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ABSTRACT
The School of Graduate Studies
The University of Alabama in Huntsville

Degree ______ Master of Science ______ Program ______ Earth System Science ______

Name of Candidate ______ Kel Markert

Title ______ Investigation into the effects of climate variability and land cover change on the hydrologic system of the Lower Mekong Basin

The Lower Mekong Basin is an economically and ecologically important region that experiences hydrologic hazards such as floods and droughts, which can directly affect human well-being and limit economic growth and development. To effectively develop long-term plans for addressing hydrologic hazards, the regional hydrological response to climate variability and land cover change needs to be evaluated. This research aims to investigate how climate variability, specifically variations in the precipitation regime, and land cover change will affect hydrologic parameters both spatially and temporally within the Lower Mekong Basin achieved through hydrologic modeling. This study found that the Lower Mekong Basin hydrologic system is sensitive to climate variability and less so to land cover changes. These findings will help the Lower Mekong Basin by supporting individual country policy to plan for future hydrologic changes as well as policy for the basin as a whole.

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CHAPTER I

INTRODUCTION

This chapter provides an overarching introduction to the research. First the issues involved in the theme of this research along with the motivation behind this work is introduced, followed by the research objectives, hypotheses, expected results. Lastly, the outline of the thesis is provided.

1.1 Problem statement

The Lower Mekong Basin (LMB) is an economically and ecologically important region that supports approximately 70 million people and is poised to experience significant changes to the environmental system from climate variability and human influences in the coming decades. The climate variability and change often manifest themselves into monsoon variabilities, El Niño and La Niña, and other extreme weather events - resulting in large scale frequent flooding or droughts that directly influence the well-being and economic status of the region. For example, the record breaking flood that occurred in September 2011 totaled an estimated 573,000 people affected, 185 people killed, and 76,000 hectares of cropland inundated across Cambodia, Laos, and
Vietnam [Ponnudurai, 2011]. From 2000 to 2010 the Mekong basin has reported 39 floods resulting in 1188 days of flooding, 2877 people dead, 10.8 million people displaced, and 2.65 million dollars in economic damage [Brakenridge, 2016]. On the other end of the spectrum, in 2010 Thailand experienced its worst drought in 20 years affecting 7.6 million people [Marks, 2011]. Recently, the Royal Irrigation Department of Thailand has claimed Thailand is experiencing its worst water shortage in more than a decade causing the government to invest 1.8 million dollars to mitigate the drought [Kossov, 2016]. A recent study estimated the average annual economic loss in rice production due to drought in northeast Thailand is 10 million dollars. Droughts also have significant impacts on fisheries with an average annual economic loss of 15 million dollars [MRC, 2012].

Flooding and drought events have major implications for the development of the region and therefore must be carefully monitored and mitigated. