SEAT)	Thailand (SEAT)	Vietnam (SEAT)	Thailand (FAO)
Elevation	0.2	**22.9**	**24**	0.3	**10.3**
Land use (dry)	3.8	1.1	0.9	3.3	**11**
Land use (rainy)	12	5	5.3	1.9	6.2
Population	2.1	0.6	0.5	1.5	9.1
Rivers distance	2.7	2.2	1.2	4.3	4.8
Roads distance	4.3	0.3	0.7	10.8	6.6
Sea distance	**16.7**	**38.6**	**16.3**	**19.1**	7.9
Slope	0	0.2	0.3	0.1	2.6
Soil clay content	0.1	0.5	0.6	0.2	2.9
Soil pH	3.2	6.1	6.2	0.2	2.3
Urban distance (large)	12.2	**12.5**	10	5.1	8.2
Urban distance (medium)	**12.3**	3.7	4.3	7.8	**19.9**
Water balance (dry)	**18.9**	1.1	7.4	**18.6**	1.7
Water balance (rainy)	9.1	1	**20.3**	**14.9**	1.5
Water temperature (dry)	0	1	0	0.2	1.1
Water temperature (rainy)	9.1	0.9	0.3	3.8	1.1
Waterbodies distance	2	2.2	1.6	8	2.9

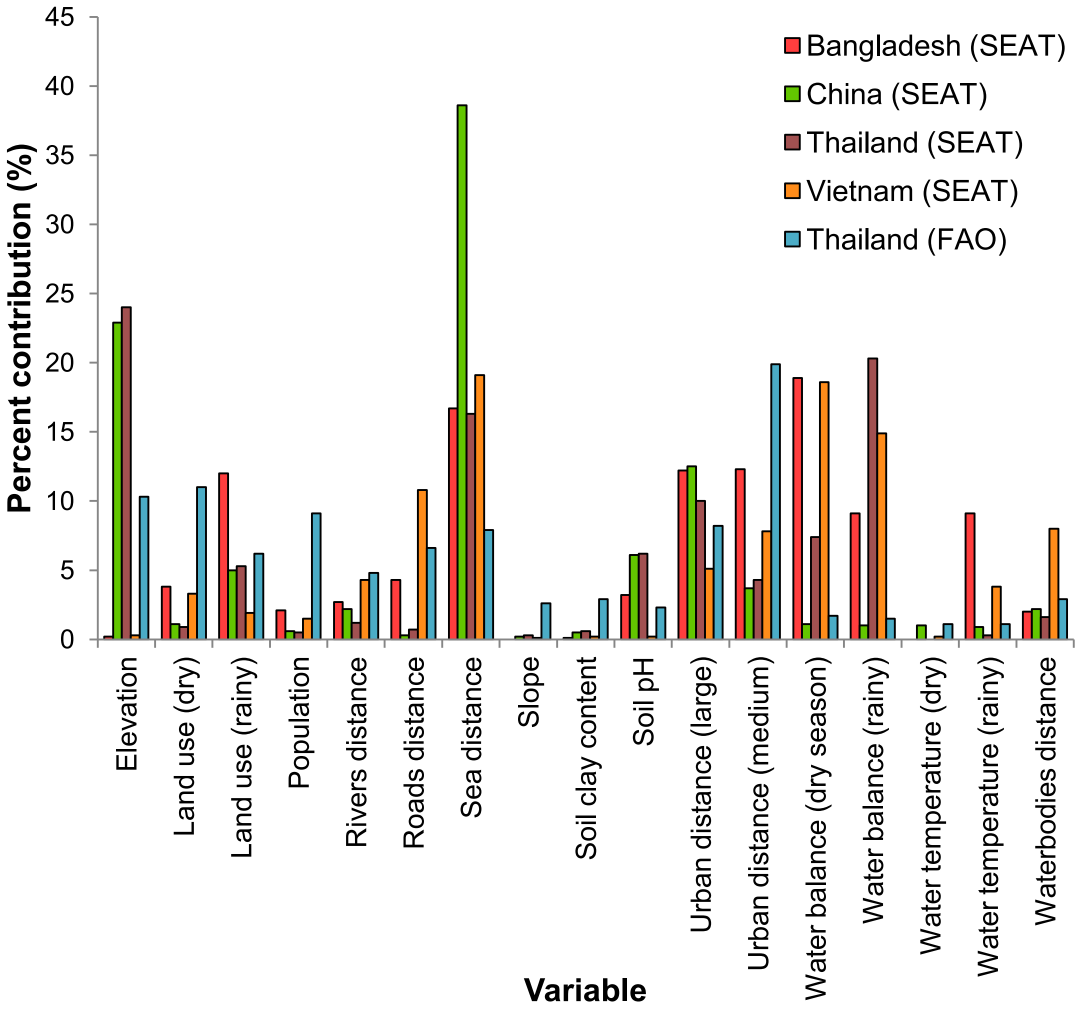


Figure 6.2: Percentage contribution analysis

The results show that distance to sea is an important variable for all of the SEAT farms (Table 6.2 and Fig. 6.2) which is confirmed by their distribution, where many of the farms are located in coastal areas (Fig. 6.1). The SEAT farms in China are all located in areas adjacent to the sea (most are within a few km) which explains the high value of 38.6%. The distance to sea is not an important variable for the FAO farms which again is explained by the location of input points (Fig. 6.1). Water balance (dry and rainy season) is also an important variable. This variable represents the availability of water; taking into account inputs from precipitation against losses from evaporation and seepage from ponds. This would be an important variable for aquaculture as many farms may depend on precipitation as a source of water in addition to other water resources such as perennial streams and rivers which often rely on rainfall (Aguilar-Manjarrez and Nath, 1998). The results in Table 6.2 and Fig. 6.2 also show that several variables (notably slope, soil clay content and water temperature (dry)) did not contribute significantly to any of the models.

It is also interesting to note there are lower percentages for distance to rivers and distance to waterbodies suggesting they had a lower influence for the distribution of the SEAT farms. The results from the SEAT survey (Murray *et al.*, 2011) indicate that farms are mainly reliant on pumped groundwater and rainfall in Bangladesh and pumped groundwater and seawater in China. However, most of the farms in Thailand and Vietnam sourced their water from canals and rivers. This suggests that the results of the Maxent analysis do not always truly reflect the important variables for farm management and results should be interpreted with caution. Instead, Maxent should be used to explain the distribution of the selected points and the model found no significant influence of distance to rivers with regard to SEAT farm location. This could be due to the Maxent modelling process or it could also be a consequence of the SEAT farm sampling strategy which did not have a representative geographic spread.

Elevation is one of the most significant variables for SEAT farms in both China and Thailand; these are the two study areas with the most variation in elevation which could explain why there is a greater influence than in Bangladesh and Vietnam where the land is relatively low-lying and flat throughout. Urban distance (both medium and large towns/cities) and water balance (both seasons) also influence the models. Urban areas are important for access and markets so it is understandable how they could influence farm location. However urban areas can also be a source of pollution and this may affect site suitability. The percent contribution analysis only shows what variables influence the models and not how or why they are important. This is discussed below when considering response curves.

6.4.3. Jackknife test of variable importance

The results of the percentage contribution are only heuristically defined as they depend on the particular path that the algorithm uses to develop the model (Phillips, 2006). An alternative estimate of variable importance is the Jackknife test of variable importance. The Jackknife approach excludes one variable at a time as the model runs, which provides information on variable performance, particularly, how important each variable is at explaining the distribution of points (farms) and how much unique information each variable provides (Baldwin, 2009).

The variable with the highest gain (most significant) when used in isolation for three of the SEAT models (Bangladesh, Thailand and Vietnam) is water balance (dry season), whilst distance to sea is the variable with highest gain for China (Fig. 6.3). These variables had the most influence over model development. It is interesting to note that water balance (dry season) is the most important variable for model development in three out of the four study areas, suggesting it is a common trend amongst the SEAT farms. For each study area, the green bars show that no single variable contains a substantial amount of unique information as there was no decrease in training gain when each variable was omitted. With regard to FAO NASO data, the most significant variable when used in isolation is urban distance (medium), which is also the variable which is most informative to model development (Fig. 6.3).

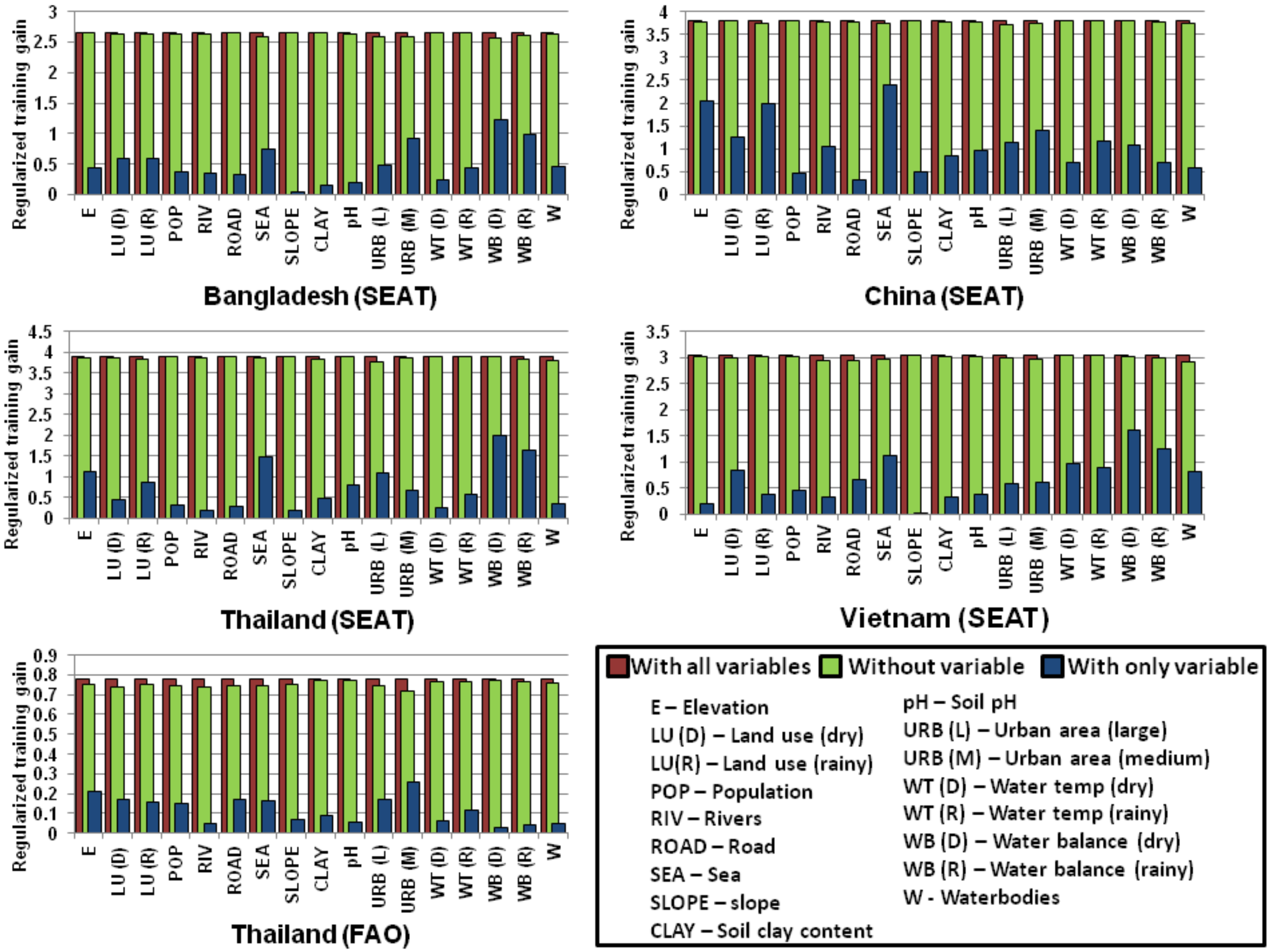


Figure 6.3: Results of the Jackknife test of variable importance

6.4.4. Response curves

Variable response curves are determined when Maxent creates a univariate model and the curves represent the range of values within the variable associated with the input points (Santos *et al*., 2013). The response curves show the probability of farms being located in areas with a particular value of variable. Response curves for the top three variables for each model (Table 6.2 and Fig. 6.2) are shown in Fig. 6.4. Some common trends can be seen in the response curves. As the distance from the sea increases the response of the model decreases (Figs 6.4B, 6.4D, 6.4I, 6.4J). Even the SEAT farms in Thailand, which were located in two clusters (one for inland culture and one for coastal culture as shown in Fig. 6.1), had a moderately high probability of being located in areas which were relatively close to the sea (within 35km) compared to the rest of the study area (Fig. 6.4I). Additionally, the response for elevation for China and Thailand decreases with increasing elevation (Figs 6.4E and 6.4G). Both of these responses would be expected as many of the SEAT farms were located in low-lying coastal areas (Fig 6.1).

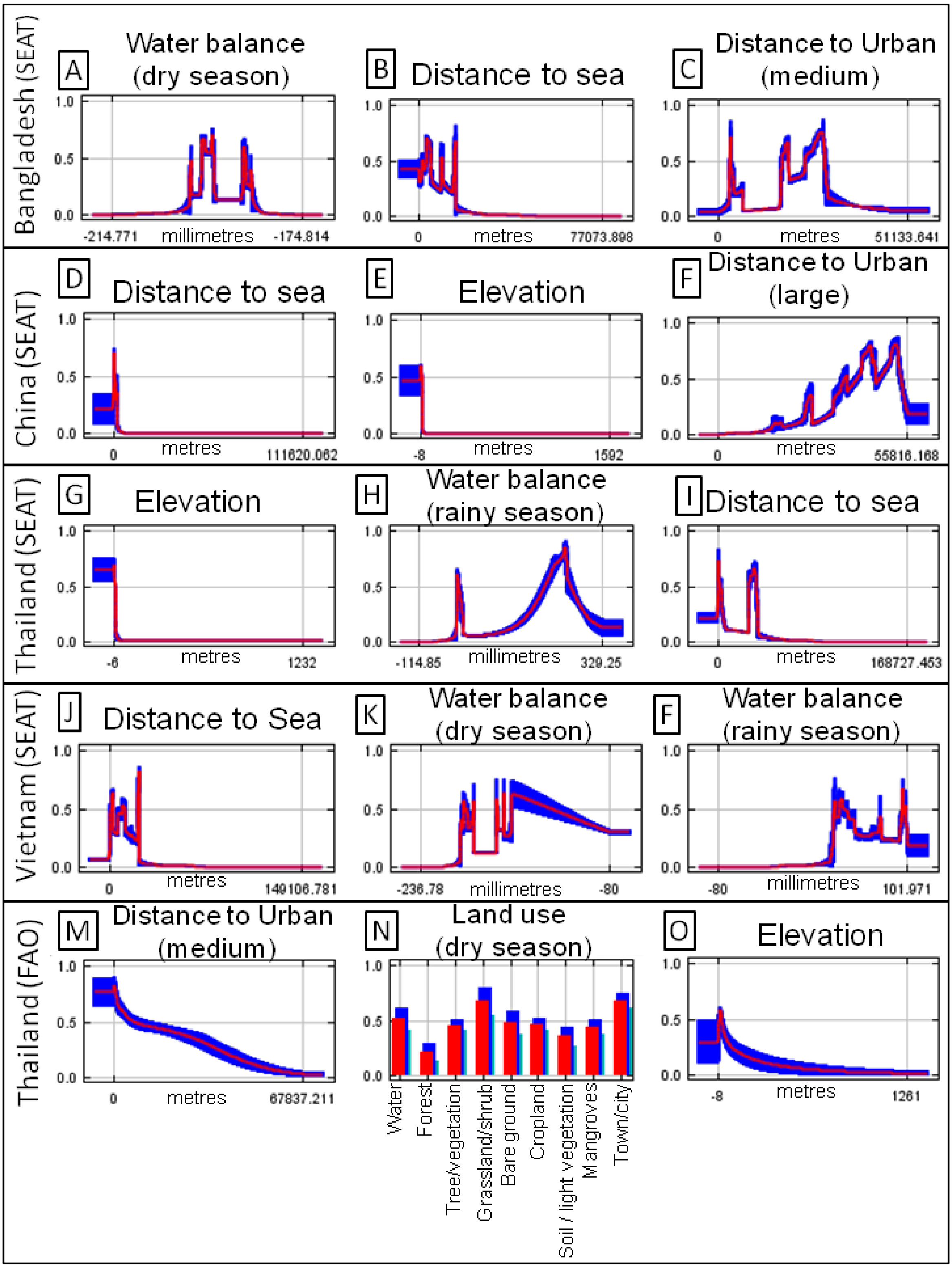


Figure 6.4: Response curves of the top three variables for each model

Note: the curves show the mean response of the 100 replicate runs (red) and the mean +/- standard deviation (blue, two shades for categorical variables).

Strictly, the Thailand (FAO) model should not be directly compared to the SEAT models as the input data is different (Fig. 6.1). However it is still interesting to compare the response curves. As with the SEAT farms, the FAO farms have a higher probability of being located in areas of lower elevation (Fig. 6.4O). Figure 6N shows the response for Land use (dry) for the Thailand (FAO) model. Land use is categorical data rather than a continuous variable which is why the results are presented in a different way. The results should be interpreted with caution as, unlike the SEAT data, the FAO points refer to general areas where aquaculture is practiced rather than actual farms, thus the results may not be entirely representative.

Water balance has some of the highest percentage contributions for each of the SEAT study areas (Table 6.2 and Fig. 6.2) and the results of the Jackknife test (Fig. 6.3) suggest that water balance (dry) is the most important variable in three of the study areas. Therefore it is interesting to examine the response curves for water balance in more detail (Fig. 6.5). The results show there is a higher probability of farms in locations which experience a slight negative water balance in the dry season, a phenomenon that may be expected. This could identify a potential area for concern at a wider catchment if there are multiple farms and activities sharing water resources as farmers may be more reliant on external water sources. However, Fig. 6.5 also shows that the average negative water balance is generally no more than -200mm (0.2 metres) for each study area suggesting that it may not be a significant issue. This identifies a potential issue which would be difficult to assess without the use of spatial analysis and highlights the advantage of using Maxent to analyse variables as it can provide information on the conditions experienced which decision makers can then use to assess if there is a problem or not.

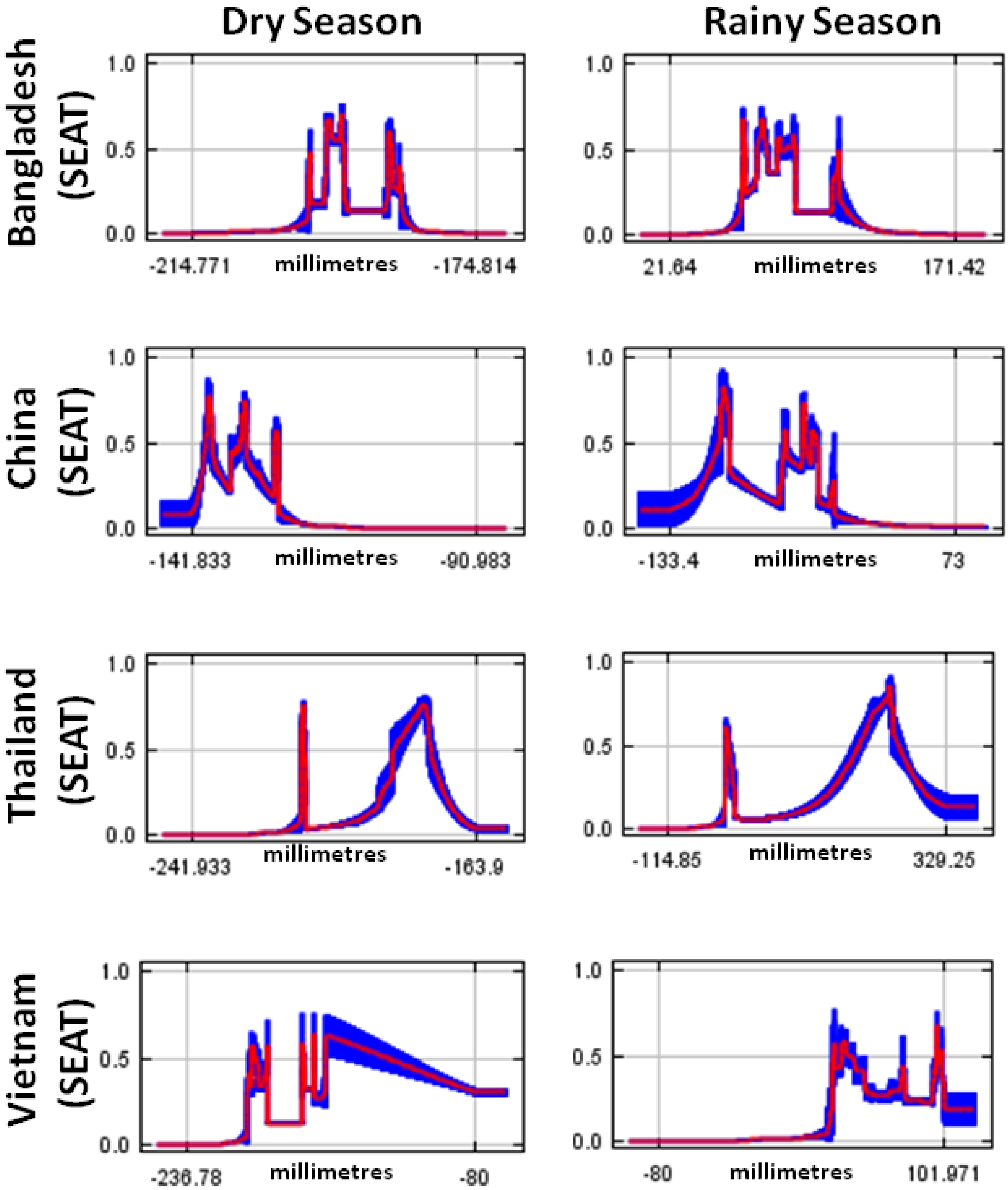


Figure 6.5: Response curves for the water balance variable for the four SEAT models

Note: the curves show the mean response of the 100 replicate runs (red) and the mean +/- standard deviation (blue).

6.4.5. Predicted distribution of farms

Three output formats are available within the Maxent model; raw, cumulative and logistic. The default option for Maxent is the logistic output as it gives an estimate between 0 to 1 and is the easiest to conceptualise (Phillips, 2006). For this reason the logistic option was used in this study. The model output is shown in Fig. 6.6. Areas with higher scores have better predicted conditions and therefore are the most suitable areas given the input data. The SEAT models should be interpreted as suitability for similar farms rather than suitability of the entire area for general shrimp culture, whereas the FAO model illustrates the potential of using data that is more widely distributed across the catchment. Several key areas have been highlighted within each area to show the detail included in the model.

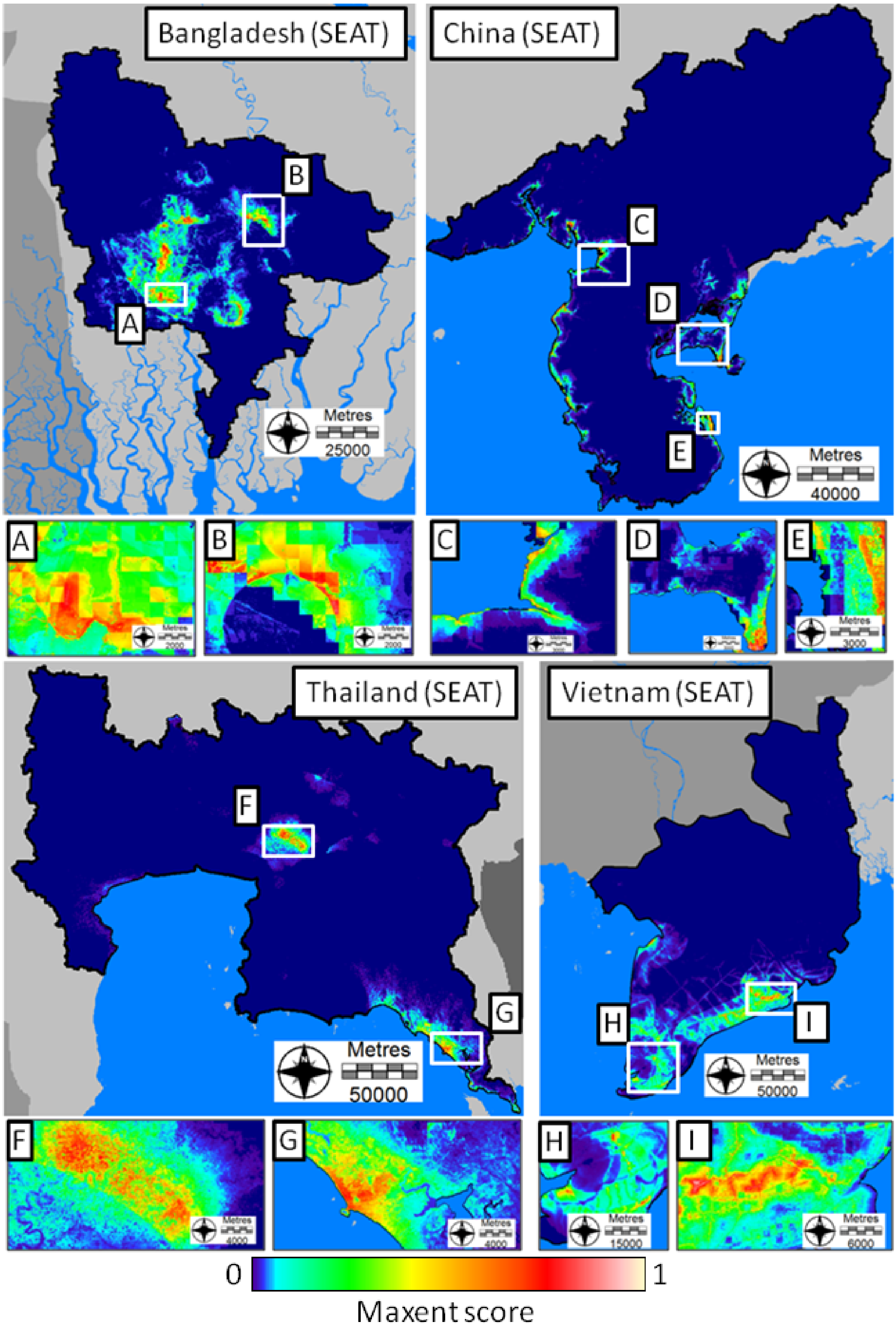


Figure 6.6: Predicted distribution of the SEAT farms using the Maxent model. The higher the Maxent score the higher the suitability of the area for conditions similar to those experienced by the SEAT farms.

The results from the SEAT models show a narrow range of suitability across the catchments (Fig. 6.6). The areas of high suitability are focussed on the clustered areas where the SEAT farms are located. This suggests that areas with similar variables as the SEAT farms are generally found within the same areas. This would be expected and the narrow range of suitability could be explained by the inclusion of distance variables which might be influencing the final outcome. The results from the percentage contribution also suggest that distance factors, particularly the distance to sea, contributed highly to the model outcome (Table 6.2 and Fig. 6.2). This is further highlighted by looking at the results for China in more detail as all of the areas that have a higher Maxent score are located very close to the sea (Fig. 6.6C, 6.6D, 6.6E) and Table 6.2 shows that the distance to the sea variable contributed highly to the final model (38.6%). Furthermore, the results of Figure 6.4D show that the probability of SEAT farms is highest within 3km from the sea with no SEAT farms located beyond 3km. The results appear to be representative of the existing SEAT farms for China which are all located in the low lying coastal areas next to the sea.

The output of the Maxent model for Thailand (FAO) is shown in Fig. 6.7 and there are significant differences between the results in Fig. 6.6 and Fig. 6.7. The results are distributed across the study area due to the spread of the input data points (Fig. 6.1). However, although there is a more widespread distribution it can be seen that the highly suitable areas are still located in clusters (Figs 6.7A and 6.7B), albeit larger "hotspots" than those shown in Figs 6.6F and 6.6G. The area highlighted in Fig. 6.7B is a significant area of inland shrimp production and the Maxent results have moderately high scores in this area. However, the area highlighted in Figure 6.7C, is also one of the most productive areas for shrimp culture in Thailand and the output from the FAO model indicates that it has a low score. Again, this highlights how important the distribution of the input points are and general points which are not farm specific may miss key areas.

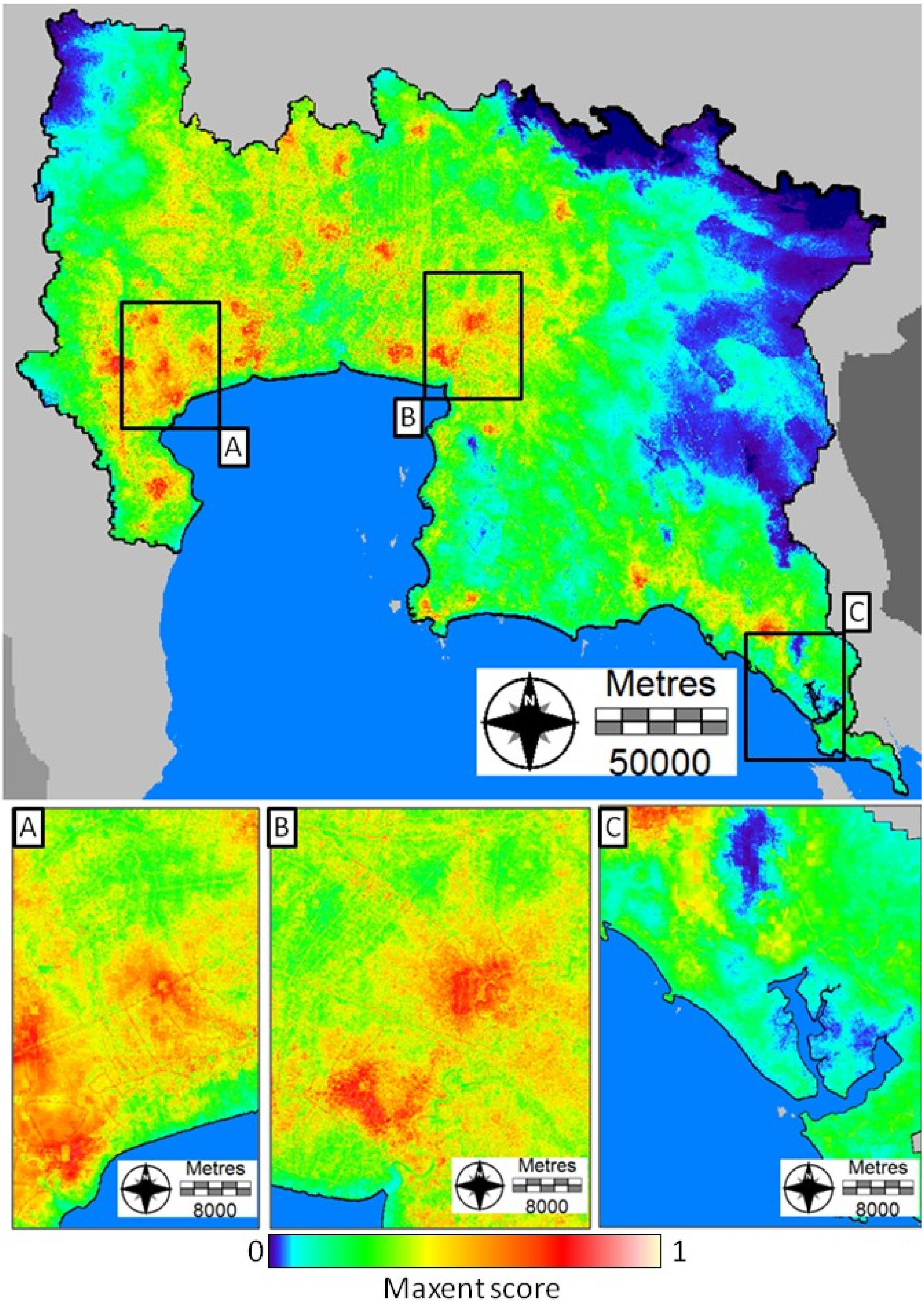


Figure 6.7: Predicted distribution of the FAO farms using the Maxent model. The higher the Maxent score the higher the suitability of the area for conditions similar to those experienced by the FAO farms.

Figure 6.8 shows a comparison between the results for Thailand using the FAO NASO and SEAT datasets. The only difference in the models is the input farm locations; which have been included in Fig. 6.8 as guidance. Using the FAO points in Maxent results in a larger predicted area of suitability than the SEAT farms due to the differences in input data. The FAO data is more widespread but is not site specific as the points only indicate that shrimp aquaculture occurs within that area but not necessarily that specific pixel therefore hotspots of known aquaculture locations can have lower Maxent scores due to unrepresentative input data (Fig. 6.8B and 6.8F). On the other hand, the SEAT data is comprised of specific farms which are located in that pixel, but are clustered in fewer locations. As a result there is a very narrow range of suitability and areas beyond the cluster which may be suitable for shrimp culture have low scores (Fig. 6.8G; Fig. 6.8H).

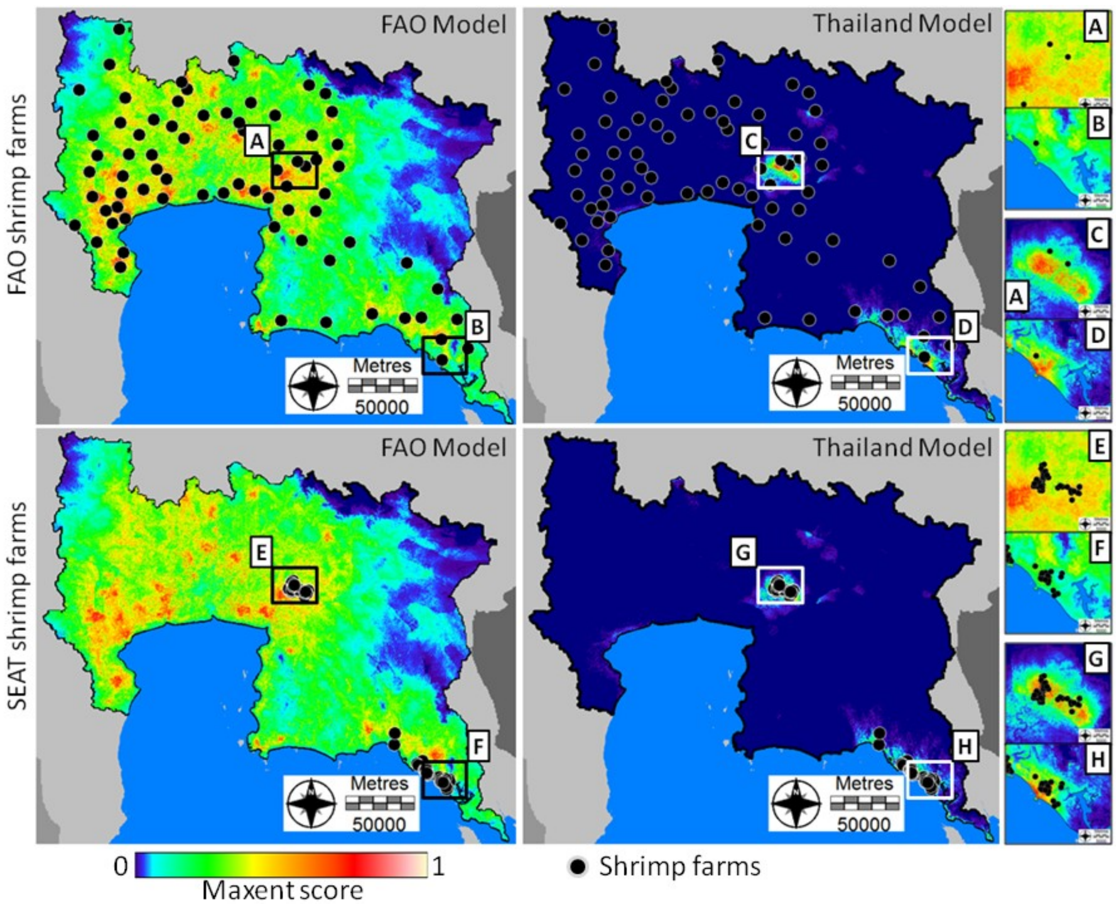


Figure 6.8: Comparison of the Maxent model results for Thailand using the SEAT and FAO data

6.5. Discussion

It is essential that the shrimp industry, in addition to all other aquaculture sectors, aims for sustainable production. Whilst it is important to identify new areas for development using optimal values, expert weightings and spatial models (Nath, 2000; Ross *et al*., 2009), such as those developed by McLeod *et al.* (2002), Salam *et al*. (2003) and Giap *et al*. (2005), it is also vital that the locations of existing farms are assessed. The use of land and water is a source of conflict and consequently the variables associated with farm location should be assessed to ensure the area is suitable for aquaculture. Increased production of food is reliant not only on new farms but also existing systems and stakeholders need to understand why aquaculture is located in certain areas as this allows decision makers to identify trends, opportunities and concerns related to sustainable development and integrated catchment management.

As noted by Baldwin (2009) most studies have focussed on using Maxent for species distribution modelling rather than determining important habitat characteristics. However, some recent studies such as Blach-Overgaard *et al*. (2010) and Flory *et al*. (2012) have used Maxent to assess the importance of the variables that determine distribution. Baldwin (2009) also highlights the potential for Maxent to assess the relationship between variables and location. Applications of Maxent are constantly evolving and as a result the software is regularly updated to include new capabilities and change program defaults to help users (Elith *et al*., 2011). The results presented here are the first step towards using Maxent within aquaculture to assist decision makers assessing the suitability of large catchments for aquaculture.

Maxent can be used to identify common trends between farm locations and variables. The results of this study show that the distance to sea and elevation are both important variables for the SEAT study areas (Table 6.2 and Fig. 6.2). This is consistent with the location of the input variables where many of the SEAT farms are situated in low lying coastal areas (Fig. 6.1), highlighting the effective use of Maxent to evaluate the variables associated with site location and aquaculture. Identifying common trends between farms and variables provides extra knowledge for decision makers who can use the information to develop planning and management strategies for sustainable aquaculture.

It is also important to interpret the percentage contribution results with caution as they are heuristically defined and dependent on the model algorithm. The results indicate that the distance to rivers have a low influence for the models (Table 6.2 and Fig. 6.2). However, the SEAT farmer survey (Murray *et al*., 2011) indicates that in Thailand and Vietnam many farms use water from rivers and canals for their ponds. The model evaluates the location of the points across the spatial variables and assesses the probable distribution across the catchment, identifying areas with comparable conditions where similar farms could occur. It does not assess the likelihood of farm management operations, such as water supply, it only considers the relevance of the variable contribution towards the pattern of distribution of the input farms. Therefore, the low percentage contribution indicates that the model had no significant influence from the distance to rivers.

One of the most important variables in terms of model development across the SEAT study areas is water balance (Fig. 6.3). However, further analysis, using the response curves (Fig. 6.5), is required to identify the actual conditions of water balance that the SEAT farms experience. Fig. 6.5 shows that some farms are likely to be distributed in areas with a moderately high probability of a negative water balance. However, as the average deficit in the dry season is no greater than 200mm (0.2 metres) there may not be a significant issue depending on the number of farms and other stakeholders using communal water sources. The use of response curves allows the analysis of the conditions experienced by farm locations across the variables and highlight issues which may be difficult to identify otherwise.

The results also show that it is essential to have suitable input data. Fig. 6.8 shows the comparison between the results from the SEAT farms and the FAO points. There are advantages and disadvantages to the use of each type of input points (clustered or widely distributed) and Fig. 6.8 shows the potential use for both as suitability informants. If decision makers are looking to assess the overall suitability of a large catchment they can use points which are distributed throughout the region similar to the FAO data. This will provide a representative geographical spread and will evaluate the whole catchment for similar suitable conditions. However, the FAO model indicates low suitability for farms in the south east of the study area where there are clusters of shrimp farms (Fig. 6.8F) illustrating how suitable areas can be missed if the model does not use sufficient representative points. On the other hand, the results of the SEAT data show that the suitability is clustered around the input points with a narrow range of high scores (Figs 6.8G, 6.8H). Whilst this may not be useful for a catchment wide approach, it allows decision makers to identify new areas which have similar conditions to the selected farm type (in this case the SEAT farms). This would enable the use of pre-identified suitable farms to be used as a template and established in other similar areas with the aim of more successful and sustainable development.

The narrow range of predicted distribution in the results may also be due to Maxent as it frequently overfits results and predicted distributions are often clustered around points (Baldwin, 2009) as shown in this study. This can be adjusted using the regularization coefficient (Phillips and Dudik, 2008; Baldwin, 2009; Warren and Seifert, 2011; Merrow *et al*., 2013). However, Anderson and Gonzales Jr (2011) suggest that optimal regularization settings may depend on the feature classes used and the number and characteristics of variables in addition to the number of localities and their bias. This would make it difficult to compare multiple areas as different regularization settings may be required and therefore the results may not be entirely suitable for comparison. Consequently, this study used the default settings for regularization as recommended by Phillips and Dudik (2008) to compare the study areas. However, if Maxent was used to evaluate a single area for site suitability then it may be more appropriate to adjust the regularization value so the results are not as clustered.

Any model will have different results depending on the settings and the same is true for Maxent. As noted by Warren and Seifert (2011) further work is needed on the settings as there is little guidance available at present. This study has used a transparent approach where settings are noted and users can then determine the usefulness of the results themselves. The use of Maxent as a method of site selection for agriculture has been highlighted by Evans *et al*. (2010) and this study has also shown there is the potential to use this approach in aquaculture. Furthermore, Maxent has the ability to provide a valuable insight into key variables associated with farm location which can help to inform future site selection studies.

Presently, the main advantage of Maxent for aquaculture appears to be the response curves which provide information on the conditions experienced by the farms. This allows identification of trends across multiple study areas and can be used to consider the key conditions that are experienced by successful or unsuccessful systems. Use as a site suitability tool across a large catchment is limited without sufficient representative input points. However, there is scope to develop it as a tool to assess suitability of further areas for specific farm types. Furthermore, the probability of suitable areas is based on similar conditions rather than optimal locations and provides an alternative method of assessment.

Spatial models have the potential to play a vital role in the EAA (Aguilar-Manjarrez *et al*., 2008) and it is important that the industry considers new methods that may not have been developed primarily for aquaculture. This work has shown that Maxent could be a useful tool for integrated management and assessment of sustainable aquaculture across large catchments. However, it is recommended that the input points indicate actual locations where the farms are located within the pixel as that is more representative. Although the study used shrimp farming as an example, the approach can be applied to other species, systems and study areas. Additionally, Maxent is dependent on the input variables and different results would be obtained using alternatives. Further application of this technique would be beneficial as modelling is an iterative process where methodologies are adapted, improved and refined with each application.

CHAPTER 7

USING GIS BASED MODELS TO IDENTIFY POTENTIAL RISKS OF NON-POINT SOURCE POLLUTION IN LARGE CATCHMENTS OF IMPORTANCE TO AQUACULTURE

7.1. Introduction

The most fundamental resource within an aquaculture system is water and wider environmental issues such as pollution can have a detrimental impact on water quality, which in turn can have serious consequences for a farm. However, it can be difficult to identify and monitor pollution, particularly non-point source pollution (NPSP), which is generated from diffuse sources with no single point of entry and is often widespread across a large area; unlike point source pollution which is discharged into the environment through a single identifiable source such as a pipe (Frid and Dobson, 2002; Cech, 2010). Additionally, because NPSP is often intermittent and associated with seasonal land management practices and heavy rainfall (Carpenter *et al*., 1998) it can be difficult to measure.

Pollutants found in NPSP can include sediments, nutrients, salt, animal waste, organic matter, bacteria, oils, metals, pesticides, fertilisers and other toxic chemicals (Cech, 2010), all of which can have significant implications for water quality. Generally phosphorus is a limiting factor in freshwater lakes and reservoirs (Schindler, 1978) and although phosphorus can be limiting in coastal ecosystems (Howarth and Marino, 2006), nitrogen is the main limiting factor to primary productivity and eutrophication in coastal marine waters (Ryther and Dunstan, 1971). Eutrophication is the main problem facing most surface waters worldwide and is a result of an increase in phytoplankton growth and productivity resulting from an increase in dissolved nutrients (Pillay, 2004;

Smith and Schlinder, 2009). Potential negative impacts of eutrophication on all aquatic environments include oxygen depletion, reductions in species diversity, increased incidences of fish kills and contribution to Harmful Algal Blooms (HABs) (Anderson *et al*., 2002; Smith and Schlinder, 2009). NPSP is one of the major contributors to eutrophication resulting in problems in rivers, lakes, estuaries and coastal environments (Carpenter *et al*., 1998).

Excess nutrients are not only a problem for the wider environment; they can also have significant implications for aquaculture production. Accumulation of nitrogenous compounds such as ammonia and nitrite can lead to a deterioration of water quality and can be toxic to fish and shellfish (Hargreaves, 1998). Eutrophication can also contribute to Harmful Algal Blooms (HABs) (Anderson *et al*., 2002; Gilbert *et al*., 2010) and toxins produced by cyanobacteria can poison aquaculture species and/or harm human consumers (Smith *et al*., 2008; O'Neil *et al*., 2012). Secondary metabolites from cyanobacteria can also result in damage to internal organs and "off-flavour" issues where odorous compounds accumulate in tissue and water, spoiling the product (Smith *et al*., 2008). Cyanobacterial blooms are stimulated by high temperatures and anthropogenic nutrient loads (O'Neil *et al*., 2012). Therefore, it is essential to consider potential sources of excess nutrients before a problem occurs.

Aquaculture itself can also create new issues or exacerbate existing water quality problems by releasing extra nutrients into the environment. At a local scale, farmers can mitigate against nutrient enrichment through farm management practises. Tucker and Hargreaves (2008) discuss the best management practices for aquaculture which can be used to reduce nutrient input into the environment. On the other hand, aquaculture can capitalise on excess nutrients in the water as extractive organisms (bivalve molluscs and seaweed) can be successfully cultured in nutrient rich water, providing a commercial product and reducing the level of nutrients (Neori *et al*., 2004). This feature can be further developed into an Integrated Multi-Trophic Aquaculture

(IMTA) system where extractive organisms extract their nutrition from the effluents of fed species such as fish or shrimp providing multiple species for market, in theory reducing the overall environmental impact of the fed species (Neori *et al*., 2007). Such integrated systems generally retain more of the input nutrients than monocultures. Nevertheless, in many cases a major fraction of the nutrients still remains unused (Verdegem, 2013). Therefore even if such a system is used it is still important to ensure the aquatic system is not under excessive nutrient loading and the system is within the carrying capacity for the ecosystem as discussed by Ross *et al*. (2013).

At a wider scale, control of NPSP focuses on land management practices across the catchment and the most significant barriers to controlling nonpoint source pollution are social, political and institutional (Carpenter *et al*., 1998). Difficulties in regulating NPSP are numerous. Control policies such as taxes and fines require substantial information and transaction costs, whilst schemes which encourage voluntary compliance with water quality standards have been criticised for not providing sufficient economic incentives (Li, 2013). The main problem that authorities face is a lack of data. Often they can only obtain information about ambient pollution levels rather than individual emissions due to the difficulties in identifying and measuring NPSP and the technical constraints and the excessive cost that would be involved in a wide scale monitoring program (Camacho-Cuena and Requate, 2012). As stated by Moltz *et al*. (2011) when aiming to implement a NPSP prevention programme, the success and sustainability of the operation is determined by the ability to target priority areas whilst making effective use of limited time and funds.

Spatial models can be used to simulate complex environmental processes and predict the potential scenarios that could occur within a geographical context (Mulligan and Wainwright, 2004). Such models can be used to identify key areas in need of further investigation and/or assistance in an efficient manner. There are many models that are used to assess NPSP (Knisel, 1980; Beasley and Huggins, 1985; Young *et al*., 1989;

Bouraoui and Dillaha, 2000; Arnold *et al*., 2012), however, as noted by Munafò *et al*. (2005) non-point source models, particularly statistical or physically based models, can be complex and require large amounts of data. Therefore it is difficult or impossible to apply such models to many study areas, particularly large catchments. Recently, there have been efforts by various studies to develop simplified spatial models. Munafò *et al.* (2005) developed a method (PNPI tool) to assess river pollution from non-point sources using widely available data. A similar approach was used by Zhang and Huang (2011) to develop a model using a multi-criteria analysis approach for a large river basin in China. Moltz *et al*. (2011) also used GIS to develop a NPSP risk assessment for the Rio Grande Basin, USA. These models aim to simplify a complex issue and allow decision makers a more efficient method of identifying specific areas which require further attention or analysis.

NPSP is a seasonal issue (Carpenter *et al*., 1998), however, few large scale studies have incorporated this seasonality into their structure. This study builds upon work by previous studies (Munafò *et al*., 2005; Moltz *et al*., 2011; Zhang and Huang, 2011) to produce seasonal NPSP models for both nitrogen and phosphorus. The overall aim of the study was to produce GIS-based models which could be applied to large catchments of importance to aquaculture, allowing key stakeholders and decision makers extra information to assess the risk of NPSP to significant areas and identify the need for further analysis or assistance. The model is also fundamentally linked to the EAA which encourages evaluation of the impact from and to aquaculture and the wider environment.

7.2. Methodology

7.2.1 Model structure and development

Models were developed for each study area (Fig. 2.2) with a 30m spatial resolution and georeferenced using the UTM system. Analysis was performed using IDRISI Selva [Clarks Labs, MA, USA] and macro models were also produced to efficiently run the individual model components for different study areas (see appendix). The overall framework comprises of five indices; nutrient generation, runoff, transport, rainfall and population which are combined to produce the final model outputs (Fig. 7.1).

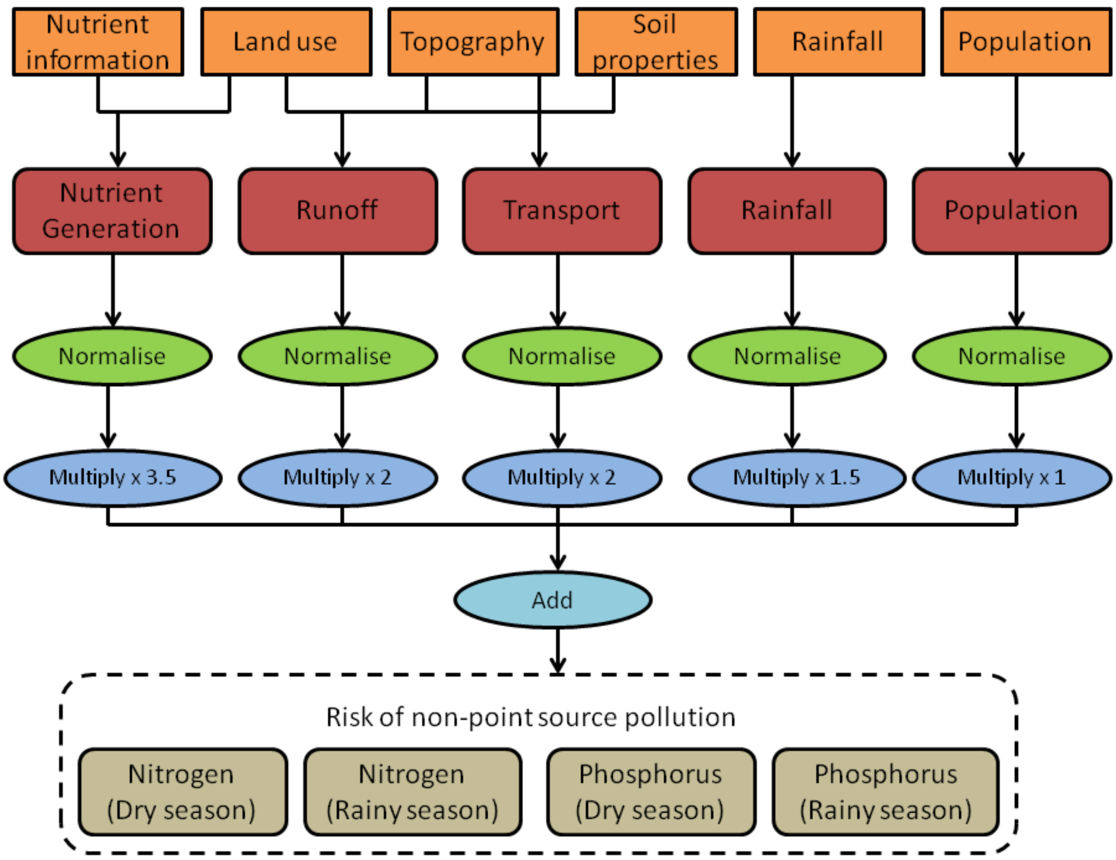


Figure 7.1: Model framework

7.2.2. Nutrient generation submodel and index

The nutrient generation index represents the amount of nitrogen or phosphorus that would be generated by different land use types. Nutrient loading into the environment can be predicted using export coefficients which represent the rate at which a nutrient (or pollutant) is exported from a particular source, such as land use type, to the wider environment (Hanrahan, 2009). The export coefficient technique has been widely used as a method for predicting nutrient loading since it was first developed in the 1970's (Hanrahan, 2009). New export coefficients can be developed for land use types in a study area by monitoring the catchment to isolate the individual land use contributions to pollutant loading as described in Shrestha *et al*. (2008), or existing export coefficients can be applied to land use categories. Seasonal land use maps were classified from Landsat 7 ETM + satellite imagery using the remote sensing tools incorporated in IDRISI (Chapter 4). Export coefficients were then assigned to each land use category (Table 7.1) and converted to kg/pixel/season, where each pixel represents an area of $900m^2$ (spatial resolution is 30m).

Some of the land use categories within the land use maps are quite broad and contain several different types of a particular land use. A lot of the land that is classed as trees/heavy vegetation contains orchards or tree crops, particularly in the areas located near aquaculture systems, therefore this category was assigned an export coefficient for orchards (Ma et *al.,* 2011). Orchards have much higher export rates for phosphorus than would be expected from wooded areas and consequently there may be some overestimation of risk of phosphorus NPSP for areas classed as trees/heavy vegetation which are not orchards.

Atmospheric deposition through rainfall is also a source of pollutants (Ma *et al*., 2011). The nitrogen and phosphorus content of rainfall for every pixel in the study area was calculated using values obtained from Ma *et al*. (2011); 165 $x10^{-8}$ $t/m^3/yr$ for nitrogen and 5 x 10^{-8} t/m^3/yr for phosphorus. The volume (m^3) of each pixel was calculated using the length and width of the cell multiplied by the height of rainfall. This allowed a value (kg/pixel/season) to be determined as with all of the other land use types. Generally, bare ground will generate little or no nutrients. Therefore, no export coefficient was applied to this category and pixels of this type only had the nutrient content of rainfall. Studies have shown that mangroves are often net consumers of both nitrogen and phosphorus and can be considered nutrient sinks (Alongi, 1996; Rivera-Monroy *et al*., 1999; Wösten *et al*., 2003). Hence for this study, mangroves were assigned a value of 0 representing no nutrient generation.

Table 7.1: Export coefficients assigned to each land use category

Land use type	Export coefficient (t/km^2/yr)		References
	Nitrogen	Phosphorus	
Forest	0.250	0.015	Ma. (2011)
Trees / heavy vegetation/ orchards	0.180	0.520	Ma. (2011)
Grassland / shrubland	0.600	0.080	Ma. (2011)
Bare ground	Rainfall	Rainfall	Ma. (2011)
Agriculture	2.150	0.430	Ma. (2011)
Soil / light vegetation	1.100	0.020	Ma. (2011)
Mangroves	0	0	Alongi (1996); Rivera-Monroy *et al*., (1999); Wösten *et al*. (2003)
Town/city	1.300	0.180	Ma. (2011)

7.2.3 Runoff submodel and index

The runoff index takes into account the soil permeability, land use and slope to account for the potential for runoff. The efficiency of runoff generation is calculated based on the curve number equation retention parameter (S) (Zhang and Huang, 2011). The soil retention parameter characterises the catchments potential for abstracting and retaining moisture, and thus, the direct runoff potential (Ponce and Hawkins, 1996). The curve number method is a popular technique as it is simple to use and is often the only way to make approximate estimates of overland flow for ungauged watersheds (Yoo & Boyd, 1994). This technique has been used in many NPSP models and is particularly useful for modelling large catchments as shown by Hong *et al*., (2007) who used the curve number method to simulate runoff from major river basins around the world. Curve numbers represent the runoff potential and how permeable the soil is; a lower curve number indicates low runoff potential, whereas a larger number indicates higher runoff potential. Curve numbers (CN_2) for moderate soil moisture (AMCII) presented in Table 7.2 were obtained from USDA SCS (1986) and Shi *et al.* (2007).

Table 7.2: Curve numbers (CN_2) for the different land use categories and hydrological soil groups

Land use type	Curve numbers for hydrological soil group			
	A	B	C	D
Forest	25	55	70	77
Trees/orchard	40	62	76	82
Grassland/shrubs	36	60	74	80
Bare	98	98	98	98
Crops	67	78	85	89
Soil/fallow fields/light vegetation	72	82	88	90
Mangroves	32	58	72	79
Town/City	90	93	94	95

Layers representing the four hydrological soil groups were reclassified from the seven drainage classes used in the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). The values of CN_2 in Table 7.2 are only suitable for a 5% slope and therefore must be adjusted (CN_{2s}) to take into account the different slopes (θ) as described by Zhang and Huang (2011). A layer representing % slope was produced from the SRTM DEM. In order to calculate CN_{2s}, Equation 7.1 was first used to determine CN_3 which is the curve number for high moisture condition (AMCIII). Equation 7.2 was then used to calculate CN_{2s} and finally this value was used in Equation 7.3 to calculate S which is the retention parameter. A lower retention parameter results in higher potential for runoff (Soltani and Sinclair, 2012).

$$CN_3 = CN_2 \exp\left[0.00673(100 - CN_2)\right]$$ [Equation 7.1]

$$CN_{2s} = \frac{(CN_3 - CN_2)}{3}\left[1 - 2\exp(-13.86\theta)\right] + CN_2$$ [Equation 7.2]

$$S = 25.4\left(\frac{1000}{CN_{2s}} - 10\right)$$ [Equation 7.3]

7.2.4 Transport submodel and index

The transport index represents the potential movement of surface runoff and the subsequent potential for NPSP. The movement of surface water on land, and subsequent soil erosion, is dependent on both the length and inclination of the slope (Wischmeier and Smith 1978; Brooks *et al*., 2013). Slope length and slope steepness are the two components of the LS factor, also known as the topographic factor, which is part of the Universal Soil Loss Equation (USLE). The USLE is a mathematical model which has been widely used throughout the world to predict and estimate soil loss (Blanco and Lal, 2008). The LS factor is used within the USLE to represent the expected ratio of soil loss from the area of interest to the standard USLE plot (Wischmeier and Smith 1978; Blanco and Lal, 2008). Slope length represents overland flow from the point of origin to where deposition begins or the runoff reaches a defined channel (Brooks *et al*., 2013). Therefore as increasing values of LS indicate steeper and/or longer slopes it can represent the potential for runoff and the associated erosion which leads to NPSP.

There are many different methods that can be employed to calculate the LS factor. This study followed a similar methodology to Lufafa *et al*. (2003) where the LS factor was calculated using two equations depending on the steepness of the slopes. Equation 7.4 was used for slopes with a steepness below 21% (Wischmeier and Smith,

1978) and Equation 7.5 was used for slopes with a steepness above 21% (Gaudasamita *et al.,* 1987, in Lufafa *et al.,* 2003).

$$LS\ (slopes < 21\%) = \left(\frac{\lambda}{22.1}\right)^{m} (65.41 \sin^2 S + 4.56 \sin S + 0.065) \qquad \text{[Equation 7.4]}$$

$$LS\ (slopes > 21\%) = \left(\frac{\lambda}{22.1}\right)^{0.7} (6.432 \sin(S^{0.79}) \times \cos(S)) \qquad \text{[Equation 7.5]}$$

Where:

λ is slope length (m)

S= slope (radians)

m = 0.5 if slope ≥5%

0.4 if slope between 3 - 5%

0.3 if slope between 1-3%,

0.2 if slope <1%

Slope and aspect were calculated from the SRTM DEM (Shuttle Radar Topography Mission Digital Elevation Model) (NASA, 2009). The DEM was modified within the software to remove any spurious pits (also known as sinks or depressions). These pits are pixels where the surrounding pixels are all at a higher elevation which often results in problems for hydrological modelling as they disrupt the natural flowlines and drainage topography (Hugget and Cheesman, 2002; Reuter *et al.*, 2009). Some depressions may be naturally occurring or endorheic lakes, however, often they result from errors in the interpolation, incorrect data, insufficient information or problems with the pixel resolution during DEM production (Hugget and Cheesman, 2002). Therefore it was decided to remove the depressions through pit removal prior to further analysis.

The aspect layer was used to identify the direction of flow. This layer was then reclassified, using a method described by Pérez (2002), so that values between 0 - 22.5°, 67.5 - 112.5°, 157.5 - 202.5°, 247.5 - 292.5° and 337.5 - 360° were given the value of the length of one side of a pixel and values between 22.5 - 67.5°, 112.5 - 157.5°, 202.5 - 247.5° and 292.5 - 337.5° were given the value of the diagonal distance of the pixel. The resulting reclassified layer represents flow direction length and was used to calculate slope length (λ) in Equation 7.6, which was subsequently used in equation 7.4 and 7.5 to calculate the LS factor.

$$Slope\ length\ (\lambda) = \frac{Flow\ direction\ length}{cos\theta} \qquad \text{[Equation 7.6]}$$

Where: θ is the slope angle.

7.2.5. Rainfall index

The rainfall index represents the potential for rainfall to drive runoff and subsequent NPSP. Rainfall can detach soil particles and initiate the transport of the detached particles and pollutants in runoff (Blanco and Lal, 2008); therefore, higher levels of rainfall will result in increased runoff. The seasonal distribution of rainfall across each of the study areas was sourced from the WorldClim dataset (Hijmans *et al.*, 2005).

7.2.6 Population index

The population index used data obtained from the LandScan 2008 database (Oak Ridge National Laboratory, 2008) and represents population pressure on the environment and the subsequent potential for nutrient input into the environment. In Asia, water resources such as the rivers, lakes and coastal areas are important not only as sources of food but also for irrigation, transport, waste disposal and washing (McGregor, 2008). Less than 50% of all domestic wastewater in Asia is treated before it re-enters the environment and in major metropolitan areas over 95% of waste water is discharged without any prior treatment directly into rivers (Zhao *et al*., 2006). Therefore as areas with higher population are likely to have a significant impact on NPSP it is important to account for the potential population pressure and include this index within the overall model.

7.2.7 Normalisation and final model development

As the individual attributes were measured on different scales the data had to be normalized to obtain a comparable monotonic linear scale ranging between 0 and 1 (Voogd, 1983; Witten *et al.*, 2011). Across large areas such as those included in this study there can be a great variation in variables, therefore a log transformation was performed on each index to account for such variation and reduce the influence of extreme outliers prior to normalisation and overall inclusion in the model. Equation 7.7 from Voogd (1983) shows the calculation involved in the normalization process; where R_i is the raw score. This equation is also the basis for the Fuzzy module within IDRISI which can also be used to normalize attributes (Eastman, 2012). Models were normalized twice so that one output represented the risk within one area during one season and the other model represented the risk during one season across all study areas. Weightings were applied to each index after normalization and before combination in the final model development (Equation 7.8). These weightings were determined after discussions with experts on hydrology and the environment, in addition to literature reviews and the consultation of previous studies by Munafo *et al*. (2005) and Zhang and Huang (2011).

$$standardized\ score = \frac{R_i - minR_i}{\max R_i - min\ R_i}$$ [Equation 7.7]

$$Final\ model = 3.5N + 2T + 2Ru + 1.5Ra + P$$ [Equation 7.8]

Where: N =Nutrient generation index

T = Transport index

Ru = Runoff index

Ra = Rainfall index

P = Population index

7.2.8. Assessment of model results

Water quality data for the study area in Vietnam was obtained from the Mekong River Commission (MRC, 2013). There were 31 sample stations located within the study area which had measurements between 2005 and 2010. Values for total nitrogen (mgL) and total phosphorus (mgL) were extracted from the database and average values were calculated for the dry season and rainy season using this data. The data was then normalized on a 0 to 1 scale to make it easier to interpret in relation to the model. As no detailed information was available on potential additional point source inputs of nutrients it was decided that it would not be representative to use this data in statistical tests. The vector layer representing the measured levels of total nitrogen and total phosphorus were superimposed on top of the individual models for Vietnam to assess the model results as a step towards model validation.

7.3. Results

7.3.1. Individual models

These models have been normalized on an individual basis and therefore should not be compared to each other. The purpose of the models is to indicate the areas of risk of NPSP (either nitrogen or phosphorus) *within* the selected study area and season which allows users to identify areas which may need further investigation. Although the models cannot be directly compared to one another they can be evaluated within a study area to identify patterns in the spatial distribution of risk of NPSP. The results also show the locations of the SEAT farms and hence possible implications for aquaculture in the catchment.

The results from the individual models for Bangladesh are shown in Fig. 7.2. Across all four models there is a general trend where the eastern side of the study area has a higher risk of NPSP (Fig. 7.2). During the dry season the rainfall is heavier in the middle and east of the study area, whereas during the rainy season, rainfall is higher in the south east of the study area. The prawn farms in the east of the study area are at higher risk from nitrogen NPSP (Fig. 7.2A) than the shrimp farms in the south west (Figs 7.2B and 7.2C). However, during the rainy season the prawn farms (Fig. 7.2D) have a lower level of risk compared to the shrimp farms in the south of the study area (Fig. 7.2F). Likewise, the prawn farms are also at higher risk from phosphorus NPSP in the dry season than the shrimp farms (Figs. 7.2G, 7.2H, 7.2I), whilst in the rainy season the shrimp farms in the south of the study area have the highest risk of phosphorus NPSP (Figs 7.2J, 7.2K, 7.2L). As with all of the other study areas (for all seasons and nutrients), the areas with the lowest risk of NPSP are the areas covered by mangroves which are generally considered to be nutrient sinks and are usually uninhabited. In Bangladesh this is the south of the study area which is covered by part of the Sundarbans mangrove forest.

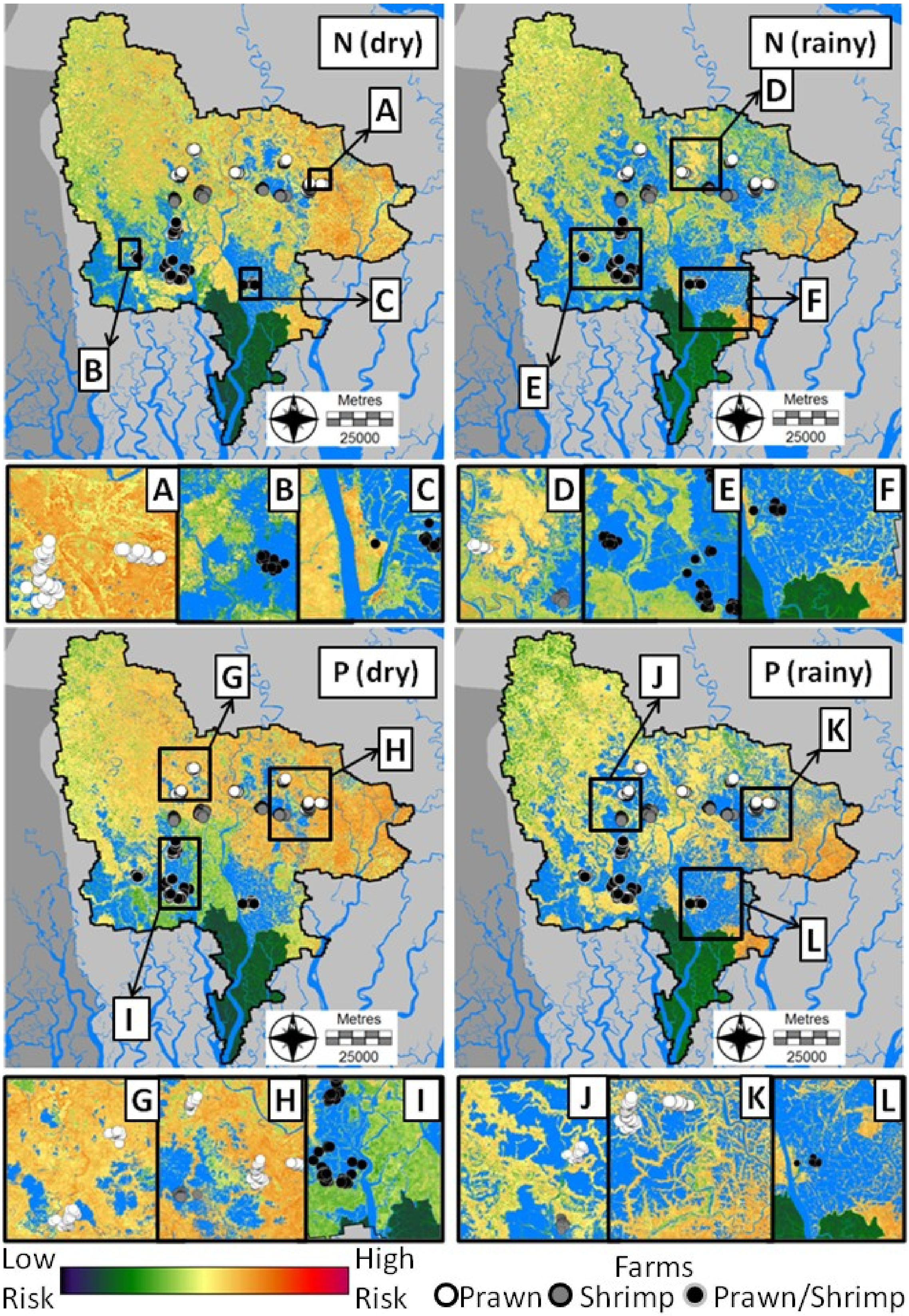


Figure 7.2: The risk of NPSP across the study area in Bangladesh

The results for the study area in China are shown in Fig. 7.3. The risk of NPSP of nitrogen and phosphorus is generally higher in lower lying areas. In the dry season, inland areas, such as those occupied by tilapia farms, are at higher risk from nitrogen and phosphorus NPSP than the coastal shrimp farms, suggesting that these inland areas would benefit from further monitoring and investigation during the dry season. These areas also have high population levels which can also contribute to increased NPSP. During the rainy season, there is a moderate to high risk of NPSP across many of the areas used for aquaculture (Figs. 7.3D, 7.3E, 7.3F, 7.3J, 7.3K, 7.3L) which is due to the seasonal distribution of rainfall and the changing patterns of land use. Generally, areas in the east that are used for shrimp culture tend to have lower risks of NPSP than those in the west.

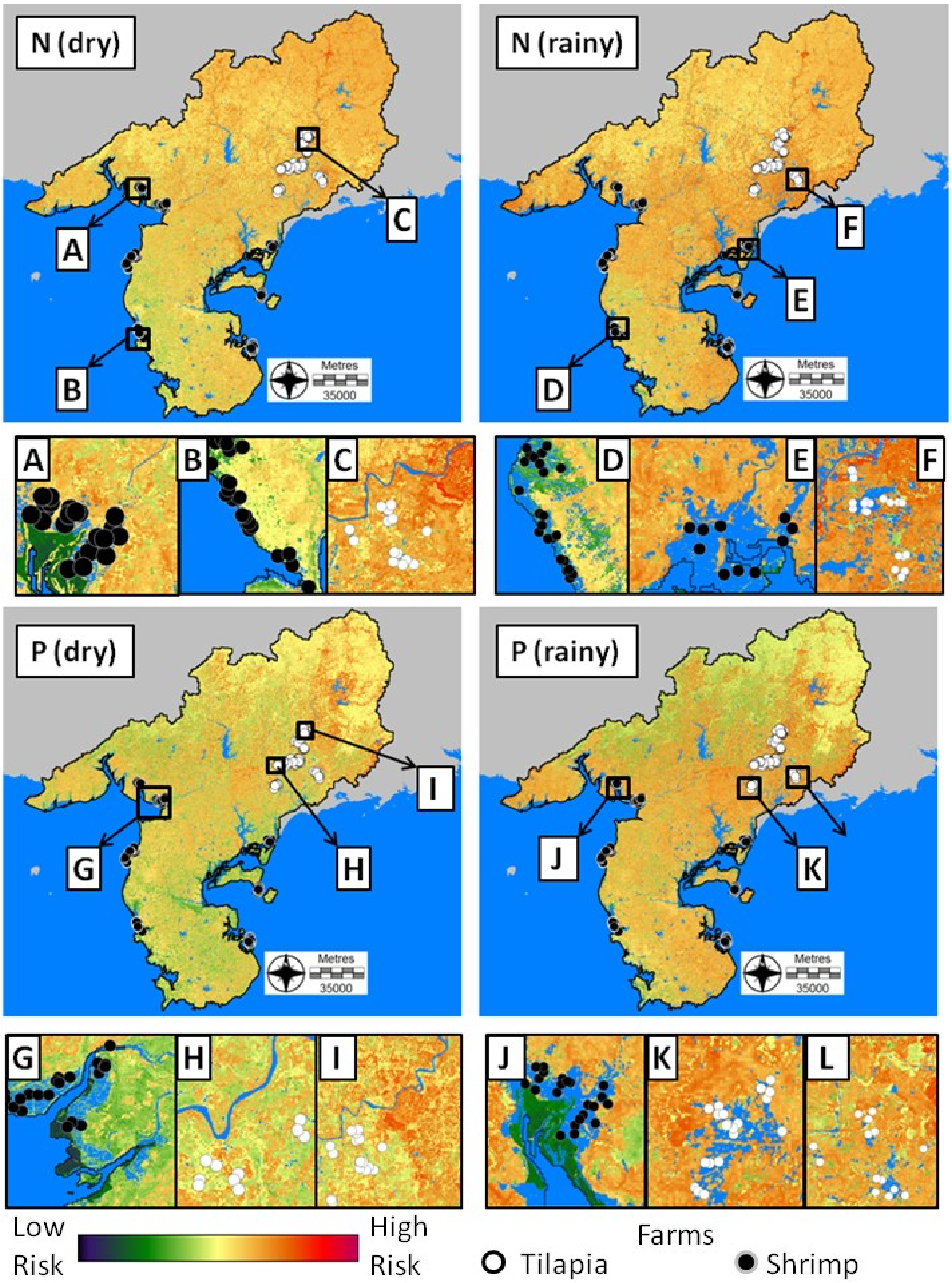


Figure 7.3: The risk of NPSP across the study area in China

Fig 7.4 shows the results from the NPSP models for the study area in Thailand. In both seasons there is a moderate to high risk of nitrogen NPSP across the study area, particularly in the east. Areas along the west and central coast of the Gulf of Thailand, where tilapia culture occurs (Fig. 7.4A and 7.4B), have a lower risk of nitrogen NPSP than the shrimp areas of the south eastern coast (Fig. 7.4C). This is similar in the rainy season and regulators may need to prioritise monitoring schemes in the south east. Similarly, the south eastern coast of the study area has the highest risk of NPSP for phosphorus in both the dry and rainy seasons (Figs. 7.4I and 7.4K). This area has higher levels of rainfall and there is greater runoff due to the soil drainage properties which contribute to increased potential for NPSP. Some inland areas in the eastern section also have the higher risk of phosphorus NSPSP in the dry season (Fig. 7.4H) compared to central and north western areas (Fig 7.4G). Areas in the north west have soils with high water retention parameters and therefore there is a lower risk of runoff, which, combined with lower rainfall levels, results in a lower risk of NPSP.

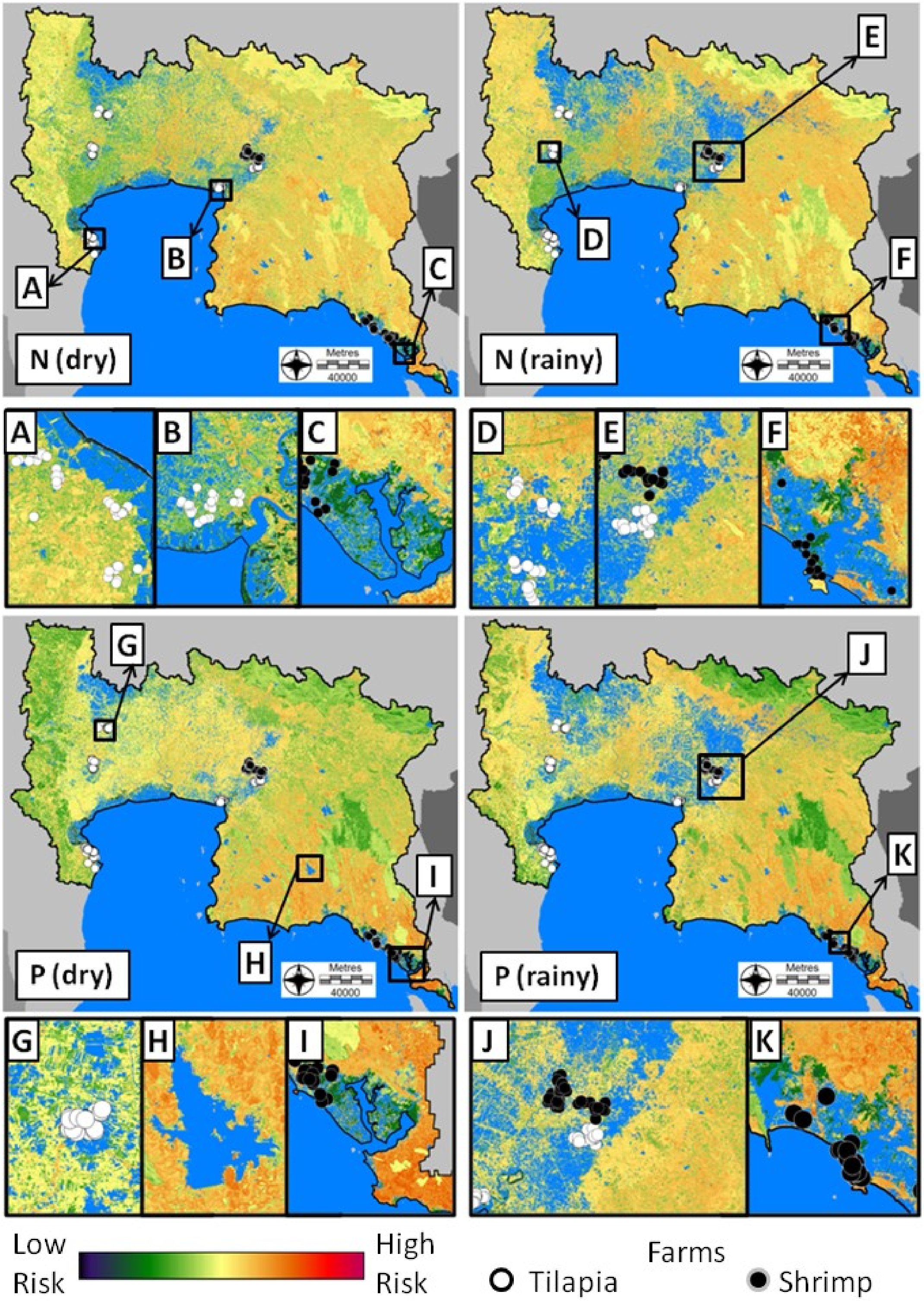


Figure 7.4: The risk of NPSP across the study area in Thailand

In the dry season in Vietnam some of the areas with the highest risks for nitrogen and phosphorus NPSP are inland where many pangasisus farms are sited (Figs. 7.5A and 7.5G), whilst areas of lower risk are located nearer the mouth of the Mekong (7.5B and 7.5H). There is extensive agricultural land throughout the region which contributes to the risk of NPSP; however, areas in the east, such as those shown in Figs. 7.5B and 7.5H have lower levels of rainfall than those in the west (Figs 7.5A and 7.5G) which accounts for the seasonal difference. Downstream areas of the Mekong could also be at risk from higher nutrient loads which are washed down the river from further upstream; although, as the Mekong is a large river, dilution effects and the natural assimilative capacity of the river (Yoo and Boyd, 1999) may prevent nutrient build up. Shrimp farms in the east of the study area have a higher risk of nitrogen NPSP in the dry season (Fig. 7.5C) than those in the south, whilst there is a higher level of risk of phosphorus for farms in the south (Fig. 7.5I). Therefore monitoring should take place at eastern and southern sites to ensure there is no excess nutrient build up. In the rainy season there is a lower risk of nitrogen NPSP at the pangasius farms compared to the coastal shrimp farms (Figs. 7.5D, 7.5E, 7.5F). Likewise, the risk of phosphorus NPSP is higher in the south of the study area near the shrimp farms than the phosphorus farms (Figs. 7.5J, 7.5K, 7.5L). During the rainy season, rainfall is higher in the south of the study area where shrimp farming is practiced, compared to the inland areas where pangasius is cultured which accounts for increased risk of NPSP of both nitrogen and phosphorus in these area.

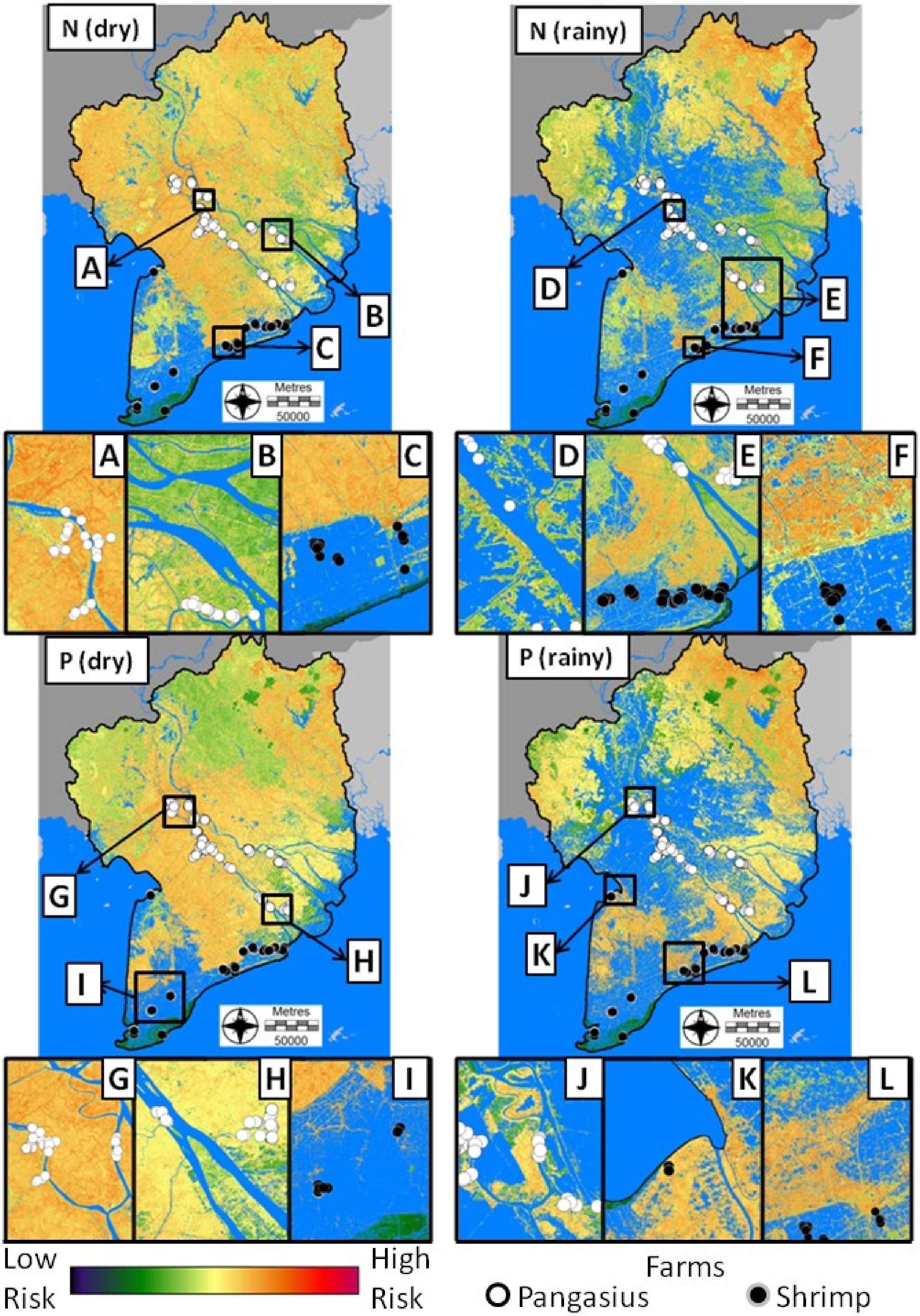


Figure 7.5: The risk of NPSP across the study area in Vietnam

7.3.2. Assessment of model results

The comparison between the models for nitrogen and the MRC measurements of nitrogen for the Vietnamese study area are shown in Figure 7.6. During the dry season, the results show that moderately high levels of nitrogen were found in the west of the study area where the model indicated there would be moderate to high risk of nitrogen NPSP (Fig. 7.6A). Furthermore, Fig. 7.6B shows areas which were predicted to have both low and moderate risks of NPSP and the measured values are similar in this area. In the rainy season many of the measured points occur in areas covered by water and consequently it is difficult to compare them to the model results. However, Fig. 7.6C shows the highest values were found in the south of the study area in an area the model predicted would have a moderately high risk of NPSP. Additionally, lower values were found in Fig. 7.6D where the model predicted a lower risk of NPSP. It must be noted that, particularly during the dry season in the main Mekong River, there are some areas where the model predicted a moderately high level of NPSP and the measured values indicate lower measurements. This could be due to the dilution action within the river which could suggest that the Mekong can tolerate higher levels of nutrient input than smaller rivers/bodies of water therefore measured levels of nitrogen in the Mekong are lower.

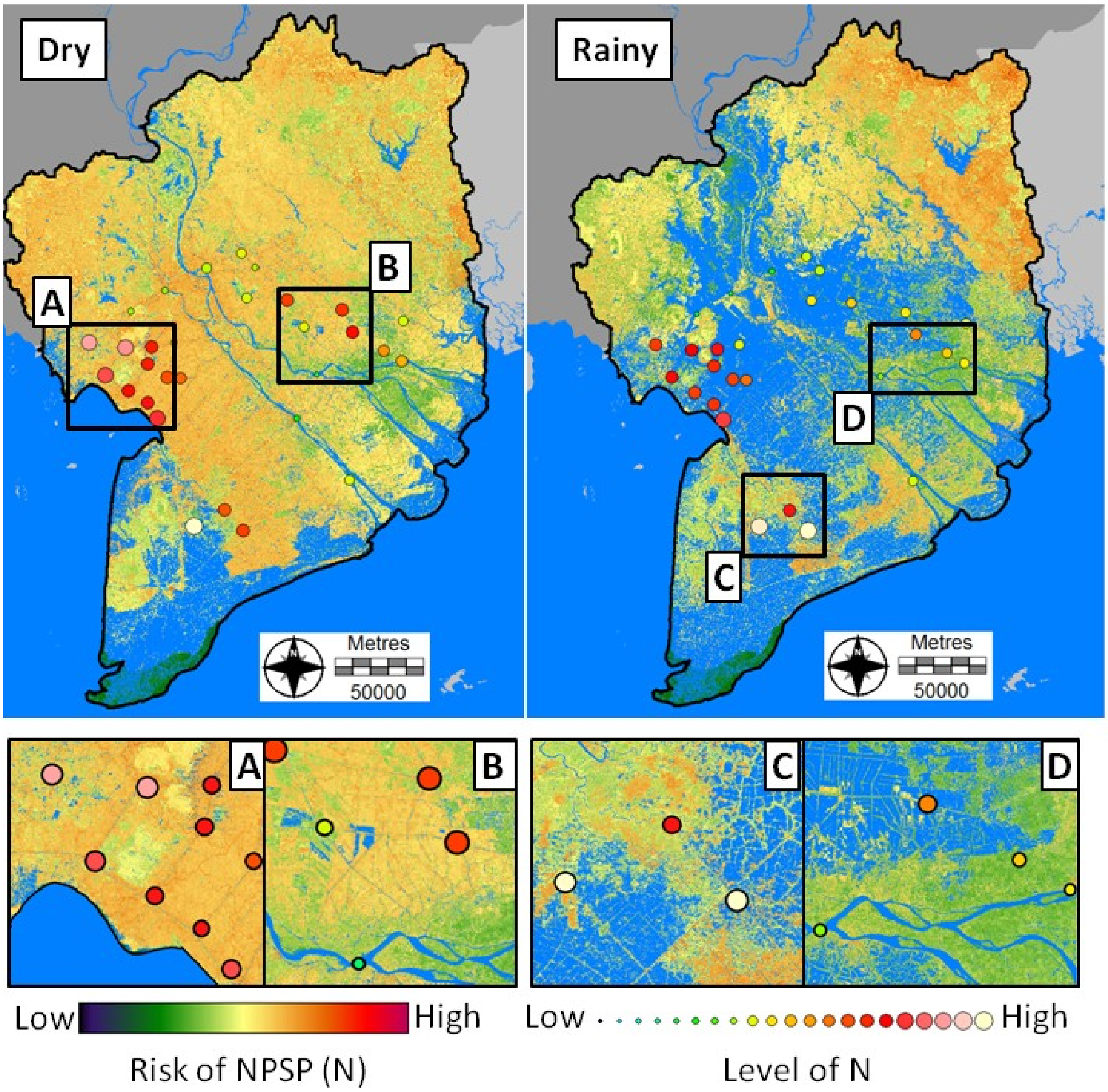


Figure 7.6: Assessment of the nitrogen NPSP model results using measurements of nitrogen (N) from MRC (2012)

The comparison between the models for nitrogen and the MRC measurements of phosphorus for the Vietnamese study area are shown in Figure 7.7. In the dry season, higher levels of phosphorus were found in areas where the model predicted higher risks of NPSP (Fig. 7.7A and 7.7B). While, in the rainy season, lower levels of phosphorus were found in the west of the study area (Fig 7.7C) where the model indicated risks of NPSP would be lower. Additionally, higher levels of NPSP were also found in the west and south of the study area as predicted by the model. The highest value of phosphorus was found near the mouth of the Mekong River in the west of the study area (Fig. 7.7D), this area has a moderately high risk of NPSP and there could also be higher levels of phosphorus due to increased river flows transporting more nutrients.

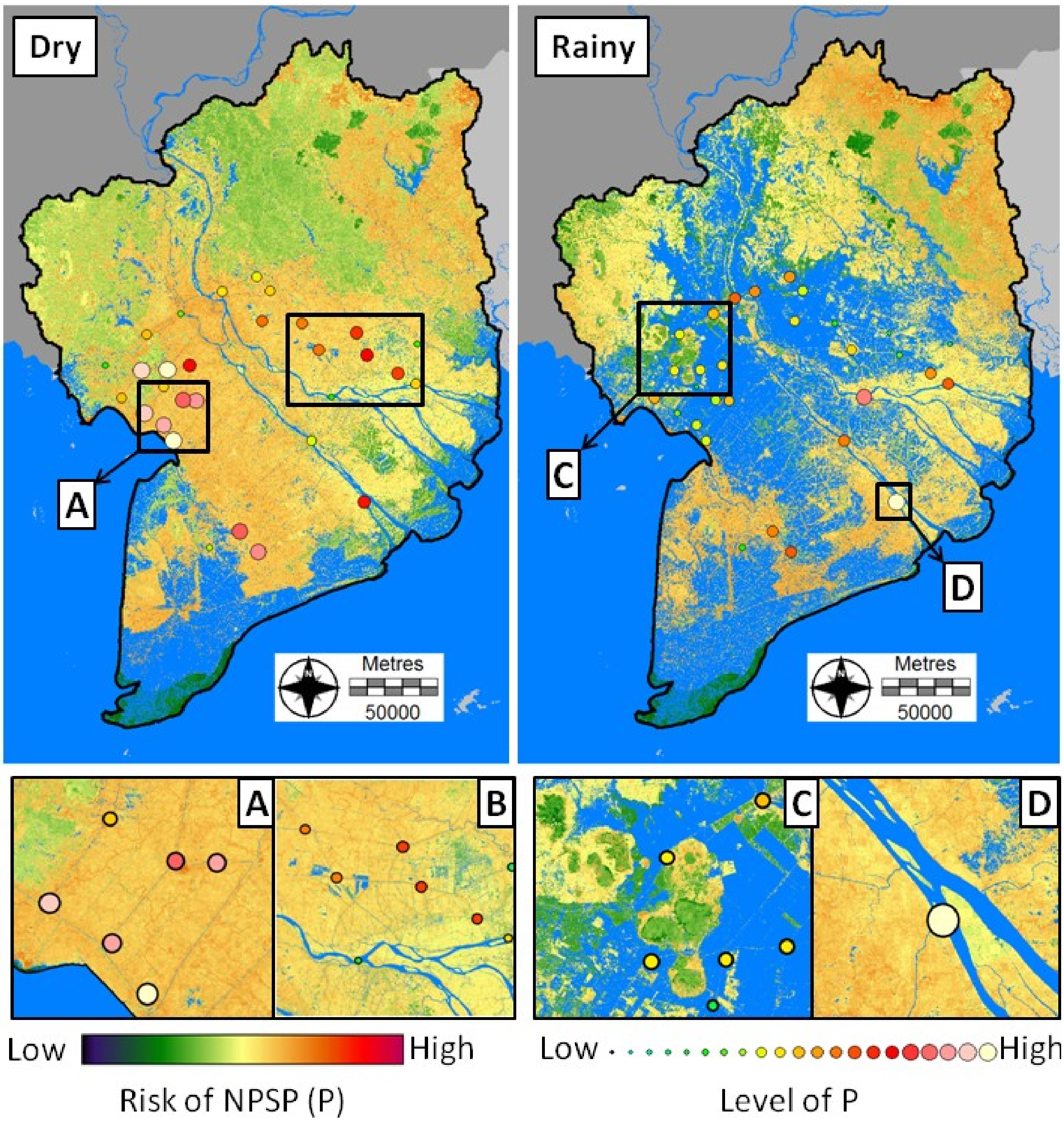


Figure 7.7: Assessment of the phosphorus NPSP model results using measurements of phosphorus (P) from MRC (2012)

The results (Figs. 7.6 and 7.7) show similarities between the model outputs and the measured levels of nitrogen and phosphorus. However as the results are qualitative rather than quantitative it is difficult to produce an actual level of accuracy. The model assessment is a positive step to model validation and consequently the model can be considered partly validated with further detailed assessment required to ensure the model is representative.

7.3.3. Comparison across multiple areas

The models were re-run to allow a comparison between different areas after normalisation using data from all of the study areas so that models from the four scenarios (nitrogen dry season, nitrogen rainy season, phosphorus dry season and phosphorus rainy season) can be directly compared to other models within the same category. The results in Fig. 7.8 show that all study areas experience varying levels of risk within their boundary; however, there is no single study area that has significantly more or less risk than the others. This indicates that NPSP is an issue which should be considered in every area. The results in Fig. 7.8 also follow similar distribution patterns as the individual models (Figs. 7.2, 7.3, 7.4, 7.5). Whilst it is useful for decision makers to use the results presented in Fig. 7.8 to assess if different regions have higher levels of risk than others, the individual models would be more useful to establish monitoring programs as they are representative of the conditions within an actual catchment.

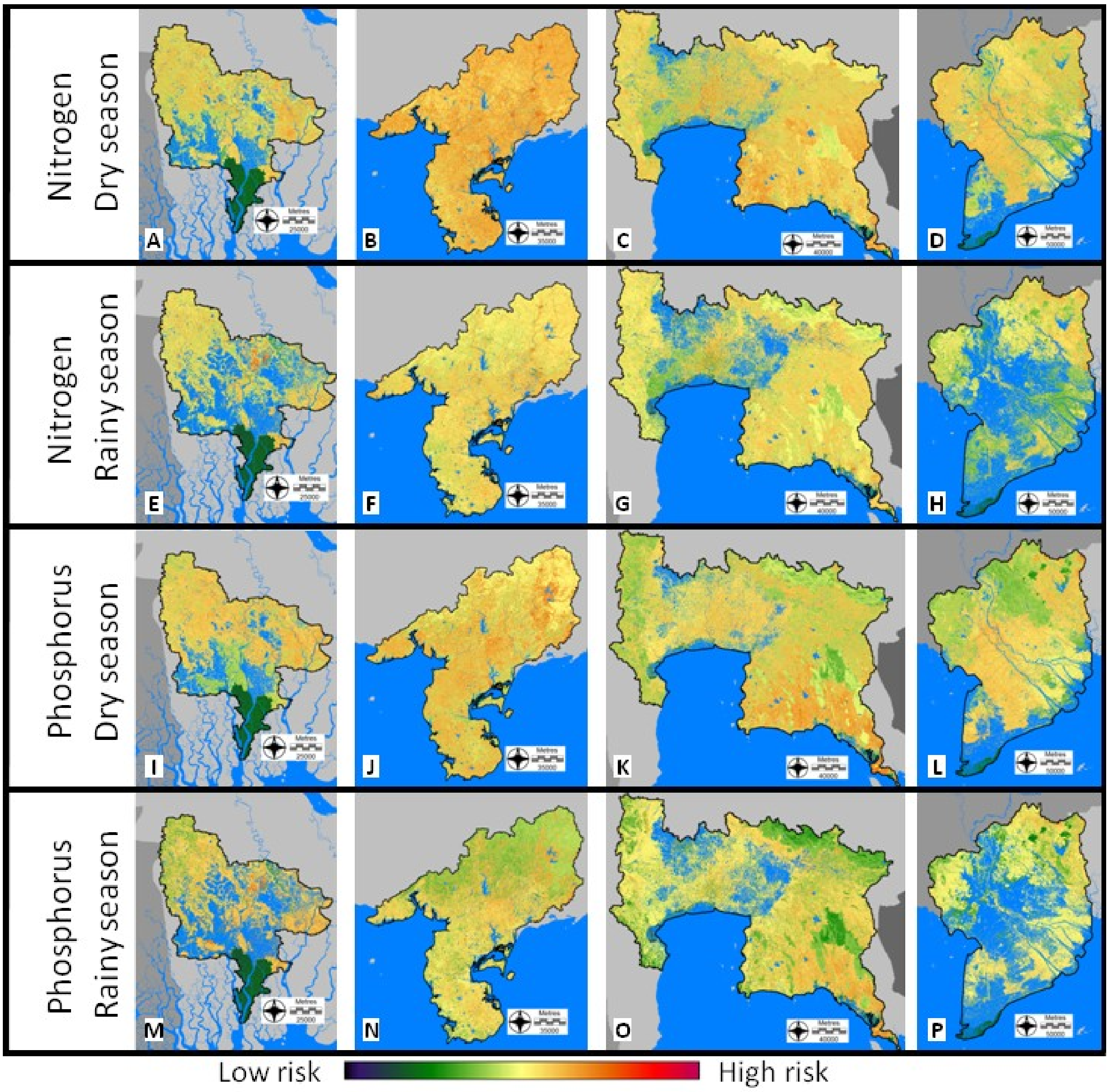


Figure 7.8: The risk of non-point source pollution across multiple study areas

Note: Bangladesh, China, Thailand and Vietnam for nitrogen in the dry season (A, B, C, D), nitrogen in the rainy season (E, F, G, H), phosphorus in the dry season (I, J, K, L) and phosphorus in the rainy season (M, N, O, P).

7.4. Discussion

In order to maintain a healthy, functioning ecosystem which can sustain not only itself but also local communities, regional economies and resource-based industries such as aquaculture, it is essential to ensure that all components of the ecosystem are sustainably managed (Frankic and Hershner, 2003). Although the ecosystem approach to aquaculture promotes sustainable development and integrated management within the wider ecosystem (Soto *et al*., 2008), many environmental monitoring programmes only assess the impacts of individual farms in isolation from other farms or sources of pollution that are located in the same area (Fernandes *et al.,* 2001). The impacts from aquaculture and other industries in the same catchment should also be assessed to understand all of the interacting processes occurring within the area. However, whilst point sources can be easily identified, measured and monitored it is difficult to assess NPSP as it is generated from diffuse sources and is widespread across large areas (Frid and Dobson, 2002; Cech, 2010). Models can be used to simulate the environment and predict the movement and fate of pollutants across different temporal and spatial scales (Blanco and Lal, 2008).

Developing NPSP models is a complicated task and there are many different approaches to modelling erosion, transport and nutrient generation. Merrit *et al*. (2003) suggested that complex and dynamic models may be no more superior than simple empirical based models due to insufficient and heterogeneous data. On the other hand, often empirical models do not account for spatial variability, are based on deriving responses from data observations and use unrepresentative assumptions about the physics of the area (Drewry *et al*., 2006). As with any modelling process it is essential to acknowledge the limitations of models, which are not alternatives to observations, but, powerful tools in providing further understanding and developing and testing theory (Mulligan and Wainwright, 2004). This is highlighted in this study where the spatial models have not been designed to replace more complex and site specific studies; their intended use is across large catchments to identify areas in need of further investigation or assistance. As discussed by Moltz *et al*. (2011), such large catchments are difficult to model using data-intensive, highly complicated, process-based models and a coarser level of data and modelling processes can be employed to provide an initial identification of select areas within the larger region which would be at risk from high nutrient loading and therefore require further attention. This simplifies the process and makes monitoring programmes more efficient. Identifying "hotspots" enables attention, time and resources to be focussed on the areas most in need (Moltz *et al*., 2011).

The modelling approach in this study uses five indices to assess the potential risk of NPSP (nitrogen and phosphorus) in the dry and rainy seasons (Figure 7.1). The results of the individual models (Figs. 7.2, 7.3, 7.4, 7.5) can be used to identify the risk of NPSP within individual study areas. These can then be used to prioritise areas for monitoring and/or target areas which may need to employ mitigation procedures. An example of this is the study area in Thailand (Fig. 7.4) where the risk of NPSP is highest in the south eastern coastal area compared to the western and central coastline. The area in the south east has a significant shrimp industry and production could be significantly impacted due to poor water quality as a result of excess nutrient loading. Furthermore, the results also show that, particularly in the dry season, inland areas of the Mekong delta have a higher risk of NPSP than coastal areas (Fig. 7.5). This is an area with extensive aquaculture and agriculture industries and production in both sectors could be negatively impacted due to NPSP if it is not closely monitored. This could even have implications for local and regional food security as production could be impaired or even spoiled due to detrimental water quality.

The results are also useful as they allow users to focus on specific areas which have the potential to be at risk from NPSP rather than waiting until an event has occurred. A seasonal approach generates further information as NPSP is associated with seasonal land management practices and rainfall (Carpenter *et al*., 1998). This is also useful for aquaculture as regulators can identify the different risks across a geographical area for particular seasons where aquatic systems are at higher risk of nutrient loading and target key areas to measure, monitor and even establish mitigation procedures. This is particularly important for an area such as China where low temperatures restrict year round culture and consequently farmers have to ensure that their farms are not at risk when they are in operation. The results in Fig. 7.3 suggest that tilapia farms are in a high risk area compared to the rest of the study area for both nitrogen and phosphorus, thus, it may be necessary to establish monitoring schemes in this area.

Although primarily aimed at regulators and policy makers evaluating the sustainability and suitability of large catchments for aquaculture, the models could also be used at a local scale by farmers to identify particular sites which may have greater risks of NPSP than others. Potential mitigation methods can be employed, where required, to prevent NPSP from reaching the aquatic system or to treat the water entering or leaving the farm. The development of barrier methods such as embankments can be used to minimise runoff entering a pond and water can be screened at the inflow/outflow to remove suspended solids and sediments (Yoo and Boyd, 1994). On the other hand, if there are excess nutrients within the pond then there may be the opportunity for polyculture with other species or the potential to develop an integrated system such as IMTA. The models could be used to identify areas (coastal or inland) where there would be a build-up of nutrients and the potential to use extractive organisms (such as molluscs and seaweeds) to reduce the level of nutrient and provide a commercial crop (Neori *et al*., 2004). The present models only focus on nitrogen and phosphorus within NPSP and do not evaluate other potential pollutants which are included in runoff such as chemicals that could contaminate the areas and have negative impacts for farming systems. Consequently, the models are indicative and designed to identify potential areas; based upon this further site specific field tests can be made before a definitive site selection decision is made.

There is an additional level of output where the models were run with data from all study areas included in their normalization so that the results could be compared between one another (Fig. 7.8). This allows the user to assess the risk of NPSP for each of the four model types (nitrogen dry season, nitrogen rainy season, phosphorus dry season and phosphorus rainy season) across the four study areas. The results show that all study areas have varying levels of risk within their boundaries. However, in this case, no single study area is better or worse than the others (Fig. 7.8). The potential application of this output is that regulators and decision makers can assess one study area relative to another and evaluate risks across multiple areas. This has importance for processors looking to source products from different regions as they can assess the risk of nutrient enrichment, resulting water quality issues and potential implications for supply. Furthermore, the success and sustainability of aquaculture is dependent on the market demand for products and in recent years there has been increasing consumer awareness with regards to the environmental issues associated with the industry (Young *et al*., 1999). Using models such as those presented in this study to assess the potential risk across large areas from NPSP allows decision makers to consider implications to the system and the wider environment beyond a local scale.

As discussed by Munafo *et al.* (2005) it is difficult to validate models that are based on an index. The models presented in this study do not aim to quantify the amount of nitrogen or phosphorus entering the environment; rather they estimate the risk across large areas given the factors (indices) which generally contribute to NPSP. Additionally, the models do not account for existing mitigation methods or additional point sources and any attempt at validation would have to account for this which would be very complicated. Furthermore, as the models are index based, they only show which areas are more at risk than others and do not have a baseline level, consequently the area that is has the lowest risk could still have high levels of nitrogen and phosphorus NPSP. This study assessed the model results using a visual comparison between the model outputs and measured levels of nitrogen and phosphorus (MRC, 2012) for the study area in Vietnam. The results show there are similarities between some of the measured values and the model outputs which is a positive step towards validating the model. Further validation could involve taking random measurements across a small subcatchment, preferably one which includes no point sources, and comparing the measured values to the model results.

In order to assess the suitability of a catchment for aquaculture it is important to understand potential risks from issues such as NPSP which can have a significant impact on farm production and the wider environment. Often regulators and decision makers have insufficient information on the distribution of NPSP as many monitoring systems are primarily designed for point source pollution (Callan and Thomas, 2010). Consequently, many NPSP issues are only known about after they have occurred. The model developed in this study is designed to show the level of risk from NPSP within a catchment; enabling effective monitoring programs and/or mitigation procedures to be established. It is a simplified model which can be applied to large areas without the need for complex data sets; saving time and money, allowing priority areas to be targeted easily and efficiently. It would be difficult to assess such large areas using complex hydrological models and the required data is often either not easily available or doesn't exist for particular areas. The model can be used in almost any study area, at multiple scales, to provide effective decision support and help assess the suitability of an area for aquaculture.

CHAPTER 8

DISCUSSION

8.1. Introduction

As population continues to grow and demands for land, water and resources rise there is a need to ensure that increased food production occurs in an efficient and fair manner to meet food security requirements, whilst reducing conflict amongst competing activities and maintaining biodiversity (Ericksen *et al*., 2009; Godfray *et al*., 2010; Foley *et al*., 2011; Rice and Garcia, 2011; Tscharntke *et al*., 2012; McClanahan *et al*., 2013). Capture fisheries are unlikely to increase and therefore aquaculture will continue to expand to try and meet the demand for seafood products (Smith *et al*., 2010). Currently, aquaculture is the fastest growing food production sector in the world and is a valuable livelihood for many people (Subasinghe *et al*., 2009; De Silva and Davy, 2010). However, there are negative impacts associated with the sector, including habitat destruction, effluent discharge and potential loss of biodiversity (Naylor *et al*., 2000; Diana, 2009; De Silva, 2012). Consequently it is essential that the industry is sustainably managed and development occurs in suitable areas.

Aquaculture is highly dependent on the use of land and water, both for the area occupied by the system and the support and service functions needed to maintain production such as the provision of feed, waste treatment, access and storage (Beveridge *et al*., 1997; Boyd *et al*., 2007). The availability of suitable areas for aquaculture is a critical factor for food security as it influences both current and future production. Verburg *et al*. (2013) also note that the use of land (and water) is fundamental to food security and should be assessed at multiple scales; local, regional and global. This is in agreement with the EAA which recommends the application of the EAA principles at three similar scales; farm, watershed/aquaculture zone and global (Soto *et al*., 2008; Costa-Pierce, 2010). The EAA is a strategic approach to aquaculture development and management which integrates aquaculture within the wider ecosystem and promotes the sustainability of interlinked social-ecological systems and is discussed in detail by Soto *et al*. (2008). Whilst it is important to acknowledge the area occupied by a facility it is also essential to consider potential interactions between surrounding land use and the wider environment.

Regulators, policy makers and other stakeholders have many concerns and opinions over how areas should be managed. It is important to obtain a balance between positive economic activities, minimising conflict and protecting valuable natural resources and environmental conditions. As a result, complex and difficult decisions need to be made which can be prejudiced by personal opinion (Maier *et al*., 2008). Decision support helps to avoid biases in judgement allowing a more objective strategy to be employed which addresses multiple conflicting interests and beliefs (Myšiak *et al*., 2008). Whilst decision support tools provide extra information to solve a problem or answer a question they can also be used to qualify an action and explain why a particular decision was made. Models are an abstraction from reality which allow complex issues to be viewed simply or differently depending on the requirements of the user (Mulligan and Wainwright, 2005) and are valuable as a form of decision support. This project aimed to show how spatial models and decision support tools could be used to help decision makers evaluate the suitability of large catchments for sustainable aquaculture.

There are many spatial models and tools available to assess the suitability of areas for aquaculture (Aguilar-Manjarrez *et al*., 2008; Ross *et al*., 2009; Ross *et al*., 2013), however, often their data requirements and/or structure makes applicability to multiple catchments impossible. This is further complicated when assessing several areas which are large in size as the available data is often inadequate or does not exist and there is insufficient time, money and resources to do extensive data collection of multiple parameters. This study aimed to develop models which could be applied to each of the four study areas and other areas outwith the scope of the project. Therefore global datasets and sources were used to ensure future relevance of the models (Table 3.3).

The models can help decision makers evaluate the suitability of large catchments for new and existing aquaculture. The first stage was the development of seasonal land use models which were used to identify existing conditions across the catchment. The next step was to evaluate the suitability using optimal values for culture, whilst the third stage analysed trends amongst existing farms and key variables. Finally, the fourth step assessed the risk of non-point source pollution (NPSP) across each catchment.

8.2. Seasonal land use

An inventory of existing natural resources is the first step for a successful management plan (Frankic and Hershner, 2003). Aquaculture is highly dependent on both land and water for the space occupied by the farm and the area required for support and service functions (Beveridge *et al*., 1997; Boyd *et al*., 2007). Decision makers need to know what the land is used for and how aquaculture could impact or be impacted by the wider environment. However land cover and use is constantly changing both in the short and long term, therefore maps may become out of date after a few years. Furthermore, there are regular variations in land use between seasons (Palang *et al*., 2007) which decision makers should consider, as seasonal changes can have implications for site suitability and other wider environmental issues such as non-point source pollution.

Many important features are only discernible at high resolution; however, high resolution satellite imagery is expensive and would be too costly to apply over large catchments, particularly as the work will need to be updated frequently with newer images. Therefore, the seasonal land use models (Fig. 4.5, 4.7, 4.8 and 4.9) were developed from Landsat ETM+ satellite imagery. Landsat data is freely available for almost every area in the world, is updated frequently and, as Coe (2010) explains, it can be useful for large, regional areas. Although there are global land use/cover datasets available they often have poor accuracy, are low resolution and are only available for one time period. Furthermore, land use can change significantly over a number of years; thus, it is better to use an approach, such as the one shown in this study, to update and refine maps and models periodically to ensure the information is representative for any application.

One of the key principles of the EAA is that all stakeholders should be treated equally (Soto *et al.*, 2008). Thus, effort should be made to identify the surrounding land use and assess potential issues which may impact activities and/or livelihoods. The advantage of modelling land use across a large catchment is that it provides decision makers with an overview of potential issues within an area which would not be apparent at a local or farm specific scale. Naturally occurring seasonal events such as flooding and the changing pattern of the agricultural cycle can also be evaluated, both of which can have significant implications for aquaculture and the availability of suitable areas for sustainable development.

8.3 Site suitability models

Many of the negative environmental impacts associated with aquaculture are due to poor planning and inappropriate site selection (Kumar and Cripps, 2012). Decision makers need to know where the most suitable areas are for culture as this allows assessment on the availability of areas for food production and estimates of supply. However, across large areas it can be costly to perform detailed field assessments of multiple locations. GIS can be used to develop spatial models which indicate the availability and suitability of a catchment allowing the selection of the most suitable areas for more specific evaluation.

A multi-layered model framework (Fig. 5.1) allows decision makers to view results at multiple stages of the model. Furthermore, the framework was designed so that it can be used for multiple study areas and species. There are four major submodels (Pond, Species, System and Access) which are added together, along with constraints, to produce the overall site suitability models (Figs.5.7, 5.8, 5.9 and 5.10). To illustrate how the model could be used, areas classified as highly suitable were then extracted and typical production values were applied (Figs. 5.11, 5.12, 5.13 and 5.14 and Tables 5.10, 5.11, 5.12 and 5.13). This highlights how decision makers can use the model to estimate the availability of an area for increased food production.

Furthermore, often users only see the end result of a model and this may not be sufficiently sensitive to make robust decisions. Evaluation of the individual submodels enables identification of potential issues for existing farms such as accessibility and water availability. The suitability of the location of the SEAT farms was also assessed using the submodels to identify potential issues associated with farms which could affect the sustainability of that farm. This allows decision makers to identify the key issues which could affect production and supply from multiple farms such as access to transport networks. The advantage of this approach is that it is a quick evaluation to identify areas which may need further investigation or assistance and saves time and money which would be spent surveying every farm individually.

As discussed earlier, there are difficulties in applying the same model to multiple study areas and species. Often the required data is not available for the study area which prevents model application in that region. This study has shown how site suitability models can be developed which can be applied to almost any study area, although some important variables were omitted as there was not sufficient information for every study area. An example of this is salinity which can influence the ability to farm species (Boyd and Tucker, 1998). Unfortunately there are no availble global salinity data sets and the quality and availability of country specific data varies greatly making it impossible to incorporate into a generic model framework. However, due to the flexible and adaptable nature of the model, should this information become available in the future it can be easily included.

8.4. Analysis using Maxent

Although it is important to assess the suitability of catchments for aquaculture using site suitability models it is also useful to understand why aquaculture has been located in certain areas. This information enables decision makers to identify trends, opportunities and risks related to sustainable development and the EAA. Maxent was used to assess the suitability of large catchments for aquaculture using existing farm locations (Chapter 6). Although this software is used primarily for species distribution modelling (Phillips *et al*., 2006; Phillips and Dudik, 2008; Elith *et al*., 2011) some recent studies have used Maxent for novel purposes (Flory *et al*., 2012; Mischler, 2012; Convertino *et al*., 2013; Galletti *et al*., 2013; Peters *et al*., 2013; Santos *et al*., 2013). Furthermore, Baldwin (2009) discussed the potential of Maxent as a tool to assess the relationship between variables and location, whilst Evans *et al*. (2010) suggested that it may be useful for site suitability assessment within the agriculture industry. The work in this study has also shown that Maxent has promise as a tool for aquaculture development and management as it provides extra information for decision makers which may be difficult to obtain otherwise.

Whereas the site suitability models described earlier can be used to evaluate the suitability of large catchments using the optimal conditions for the species, the Maxent models can be used to model the suitability using existing farms as a template. This allows decision makers to identify successful and sustainable farms and to use the attributes of their locations as input data for the models to predict areas which would experience similar conditions for future development. However, as already discussed, and highlighted in Fig. 6.8, it is important that the input data is representative as many points that are too clustered, or few points that are too spread out, can impact the results of the predicted distributions. Maxent also allows the identification of variables of importance within the modelling process. However, it is important to understand that some of these variables are developed heuristically and may change if a different modelling approach is used. Additionally, the model is assessing the variables with regard to distribution rather than farm management so it is important that conclusions are not extrapolated beyond their original purpose. One of the most useful features of variable analysis is the production of response curves which show the probability of farms being located in areas with a particular value of variable (Fig. 6.4). This provides detailed analysis about the conditions experienced by farms and can be used to assess the suitability of existing and new areas for aquaculture.

Although Maxent is a relatively new technique, it does show promise for use in aquaculture. Further use of Maxent in more studies would be beneficial as it is an iterative process where the methodology should be adapted and refined with each application. The software is also regularly updated to help users and allow further applications (Elith *et al*., 2011) which could assist future work within aquaculture site suitability studies. Although time is needed to investigate and apply new tools, such as Maxent, decision makers can benefit from alternative approaches to problems and different methods of viewing complex situations.

8.5. Non-point source pollution models

Eutrophication is the main problem facing most surface waters throughout the world (Smith and Schlinder, 2009) and non-point source pollution (NPSP) is a major contributor to increased nutrient loading which can result in eutrophication (Carpenter *et al.*, 1998). Wastes generated by aquaculture can result in increased nutrient loads to the environment (Boyd, 2012; Tucker and Hargreaves, 2012) which could exacerbate environmental problems caused by NPSP. Farms can mitigate against nutrient enrichment through farm management practices (Tucker and Hargreaves, 2008) and the industry can develop methods which reduce nutrient build up such as feed composition (Cho and Bureau, 2002) and bioremediation (Chávez-Crooker and Obreque-Contreras, 2010).

When considering the suitability of an area for aquaculture it is important to assess the potential interaction between the farm and the wider environment. Decision makers need to identify areas where aquaculture systems could be at risk from the wider environment, threatening the success and sustainability of the farm, and/or areas where aquaculture can negatively impact the environment or other resource users. The NPSP models developed in this study (Figs. 7.2, 7.3, 7.4 and 7.5) can be used to assess the risk of seasonal NPSP for both nitrogen and phosphorus; enabling evaluation of the risk of NPSP within a catchment and highlighting areas which are at greater risk than others. From this, farmers can employ mitigation methods such as embankments, and other barrier methods, to minimise runoff entering a pond and, if necessary, they can screen the inflow water to remove suspended solids and sediments (Yoo and Boyd, 1994).

Many monitoring systems that are used to assess water quality were initially designed for point source pollution and as a result they are not representative of NPSP (Callan and Thomas, 2010). It would be expensive and time consuming to establish a monitoring system in every waterway throughout a catchment; however, the models presented in this study can be used to identify areas in need of assessment. Furthermore, although complex NPSP models are available (Knisel, 1980; Beasley and Huggins, 1985; Young *et al*., 1989; Bouraoui and Dillaha, 2000; Arnold *et al*., 2012) they often require detailed datasets and/or can be complicated to run (Munafò *et al*., 2005) making application across large catchments difficult. The models presented here are a simple approach which can be used across almost any study area and provide a visual estimate of risk which would be difficult to achieve outside of a spatial environment.

8.6. Using spatial models to evaluate the overall suitability of large catchments for aquaculture

All of the individual models are informative on their own; however, the information can also be combined to obtain a holistic view of the wide scale issues across a catchment. This allows a broader evaluation of suitability which is needed to ensure that appropriate decisions are made.

8.6.1. Bangladesh

The study area in Bangladesh was the smallest of the four areas evaluated; nevertheless, it still extends across 10148km^2. The culture of both prawn and shrimp is widespread throughout the area (Belton *et al*., 2011b), but as Bangladesh is one of the most densely populated areas in the world there is a need to increase food production, whilst minimising the impact on land and water resources which are already under pressure (Yu *et al*., 2010).

Prawn production mainly occurs in ghers and lasts for 9 months throughout the rainy season until the prawns are harvested in the dry season (Ahmed *et al*., 2008b). The seasonal suitability models show that much of the study area is suitable for prawn culture (Fig. 5.7); particularly in the rainy season where 5852 and 215km^2 of the area is considered suitable and highly suitable (Table 5.6). Most of this area is available in the east of the study area where many of the SEAT prawn farms are already located. However, if 5% of the highly suitable area was available for prawn culture then over 4500 ghers could be constructed (Table 5.10). This would allow the production of almost 450 tonnes of prawn, providing a source of food and income for local communities. However, the eastern side of the study area in Bangladesh also has a higher risk of NPSP than the rest of the catchment (Fig. 7.2), thus, regulators and farmers should monitor nutrient levels in the systems and surrounding environment.

The suitability models also show that the south western part of the study area would be suitable for the culture of shrimp in the dry season (Fig 5.9) which is the period commonly used for production in this region (Islam, 2004). Much of the area is already used for shrimp farms; nevertheless, 108 tonnes of shrimp could be produced if just 5% of the highly suitable area (175ha out of 3515ha or 1.75km^2 out of 35km^2) was available for culture. The results from the NPSP models show that, in the dry season, the south western part of the study area has lower risk of NPSP than the eastern areas where prawn culture occurs (Fig. 7.2).

Overall, 88.1% of the SEAT prawn farms are found to be in suitable or highly suitable areas during the rainy season (Table 5.8). The main issue of concern is the Access submodel (Fig. 5.5) which shows that 80% of farms are located in areas which are unsuitable. Many of the farms are located in rural areas which are further from transport networks and urban centres. However, as prawn farming plays a vital role in the economy of rural communities it is essential that they have the infrastructure required to support livelihoods (Ahmed *et al*., 2007). Identification of such issues through spatial modelling allows decision makers to target areas that are most in need of assistance and may otherwise have been ignored as they were not immediately apparent.

Table 5.9 shows that over 70% of shrimp farms are located in suitable or highly suitable areas during the dry season, whilst only 46.6% farms are considered suitable during the rainy season. The main difference in suitability is that during the rainy season some areas experience higher temperatures which could result in reduced growth and feeding (Wyban *et al.*, 1995; Briggs *et al.*, 2005), thus are unsuitable locations (Fig. 5.9). Although the results indicate there is more potential for prawn development than shrimp culture within the study area, the land where prawn culture could occur is also used for agriculture as shown in the land use models (Fig. 4.5). Therefore aquaculture development would have to consider the socio-economic and environmental impacts of changing the land use from agriculture to aquaculture. Some of this area may be also used for ghers which could be a solution to meet demands for both rice and prawns; reducing potential conflict. The south western part of the study area is susceptible to saltwater intrusion, especially in the dry season (Rahman *et al.*, 2000), which has decreased the suitability for agriculture and consequently shrimp farming occurs in much of this area. Therefore, although there are fewer highly suitable areas available, there are also limited alternative opportunities for food production and consequently development of shrimp ponds may be a valuable use of otherwise redundant land. However, uncontrolled expansion should be avoided and any development should occur in a sustainable manner in suitable or highly suitable locations.

Ultimately, although there are many areas available for both prawn and shrimp culture in Bangladesh, there are also other issues which may need to be addressed prior to new developments such as access to existing farms. Although there has been an improvement in transport networks within the area in the last 10 - 15 years (Paul and

Vogl, 2013) there is still room for improvement. This is not just an issue for the studied catchment as other areas of Bangladesh such as Mymensingh also have issues with poor road infrastructure and the resulting high transport costs affect production and profitability (Ahmed *et al*., 2007).

8.6.2. China

China is the largest aquaculture producer in the world (FAO, 2013) and the industry is important for local, regional and global food supplies. However, food security is an issue in China as, although the country contains 22% of the global population, it only contains 7% of the world's arable land (McBeath and McBeath, 2010). The study area is located within Guangdong, which is the most populous province in the country (Guo, 2013), largely due to the vast mineral, aquatic and plant resources and related industries and activities (Eng, 2005); including tilapia (Matala *et al*., 2013) and shrimp aquaculture (Sulit *et al*., 2005). Consequently, it is essential that the suitability of the area is evaluated to ensure that aquaculture is developing sustainably.

The site suitability models for both tilapia and shrimp (Figs. 5.7 and 5.9) show significant seasonal differences in the suitability of areas for aquaculture. This is due to the low temperatures within the dry season which are outwith the optimal ranges for culture of both tilapia and shrimp. As a result there are few suitable areas for aquaculture development during the dry season. Areas which are unsuitable during the rainy season are generally those with steep slopes, limited water resources and are difficult to access. During the rainy season, the model shows that almost half of the study area is suitable or highly suitable for tilapia ponds (Table 5.6). The areas with the highest suitability are found in the east of the study area, where farms are already located (Fig. 5.7). Approximately 21,400 ha of the area is considered to be highly suitable for tilapia culture within the rainy season (Fig. 5.12). These areas are mainly located in the east and south of the study area. Although both are considered highly suitable there is a higher risk of NPSP for both nitrogen and phosphorus during the rainy season in the east of the study area (Figs 7.3F, 7.3K, 7.3L) than in the south, therefore it may be more appropriate to locate new farms in the south. If 5% of the total area of highly suitable land was available for development it would allow the construction of over 1000 ponds (Table 5.11). Furthermore, in the rainy season there are many areas considered suitable for shrimp culture (10,795km^2 suitable and 65km^2 highly suitable) (Table 5.7), most of which are low lying coastal areas where shrimp farming already occurs (Fig. 5.8). If 5% of the highly suitable area was used to develop ponds then approximately 650 ponds could be established and 1165 tonnes of shrimp produced within that area.

Most of the coastal areas are at low risk from NPSP during the dry season (Fig. 7.3), however, during the rainy season when most of the production would occur there is a higher risk of nitrogen NPSP in the east of the study area than the west (Fig. 7.3D and 7.3E). It is important to identify such areas as farmers need to ensure they do not add to potential negative environmental impacts. China has suffered from significant eutrophication problems in marine waters which were a result of fast growing coastal cities and the mariculture industry (Fei, 2004). Intensive shrimp ponds can contribute to nitrogen loading in coastal environments (Biao *et al*., 2004) and consequently it is important to ensure that production occurs within the assimilative capacity of the local environment. Some coastal areas contain mangroves (as shown in the land use models Fig. 4.7) which are often considered to be nutrient sinks (Alongi, 1996; Rivera-Monroy *et al*., 1999; Wösten *et al*., 2003). However other farm management strategies can also minimise aquaculture wastes (Tucker and Hargreaves, 2008). Alternatively, extractive organisms, such as seaweed or bivalve molluscs, can be grown in nutrient rich water, decreasing potential eutrophication issues and providing an opportunity for an additional source of income (Fei, 2004; Neori *et al*., 2004). However, site specific assessment would be required to ensure the area is suitable and if mitigation methods do not limit the negative environmental impact then production should not occur in that area.

The seasonal issues of the catchment are also apparent when evaluating the suitability of SEAT farms. No tilapia farms are located in suitable areas during the dry season, whilst over 90% are suitable or highly suitable in the rainy season (Table 5.8). Approximately 55% of the farms are located in areas which are less than suitable for the System submodel which indicates that there could be issues with water supply (Fig. 5.5). The results also show that 15.9% of the shrimp farms are located in suitable areas (Table 5.9) during the dry season; however, this is likely to be an artificial result from combining the submodels as the Species submodel indicates that the entire study area is unsuitable or highly unsuitable for culture in the dry season (Fig. 5.3). Shrimp farming can occur in areas which are suitable in the rainy season but not in the dry season as *P. vannamei* has a short crop cycle of approximately 70 days which allows multiple harvests in the year (Yuan *et al.*, 2006) including a break when the temperatures are too cold. Over 80% of shrimp farms are located in areas considered to be suitable for culture during the rainy season (Table 5.9). The submodels also indicate that 80% of the shrimp farms are in unsuitable areas with regard to Access (Fig. 5.6). This is largely due to shrimp farms being located in coastal areas which are further away from urban settlements, which is confirmed by the results from the Maxent analysis (Fig. 6.4). However, the shrimp farms tend to be located on peninsulas which are then connected to good transport links so the unsuitability with regards to the Access submodel is not as significant an issue in China as in Bangladesh.

Essentially, any development in the Chinese study area would have to focus on the availability and suitability of areas for culture in the rainy season as the low temperatures in the dry season are unsuitable for both shrimp and tilapia. Within the catchment there is scope for the development of tilapia ponds; largely in the south and east of the catchment as the north and north west areas have steep slopes and heavy vegetation which make them unsuitable for pond construction. However, the low lying areas with gentle slopes may also compete with agriculture and expanding urban areas for resources, therefore decision makers will need to evaluate the advantages and disadvantages of any proposal to ensure minimal detrimental impact. There is already a significant tilapia industry in the eastern side of the study area, however this area has a higher risk of NPSP therefore it may be more appropriate to use the highly suitable areas in the south of the study area.

8.6.3. Thailand

The study area in Thailand is the second largest, after Vietnam, and is located in the Central region of Thailand. This area is a highly productive agricultural zone often known as the "rice bowl" (Tingting and Chuang, 2010) and it is also home to the capital city Bangkok and other cities which compete for space and resources within the area. Consequently, it is essential to ensure that aquaculture is located in the most suitable areas in terms of production, whilst minimising potential conflict with other sectors. Shrimp is the dominant species in the area; however, farmers have also made use of the agricultural irrigation networks to establish tilapia farms (Belton and Little, 2008).

Over 50% and 40% of the study area is suitable for tilapia culture in the dry and rainy seasons respectively (Table 5.6). Most of this area is the central plain where tilapia culture already occurs, however if 5% of the area classified as highly suitable during the dry season was available for development then approximately 1459 ponds could be constructed and almost 20,000 tonnes of tilapia could be produced (Table 5.12). This development would have to consider the potential implications of pond construction on the wider environment and *vice versa*. As shown in the land use models (Fig. 4.8) this is also an extensive region of agriculture and can be susceptible to flooding so it is important that decision makers consider this in planning and management strategies. Furthermore, the east of the study area has higher levels of NPSP, particularly in the rainy season (Fig. 7.4), therefore it may be more advantageous to expand production in the west of the study area, which is a less significant agricultural area and has a lower risk of NPSP.

Almost 25,000km^2 (2,500,000 ha) of the area is considered suitable or highly suitable for shrimp culture in the dry season, however, the suitable area reduces to approximately 5400km^2 (540,000 ha) in the rainy season (Table 5.7). This is due to temperatures higher than the optimal range throughout inland areas, although many coastal areas, particularly those in the south east, remain suitable for culture (Fig. 5.10). However, the NPSP models (Fig. 7.4) show the south east has the highest risk of NPSP and may require further monitoring and/or mitigation procedures. Furthermore, there are sensitive mangrove ecosystems in this area, (Fig. 4.8), which need to be protected (Huitric *et al*., 2002) limiting opportunities for pond construction. It must also be noted that the site suitability model indicates that much of the inland area is suitable for shrimp culture, particularly during the dry season (Fig. 5.10). However, inland shrimp culture in Thailand has resulted in negative environmental impacts (Flaherty *et al*., 2000; Braaten and Flaherty, 2001) and consequently the government has placed restrictions on further development in many areas (Roy *et al*., 2010). Consequently local regulations should be consulted and any attempt at inland shrimp farming should take steps to ensure the system will not adversely affect both the environment and other users.

Over 90% of the Thai tilapia farms are located in suitable or highly suitable areas in the dry season, whilst in the rainy season it is over 70% (Table 5.8). Approximately 45% of the farms were located in less than suitable areas with regard to the System submodel (Fig. 5.5). As many tilapia farms were established using irrigation networks (Belton and Little, 2008), smaller channels which did not show up on the satellite imagery may be used by the SEAT ponds. If multiple farms and activities use the same small channels then there could be excess pressure on the water resource which may result in water shortages and/or poor water quality. This would need to be investigated at a local scale and the spatial models can only be used to identify those farms which may have issues. Over 85% of the shrimp farms are in suitable or highly suitable locations in the dry season, whilst in the rainy season it decreases to just over 45% (Table 5.9). Approximately 90% of the farms are located in less than suitable areas in the dry season with regard to the System submodel (Fig. 5.6) as the System submodel weighted the distance to sea highly, and so many of the SEAT shrimp farms which were located further inland were considered unsuitable with regard to this submodel.

Ultimately, there is high potential for further development of aquaculture within the Thai study area. Shrimp is the principal aquaculture species in Thailand, accounting for over 70% of production by value (FAO, 2013b), however, as with the rest of Asia, the industry has had many problems with disease which has resulted in severe economic consequences (Flegel *et al*., 2008; Flegel, 2012). Many of the disease problems have been due to rapid expansion and poor site selection (Walker and Mohan, 2009). Therefore decision makers need to use all available resources to ensure that future expansion occurs in the most suitable areas in agreement with regulations and ensure there is no additional risk from external factors such as NPSP. The Thai aquaculture sector may also benefit from further expansion and development of other commercially friendly species such as Tilapia which currently only represents 7.6% of Thai aquaculture production by volume (FAO, 2013b). Within the study area it can be seen that urban areas such as Bangkok cover much of the land and this is likely to increase with rising populations. Consequently the suitability of an area must also consider potential urban expansion and so changing land use should be regularly monitored. However, as noted by Belton and Little (2008), the growth of the tilapia industry in Central Thailand was due to the increased demand for aquatic products from affluent consumers. Consequently, even with urbanisation, the Central region remains an optimal location for tilapia farms due to close market proximity and, as shown in this study, there are many suitable areas available for development.

8.6.4. Vietnam

The study area in Vietnam is located in the Mekong delta and extends into Cambodia due to the natural characteristics of the catchment. However, as resources are unlikely to be shared between countries, the evaluation of site suitability and individual sites used the political boundary for Vietnam so the study area did not extend into Cambodia (Fig 2.3). There is an extensive agriculture throughout the area as well as a significant aquaculture sector (Garschagen *et al*., 2012) which has expanded significantly in recent years (Phuong & Oanh, 2010) and provides the main exports from the delta; pangasius and shrimp (Fabres, 2011).

The results of the overall site suitability model for pangasius (Fig. 5.8) show there are significant areas considered suitable or highly suitable for culture. The Species submodel (Fig.5.4) shows that temperatures are within the optimal range for most of the study area throughout the year, this highlights the potential for year round production which is already current practice for many farms in the area (Sinh, 2007). If just 5% of the highly suitable area (in both seasons) was used for pangasius production it could produce over 600,000 tonnes per crop and more than 2500 ponds could be constructed (Table 5.12). Although most pangasius culture is close to the Mekong River, the model shows there is the potential to expand the production to alternative areas throughout the delta if desired. Much of this area is covered in water during the rainy season, as shown in the land use models (Fig. 4.9), and further ground truth analysis would be required to assess where the water is a result of flooding rather than rice cultivation.

Regulators should also be aware that there could be potential NPSP issues within the catchment, particularly across many areas which have been identified as suitable by the site suitability models and amongst existing pangasius farms along the Mekong. The models indicate that the farms which are upstream have a higher risk of NPSP than those downstream (Fig. 7.5) due to land use practices and the pattern of rainfall. However, as nutrients would be carried downstream by the water it is important to acknowledge that areas with high risk of NPSP upstream could also affect water quality nearer the mouth of the river. Then again, the Mekong is a large river and the dilution effects and natural assimilative capacity (Yoo and Boyd, 1999) may mitigate nutrient accumulation. Nevertheless, as new and existing farms could contribute to nutrient loading, it would be advantageous to establish monitoring schemes, particularly for those farms which are upstream to ensure there is minimal environmental impact and no excess nutrient build up in ponds.

Within the Vietnamese study area the results for the suitability model indicate there are fewer suitable areas available for shrimp culture than there are for pangasius. Most highly suitable areas are located in the low lying coastal areas, many of which already contain shrimp farming (Fig. 5.10). The model also shows there are significant areas of land available for inland culture, though as shown in the land use models (Fig. 4.9), much of this area is used for agriculture, particularly rice production which could be negatively impacted by inland shrimp culture (Flaherty and Karnjanakesorn, 1995; Ali, 2006). For this reason, the highly suitable coastal areas should be used first for development. However, there are also mangroves located in the coastal environment (Fig. 4.9) and as a result farmers and regulators would have to ensure no mangroves were destroyed during pond development. Alternatively, mangroves can be considered nutrient sinks and the NPSP models show that shrimp farms in the east of the study area have a much higher risk of NPSP than those located in the south near the mangroves (Fig. 7.5). Some farms in the south have already established integrated shrimp-mangrove systems (Binh *et al*., 1997), although yields can vary (Alonghi *et al*., 2000; Johnston *et al*., 2000) and the water quality is generally suboptimal for shrimp culture (Johnston *et al*., 2002). Consequently it is not recommended that these systems are used for wide scale food production throughout every coastal area in Vietnam and effort should be made to site farms away from mangroves by consulting the land use models (Fig. 4.9) and the site suitability models (Fig. 5.10).

Overall, over 90% of the SEAT pangasius farms are found in suitable or highly suitable locations in both seasons. Most of the farms are located in suitable or highly suitable areas for the individual submodels (Fig. 5.5), while approximately 40% of farms are located in areas which are unsuitable with regard to the Access submodel. This is because some of the farms are inaccessible by road and rely on boats. Annual floods cover large parts of the delta in the rainy season (as shown in Fig. 4.9), replenishing nutrients and supporting the highly productive fishery, consequently it is difficult to develop roads which service this natural flood system whilst enabling access to more remote areas (Douven and Buurman, 2013).

In the dry season 77.4% of shrimp farms are located in suitable or highly suitable areas, reducing to 73% during the rainy season. Approximately 90% of shrimp farms are located in areas which are less than suitable for the System submodel (Fig. 5.6), the farms may source their water from small canals which could not be identified on the satellite imagery. Small canals would be under more pressure from multiple users and may be a less sustainable method of farming. With many farms located in the same area competing for access to water it could be a significant source of conflict and site specific work would be required to assess the actual farm conditions and potential implications for other users and the environment.

Arguably, the study area in Vietnam has the greatest potential for development of all of the study areas mainly due to the availability of highly suitable areas throughout the year for both species. However, it is important that any development is carefully managed as the rapid growth of the pangasius industry has already been criticised by many as discussed by Bush and Duijf, 2011 and Little *et al*., 2012.

8.7. Conclusions

Evaluating large catchments and their suitability for aquaculture production is essential to meet the growing demand for food. Decision makers need to know that aquaculture is taking place in suitable locations with minimal environmental impact and no conflict with other activities and users. The approach developed in this study allows decision makers to identify potential conflicts between the surrounding land use and aquaculture, classify areas of suitability using optimal ranges of variables, analyse existing farm locations and assess the risk of non-point source pollution across the study areas. This allows a broader evaluation of site suitability and can be used to support planning and management strategies aimed at meeting food requirements.

Modelling is not intended to be a replacement for observations. However, it can enhance the decision making process and provide valuable information which may not otherwise be apparent. The suitability of a catchment for aquaculture is a complex issue and models can be used to visualise the issues across the region. This enables decision makers to identify areas within the catchment for further development of a particular species and/or areas where the environment may need additional protection. Recently there has been a rise in sustainability certification driven by the need to address a range of environmental and social issues associated with aquaculture (Bush *et al*., 2013). Decision support tools could provide a valuable source of information for such schemes. However, many studies focus on one particular area, species, system and/or topic making application beyond a particular purpose difficult. To ensure a fair comparison between areas, tools should use standardised data sources and model frameworks in order to avoid bias and unrepresentative results. The models developed in this study have used data that are available for almost any study area worldwide enabling further application beyond the scope of this study. This allows their application to multiple study areas, enabling a comparison of suitability across different locations.

It is important to acknowledge that global data sets may not be as sensitive or accurate as site specific data. However, site specific data are only available for certain areas and it is difficult and time consuming to collect more information across multiple large areas. Data quality and access is one of the biggest challenges in spatial modelling (Meaden, 2010) and model developers must use the best available data to meet their objectives. The models used in this study have transparent frameworks, which are easy to update and adapt as new information becomes available and they can also be modified for use with site-specific data which may provide more sensitive results. There will be other factors which influence the suitability of an area which have not been included in this study. Socio-economic issues can have a significant impact on aquaculture production and would require assessment beyond the scope of this work. Additionally, local and national regulations would have to be consulted prior to any development and farms may also wish to consider the standards set by certification schemes, particularly if they plan significant levels of production and export. As techniques and technology improve there may also be an opportunity to expand production into areas currently considered unsuitable which has not been included in the models as it is unpredictable at this stage.

The work presented here has shown that spatial models are useful decision support tools for regional, national and international strategies aiming to increase food production in suitable areas. Spatial models are ideally suited for such analysis as they can incorporate a wide range of variables; allowing an alternative view of a complex situation. The models developed and used in this project can be applied to almost any study area by a range of stakeholders providing valuable decision support and helping to assess the suitability of large catchments in a comprehensive, yet transparent, manner supporting the EAA. Ultimately, the models enable an objective approach to managing land, water and resources which should enhance productivity without detrimentally impacting the environment and other stakeholders. This is an essential step in managing large catchments as decisions need to be made now to meet food security requirements and protect the interests of future generations.

REFERENCES

Adger, W.N., Hughes, T.P., Folke, C., Carpenter, S.R., Rockström, 2005. Social-ecological resilience to coastal disasters. *Science*, 309 (5737): 1036-1039.

Aguilar-Manjarrez, J. and Crespi, V. 2013. National aquaculture sector overview map collection. User manual/Vues générales du secteur aquacole national (NASO). Manuel de l'utilisateur. 65pp.

Aguilar-Manjarrez, J. and Nath, S.S. 1998 *A strategic reassessment of fish farming potential in Africa*. CIFA Technical Paper. No. 32. Rome, FAO. 170p.

Aguilar-Manjarrez, J., Kapetskey, J.M. and Soto, D. 2010. The potential of spatial planning tools to support the ecosystem approach to aquaculture. FAO/Rome. Expert workshop. 19-21 November 2008, Rome, Italy. *FAO Fisheries and Aquaculture Proceedings*. No. 17. FAO, Rome. 176pp.

Ahmed, M. 2003. A critical evaluation of approaches to urban development in Bangladesh: case study of Khulna. In: Girard, L.F., Forte, B., Cerreta, M., De Toro, P. and Forte, F. eds. *The human sustainable city*. Ashgate Publishing Limited, Aldershot, England, pp.297-312.

Ahmed, N. 2013. Linking prawn and shrimp farming towards a green economy in Bangladesh: confronting climate change. *Ocean & Coastal Management*, 75: 33-42.

Ahmed, N., Ahammed, F. and Lecouffe, C. 2007. Socioeconomic aspects of small-scale freshwater prawn marketing systems in Mymensigh, Bangladesh. *Aquaculture Economics and Management*, 11(4): 335-353.

Ahmed, N., Allison, E.H. and Muir, J.F. 2008a. Using the sustainable livelihoods framework to identify constraints and opportunities to the development of freshwater prawn farming in southwest Bangladesh. *Journal of the World Aquaculture Society*, 39(5): 598-611.

Ahmed, N., Brown, J.H. and Muir, J.F. 2008b. Freshwater prawn farming in gher systems in southwest Bangladesh. *Aquaculture Economics & Management*, 12: 207-223.

Ahmed, N., Demaine, H. and Muir, J.F. 2008c. Freshwater prawn farming in Bangladesh : history, present status and future prospects. *Aquaculture Research*, 39 (8): 806-819.

Aitchison, A. 2009. *Beginning spatial with SQL server 2008*. Apress, California, USA . 456pp.

Aksornkoae, S. and Tokrisna, R. 2004. Overview of shrimp farming and mangrove loss in Thailand. In: Barbier, E.B. and Sathirathai, S. Eds. *Shrimp farming and mangrove loss in Thailand.* Edward Elgar Publishing Limited, Cheltenham, UK. pp. 37 - 51.

Alexander, D.E. 1993. *Natural disasters*. Kluwer Academic Publishers, The Netherlands. 650pp.

Ali, A.M.S. 2006. Rice to shrimp: land use/land cover changes and soil degradation in Southwestern Bangladesh. *Land Use Policy*, 23(4): 421-435.

Allsopp, M., Page, R., Johnston, P. and Santillo, D. 2009. *State of the World's Oceans.* Springer Science and Business Media B.V., Netherlands. 270pp.

Alongi, D.M. 1996. The dynamics of benthic nutrient pools and fluxes in tropical mangrove forests. *Journal of Marine Research*, 54: 123 - 148.

Alongi, D.M., Johnston, D.J. and Xuan, T.T. 2000. Carbon and nitrogen budgets in shrimp ponds of extensive mixed shrimp-mangrove forestry farms in the Mekong delta, Vietnam. *Aquaculture Research*, 31(4): 387-399.

Anderson, D.M., Gilbert, P.M. and Burkholder, J.M. 2002. Harmful algal blooms and eutrophication: nutrient sources, composition and consequences. *Estuaries*, 25(4b): 704-726.

Anderson, J.R., Hardy, E.E., Roach, J.T. and Witmer, R.E. 1976. A land use and land cover classification system for use with remote sensor data. Government Printing Office, Washington DC. Professional Paper 964. 28pp.

Anderson, R.P. and Gonzalez Jr., I. 2011. Species-specific tuning increases robustness to sampling bias in models of species distributions: an implementation with Maxent. *Ecological Modelling*, 222(14): 2796-2811.

Anh, P.T., Kroeze, C., Bush, S.R. and Mol, A.P.J. 2010a. Water pollution by intensive brackish shrimp farming in south-east Vietnam: causes and options for control. *Agricultural Water Management*, 97(6): 872-882.

Anh, P.T., Kroeze, C., Bush, S.R. and Mol, A.P.J. 2010b. Water pollution by pangasius production in the Mekong Delta, Vietnam: causes and options for control. *Aquaculture Research,* 42(1): 108-128.

Arnold, J.G., Kiniry, J.R., Srinivasan, R., Williams, J.R., Haney, E.B. and Neitsch, S.L. 2012. *Soil and water assessment tool, version 2012*. Texas Water Resources Institutes, Texas, USA. 650pp.

Azad, A.K., Jensen, K.R. and Lin, C.K. 2009. Coastal aquaculture developmet in Bangladesh: unsustainable and sustainable experiences. *Environmental Management,* 44(4): 800-809.

Baldwin, R.A. 2009. Use of maximum entropy modeling in wildlife research. *Entropy*, 11: 854 - 866.

Barbier, E.B. and Cox, M. 2004. Analysis of shrimp farm expansion and manrove conversion in Thailand 1979-1996. In: Barbier, E.B. and Sathirathai, S. Eds. *Shrimp farming and mangrove loss in Thailand.* Edward Elgar Publishing Limited, Cheltenham, UK. pp. 52- 72.

Bean, C. and Xinping, W. 2006. *China's tilapia production situation 2006*. USDA Foreign Agricultural Service GAIN report. 8pp.

Beasley, D.B. and Huggins, L.F. 1985. *ANSWERS Areal Nonpoint Source Watershed Environment Response Simulation - User Manual*. Agricultural Engineering Department, Purdue University, West Lafayette, Indiana, USA. 57pp.

Belton, B. and Little, D. 2008. The development of aquaculture in Central Thailand: domestic demand versus export-led production. *Journal of Agrarian Change*, 8(1): 123-143.

Belton, B., Haque, M.M., Little, D.C. and Sinh, L.X. 2011a. Certifying catfish in Vietnam and Bangladesh: Who will make the grade and will it matter? *Food Policy*, 36 (2): 289-299.

Belton, B., Karim, M., Thilsted, S., Murshed-E-Jahan,K., Collis, W. And Phillips, M. 2011b. *Review of aquaculture and fish consumption in Bangladesh*. Studies and Reviews 2011-53. The WorldFish Center, Malaysia. 76pp.

Belton, B., Little, D.C. and Sinh, L.X. 2011c. The social relations of catfish production in Vietnam. *Geoforum*, 42(5): 567-577.

Belton, B., Turongruang, D., Bhujel, R. and Little, D.C. 2009. The history, status, and future prospects of monosex tilapia culture in Thailand. *Aquaculture Asia Magazine*, April-June 2009: 16-19.

Beveridge, M.C.M., Phillips, M.J. and Macintosh, D.J. 1997. Aquaculture and the environment: the supply of and demand for environmental goods and services by Asian aquaculture and implications for sustainability. *Aquaculture Research*, 28: 797-807.

Biao, X. and Kaijin, Y. 2007. Shrimp farming in China: Operating characteristics, environmental impact and perspectives. *Ocean & Coastal Management*, 50 (7): 538-550.

Biao, X., Zhuhong, D. and Xiarong, W. 2004. Impact of the intensive shrimp farming on the water quality of the adjacent coastal creeks from Eastern China. *Marine Pollution Bulletin*, 48 (5-6): 543-553.

Binh, C.T., Phillips, M.J. and Demaine, H. 1997. Integrated shrimp-mangrove farming systems in the Mekong detla of Vietnam. *Aquaculture Research*, 28(8):599-610.

Blach-Overgaard, A., Svenning, J.C., Dransfield, J., Greve, M. and Balslev, H. 2010. Determinants of palm species distributions across Africa: the relative roles of climate, non-climatic environmental factors, and spatial constraints. *Ecography*, 33(2): 380-391.

Blanco, H. and Lal, R. 2008. *Principles of soil conservation and management*. Springer, London. 617pp.

Bose, A.N., Ghosh, S.N., Yang, C.T. and Mitra, A. 1991. *Coastal Aquaculture Engineering*. Routledge, Chapman and Hall Inc, New York, USA. 373pp.

Bostock, J. 2011. The application of science and technology development in shaping current and future aquaculture production systems. *Journal of agricultural science*, 149: 133-141.

Bouraoui, F. and Dillaha, T. 2000. "ANSWERS-2000: Non-point-source nutrient planning model. *Journal of Environmental Engineering*, 126(11): 1045-1055.

Bowden, T.J., Thompson, K.D., Morgan, A.L. Gratacap, R.M.L. and Nikoskelainen, S. 2007. Seasonal variation and the immune response: a fish perspective. *Fish and Shellfish Immunology*, 222(6): 695-706.

Boyd, C. 2012. Water quality. In: Lucas, J.S. and Southgate, P.C. eds. *Aquaculture:Farming aquatic animals and plants*. Blackwell Publishing Ltd, West Sussex, UK. pp. 52-83.

Boyd, C.E. 1995. *Bottom soils, sediment, and pond aquaculture*. Chapman & Hall, London. 348pp.

Boyd, C.E. 2008. Better management practices for marine shrimp aquaculture. In: Tucker, C.S. and Hargreaves, J.A. eds. *Environmental best management practices for aquaculture*. Blackwell Publishing, Oxford, UK. pp. 227-260.

Boyd, C.E. and Schmittou, H.R. 1999. Achievement of sustainable aquaculture through environmental management. *Aquaculture Economics & Management*, 3 (1): 59 - 69.

Boyd, C.E. and Tucker, C.S. 1998. *Pond aquaculture water quality management*. Kluwer Academic Publishers, The Netherlands. 700pp.

Boyd, C.E., Tucker, C., McNevin, A., Bostick, K. and Clay, J. 2007. Indicators of resource use efficiency and environmental performance in fish and crustacean aquaculture. *Reviews in Fisheries Science*, 15: 327-360.

Boyd, C.E., Wood, C.W. and Thunjai, T. (2002) *Aquaculture pond bottom soil quality management*. Pond dynamics/Aquaculture CRSP, Corvallis, Oregon. 41pp.

Braaten, R.O. and Flaherty, M. 2000. Hydrology of inland brackishwater shrimp ponds in Chachoengsao, Thailand. *Aquacultural Engineering*, 23; 295-313.

Braaten, R.O. and Flaherty, M. 2001. Salt balances of inland shrimp ponds in Thailand: implications for land and water salinization. *Environmental Conservation*, 28(4): 257-367.

Brennan, D., Clayton, H., Preston, N. and Be, T.T. 2006. Economic issues in promoting sustainable shrimp farming: a case study of the rice-shrimp system in the Mekong Delta. In: Leung, P.S. and Engle, C. eds. *Shrimp culture: economics, market and trade*. Blackwell Publishing Ltd, Oxford, UK. pp.131-142.

Brett, J.R. and Groves, T.D.D. 1979. Physiological energetics. In: Hoar, W.S., Randall, D.J. and Brett, J.R. eds. *Fish Physiology*, Vol. 8. Academic Press, New York, pp. 279-352.

Briggs, M., Funge-Smith, S., Subasinghe, R.P. and Phillips, M. 2005. Introductions and movement of two penaeid shrimp species in Asia and the Pacific. FAO *Fisheries Technical Paper 476*. FAO, Rome, 78pp.

Brinkhoff, T. (2011) City Population. [Internet] Available from: http://www.citypopulation.de [Accessed 01/08/2011].

Brooks, K.N., Ffolliott, P.F. and Magner, J.A. 2013. *Hydrology and the management of watersheds*. Fourth edition. Wiley Blackwell, Oxford, UK. 545pp.

Bush, S.R. and Duijf, M. 2011. Searching for (un)sustainability in pangasius aquaculture: a political economy of quality in European retail. *Geoforum*, 42(2): 185-196.

Bush, S.R., Belton, B., Hall, D., Vangergeest, P., Murray, F.J., Ponte, S., Oosterveer, P., Islam, M.S., Mol, A.P.J., Hatanaka, M., Kruijssen, F., Ha, T.T.T., Little, D.C., Kusumawati, R. 2013. Certify sustainable aquaculture? *Science*, 341(6150): 1067-1068.

Callan, S.J. and Thomas, J.M. 2010. *Environmental economics and management: theory, policy and applications*. 5th edition. South-Western Cengage Learning, Ohio, USA. 545pp.

Camacho - Cuena, E. and Requate, T. 2012. The regulation of non-point source pollution and risk preferences: as experimental approach. *Ecological Economics*, 73: 179 -187.

Campbell, I.C. 2009. *The Mekong: Biophysical environment of an International River Basin*. Elsevier, Amsterdam. 464pp.

Campbell, J.B. 2007. *Introduction to remote sensing*. 4th edition. The Guilford Press, New York. 626pp.

Carpenter, S.R., Caraco, N.F., Correll, D.L., Howarth, R.W., Sharpley, A.N. and Smith, V.H. 1998. Nonpoint pollution of surface waters with Phosphorus and Nitrogen. *Ecological Applications*, 8(3): 559-568.

Carver, S.J. 1991. Integrating multi-criteria evaluation with geographical information systems. International Journal of Geographical Information Systems, 5(3): 321-339.

Cech, T.V. 2010. *Principles of water resources: history, development, management and policy.* 3rd edition, John Wiley & Sons Inc, New Jersey, USA. 576pp.

Chakraborti, D., Rahman, M.M., Das, B., Murrill, M., Dey, S., Mukherjee, S.C., Dhar, R.K., Biswas, B.K., Chowdhury, U.K., Roy, S., Sorif, S., Selim, M., Rahman, M., Quamruzzaman, Q. 2010. Status of groundwater arsenic contamination in Bangladesh: A 14-year study report. *Water research*, 44(19): 5789-5802.

Chandler, J. 1994. Integrated catchment management planning. *Journal of the Institution of water and environmental management*, 8(1): 93- 96.

Chávez-Crooker, P. and Obreque-Contreras, J. 2010. Bioremediation of aquaculture wastes. *Current Opinion in Biotechnology*, 21(3): 313-317.

Cheevaporn, V. and Menasveta, P. 2003. Water pollution and habitat degradation in the Gulf of Thailand. *Marine Pollution Bulletin*, 47(1-6): 43 - 51.

Chen, J. 2007. Rapid urbanization in China: a real challenge to soil protection and food security. *Catena*, 69(1): 1-15.

Cho, C.Y. and Bureau, D.P. 2001. A review of diet formulation strategies and feeding systems to reduce excretory and feed wastes in aquaculture. *Aquaculture Research*, 32(s1): 349-360.

Cho, Y., Lee, W.C., Hong, S., Kim, H.C. and Kim, J.B. 2012. GIS-based suitable site selection using habitat suitability index for oyster farms in Geoje-Hansan Bay, Korea. *Ocean & Coastal Management*, 56: 10-16.

Chowdhury, N.T. 2010. Water management in Bangladesh: an analytical review. *Water Policy*, 12: 32-51.

Coe, A.L. 2010. *Geological field techniques*. Blackwell Publishing Ltd, Milton Keynes, UK. 323pp.

Congalton, R.G. and Green, K. 1999. *Assessing the accuracy of remotely sensed data: principles and practices*. CRC Press Inc, Florida, USA. 137pp.

Convertino, M., Troccoli, A., Catani, F. 2013. Detecting fingerprints of landslide drivers: a maxent model. *Journal of Geophysical Research Earth Surface*, 118(3): 1367-1386.

Corbin, J.S. and Young, G.L. 1997. Planning, regulation and administration of sustainable aquaculture. In: Bardach, J.E. (ed) *Sustainable aquaculture*. John Wiley & Sons Inc, Canada. pp. 201-234.

Corner, R.A., Brooker, A.J., Telfer, T.C. and Ross, L.G. 2006. A fully integrated GIS-based model of particulate waste distribution from marine fish-cage sites. *Aquaculture*, 258(1-4): 299-311.

Costa-Pierce, B.A. 2010. Sustainable ecological aquaculture systems: the need for a new social contract for aquaculture development. *Marine Technology Society Journal*, 44(3): 88-112.

Cowan, V.J., Lorenzen, K. and Funge-Smith, S.J. 1999. Impact of culture intensity and monsoon season on water qulaity in Thai commercial shrimp ponds. *Aquaculture Research*, 30(2): 123-133.

Danh, V.T. and Mushtaq, S. 2001. Living with floods: an evaluation of the resettlement program of the Mekong Delta of Vietnam. In: Stewart, M.A. and Coclanis, P.A. eds. *Environmental Change and Agricultural Sustainability in the Mekong Delta*. Springer, Netherlands. pp 181-204.

Datta, D.K., Roy, K. And Hassan, N. 2010. Shrimp culture: trend consequences and sustainability in the South-western coastal region of Bangladesh. In: Ramanathan, A.L., Bhattacharya, P., Dittmar, T., Prasad, M.B.K. and Neupane, B. eds. *Management and sustainable development of coastal zone environments*. Springer, The Netherlands. pp. 227-244.

Davis, B.E. 2001. *GIS: A visual approach*. 2nd edition. OnWord Press, New York, USA. 439pp.

De Silva, S.S. 2012. Aquaculture: a newly emergent food production sector - and perspectives of its impacts on biodiversity and conservation. *Biodiversity and Conservation*, 21(21), pp 3187 -3220.

De Silva, S.S. and Davy, F.B. 2010. Aquaculture successes in Asia: contributing to sustained development and poverty alleviation. In: De Silva, S.S. and Davy, F.B. eds. *Success stories in Asian aquaculture*. Springer, The Netherlands. pp1-14.

De Silva, S.S., Nguyen, T.T.T., Abery, N.W. and Amarasinghe, U.S. 2006. An evaluation of the role and impacts of alien finfish in Asian inland aquaculture. *Aquaculture Research*, 37(1): 1 - 17.

De Silva, S.S., Subasinghe, R.P., Bartley, D.M. and Lowther, A. 2004. Tilapias as alien aquatics in Asia and the Pacific: a review. *FAO Fisheries Technical Paper*. No. 453, Rome, FAO. 65pp.

de Smith, M.J., Goodchild, M.F. and Longley, P. 2009. *Geospatial analysis a comprehensive guide to principles, techniques and software tools*. Matador, Leicester, UK. 560pp.

Deb, A.K. 1998. Fake blue revolution: environmental and socio-economic impacts of shrimp culture in the coastal areas of Bangladesh. *Ocean & Coastal Management*, 41(1): 63-88.

Dey, M.M., Alam, M.F. and Bose, M.L. 2010. Demand for aquaculture development: perspectives from Bangladesh for improved planning. *Reviews in Aquaculture,* 2(1): 16-32.

Dey, M.M., Bose, M.L. and Alam, M.F. 2008. *Recommendation domains for pond aquaculture. Country case study: development and status of freshwater aquaculture in Bangladesh*. WorldFish Center Studies and Reviews No. 1872. The WorldFish Center, Penang, Malaysia. 73pp..

Diana, J.S. 2009. Aquaculture production and biodiversity conservation. *BioScience*, 59(1): 27-38.

Dierberg, F.E. and Kiattisimkul, W. 1996. Issues, impacts and implications of shrimp aquaculture in Thailand. *Environmental Management*, 20(5): 649-666.

Douglas, I. 2005. The Mekong River Basin. In: Gupta, A. ed. *The Physical Geography of Southeast Asia.* Oxford University Press, Oxford, UK, pp.219-236.

Douven, W. and Buurman, J. 2013. Planning practice in support of economically and environmentally sustainable roads in floodplains: the case of the Mekong delta floodplains. *Journal of Environmental Management*, 128: 161-168.

Dowling, N.G., Greenfield, S.M. and Fischer, K.S. 1997. *Sustainability of rice n the global food system*. CAB International, Wallingford, UK. 275pp.

Drewry, J.J., Newham, L.T.H., Greene, R.S.B., Jakeman, A.J. and Croke, B.F.W. 2006. A review of nitrogen and phosphorus export to waterways: context for catchment modelling. *Marine and Freshwater Research*, 58: 757-774.

Dudgeon, D. 2000. The ecology of tropical Asian rivers and streams in relation to biodiversity conservation. *Annual Review of Ecology and Systematics*, 31; 239 - 263

Eastman, J.R. 2012. *IDRISI Selva Manual*. Clark Labs, Worcester 324pp.

Elith, J., Graham, C.H., Anderson, R.P., Dudik, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J.McC.M., Peterson, A.T., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R.E., Soberón, J., Williams, S., Wisz, M.S. and Zimmermann, N.E. 2006. Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29(2): 129-151.

Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E. and Yates, C.J. 2011. A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, 17: 43-57.

El-Sayed, A.F.M. 2006. *Tilapia Culture.* CABI Publishing, Wallingford, UK. 277pp.

Eng, J.Y. 2005. *China investment environment and strategies: the key to winning in the Greater China market.* iUniverse, Lincoln, New England, USA. 465pp.

Engle, C.R. 2011. *Aquaculture economics and financing: management and analysis*. Wiley-Blackwell, Iowa, USA. 274pp.

Ericksen, P.J., Ingram, J.S.I. and Liverman, D.M. 2009. Food security and global environmental change: emerging challenges. *Environmental Science and Policy*. 12(4): 373 - 377.

ESA. 2011. GlobCover. [Internet] European Space Agency, Paris, France. Available < http://due.esrin.esa.int/globcover/> [Accessed: 18/08/2013]

Evans, J.M., Fletcher, R.J. and Alavalapati, J. 2010. Using species distribution models to identify suitable areas for biofuel feedstock production. *GCB Bioenergy*, 2: 63-78.

Fabres, B. 2011. Think global, act global in the Mekong Delta? Environmental change, civil society, and NGOs. In: Stewart, M.A. and Coclanis, P.A. eds. *Environmental change and agricultural sustainability in the Mekong Delta*. Springer, Netherlands. pp. 7-34.

Faisal, I.M. and Parveen, S. 2004. Food security in the face of climate change, population growth, and resource constraints: implications for Bangladesh. *Environmental Management*, 34(4): 487-498.

Falconer, L., Hunter, D.C., Telfer, T.C. and Ross, L.G. 2013. Visual, seascape and landscape analysis to support coastal aquaculture site selection. *Land Use Policy*, 34: 1-10.

FAO .1995. *Simple methods for aquaculture. Pond construction for freshwater fish culture. Building earthen ponds*. FAO, Rome. 355pp.

FAO. 2012. *State of world fisheries and aquaculture 2012*. FAO, Rome. 230pp.

FAO, 2013a. Ecosystem Approach. [Internet] FAO, Rome. Available from < http://www.fao.org/biodiversity/cross-sectoral-issues/ecosystem-approach/en/> Date accessed: 02/09/2013.

FAO. 2013b. FishStatJ. [Internet] FAO, Rome. Available from <http://www.fao.org/fishery/statistics/software/fishstatj/> Date accessed: 05/09/2013.

FAO. 2013c. NASO aquaculture maps collection. [Internet] FAO, Rome. Available: < http://www.fao.org/fishery/naso-maps/naso-maps/en/> Date accessed: 05/07/2013.

FAO/IIASA/ISRIC/ISS-CAS/JRC. 2012. *Harmonized World Soil Database (version 1.2)*. FAO, Rome, Italy and IIASA, Laxenburg, Austria.

Faruque, H.S.M. and Ali, M.L., 2005. Climate change and water resources management in Bangladesh. In: Mirza, M.M.Q. and Ahmad, Q.K. eds. *Climate change and water resources in South Asia*. Taylor & Francis Group plc, London, UK, pp 231-254.

Fei, X. 2004. Solving the coastal eutrophication problem by large scale seaweed cultivation. *Hydrobiologia*, 512: 145-151.

Fernandes, T.F., Eleftheriou, A., Ackefors, H., Elftheriou, M., Ervik, A., Sanchez-Mata, A., Scanlon, T., White, P., Cochrane, S., Pearson, T.H. and Read, P.A. 2001. The scientific principles underlying the monitoring of the environmental impacts of aquaculture. *Journal of Applied Ichthyology*, 17: 181-193.

Ferrier, R.C. and Jenkins, A. 2010. The catchment management concept. In: Ferrier, R.C. and Jenkins, A. eds. *Handbook of catchment management*. Blackwell Publishing Ltd., Oxford, UK. pp. 1-18.

Fielding, A.H. and Bell, J.F. 1997. A review of methods for the assessment of prediction errors in conversation presence/absence models. *Environmental Conservation*, 24(1): 38-49.

Flaherty, M. and Karnjanakesorn, C. 1995. Marine shrimp aquaculture and natural resource degradation in Thailand. *Environmental Management*, 19(1): 27-37.

Flaherty, M. and Vangergeest, P. 1998. "Low-salt" shrimp aquaculture in Thailand: Goodbye coastline, Hello Khon Kaen! *Environmental Management*, 22(6): 817-830.

Flaherty, M., Szuster, B., and Miller, P. 2000. Low salinity inland shrimp farming in Thailand. *Ambio: A Journal of the Human Environment*, 29(3): 174-170.

Flaherty, M., Vandergeest, P. and Miller, P. 1999. Rice paddy or shrimp pond: tough decisions in rural Thailand. *World development*, 27(12): 2045 - 2060.

Flegel, T.W. 2012. Historic emergence, impact and current status of shrimp pathogens in Asia. *Journal of Invertebrate Pathology*, 110(2): 166-173.

Flegel, T.W., Lightner, D.V., Lo, C.F. and Owens, L. 2008. Shrimp disease control: past, present and future. In: Bondad-Rentaso, M.G., Mohan, C.V., Crumlish, M. and Subasinghe, R.P. eds. *Diseases in Asian Aquaculture VI*. Fish Health Section. Asian Fisheries Society, Manila, Philippines, 355-378.

Flory, A.R., Kumar, S., Stohlgren, T.J. and Cryan, P.M., 2012. Environmental conditions associated with bat white-nose syndrome mortality in the north-eastern United States. *Journal of Applied Ecology*, 49: 680-689.

Foley, J.A., DeFries, R., Asner G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N. And Snyder, P.K. 2005. Global consequences of land use. *Science*, 309(5734): 570-574.

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, Sheehan, J., Siebert, S., Tilman, D. and Zaks, D.P.M. 2011. Solutions for a cultivated planet. *Nature*, 478, 337-342.

Foody, G.M. 2002. Status of land cover classification accuracy assessment. *Remote sensing of the environment*, 80: 185-201.

Frankic, A. and Hershner, C. 2003. Sustainable aquaculture: developing the promise of aquaculture. *Aquaculture International*, 11: 517 - 530.

Frid, C. and Dobson, M. 2002. *Ecology of aquatic management*. Pearson Education Ltd, Essex, UK. 274pp.

Fu, C., Jiang, Z., Guan, Z., He, J. and Xu., Z. 2008. *Regional climate studies of China*. Springer, Berlin. 489pp.

Galletti, C.S., Ridder, E., Falconer, S.E. and Fall, P.L. 2013. Maxent modelling of ancient and modern agricultural terraces in the Troodos foothills, Cyprus. *Applied Geography*, 39: 46 -56.

Garschagen, M., Diez, J.R., Nhan, D.K and Kraas, F. 2012. Socio-economic development in the Mekong Delta: Between the prospects for progress and the realms of reality. In: Renaud, F.G. and Kuenzer, C. eds. *The Mekong Delta System*. Springer, London, pp.83-132.

Giang, H.T., Giang, T., Ut, V.N., Phuong, H.T. 2008. Bien dong yu to moi truong trong ao nuoi ca tra tham canh o An giang. *Tap chi khoa hoc*, 1: 1-9. (In Vietnamese).

Giap, D.H., Yi, Y. and Yakupitiyage, A. 2005. GIS for land evaluation for shrimp farming in Haiphong of Vietnam. *Ocean & Coastal Management*, 48(1): 51-63.

Gilbert, P.M., Allen, J.I., Bouman, A.F., Brown, C.W., Flynn, K.J., Lewitus, A.J. and Madden, C.J. 2010. Modeling of HABs and eutrophication: status, advances, challenges. *Journal of Marine Systems*, 83(3-4): 262-275.

Giupponi, C. 2007. Decision support systems for implementing the European Water Framework Directive: The MULINO approach. *Environmental Modelling and Software*, 22(2): 248 - 258.

Godfray, H.C.J., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C. 2010. Food security: The challenge of feeding 9 billion people. *Science*, 327: 812-818.

Gong, P., Wang, J., yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., Zhang, H., Zhu, P., Zhao, Z., Zhang, H., Zheng, Y., Ji, L., Zhang, Y., Chen, H., Yan, A., Guo, J., Yu, L., Wang, L., Liu, X., Shi, T., Zhu, M., Chen, Y., Yang, G., Tang, P., Xu, B., Giri, C., Clinton, N., Zhu, Z., Chen, J. and Chen, J. 2013. Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing*, 34(7): 2607-2654.

Goodchild, M.F. 2008. The use cases of digital earth. *International Journal of Digital Earth*, 1(1): 31-42.

Google. 2013. Google Maps. [Internet]. Google, California, USA. Available https://maps.google.co.uk/ Date accessed: 12/08/2013.

Google Earth. 2013. Google Earth (Version 7.1.1.1888) [Software]. Google, California, USA. Available from: < http://www.google.com/earth/index.html>

Gopi, S. 2005. *Global Positioning System : Principles and Applications*. Tata McGraw-Hill Publishing Company Limited, New Delhi. 337pp.

Green, E.P., Clark, C.D., Mumby, P.J., Edwards, A.J. and Ellis, A.C. 1998. Remote sensing techniques for mangrove mapping. *International Journal of Remote Sensing,* 19(5): 935-956.

Guimrães, A.S., Travassos, P., Filho, P.W.M.E.S., Goncalves, F.D. and Costa, F. 2010. Impact of aquaculture on mangrove areas in the northern Pernambuco Coast (Brazil) using remote sensing and geographic information system. *Aquaculture Research*, 41: 828-838.

Guo, R. 2013. *Regional China: a business and economic handbook*. Palgrave Macmillan, Hampshire, UK. 416pp.

Gupta, A. and Liew, S.C. 2007. The Mekong from satellite imagery: a quick look at a large river. *Geomorphology*, 85(3-4): 259-274.

Ha, D.T., Thao, T.D., Khiem, N.T., Trieu, M.X., Gerpacio, R.V. and Pingali, P.L. 2004. *Maize in Vietnam: Production systems, constraints and research priorities*. International Maize and Wheat Improvement Center, CIMMYT, Mexico. 42pp.

Ha, T.T.P., van Dijk, H., Bosma, R. and Sinh, L.X. 2013. Livelihood capabilities and pathways of shrimp farmers in the Mekong Delta, Vietnam. *Aquaculture Economics and Management*, 17: 1-30.

Haining, R. 2003. *Spatial data analysis: theory and practice.* Cambridge University Press, Cambridge, UK. 454pp.

Hajek, B.F. and Boyd, C.E. 1994 Rating soil and water information for aquaculture. *Aquacultural Engineering*, 13 : 115 - 128.

Hanrahan, G. 2009. *Modelling of pollutants in complex environmental systems, volume 1*. ILM Publications, Hertfordshire, 376pp.

Hargreaves, J.A. 1998. Nitrogen biogeochemistry of aquaculture ponds. *Aquaculture*, 166(3-4): 181-212.

Harvey, M. and Pilgrim, S. 2011. The new competition for land: food, energy and climate change. *Food Policy*, 36(1): S40-S51.

Herzfeld, U.C. 2004. *Atlas of Antarctica: Topographic maps from geostatistical analysis of satellite radar altimeter data*. Springer, New York, USA. 364pp.

Heywood, I., Cornelius, S. & Carver, S. 2002. *An introduction to Geographical Information Systems*. 2nd Edition. Pearson Education Limited, Essex. 295pp

Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis, 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25: 1965-1978.

Hishamunda, N., Bueno, P.B., Ridler, N. and Yap, W.G. 2009. Analysis of aquaculture development in Southeast Asia: a policy perspective. *FAO Fisheries and Aquaculture Technical Paper*. No. 509. Rome, FAO. 69pp.

Hoare, T.D. 2004. *Thailand: a global studies handbook*. ABC-CLIO Inc, California, USA. 283p.

Hong, Y., Adler, R.F., Hossain, F., Curtis, S. and Huffman, G.J. 2007. A first approach to global runoff simulation using satellite rainfall estimation. *Water Resources Research*, 43(2):285-294.

Hori, H. 2000. *The Mekong: environment and development*. United Nations University Press, Tokyo, Japan. 398pp.

Hossain, M.S. and Das, N.G. 2010. GIS-based multi-criteria evaluation to land suitability modelling for giant prawn (Macrobrachium rosenbergii) farming in Companiogonj Upazila of Noakhali, Bangladesh. *Computers and Electronics in Agriculture,* 70(1): 172-186.

Howarth, R.W. and Marino, R. 2006. Nitrogen as the limiting nutrient for eutrophication in coastal marine ecosystems: evolving views over three decades. *Limnology and Oceanography*, 51 (1, part 2): 364-376.

Huggett, R. and Cheesman, J. 2002. *Topography and the environment*. Pearson Education Limited, Essex, UK. 292pp.

Huitric, M., Folke, C. and Kautsky, N. 2002. Development and government policies of the shrimp farming industry in Thailand in relation to mangrove ecosystems. *Ecological Economics*, 40(3): 441-455.

Hung, N.N., Delgado, J.M., Tri, V.K., Hung, L.M., Merz, B., Bárdossy, A. and Apel, H. 2012. Floodplain hydrology of the Mekong Delta, Vietnam. *Hydrological Processes*, 26(5): 674-686.

Hutanuwatr, K., Bolin, B., Pijawka. 2013. Vulnerability and disaster in Thailand: scale, power and collaboration in post-tsunami recovery. In: Pfeifer, K. Pfeifer, N. (eds). *Forces of nature and cultural responses*. Springer, London, pp. 69-92.

Iftekhar, M.S. and Saenger, P. 2008. Vegetation dynamics in the Bangladesh Sundarbans mangroves: a review of forest inventories. *Wetlands Ecology and Management*, 16: 291 - 312.

Islam, M.S. 2003. Perspectives of the coastal and marine fisheries of the Bay of Bengal, Bangladesh. *Ocean & Coastal Management*, 46(8): 763-796.

Islam, M.S. and Haque, M. 2004. The mangrove-based coastal and nearshore fisheries of Bangladesh: ecology, exploitation and management. *Reviews in fish biology and fisheries*, 14: 153-180.

Islam, M.S., Sarker, M.J., Yamamoto, T., Wahab, M.A. and Tanaka, M. 2004. Water and sediment quality, partial mass budget and effluent N loading in coastal brackishwater shrimp farms in Bangladesh. *Marine Pollution Bulletin*, 48(5-6): 471-485.

Ito, S. 2004. Globalization and Agrarian change: A case of freshwater prawn farming in Bangladesh. *Journal of International Development*, 16; 1003-1013.

IUCN and UNEP-WCMC .2012. The World Database on Protected Areas (WDPA) [online] UNEP-WCMC, Cambridge, UK. Available at www.protectedplanet.net Date accessed: 27/09/2011.

Jackson, J.B.C., Kirby, M.X., Berger, W.H., Bjorndal, K.A., Botsford, L.W., Bourque, B.J., Bradbury, R.H., Cooke, R., Erlandson, J., Estes, J.A., Hughes, T.P., Kidwell, S., Lange, C.B., Lenihan, H.S., Pandolfi, J.M., Peterson, C.H., Steneck, R.S., Tegner, M.J. and Warner, R.R. 2001. Historical overfishing and recent collapse of coastal ecosystems. *Science*, 293 (5530): 629-637.

Johnson, A. 2004*. Plane and Geodetic Surveying: The Management of Control networks*. Spon Press, London. 208pp.

Johnston, D., Lourey, M., Tien, D.V., Luu, T.T. and Xuan, T.T. 2002. Water quality and plankton densities in mixed shrimp-mangrove forestry systems in Vietnam. *Aquaculture Research*, 33(10): 785-798.

Johnston, D., Trong, N.V., Tien, D.V. and Xuan, T.T. 2000. Shrimp yields and harvest characteristics of mixed shrimp-mangrove forestry farms in southern Vietnam: factors affecting production. *Aquaculture*, 188(3-4): 263-284.

Kapetsky, J.M. 1994. A strategic assessment of warm-water fish farming potential in Africa. *CIFA Technical Paper, no 27*. FAO, Rome. 67pp.

Kapetsky, J.M., and Nath, S.S. 1997. A strategic assessment of the potential for freshwater fish farming in Latin America. *COPESCAL Technical Paper* N. 10. Rome, FAO. 128 pp.

Karim, M.F. and Mimura, N. 2008. Impacts of climate change and sea-level rise on cyclonic storm surge floods in Bangladesh. *Global Environmental Change*, 18(3): 490-500.

Kautsky, N., Berg, H., Folke, C., Larsson, J. and Troell, M. 1997. Ecological footprint for assessment of resource use and development limitations in shrimp and tilapia aquaculture. *Aquaculture Research*, 28: 753-766.

Kautsky, N., Rönnbäck, P., Tedengren, M. and Troell, M. 2000. Ecosystem perspectives on management of disease in shrimp pond farming. *Aquaculture,* 191(1-3): 145-161.

King, M. 2007. *Fisheries biology, assessment and management*. Fishing News Books, Oxford. 400pp.

Knisel, W.G. 1980. CREAMS: a field-scale model for chemicals, runoff and erosion from agricultural management systems*. USDA Conservation research report,* USA. 640pp.

Koh, L.P. and Ghazoul, J. 2008. Biofuels, biodiversity, and people: understanding the conflicts and finding opportunities. *Biological Conservation*, 141(10): 2450-2460.

Komori, D., Nakamura, S., Kiguchi, M., Nishijima, A., Yamazaki, D., Suzuki, S., Kawasaki, A., Oki, K. and Oki, T. 2012. Characteristics of the 2011 Chao Phraya River flood in Central Thailand. *Hydrological Research Letters*, 6: 41 - 46.

Krairapanond, N. and Atkinson, A. 1998. Watershed management in Thailand: concepts, problems and implementation. *Regulated Rivers: research and management,* 14: 485 - 498.

Kumar, D. 2011. Carp polyculture in India. In: Fotedar R. and Phillips, B. eds. *Recent advances and new species in aquaculture*. Wiley-Blackwell, West Sussex, UK. 416pp.

Kumar, M. and Cripps, S. 2012. Environmental aspects. In: Lucas, J.S. and Southgate, P.C. eds. *Aquaculture: farming aquatic animals and plants.* Second edition. Blackwell Publishing Ltd., West Sussex, UK, pp. 84-106.

Kumar, S., Spauling, S.A., Stohlgren, T.J., Hermann, K.A., Schmidt, T.S. and Bahls, L.L. 2009. Potential habitat distribution for the freshwater diatom *Didymosphenia germinata* in the continental US. *Frontiers in Ecology and the Environment*, 7: 415-420.

Le, N.X. 1994. Ca Tra (*Pangasius micromenus* Bleeker) mot so dac diem sinh hoc va sinh san nhan tao. *Tap chi thuy san*, Vol 1, pp 13-17. (In Vietnamese).

Lebel, L., Mungkung, R., Gheewala, S.H. and Lebel, P. 2010. Innovation cycles, niches and sustainability in the shrimp aquaculture industry in Thailand. *Environmental Science & Policy*, 13 (4): 291-302.

Lebel, L., Tri, N.H., Saengnoree, A., Pasong, S., Buatama, U. and Thoa, L.K. 2002. Industrial transformation and shrimp aquaculture in Thailand and Vietnam: pathways to ecological, social and economic sustainability? *Ambio,* 31(4): 311 - 323.

Lem, A. 2006. An overview of global shrimp markets and trade. In: Leung, P.S. and Engle, C.R. eds. *Shrimp culture: economics, market and trade*. Blackwell Publishing, Iowa, USA, pp. 3-10.

Leung, P.S. and Tran, L.T. 2000. Predicting shrimp disease occurrence: artificial neural networks vs. logistic regression. *Aquaculture*, 187(1-2): 35-49.

Li, Y. 2013. The voluntary-threat approach to control nonpoint source pollution under uncertainty. *Journal of Environmental Management*. 129: 69-72.

Lillesand, T., Kiefer, R.W. and Chipman, J. 2008. *Remote sensing and image interpretation.* 6th edition. John Wiley and Sons Inc, New Jersey, USA.756pp.

Little, D.C., Bush, S.R., Belton, B., Phuong, N.T., Young, J.A. and Murray, F.J. 2012. Whitefish wars: Pangasius, politics and consumer confusion in Europe. *Marine Policy*, 36(3): 738-745.

Liu, J. and Diamond, J. 2008. Revolutionizing China's environmental protection. *Science*, 319: 37-38.

Liu, J. and Li, Z. 2010. The role of exotics in Chinese inland aquaculture. In: De Silva, S.S. and Davy, F.B. eds. *Success stories in Asian aquaculture*. Springer, New York, pp. 175-188.

Liu, J.G. and Mason, P.J. 2009. *Essential image processing and GIS for remote sensing*. Wiley-Blackwell, Oxford. 443pp.

Liu, L., Zhang, Z., Zhang, W., Murray, F. and Little, D. 2012. Tilapia aquaculture in China: low market prices, other issues challenge as sector seeks sustainability. *Global Aquaculture Advocate*, March/April 2012: 20 -21.

Liu, Y., Gupta, H., Springer, E. and Wagener, T. 2008. Linking science with environmental decision making: experiences from an integrated modeling approach to sustainable water resources management. *Environmental Modelling and Software*, 23 (7): 846 - 858.

Longdill, P.C., Healy, T.R. and Black, K.P. 2008. An integrated GIS approach for sustainable aquaculture management area site selection. *Ocean & Coastal Management,* 51(8-9): 612-624.

Longley, P.A., Goodchild, M.F., Maguire, D.J. & Rhind, D.W. 2005. *Geographic Information Systems and Science*. 2nd edition. John Wiley & Sons, West Sussex, UK. 536pp.

Lucas, J.S. 2012. Introduction. In: Lucas, J.S. and Southgate, P.C. eds. *Aquaculture: farming aquatic animals and plants*. Wiley-Blackwell, Oxford, UK, pp. 1 -17.

Lufafa, A., Tenywa, M.M., Isabirye, M., Majaliwa, M.L.G. and Woomer, P.L. 2003. Prediction of soil erosion in a Lake Victoria basin catchment using a GIS-based Universal Soil Loss model. *Agricultural Systems*, 76(3): 883-894.

Ma, X., Li, Y., Zhang, M., Zheng, F. and Du, S. 2011. Assessment and analysis of non-point source nitrogen and phosphorus loads in the three forges reservoir area of Hubei province, China. *Science of the Total Environment*, 412-413: 154 - 161.

Maier, H.R., Ascough II, J.C., Wattenbach, M., Renschler, C.S., Labiosa, W.B. and Ravalico, J.K. 2008. Uncertainty in Environmental decision making: issues, challenges and future directions. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E. and Chen, S.H. eds. *Environmental modelling, software and decision support: state of the art and new perspectives*. Elsevier, Oxford, UK, pp. 69-86.

Matala, M.P., Kpundeh, M.D. and Yongming, Y. 2013. Production and marketing systems of farmed tilapia in China. *International Journal of Fisheries and Aquaculture*, 5(2): 12-18.

McBeath, J.H. and McBeath, J. 2010. Environmental *change and food security in China.* Springer Science + Business Media B.V, London. 303pp.

McClanahan, T., Allison, E.H. and Cinner, J.E. 2013. Managing fisheries for human and food security. *Fish and Fisheries*. DOI: 10.1111/faf.12045

McGregor, A. 2008. *Southeast Asian Development*. Routledge, Oxon, UK. 251pp.

McLeod, I., Pantus, F. and Preston, N. 2002. The use of a geographical information system for land-based aquaculture planning. *Aquaculture Research*, 33; 241-250.

Meaden, G. 2010. Geographical Information Systems (GIS) in Fisheries Management and Research. In: Megrey, B.A., Moksness, E. (eds) *Computers in Fisheries research*. 2nd edition. Springer, USA, pp. 93 – 120.

Merino, G., Barange, M., Blanchard, J.L., Harle, J., Holmes, R., Allen, I., Allison, E.H., Badjeck, M.C., Dulvy, N.K., Holt, J., Jennings, S., Mulloh, C. and Rodwell, L.D. 2012. Can marine fisheries and aquaculture meet fish demand from a growing human population in a changing climate? *Global Environmental Change*, 22(4): 795-806.

Merow, C., Smith, M.J. and Silander, J.A. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 36: 1-12.

Merrit, W.S., Letcher, R.A. and Jakeman, A.J. 2003. A review of erosion and sediment transport models. *Environmental Modelling and Software*, 18: 761 - 799.

Miao, W. And Yuan, Y. 2007. Development trends and future prospects for shrimp culture in Thailand. In: Leung, P., Lee, C.S. and O'Bryen, P.J. eds. *Species and system selection for sustainable aquaculture*. Blackwell Publishing, Iowa, USA, pp. 269-282.

Millet, I. and Wedley, W.C. 2002. Modelling risk and uncertainty with the analytic hierarchy process. *Journal of Multi-Criteria Decision Analysis*, 11: 97-107.

Miller, F. 2007. Seeing "water blindness": water control in agricultural intensification and environmental change in the Mekong Delta, Vietnam. In: Connell, J. and Waddell, E. eds. *Environment, Development and Change in rural Asia-Pacific, between local and global*. Routledge, Oxon, UK, 186-207pp.

Mischler, P., Kearney, M., McCarroll., J.C., Scholte, R.G.C., Vounatsou, P. and Malone, J.B. 2012. Environmental and socio-economic risk modelling for Chagas disease in Bolivia. *Geospatial health*, 6(3): s59-s66.

Mittelmark, J. and Landkammer, D. (1990) *Design and construction of diversion ponds for aquaculture.* Department of fisheries and Wildlife, University of Minnesota, USA. 24pp.

Moltz, H.L., Rast, W., Lopes, V.L. and Ventura, S.J. 2011. Use of spatial surrogates to assess the potential for non-point source pollution in large watersheds. *Lakes & Reservoirs: Research and Management*, 6: 3 - 13.

MRC. 2013. Mekong River commission for Sustainable development. [Internet]. Mekong River Commission, Vientiane, Laos. Available: http://www.mrcmekong.org/

Mulligan, M. and Wainwright, J., 2005. Modelling and model building. In: Wainwright, J. Mulligan, M. eds. *Environmental modelling: Finding simplicity in com*plexity. John Wiley and Sons Ltd, West Sussex, England. 408pp.

Munafò, M., Cecchi, G., Baiocco, F. and Mancini, L. 2005. River pollution from non-point sources: a new simplified method of assessment. *Journal of Environmental Management,* 77: 93-98.

Muňoz, J.L. Echeverría, C., Marcé, R., Riss, W., Sherman, B. and Iriarte, J.L. 2013. The combined impact of land use change and aquaculture on sediment and water quality in oligotrophic Lake Rupanco (North Patagonia, Chile, 40.8°S). *Journal of Environmental Management*, 128: 283 - 291.

Murray, F., Zhang, W., Nietes-Satapornavit, A., Tanh, L.P., Haque, M.M., Henriksson, P. and Little, D. 2011. *Report of Boundary Issues.* SEAT Project report D.2.8, University of Stirling, UK. 83pp.

Myšiak, J., Brown, J.D., Jansen, J.M.L. and Quinn, N.W.T. 2008. Environmental policy aid under uncertainty. In: Jakeman, A.J., Voinov, A.A., Rizzoli, A.E. and Chen, S.H. eds. *Environmental modelling, software and decision support: state of the art and new perspectives*. Elsevier, Oxford, UK, pp. 87-100.

NASA. 2009. *Shuttle Radar Topography Mission: The mission to map the world*. [Internet]. NASA, Washington D.C. Available from <http://www2.jpl.nasa.gov/srtm/> Date accessed: 05/09/2011.

NASA. 2011. ASTER Global Digital Elevation Map. [Internet]. NASA, Washington D.C. Available from <http://asterweb.jpl.nasa.gov/gdem.asp> Date accessed: 05/09/2011.

Nath, S.S., Bolte, J.P., Ross, L.G. and Aguilar-Manjarrez, J.A. 2000. Applications of geographical information systems (GIS) for spatial decision support in aquaculture. *Aquacultural Engineering*, 23: 233-278.

National Academy of Sciences, 2002. *Down to Earth: Geographic Information for sustainable development in Africa*. The National Academies Press, Washington D.C. 155pp.

National Park Office. 2004. *National parks in Thailand*. National Park Office, National Park, Wildlife and Plant Conservation department, Bangkok. 280pp.

Navas, J.M., Telfer, T.C. and Ross, L.G. 2011. Spatial modeling of environmental vulnerability of marine finfish aquaculture using GIS-based neuro-fuzzy techniques. *Marine Pollution Bulletin*, 62(8): 1786-1799.

Naylor, R.L., Goldburg, R.J., Primavera, J.H., Kautsky, N., Beveridge, M.C.M., Clay, J., Folke, C., Lubchenco, J. Mooney, H. and Troell, M. 2000. Effect of aquaculture on world fish supplies. *Nature,* 405: 1017-1024.

Naylor, R.L., Hardy, R.W., Bureau, D.P., Chiu, A., Elliot, M., Farrell, A.P., Forster, I., Gatlin, D.M., Goldburg, R.J., Hua, K. and Nichols, P.D. 2009. Feeding aquaculture in an era of finite resources. *Proceedings of the National Academy of Sciences of the United States of America*, 106(36): 15103-15110.

Neiland, A.E., Soley, N., Varley, J.B. and Whitmarsh, D.J. 2001. Shrimp aquaculture: economic perspectives for policy development. *Marine Policy*, 25: 265-279.

Neori, A., Chopin, T., Troell, M., Buschmann, A.H., Kraemer, G.P., Halling, C., Shpigel, M. and Yarish, C. 2004. Integrated aquaculture: rationale, evolution and state of the art emphasizing seaweed biofiltration in modern mariculture. *Aquaculture*, 231(1-4): 361-391.

Neori, A., Troell, M., Chopin, T., Yarish, C., Critchley, A., and Buschmann, A.H. 2007. The need for a balanced ecosystem approach to blue revolution aquaculture. *Environment: Science and Policy for sustainable development* , 49(3): 37-43.

New, M.B. 2002. Farming freshwater prawns: a manual for the culture of the giant river prawn (*Macrobrachium rosenbergii*). *FAO Fisheries Technical Papter 428.* FAO, Rome. 212pp.

New, M.B. and Kutty, M.N. 2010. Commercial freshwater prawn farming and enhancement around the world. In: New, M.B., Valenti, W.C., Tidwell, J.H., D'Abramo, L.R. and Kutty, M.N. eds. *Freshwater prawns biology and farming*. John Wiley and Sons Ltd, Oxford, UK, pp. 346-399.

Nhuong T.V., Luu L.T., Tu T.Q., Tam P.M. and Nguyet T.T.A. 2002. *Vietnam shrimp farming review*. Individual Partner Report for the Project: Policy Research for Sustainable Shrimp Farming in Asia. European Commission INCO-DEV Project PORESSFA No. IC4–2001-10042, CEMARE University of Portsmouth, UK, and RIA1, Bac Ninh, Vietnam. 21pp.

Nijkamp, P. and Vreeker, R. 2000. Sustainability assessment of development scenarios: methodology and application to Thailand. *Ecological Economics*, 33(1): 7 -27.

Nitivattananon, V. and Noonin, C. 2008. Thailand urban environmental management: case of environmental infrastructure and housing provision in Bangkok metropolitan region. In: Kidokoro, T., Okata, J., Matsumura, S. and Shima, N. eds. *Vulnerable cities: realities, innovations and strategies*. Springer, Japan, pp. 187-208.

Oak Ridge National Laboratory. 2008. Landscan population database 2008. [Internet] Oak Ridge National Laboratory, Tennessee, USA. Available from : <http://web.ornl.gov/sci/landscan/> Date accessed: 07/06/2011.

Oak Ridge National Laboratory. 2013. Landscan. [Internet] Oak Ridge National Laboratory, Tennessee, USA. Available from : <http://web.ornl.gov/sci/landscan/> Date accessed: 25/08/2013.

O'Neil, J.M., Davis, T.W., Burford, M.A. and Gobler, C.J. 2012. The rise of harmful cyanobacteria blooms: the potential roles of eutrophication and climate change. *Harmful Algae*, 14: 313-334.

Páez-Osuna, F. 2001. The environmental impact of shrimp aquaculture: causes, effects, and mitigating alternatives. *Environmental Management*, 28(1): 131-140.

Palang, H., Printsmann, A. and Soovali, H. 2007. Seasonality and landscapes.In: Palang, H., Soovali, H. and Printsmann, A. eds. *Seasonal landscapes*. Springer, The Netherlands, pp2-16.

Pankhurst, N.W. and Porter, M.J.R. 2003. Cold and dark or warm and light: variations of the theme of environmental control of reproduction. *Fish Physiology and Biochemistry*, 28: 385-389.

Parker, R. 2012. *Aquaculture Science*. 3rd edition. Delmar, New York, USA. 672pp.

Paul, B.G. and Vogl, C.R. 2013. Organic shrimp aquaculture for sustainable household livelihoods in Bangladesh. *Ocean & Coastal Management*, 71: 1 -12.

Paulson, D. and Zahir, S. 1995. Consequences of uncertainty in the analytical hierarchy process: a simulation approach. *European Journal of Operational Research*, 87: 45 - 56.

Peng, Z.R. and Tsou, M.H. 2003. *Internet GIS : Distributed geographic information services for the internet and wireless networks*. John Wiley & Sons, New Jersey, USA. 681pp.

Penna, A.N. and Rivers, J.S. 2013. *Natural disasters in a global environment.* John Wiley & Sons Ltd, West Sussex, UK. 340pp.

Penning-Roswell, E.C., Sultana, P. and Thompson, P.M. 2012. The "last resort"? Population movement in response to climate-related hazards in Bangladesh. *Environmental Science & Policy*, 27(1): S44-S59.

Pérez, O. 2002. *GIS-based models for optimisation of marine cage aquaculture in Tenerife, Canary Islands*. PhD thesis, University of Stirling, UK. 332pp.

Peters, M.P., Iverson, L.R., Matthews, S.N., Prasad, A.N. 2013. Wildfire hazard mapping: exploring site conditions in eastern US wildfire-urban interfaces. International Journal of Wildland Fire, 22(5): 567-578.

Phalan, B. 2009. The social and environmental impacts of bioefuels in Asia: an overview. *Applied Energy*, 86(1): S21-S29.

Phillips, S. 2006. *A brief tutorial on Maxent.* AT & T Research. Available: http://www.cs.princeton.edu/~schapire/maxent/tutorial/tutorial.doc. Date accessed: 10/06/2013.

Phillips, S.J. and Dudik, M. 2008. Modeling of species distributions with Maxent: new extensions and comprehensive evaluation. *Ecography,* 31(2): 161-175.

Phillips, S.J., Anderson, R.P. and Schapire, R.E. 2006. Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, 190: 231-259.

Phillips, S.J., Dudik, M. and Schapire, R.E. 2004. A maximum entropy approach to species distribution modeling. In: Proceedings of the 21st International Conference on Machine Learning, Banff, Canada, 4-8 July 2004. ACM Press, New York, pp. 655-662.

Phuong, N.T. and Oanh, D.T.H. 2010. Striped catfish aquaculture in Vietnam: a decade of unprecedented development. In: De Silva, S.S. and Davy, F.B. eds. *Success stories in Asian Aquaculture*. Springer Science and Business Media, London, pp. 133-150.

Pillay, T.V.R. 2004. *Aquaculture and the environment*. 2nd edition. Blackwell Publishing Ltd, Oxford. 196pp.

Piumsombun, S., Rab, M.A., Dey, M.M. and Srichantuk, N. 2005. The farming practices and economics of aquaculture in Thailand. *Aquaculture Economics and Management*, 9: 265-287.

Pomeroy, R.S., Ratner, B.D., Hall, S.J., Pimoljinda, J. and Vivekanandan, V. 2006. Coping with disaster: rehabilitating coastal livelihoods and communities. *Marine Policy*, 30(6): 786-793.

Ponce, V.M. and Hawkins, R.H. 1996. Runoff curve number: has it reached maturity? *Journal of Hydrologic Engineering*, 1 (1): 11 - 19.

Primavera, J.H. 1997. Socio-economic impacts of shrimp culture. *Aquaculture Research*, 28:815-827.

Radiarta, I.N., Satioh, S.I. and Yasui, H. 2011. Aquaculture site selection for Japanese kelp (Laminaria japonica) in southern Hokkaido, Japan, using satellite remote sensing and GIS-based models. *ICES Journal of Marine Science*, 68(4): 773-780.

Rahman, M.M., Hassan, M.Q., Islam, M.S. and Shamsad, S.Z.K.M. 2000. Environmental impact assessment on water quality deterioration caused by the decreased Ganges outflow and saline water intrusion in south-western Bangladesh. *Environmental Geology*, 40(1-2): 31 - 40.

Rakwatin, P., Sansena, T., Marjang, N. and Rungsipanich, A. 2013. Using multi-temporal remote-sensing data to estimate 2011 flood area and volume over Chao Phraya River basin, Thailand. *Remote sensing letters*, 4(3): 243 - 250

Rathmann, R., Szklo, A. And Schaeffer, R. 2010. Land use competition for production of food and liquid biofuels: an analysis of the arguments in the current debate. *Renewable Energy*, 35(1): 14-22.

Raux, P., Bailly, D. and Nhuong, T.V. 2006. Vietnamese shrimp farming at a key point in its development: a review of issues examining whether development is being carried out in a sustainable way. 107-130pp. In : Leung, P.S. & Engle, C.R. eds. *Shrimp culture: economics, market and trade.* Blackwell Publishing Ltd, Oxford, UK, pp. 107-130.

Reuter, H.I., Hengl, T., Gessler, P. and Soille, P. 2009. Chapter 4 preparation of DEMs for Geomorphometric analysis. *Developments in Soil Science*, 33: 87-120.

Rice, J.C. and Garcia, S.M. 2011. Fisheries, food security, climate change and biodiversity: characteristics of the sector and perspectives on emerging issues. *ICES Journal of Marine Science*, 68(6): 1343-1353.

Riehl, R. and Baensch, H.A. 1996. *Aquarien Atlas, Band 1.* 10th edition. Mergus Verlag GmBH, Germany. 992pp. (In German).

Rigg, J., Law, L., Tan-Mullins, M. and Grundy-Warr, C. 2005. The Indian Ocean tsunami: socio-economic impacts in Thailand. *The Geographical Journal*, 171(4): 374-379.

Rivera-Monroy, V.H., Torres, L.A., Bahamon, N., Newmark, F. and Twilley, R.R. 1999. The potential use of mangrove forests as nitrogen sinks of shrimp aquaculture pond effluents: the role of denitrification. *Journal of the World Aquaculture Society*, 30(1): 12-25.

Rodriguez-Bachiller, A. and Wood, G. 2009. Geographical Information Systems (GIS) and EIA. In: Morris, P. & Therivel, R. *Methods of Environmental Impact Assessment*. 3rd edition. Spon Press, London, pp. 434 -459.

Ross, L.G. 2000. Environmental physiology and energetics. In: Beveridge, M.C.M. and McAndrew, B.J. eds. *Tilapias: Biology and Exploitation.* Kluwer Academic Publishers, The Netherlands, pp. 89-128.

Ross, L.G., Falconer, L., Campos Mendoza, A. and Martinez Palacios, C.A. 2011. Spatial modelling for freshwater cage location in the Presa Adolfo Mateos Lopez (El Infiernillo), Michoacán, México. *Aquaculture Research*, 42(6): 797 - 807.

Ross, L.G., Handisyde, N. and Nimmo, D.C. 2009. Spatial decision support in aquaculture: the role of geographical information systems and remote sening. In: Burnell, G. and Allan, G. *New technologies in aquaculture*. Woodhead Publishing Limited, Cambridge, UK. pp. 707-749.

Ross, L.G., Telfer, T.C., Falconer, L., Soto, D. & Aguilar-Manjarrez, J., eds. 2013. Site selection and carrying capacities for inland and coastal aquaculture. FAO/Institute of Aquaculture, University of Stirling, Expert Workshop, 6–8 December 2010. Stirling, the United Kingdom of Great Britain and Northern Ireland. *FAO Fisheries and Aquaculture Proceedings No. 21*. Rome, FAO. 46 pp. Includes a CD–ROM containing the full document (282 pp.).

Roy, L.A., Davis, D.A., Saoud, I.P., Boyd, C.A., Pine, H.J. and Boyd, C.E. 2010. Shrimp culture in inland low salinity waters. *Reviews in Aquaculture*, 2(4): 191-208.

Ryther, J.H. and Dunstan, W.M. 1971. Nitrogen, phosphorus, and eutrophication in the coastal marine environment. *Science*, 171(3975):1008-1013.

Saaty, T.L. 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology*, 15: 234-281.

Saaty, T.L. and Vargas, L.G. 2012. Models, methods, concepts and applications of the analytical hierarchy process. Springer, The Netherlands. 342pp.

Sakamoto, T., Phung, C.V., Kotera, A., Nguyen, K.D. and Yokozawa, M. 2009. Analysis of rapid expansion of inland aquaculture and triple rice-cropping areas in a coastal area of the Vietnamese Mekong Delta using MODIS time-series imagery. *Landscape and Urban Planning*, 921: 34 - 46.

Salam, M.A. 2000. *The potential of geographical information system-based modelling for aquaculture development and management in south western Bangladesh*. PhD thesis, University of Stirling, UK. 318pp.

Salam, M.A., Khatun, N.A. & Ali, M.M. 2005. Carp farming potential in Barhatta Upazilla, Bangladesh: a GIS methodological perspective. *Aquaculture*, 245 (1-4): 75-87.

Samama, N. 2008. *Global Positioning: Technologies and Performance.* John Wiley & Sons Inc, New Jersey, USA. 419pp.

Santos, H., Rodrigues, L., Jones, G. and Rebelo, H. 2013. Using species distribution modelling to predict bat fatality risk at wind farms. *Biological Conservation*, 157: 178-186.

Schindler, D.W. 1978. Factors regulating phytoplankton production and standing crop in the world's freshwaters. *Limnology and oceanography*, 23: 478-486.

Sebesvari, Z., Le, H.T.T., Toan, P.V., Arnold, U. and Renaud, F.G. 2012. Agriculture and water quality in the Vietnamese Mekong Delta. In: Renaud, F.G. and Kuenzer, C. eds. *The Mekong Delta System.* Springer, The Netherlands, pp. 331-361.

Seto, K.C., Woodcock, C.E. and Kaufmann, R.K. 2004. Changes in land cover and land use in the Pearl river delta, China. In: Gutman, G., Janetos, A.C., Justice, C.O., Moran, E.F., Mustard, J.F., Rindfuss, R.R., Skole, D., Turner, B.L. and Cochrane, M.A. eds. *Land Change Science: observing, monitoring and understanding trajectories of change of the Earth's surface*. Springer, The Netherlands, pp. 227-242.

Shepherd, G. 2008. *The Ecosystem Approach: learning from experience*. IUCN, Gland, Switzerland. 111pp.

Sheppard, S.R.J. and Cizek, P. 2009. The ethics of Google Earth: crossing thresholds from spatial data to landscape visualisation. *Journal of Environmental Management,* 90 (6): 2102-2117.

Shi, P.J., Yuan, Y., Zheng, J., Wang, J.A., Ge, Y. and Qiu, G.Y. 2007. The effect of land use/cover change on surface runoff in Shenzen region, China. *Catena*, 69: 31-35.

Shih, Y.C., Chou, C.L. and Chiau, W.Y. 2009. Geographic information system applied to measuring benthic environmental impact with chemical measures on mariculture at Penghu Islet in Taiwan. *Science of the Total Environment*, 407(6): 1824-1833.

Shrestha, S., Kazama, F. and Newham, L.T.H. 2008. A framework for estimating pollutant export coefficients from long-term in-stream water quality monitoring data. Environmental Modelling & Software, 23: 182-194.

Siddique, M.A.L. and Volpe, J.P. 2009. Eco-Friendly sustainable shrimp aquaculture in Bangladesh: Minimising coastal degradation. In: Moksness, E., Dahl, E. & Støttrup, J.G. (eds). *Integrated Coastal Zone Management*. Blackwell Publishing Ltd, Oxford, UK, pp. 116-130.

Sifa, L, Chenhong, L., Dey, M., Gagalac, F. and Dunham, R. 2002. Cold tolerances of three strains of Nile tilapia, Oreochromis niloticus, in China. *Aquaculture*, 213(1-4): 123-129.

Silva, C., Ferreira, J.G., Bricker, S.B., DelValls, T.A., Martín-Díaz, M.L. and Yáñez, E. 2011. Site selection for shellfish aquaculture by means of GIS and farm-scale models, with an emphasis on data-poor environments. *Aquaculture*, 318(3-4):444-457.

Sinh, L.X. 2007. Issues related to sustainable farming of catfish (Pangasius spp.) in Vietnam. In: Leung, P., Lee, C.S. and O'Bryen, P.J. eds. *Species and system selection for sustainable aquaculture.* Blackwell Publishing, Iowa, USA, pp. 333-346.

Smith, J.L., Boyer, G.L. and Zimba, P.V. 2008. A review of cyanobacterial odorous and bioactive metabolites: impacts and management alternatives in aquaculture. *Aquaculture*, 280: 5 -20.

Smith, M.D., Roheim, C.A., Crowder, L.B., Halpern, B.S., Turnipseed, M., Anderson, J.L., Asche, F., Bourillón, Guttomsen, A.G., Khan, A., Liguori, L.A., McNevin, A., O'Connor, M.I., Squires, D., Tyedmers, P., Brownstein, C., Carden, K., Klinger, D.H., Sagarin, R., Selkoe, K.A. 2010. Sustainability and global seafood. *Science*, 327: 784-786.

Smith, V.H. and Schindler, D.W. 2009. Eutrophication science: where do we go from here? *Trends in Ecology and Evolution,* 24(4): 201-207.

Sodhi, N.S., Koh, L.P., Brook, B.W. and Ng, P.K.L. 2004. Southeast Asian biodiversity: an impending disaster. *Trends in Ecology and Evolution*, 19(12): 654 – 660.

Soltani, A. and Sinclair, T.R. 2012. *Modeling physiology of crop development, growth and yield*. CABI International, Oxford, UK. 322pp.

Soto, D., Aguilar-Manjarrez, J. and Hishamunda, N. 2008,. eds. Building an ecosystem approach to aquaculture. FAO/Universitat de les Illes Balears Expert Workshop. 7-11 May 2007, Palma de Mallorca, Spain. *FAO Fisheries and Aquaculture Proceedings. No. 14*. Rome, FAO. 2008. 221p.

Spalding, M., Kainuma, M. and Collins, L. 2010. *World atlas of mangroves.* Earthscan, London. 319pp.

Spencer, J., Frizzelle, B.G., Page, P.H. & Vogler, J.B. 2003. *Global Positioning system: a field guide for the social sciences*. Blackwell Publishing Ltd, Oxford, UK. 232pp.

Stehman, S.V. 2001. Statistical rigor and practical utility in thematic map accuracy assessment. *Photogrammetric Engineering & Remote Sensing*, 67(6): 727-734.

Stewart, M.A. and Coclanis, P.A. 2011. Introduction. In: Stewart, M.A. and Coclanis, P.A. eds. *Environmental change and agricultural sustainability in the Mekong Delta*. Springer, Netherlands, 1-3.

Subasinghe, R., Soto, D. and Jia, J. 2009. Global aquaculture and its role in sustainable development. *Reviews in aquaculture*, 1(1): 2 - 9.

Sugumaran, R. and Degroote, J. 2011. *Spatial decision support systems: principles and practices.* CRC Press, Florida, USA. 486pp.

Sulit, V.T., Aldon, A.E.T., Tendencia, I.T., Ortiz, A.M.J., Alayon, S.B. and Ledesma, A.S. 2005. *Regional technical consultation on the aquaculture of penaenus vannamei and other exotic shrimps in Southeast Asia*. SEAFDEC, Manila, Philippines,. 99pp.

Sullivan, T. 2002. *Evaluating Environmental Decision Support Tools*. Environmental and Waste Technology Division, Brookhaven National Laboratory, New York. 57pp.

Szuster, B.W. 2006. Review of shrimp farming in central Thailand. In: Leung, P.S. and Engle, C. Eds. *Shrimp culture: economics, market and trade*. Blackwell Publishing, Iowa, USA, 155-166.

Tacon, A.J. and Metian, M. 2013. Fish matters: importance of aquatic foods in human nutrition and global food supply. *Reviews in Fisheries Science*, 21(1): 22-38.

Thunjai, T., Boyd, C.E. and Boonyaratpalin, M. 2004. Bottom soil quality in tilapia ponds of different age in Thailand. *Aquaculture Research*, 35(7): 698-705.

Tingting, L. and Chuang, L. 2010. Study on extraction of crop information using time-series MODIS data in the Chao Phraya Basin of Thailand. *Advances in Space Research*, 45(6): 775-784.

Tokrisna, R. 2006. Utilization of coastal areas for shrimp farming in Southern Thailand. In: Leung, P.S. and Engle, C. Eds. *Shrimp culture: economics, market and trade.* Blackwell Publishing, Iowa, USA, pp. 143-154.

Trabucco, A., and Zomer, R.J. 2009. *Global Aridity Index (Global-Aridity) and Global Potential Evapo-Transpiration (Global-PET) Geospatial Database*. CGIAR Consortium for Spatial Information. [Internet] CGIAR-CSI, available <http://www.csi.cgiar.org> Date accessed: 24/01/2012

Tran, P., Marincioni, F., Shaw, R., Sarti, M. and An, L.V. 2008. Flood risk management in Central Viet Nam: challenges and potentials. *Natural Hazards*, 46: 119-138.

Tscharntke, T., Clough, Y., Wagner, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J. and Whitbread, A. 2012. Global food security, biodiversity conservation and the future of agriculture intensification. *Biological Conservation*, 151, 1: 53-59.

Tucker, C. and Hargreaves, J. 2012. Ponds. In: Tidwell, J.H. eds. *Aquaculture production systems.* John Wiley & Sons Inc, Oxford, UK, pp. 191-244.

Tucker, C.S. and Hargreaves, J.A. 2008. *Environmental Best Management practices for aquaculture*. Blackwell Publishing Ltd, Oxford, UK. 592pp.

Tucker, C.S., Hargreaves, J.A. & Boyd, C.E. 2008. Better management practices for freshwater pond aquaculture. In Tucker, C.S. & Hargreaves, J.A. eds. Environmental best management practices for aquaculture. Blackwell Publishing Ltd, Oxford, pp. 151-226.

U.N. 2013. *World Statistics Pocketbook, 2013 edition*. Series V, no 37, Statistical Services branch of the Statistics division, department of economic and Soical affairs of the United Nations Secretariat, New York, U.S.A. 251pp.

UN. 2008. United Nations Thailand. [Internet] United Nations, Thailand. Available: <http://www.un.or.th/thailand/geography.html> Date accessed: 12/08/2013.

USDA SCS. 1986. *Urban hydrology for small watersheds*. Technical Release 55. USDA, Washington DC. 164pp.

USGS. 2010. HydroSHEDS: Hydrological data and maps based on shuttle elevation derivatives at multiple scales. [Internet] USGS, Virginia, USA. Available: <http://hydrosheds.cr.usgs.gov/index.php> Date accessed: 30/03/2011.

USGS. 2011. HYDRO1K. [Internet] USGS, Virginia, USA. Available: <https://lta.cr.usgs.gov/HYDRO1K>. Date accessed: 19/01/2011.

USGS. 2013. Landsat missions. [Internet] Available: http://landsat.usgs.gov/ Date accessed: 12/09/2013.

Valavanis V.D. (2002) *Geographic Information Systems in Oceanography and Fisheries*. Taylor & Francis, London, UK, 209pp.

van Brakel, M.L. & Ross, L.G. 2011. Aquaculture development and scenarios of change in fish trade and market access for the poor in Cambodia. *Aquaculture Research*, 42(7): 931-942.

Veeck, G., Pannell, C.W., Smith, C.J. and Huang, Y. 2011. *China's geography: globalization and the dynamics of political, economic and social change*. second edition, Rowan & Littlefield Publishers Inc, Plymouth UK. 381pp.

Verburg, P.H., Mertz, O., Erb, K.H., Haberl, H. and Wu, W. 2013. Land system change and food security: towards multi-scale land system solutions. *Current Opinion in Environmental Sustainability*, 5(5): 494-502.

Verdegem, M.C.J. 2013. Nutrient discharge from aquaculture operations in function of system design and production environment. *Reviews in Aquaculture*, 4: 1-14.

Vincenzi, S., Caramori, G., Rossi, R. and De Leo, G.A. 2006. A GIS-based habitat suitability model for commercial yield estimation of *Tapes philippinarum in a Mediterranean coastal lagoon (Sacca di Goro, Italy). Ecological Modelling, 193(1-2): 90-104.*

Voogd, H. 1983. *Multicriteria evaluation for urban and regional planning*. Pion, London. 367pp.

Wahab, M.A., Ahmad-Al-Nahid, S., Ahmed, N., Haque, M.M. and Karim, M. 2012. Current status and prospects of farming the giant river prawn *Macrobrachium rosenbergii* (De Man) in Bangladesh. *Aquaculture Research*, 43: 970-983.

Walker, P.J. and Mohan, C.V. 2009. Viral disease emergence in shrimp aquaculture: origins, impact and the effectiveness of health management strategies. *Reviews in Aquaculture*, 1(2): 125-154.

Warren, D.L. and Seifert, S.N. 2011. Ecological niche modeling in Maxent: the importance of model complexity and the performance of model selection criteria. *Ecological applications*, 21(2): 335 - 342.

Webster, D. 2004. Bangkok. In: Gugler, J. eds. *World cities beyond the west: globalization, development and inequality*. The Press Syndicate of the University of Cambridge, Cambridge, UK. pp. 82 – 118.

Whyte, M. And Lin, ,Y.J. *Bangladesh*. Marshall Cavendish, New York, USA. 145pp

Williams, M.J. 1997. Aquaculture and sustainable food security in the developing world. In: Bardach, J.E. eds. *Sustainable aquaculture.* John Wiley and Sons Inc, Canada, pp. 15-52.

Wischmeier, W.H., and Smith, D.D. 1978. *Predicting rainfall eroision losses - a guide to conservation planning*. US. Department of Agriculture, Agriculture Handbook No. 537. 67pp.

Witten, I.H., Frank, E. and Hall, M.A., 2011. *Data mining: practical machine learning tools and techniques*. 3rd edition. Elsevier Inc, Massachusetts, USA. 629pp.

Worm, B., Hilborn, R., Baum, J.K., Branch, T.A., Collie, J.S., Costello, C., Fogarty, M.J., Fulton, E., Hutchings, J.A., Jennings, S., Jensen, O.P., Lotze, H.K., Mace, P.M., McClanahan, T.R., Mjnto, C., Palumbi, S.R., Parma, A.M, Ricard, D., Rosenberg, A.M., Watson, R. and Zeller, D. 2009. Rebuilding global fisheries. *Science*, 235: 578-585.

Wösten, J.H.M., de Willigen, P., Tri, N.H., Lien, T.V. and Smith, S.V. 2003. Nutrient dynamics in mangrove areas of the Red River Estuary in Vietnam. *Estuarine, Coastal and Shelf Science*, 57: 65-72.

Wulder, M.A., Franklin, S.E., White, J.C., Linke, J. and Magnussen, S. 2006. An accuracy assessment framework for large-area land cover classification products derived from medium-resolution satellite data. *International Journal of Remote Sensing*, 27(4): 663-683.

Wyban, J., Walsh, W.A. and Godin, D.M. 1995. Temperature effects on growth, feeding rate and feed conversion of the Pacific white shrimp (Penaeus vannamei). *Aquaculture*, 138(1-4): 267-279.

Yin, R. 1998. Forestry and the environment in China: the current situation and strategic choices. *World development*, 26(12): 2153-2167.

Yin, Z.Y., Walcott, S., Kaplan, B., Cao, J., Lin, W., Chen, M., Liu, D., Ning, Y. 2005. An analysis of the relationship between spatial patterns of water quality and urban development in Shanghai, China. *Computers, Environment and Urban Systems*, 29(2): 197-221.

Yoo, K.H. and Boyd, C.E. 1994. *Hydrology and water supply for pond aquaculture*. Chapman and Hall, New York. 483pp.

Young, J.A., Brugere, C. and Muir, J.F. 1999. Green grow the fishes-oh? Environmental attributes in marketing aquaculture products. *Aquaculture Economics and Managment*, 3(1): 7-17.

Young, R.A., Onstand, C.A., Bosch, D.D. and Anderson, W.P. 1989. AGNPS. A non-point source pollution model for evaluating agricultural watersheds. *Journal of soil and water conservation*, 44(2): 168-173.

Yu, L. and Gong, P. 2012. Google Earth as a virtual globe tool for earth science applications at global scale: progress and perspectives. *International Journal of Remote Sensing*, 33(12): 3966-3986.

Yu, W.H., Alam, M., Hassan, A., Khan, A.S., Ruane, A.C., Rosenzweig, A., Major, D.C. and Thurlow, J. 2010. *Climate change risks and food security in Bangladesh*. Earthscan, London. 185pp.

Yuan, Y., Cai, J. and Leung, P.S. 2006. An overview of China's cultured shrimp industry. In: Leung, P.S. and Engle, C. eds. Shrimp culture: economics, market and trade. Blackwell Publishing, Iowa, USA, pp. 197-222.

Zhang, H. and Huang, G.H. 2011. Assessment of non-point source pollution using a spatial multicriteria analysis approach. *Ecological Modelling*, 222: 313-321.

Zhang, W., Murray, F.J., Liu, L. and Little, D.C. 2011. *Development trends and local sustainability perceptions for the international trade in seafood farmed in China*. SEAT Deliverable report 2.1a. 59pp.

Zhao, S., Peng, C., Jiang, H., Tian, D., Lei, X. & Zhou, X. (2006) Land use change in Asia and the ecological consequences. *Ecological Research*, 21: 890 - 896.

APPENDIX A : Error/confusion matrices for the land use models

Bangladesh dry season

Ground truth file - Bangladesh_ground_truth_dry
Model - Bangladesh_land_use_dry_final

Error Matrix Analysis of BANGLADESH_GROUND_TRUTH_DRY (columns : truth) against BANGLADESH_LAND_USE_DRY_FINAL (rows : mapped)

	W	T	G	B	A	
W	94	0	2	1	0	0.0309
T	1	84	5	0	0	0.0667
G	0	3	39	0	0	0.0714
B	3	0	0	47	0	0.3649
A	2	13	0	0	99	0.1316
S	0	0	4	1	0	0.0805
M	0	0	0	0	0	0.0000
TC	0	0	0	1	1	0.0870
Total	100	100	50	50	100	
ErrorO	0.0600	0.1600	0.2200	0.0600	0.0100	

	S	M	TC	Total	ErrorC
W	0	0	0	97	0.0309
T	0	0	0	90	0.0667
G	0	0	0	42	0.0714
B	18	0	6	74	0.3649
A	0	0	0	114	0.1316
S	80	0	2	87	0.0805
M	0	50	0	50	0.0000
TC	2	0	42	46	0.0870
Total	100	50	50	600	
ErrorO	0.2000	0.0000	0.1600		0.1083

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0209 (0.0875 - 0.1292)
95% Confidence Interval = +/- 0.0249 (0.0835 - 0.1332)
99% Confidence Interval = +/- 0.0327 (0.0756 - 0.1411)

KAPPA INDEX OF AGREEMENT (KIA)

Using BANGLADESH_LAND_USE_DRY_FINAL as the reference image ...

Category	KIA
W	0.9629
T	0.9200
G	0.9221
B	0.6020
A	0.8421
S	0.9034
M	1.0000
TC	0.9051

BANGLADESH_GROUND_TRUTH_DRY

Category	KIA
W	0.9284
T	0.8118
G	0.7634
B	0.9316
A	0.9877
S	0.7661
M	1.0000
TC	0.8267

Overall Kappa = 0.8744

Bangladesh rainy season

Ground truth file - Bangladesh_ground_truth_rainy
Model - Bangladesh_land_use_rainy_final

Error Matrix Analysis of BANGLADESH_GROUND_TRUTH_RAINY (columns : truth) against BANGLADESH_LAND_USE_RAINY_FINAL (rows : mapped)

	W	T	G	B	A	
W	95	0	6	6	1	0.1204
T	0	78	3	0	17	0.2277
G	0	0	41	0	0	0.0238
B	2	0	0	44	0	0.1698
A	1	20	0	0	81	0.2059
S	1	2	0	0	1	0.0404
M	1	0	0	0	0	0.0196
TC	0	0	0	0	0	0.0000
Total	100	100	50	50	100	
ErrorO	0.0500	0.2200	0.1800	0.1200	0.1900	

	S	M	TC	Total	ErrorC
W	0	0	0	108	0.1204
T	0	0	3	101	0.2277
G	1	0	0	42	0.0238
B	4	0	3	53	0.1698
A	0	0	0	102	0.2059
S	95	0	0	99	0.0404
M	0	50	0	51	0.0196
TC	0	0	44	44	0.0000
Total	100	50	50	600	
ErrorO	0.0500	0.0000	0.1200		0.1200

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0218 (0.0982 - 0.1418)
95% Confidence Interval = +/- 0.0260 (0.0940 - 0.1460)
99% Confidence Interval = +/- 0.0342 (0.0858 - 0.1542)

KAPPA INDEX OF AGREEMENT (KIA)

Using BANGLADESH_LAND_USE_RAINY_FINAL as the reference image ...

Category	KIA
W	0.8556
T	0.7267
G	0.9740
B	0.8148
A	0.7529
S	0.9515
M	0.9786
TC	1.0000

BANGLADESH_GROUND_TRUTH_RAINY

Category	KIA
W	0.9390
T	0.7355
G	0.8065
B	0.8684
A	0.7711
S	0.9401
M	1.0000
TC	0.8705

Overall Kappa = 0.8604

China dry season

Ground truth file - China_ground_truth_dry
Model - China_land_use_dry_final

Error Matrix Analysis of CHINA_GROUND_TRUTH_DRY (columns : truth) against CHINA_LAND_USE_DRY_FINAL (rows : mapped)

	W	F	T	G	B	
W	97	0	0	0	0	0.0000
F	0	88	7	10	0	0.2479
T	1	11	86	0	0	0.2252
G	0	0	0	40	0	0.0000
B	0	0	0	0	40	0.1667
A	0	0	1	0	1	0.0471
S	2	1	6	0	7	0.2091
M	0	0	0	0	0	0.0000
TC	0	0	0	0	2	0.0435
Total	100	100	100	50	50	
ErrorO	0.0300	0.1200	0.1400	0.2000	0.2000	

	A	S	M	TC	Total	ErrorC
W	0	0	0	0	97	0.0000
F	3	9	0	0	117	0.2479
T	11	0	2	0	111	0.2252
G	0	0	0	0	40	0.0000
B	0	2	0	6	48	0.1667
A	81	2	0	0	85	0.0471
S	5	87	2	0	110	0.2091
M	0	0	46	0	46	0.0000
TC	0	0	0	44	46	0.0435
Total	100	100	50	50	700	
ErrorO	0.1900	0.1300	0.0800	0.1200		0.1300

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0209 (0.1091 - 0.1509)
95% Confidence Interval = +/- 0.0249 (0.1051 - 0.1549)
99% Confidence Interval = +/- 0.0328 (0.0972 - 0.1628)

KAPPA INDEX OF AGREEMENT (KIA)

Using CHINA_LAND_USE_DRY_FINAL as the reference image ...

Category	KIA
W	1.0000
F	0.7108
T	0.7372
G	1.0000
B	0.8205
A	0.9451
S	0.7561
M	1.0000
TC	0.9532

CHINA_GROUND_TRUTH_DRY

Category	KIA
W	0.9652
F	0.8559
T	0.8336
G	0.7879
B	0.7853
A	0.7837
S	0.8458
M	0.9144
TC	0.8716

Overall Kappa = 0.8515

China rainy season

Ground truth file - China_ground_truth_rainy
Model - China_land_use_rainy_final

Error Matrix Analysis of CHINA_GROUND_TRUTH_RAINY (columns : truth)
against CHINA_LAND_USE_RAINY_FINAL (rows : mapped)

	W	F	T	G	B	
W	95	0	0	0	4	0.0686
F	0	99	0	6	0	0.1161
T	0	0	76	0	0	0.0500
G	0	1	0	44	0	0.0833
B	3	0	0	0	44	0.2414
A	1	0	23	0	1	0.2328
S	1	0	1	0	1	0.0714
M	0	0	0	0	0	0.0000
TC	0	0	0	0	0	0.0667
Total	100	100	100	50	50	
ErrorO	0.0500	0.0100	0.2400	0.1200	0.1200	

	A	S	M	TC	Total	ErrorC
W	0	0	3	0	102	0.0686
F	7	0	0	0	112	0.1161
T	1	0	3	0	80	0.0500
G	2	1	0	0	48	0.0833
B	0	4	1	6	58	0.2414
A	89	1	1	0	116	0.2328
S	1	91	1	2	98	0.0714
M	0	0	41	0	41	0.0000
TC	0	3	0	42	45	0.0667
Total	100	100	50	50	700	
ErrorO	0.1100	0.0900	0.1800	0.1600		0.1129

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0197 (0.0932 - 0.1325)
95% Confidence Interval = +/- 0.0234 (0.0894 - 0.1363)
99% Confidence Interval = +/- 0.0309 (0.0820 - 0.1437)

KAPPA INDEX OF AGREEMENT (KIA)

Using CHINA_LAND_USE_RAINY_FINAL as the reference image ...

Category	KIA
W	0.9199
F	0.8646
T	0.9417
G	0.9103
B	0.7401
A	0.7284
S	0.9167
M	1.0000
TC	0.9282

CHINA_GROUND_TRUTH_RAINY

Category	KIA
W	0.9415
F	0.9881
T	0.7290
G	0.8712
B	0.8692
A	0.8682
S	0.8953
M	0.8088
TC	0.8290

Overall Kappa = 0.8713

Thailand dry season

Ground truth file - Thailand_ground_truth_dry
Model - Thailand_land_use_dry_final

Error Matrix Analysis of THAILAND_GROUND_TRUTH_DRY (columns : truth) against
THAILAND_LAND_USE_DRY_FINAL (rows : mapped)

	W	F	T	G	B	
W	97	0	0	1	2	0.0300
F	0	97	1	0	0	0.0102
T	1	2	69	2	5	0.1977
G	0	0	0	47	0	0.0408
B	1	0	0	0	34	0.1053
A	0	1	29	0	0	0.2581
S	0	0	0	0	5	0.0917
M	0	0	1	0	0	0.0200
TC	1	0	0	0	4	0.1087
Total	100	100	100	50	50	
ErrorO	0.0300	0.0300	0.3100	0.0600	0.3200	

	A	S	M	TC	Total	ErrorC
W	0	0	0	0	100	0.0300
F	0	0	0	0	98	0.0102
T	6	0	1	0	86	0.1977
G	2	0	0	0	49	0.0408
B	0	0	0	3	38	0.1053
A	92	1	0	1	124	0.2581
S	0	99	0	5	109	0.0917
M	0	0	49	0	50	0.0200
TC	0	0	0	41	46	0.1087
Total	100	100	50	50	700	
ErrorO	0.0800	0.0100	0.0200	0.1800		0.1071

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0192 (0.0879 - 0.1264)
95% Confidence Interval = +/- 0.0229 (0.0842 - 0.1301)
99% Confidence Interval = +/- 0.0302 (0.0770 - 0.1373)

KAPPA INDEX OF AGREEMENT (KIA)

Using THAILAND_LAND_USE_DRY_FINAL as the reference image ...

Category	KIA
W	0.9650
F	0.9881
T	0.7694
G	0.9560
B	0.8866
A	0.6989
S	0.8930
M	0.9785
TC	0.8829

THAILAND_GROUND_TRUTH_DRY

Category	KIA
W	0.9650
F	0.9651
T	0.6466
G	0.9355
B	0.6616
A	0.9028
S	0.9882
M	0.9785
TC	0.8073

Overall Kappa = 0.8777

Thailand rainy season

Ground truth file - Thailand_ground_truth_rainy
Model - Thailand_land_use_rainy_final

Error Matrix Analysis of THAILAND_GROUND_TRUTH_RAINY (columns : truth)
against THAILAND_LAND_USE_RAINY_FINAL (rows : mapped)

	W	F	T	G	B	
W	95	0	0	0	1	0.0104
F	0	99	8	0	0	0.0917
T	3	1	77	3	0	0.3000
G	0	0	0	45	1	0.0217
B	1	0	0	0	46	0.1930
A	1	0	15	1	0	0.2000
S	0	0	0	1	2	0.0412
M	0	0	0	0	0	0.0000
TC	0	0	0	0	0	0.0465
Total	100	100	100	50	50	
ErrorO	0.0500	0.0100	0.2300	0.1000	0.0800	

	A	S	M	TC	Total	ErrorC
W	0	0	0	0	96	0.0104
F	0	2	0	0	109	0.0917
T	23	0	2	1	110	0.3000
G	0	0	0	0	46	0.0217
B	0	2	0	8	57	0.1930
A	76	1	1	0	95	0.2000
S	1	93	0	0	97	0.0412
M	0	0	47	0	47	0.0000
TC	0	2	0	41	43	0.0465
Total	100	100	50	50	700	
ErrorO	0.2400	0.0700	0.0600	0.1800		0.1157

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0199 (0.0958 - 0.1356)
95% Confidence Interval = +/- 0.0237 (0.0920 - 0.1394)
99% Confidence Interval = +/- 0.0312 (0.0845 - 0.1469)

KAPPA INDEX OF AGREEMENT (KIA)

Using THAILAND_LAND_USE_RAINY_FINAL as the reference image ...

Category	KIA
W	0.9878
F	0.8930
T	0.6500
G	0.9766
B	0.7922
A	0.7667
S	0.9519
M	1.0000
TC	0.9499

THAILAND_GROUND_TRUTH_RAINY

Category	KIA
W	0.9421
F	0.9882
T	0.7271
G	0.8930
B	0.9129
A	0.7223
S	0.9187
M	0.9357
TC	0.8082

Overall Kappa = 0.8680

Vietnam dry season

Ground truth file - Vietnam_ground_truth_dry
Model - Vietnam_land_use_dry_final

Error Matrix Analysis of VIETNAM_GROUND_TRUTH_DRY (columns : truth) against VIETNAM_LAND_USE_DRY_FINAL (rows : mapped)

	W	F	T	G	B	
W	95	1	0	0	1	0.0306
F	0	47	1	0	0	0.0784
T	3	2	80	5	0	0.1753
G	0	0	0	44	0	0.0833
B	0	0	0	0	44	0.1373
A	2	0	15	0	0	0.1589
S	0	0	1	1	4	0.0882
M	0	0	0	0	0	0.0000
TC	0	0	3	0	1	0.0851
Total	100	50	100	50	50	
ErrorO	0.0500	0.0600	0.2000	0.1200	0.1200	

	A	S	M	TC	Total	ErrorC
W	1	0	0	0	98	0.0306
F	0	3	0	0	51	0.0784
T	3	3	1	0	97	0.1753
G	4	0	0	0	48	0.0833
B	0	1	0	6	51	0.1373
A	90	0	0	0	107	0.1589
S	2	93	0	1	102	0.0882
M	0	0	49	0	49	0.0000
TC	0	0	0	43	47	0.0851
Total	100	100	50	50	650	
ErrorO	0.1000	0.0700	0.0200	0.1400		0.1000

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0194 (0.0806 - 0.1194)
95% Confidence Interval = +/- 0.0231 (0.0769 - 0.1231)
99% Confidence Interval = +/- 0.0304 (0.0696 - 0.1304)

KAPPA INDEX OF AGREEMENT (KIA)

Using VIETNAM_LAND_USE_DRY_FINAL as the reference image ...

Category	KIA
W	0.9638
F	0.9150
T	0.7929
G	0.9097
B	0.8513
A	0.8122
S	0.8957
M	1.0000
TC	0.9078

VIETNAM_GROUND_TRUTH_DRY

Category	KIA
W	0.9411
F	0.9349
T	0.7649
G	0.8704
B	0.8698
A	0.8803
S	0.9170
M	0.9784
TC	0.8491

Overall Kappa = 0.8857

Vietnam rainy season

Ground truth file - Vietnam_ground_truth_rainy
Model - Vietnam_land_use_rainy_final

Error Matrix Analysis of VIETNAM_GROUND_TRUTH_RAINY (columns : truth) against VIETNAM_LAND_USE_RAINY_FINAL (rows : mapped)

	W	F	T	G	B	
W	97	0	3	6	0	0.0935
F	0	44	0	0	0	0.0435
T	2	6	86	2	1	0.2321
G	0	0	0	42	0	0.0000
B	0	0	0	0	40	0.1111
A	0	0	8	0	0	0.1010
S	1	0	0	0	5	0.0714
M	0	0	0	0	1	0.0213
TC	0	0	3	0	3	0.1481
Total	100	50	100	50	50	
ErrorO	0.0300	0.1200	0.1400	0.1600	0.2000	

	A	S	M	TC	Total	ErrorC
W	0	1	0	0	107	0.0935
F	2	0	0	0	46	0.0435
T	9	2	4	0	112	0.2321
G	0	0	0	0	42	0.0000
B	0	2	0	3	45	0.1111
A	89	2	0	0	99	0.1010
S	0	91	0	1	98	0.0714
M	0	0	46	0	47	0.0213
TC	0	2	0	46	54	0.1481
Total	100	100	50	50	650	
ErrorO	0.1100	0.0900	0.0800	0.0800		0.1062

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.0199 (0.0863 - 0.1260)
95% Confidence Interval = +/- 0.0237 (0.0825 - 0.1298)
99% Confidence Interval = +/- 0.0312 (0.0750 - 0.1373)

KAPPA INDEX OF AGREEMENT (KIA)

Using VIETNAM_LAND_USE_RAINY_FINAL as the reference image ...

Category	KIA
W	0.8895
F	0.9529
T	0.7256
G	1.0000
B	0.8796
A	0.8806
S	0.9156
M	0.9770
TC	0.8395

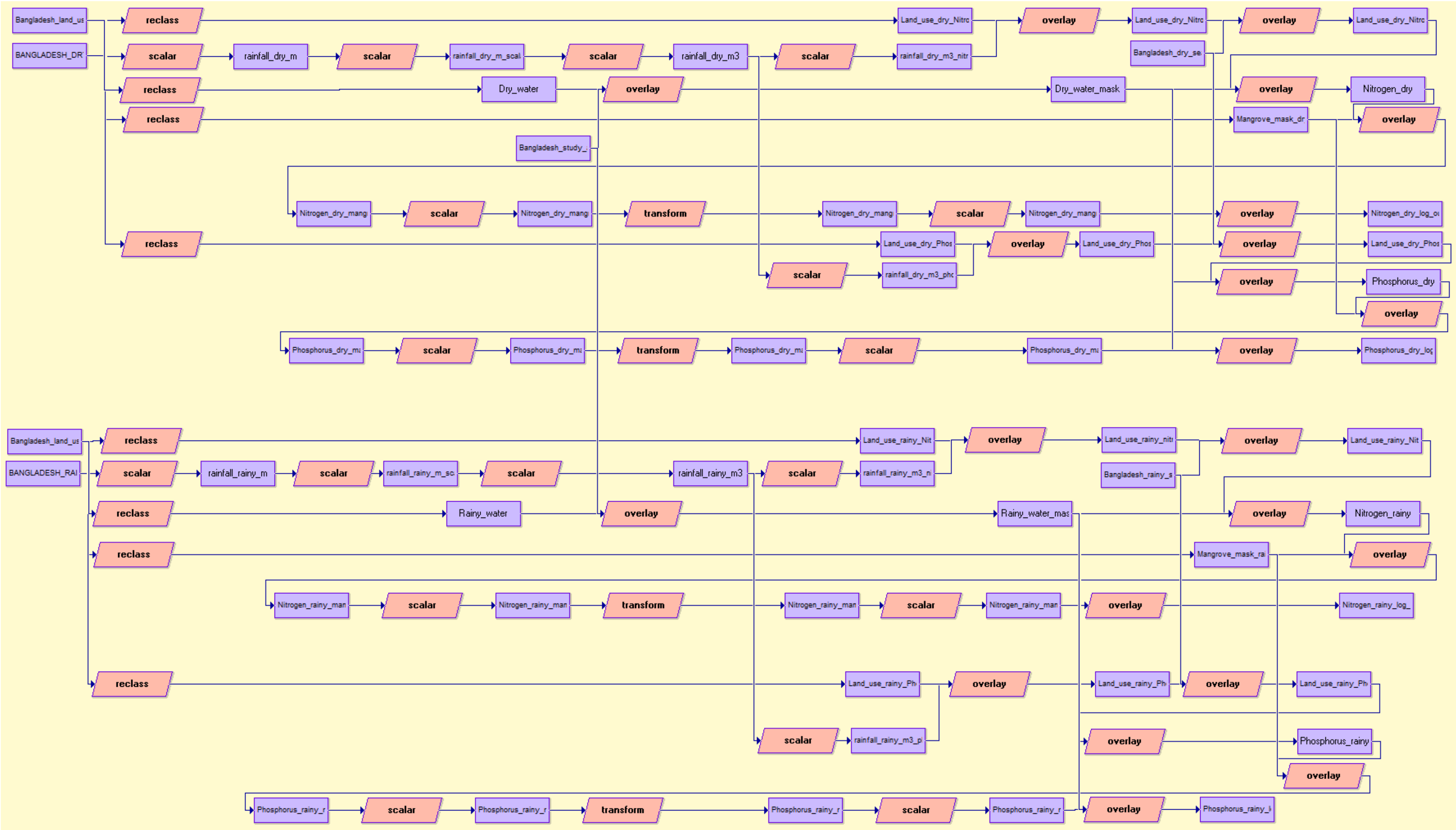
VIETNAM_GROUND_TRUTH_RAINY

Category	KIA
W	0.9641
F	0.8709
T	0.8309
G	0.8289
B	0.7851
A	0.8702
S	0.8940
M	0.9138
TC	0.9128

Overall Kappa = 0.8785

APPENDIX B : IDRISI Macro Models for the Non-point source pollution (NPSP) models

Macro model for Nutrient Generation submodel

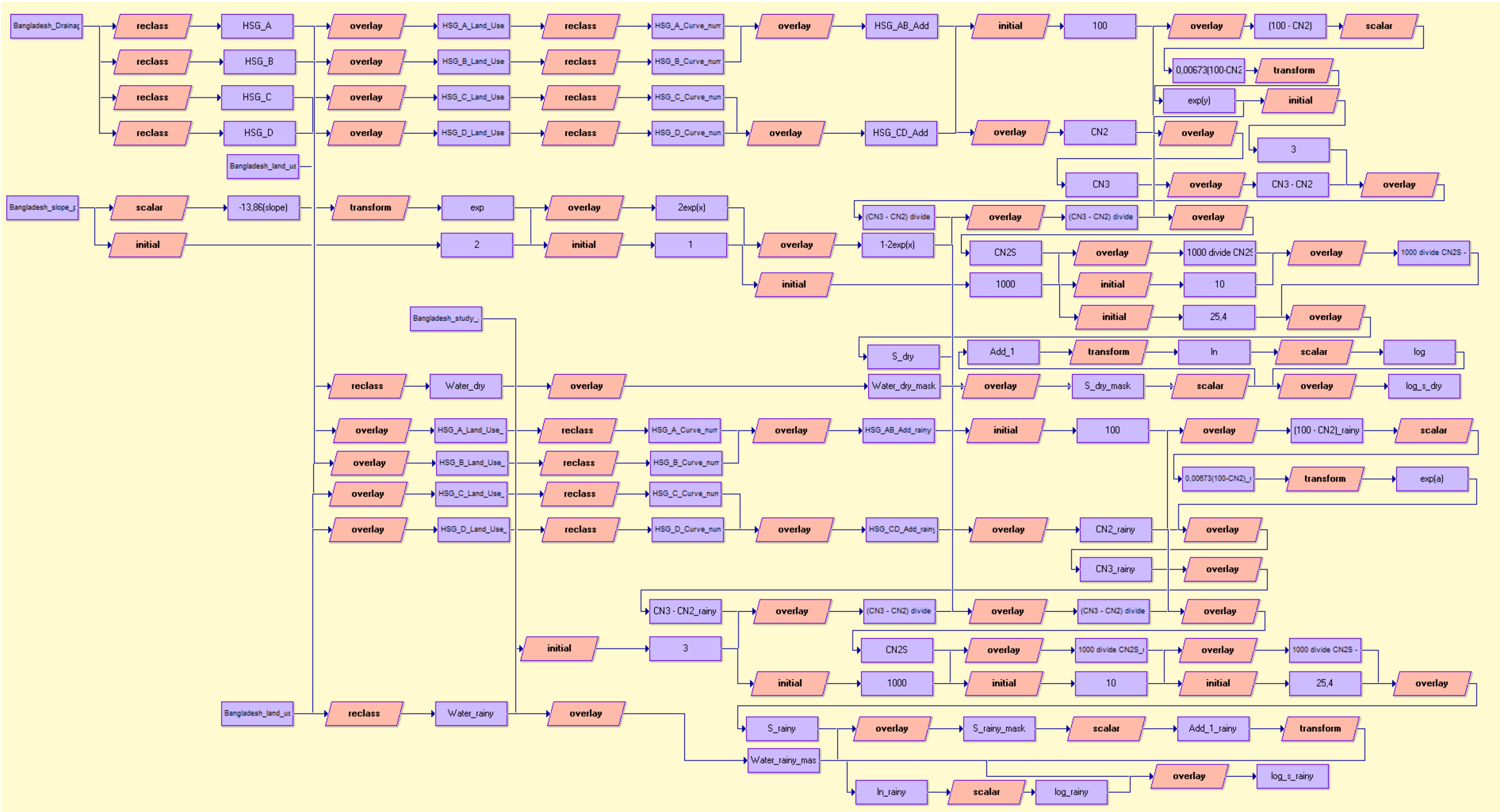


Model file: N_P Generation.imm **Submodel file**: N_P Generation.ims

Input layers required*†	.rcl files	Output*
X_Land_use_dry.rst	Gen - nitrogen.rcl	X_Submodel_generation_N_dry.rst
X_Land_use_rainy.rst	Gen - phosphorus.rcl	X_Submodel_ generation_N_rainy.rst
X_Dry_season_Y_months.rst	Mangrove_zero.rcl	X_Submodel_ generation_P_dry.rst
X_Rainy_season_Y_months.rst	Water_mask.rcl	X_Submodel_ generation_P_Rainy.rst
X_Rainfall_dry.rst		
X_Rainfall_rainy.rst		
X_Study_area.rst		

* Replace X with country name (e.g. Bangladesh)
† Replace Y with the number of months in the season (e.g. Bangladesh_dry_season_7_months)

Macro model for Runoff submodel



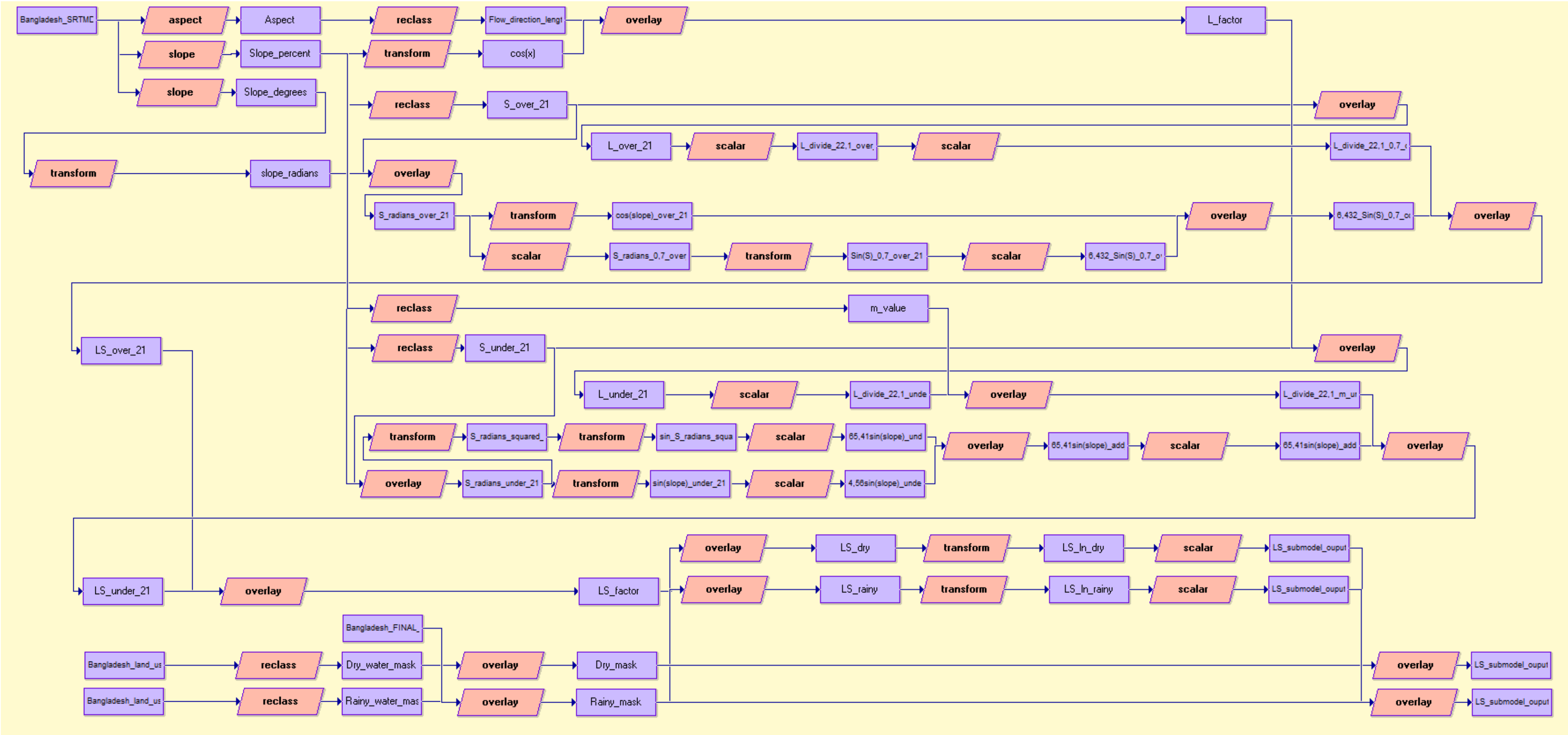
Model file: Runoff_Sub.imm

Submodel file: Runoff_sub.ims

Input layers required*	**.rcl files**	**Output***
X_Land_use_dry.rst	Curve_number_group_A.rcl	X_Submodel_runoff_dry.rst
X_Land_use_rainy.rst	Curve_number_group_B.rcl	X_Submodel_runoff_rainy.rst
X_Slope_percent.rst	Curve_number_group_C.rcl	
X_Soil_Drainage.rst	Curve_number_group_D.rcl	
X_Study_area.rst	HSG_A.rcl	
	HSG_B.rcl	
	HSG_C.rcl	
	HSG_D.rcl	
	Water_mask.rcl	

* Replace X with country name (e.g. Bangladesh)

Macro model for Transport submodel

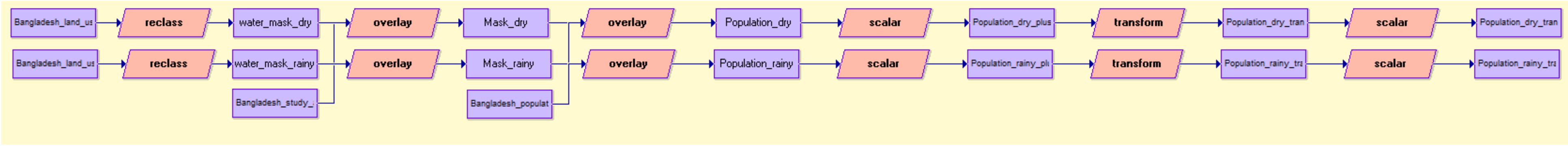


Model file: transport.imm **Submodel file**: transport.ims

Input layers required*	**.rcl files**	**Output***
X_Elevation_90m.rst	aspect.rcl	X_submodel_transport_90m_dry.rst
X_Land_use_dry_90m.rst	m_value.rcl	X_submodel_transport_90m_rainy.rst
X_Land_use_rainy_90m.rst	S_over_21.rcl	
X_Study_area _90m.rst	S_under_21.rcl	
	water_mask.rcl	

* Replace X with country name (e.g. Bangladesh)

Macro model for Population submodel

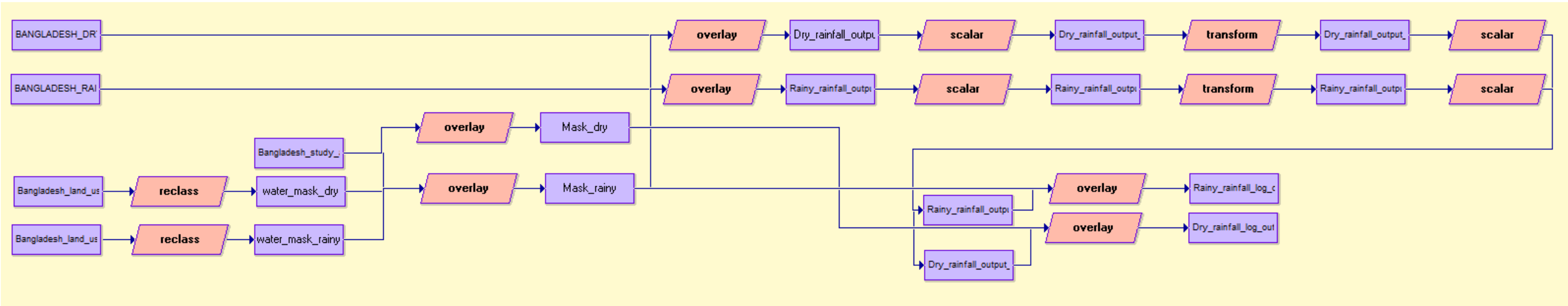


Model file: Population.imm **Submodel file**: Population.ims

Input layers required*	**.rcl files**	**Output***
X_Land_use_dry.rst	Water_mask.rcl	X_Submodel_population_dry.rst
X_Land_use_rainy.rst		X_Submodel_population_rainy.rst
X_Population.rst		
X_Study_area.rst		

* Replace X with country name (e.g. Bangladesh)

Macro model for Rainfall submodel



Model file: Rainfall.imm

Submodel file: Rainfall.ims

Input layers required*

X_Land_use_dry.rst
X_Land_use_rainy.rst
X_Rainfall_dry.rst
X_Rainfall_rainy.rst
X_Study_area.rst

.rcl files

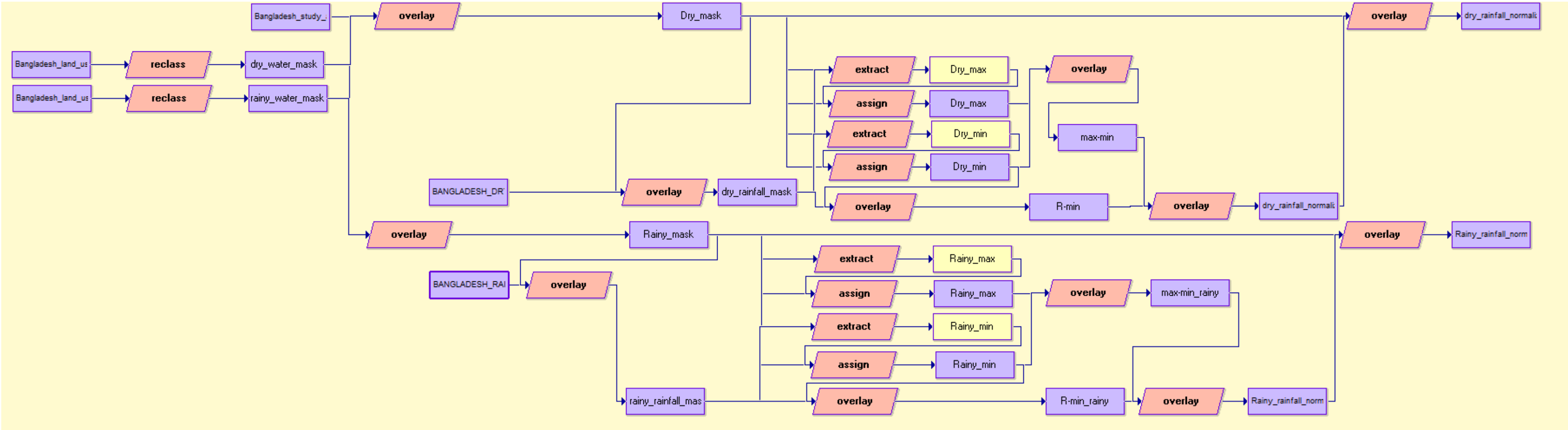
Water_mask.rcl

Output*

X_Submodel_rainfall_dry.rst
X_Submodel_rainfall_rainy.rst

* Replace X with country name (e.g. Bangladesh)

Macro model for Seasonal_one (both dry and rainy seasons)

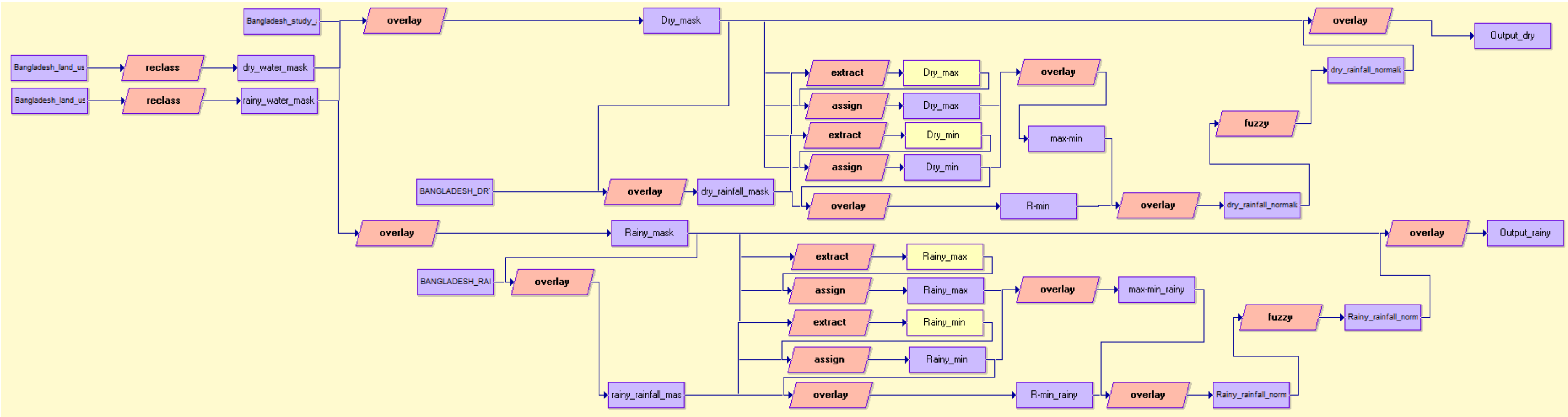


File name: seasonal_one.imm **Submodel file**: seasonal_one.ims

Input layers required*†	**.rcl files**	**Output*‡**
X_land_use_dry.rst	water_mask.rcl	X_output_seasonal_one_dry.rst
X_land_use_rainy.rst		X_output_seasonal_one_rainy.rst
X_input_dry.rst		
X_input_rainy.rst		
X_study_area.rst		

* Replace X with country name (e.g. Bangladesh)
† Replace "input" with submodel name e.g. Bangladesh_submodel_rainfall_dry
‡ Replace "output" with submodel name e.g. Bangladesh_submodel_rainfall_seasonal_individual_dry

Macro model for Rev_Sea_one (both dry and rainy seasons)



File name: rev_sea_one.imm

Submodel file: rev_sea_one.ims

Input layers required*†

X_land_use_dry.rst
X_land_use_rainy.rst
X_input_dry.rst
X_input_rainy.rst
X_study_area.rst

.rcl files

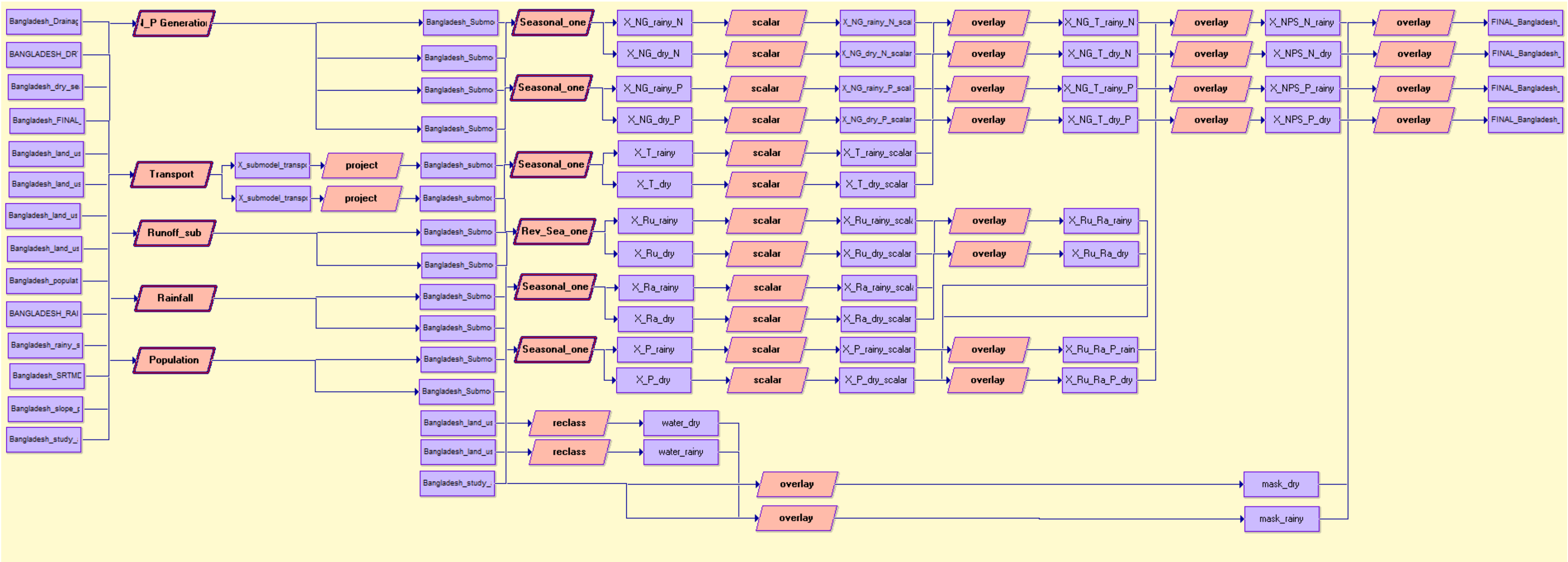
water_mask.rcl

Output*‡

X_output_rev_sea_one_dry.rst
X_output_rev_sea_one_rainy.rst

* Replace X with country name (e.g. Bangladesh)
† Replace "input" with submodel name e.g. Bangladesh_submodel_transport_dry
‡ Replace "output" with submodel name e.g. Bangladesh_submodel_transport_seasonal_individual_dry

Overall model for individual study areas (dry and rainy season)



File name: Seasonal_one_X_Final.imm*

Input layers required*	**.rcl files**	**Output**
X_Dry_season_Y_months.rst	aspect.rcl	X_NPS_N_dry.rst
X_Elevation_90m.rst	Curve_number_group_A.rcl	X_NPS_N_rainy.rst
X_Land_use_dry.rst	Curve_number_group_B.rcl	X_NPS_P_dry.rst
X_Land_use_dry_90m.rst	Curve_number_group_C.rcl	X_NPS_P_rainy.rst
X_Land_use_rainy.rst	Curve_number_group_D.rcl	
X_Land_use_rainy_90m.rst	Gen - nitrogen.rcl	
X_Population.rst	Gen - phosphorus.rcl	
X_Rainfall_dry.rst	HSG_A.rcl	
X_Rainfall_rainy.rst	HSG_B.rcl	
X_Rainy_season_Y_months.rst	HSG_C.rcl	
X_Slope_percent.rst	HSG_D.rcl	
X_Soil_Drainage.rst	m_value.rcl	
X_Study_area.rst	Mangrove_zero.rcl	
X_Study_area _90m.rst	S_over_21.rcl	
	S_under_21.rcl	
	Water_mask.rcl	

* Replace X with country name (e.g. Bangladesh)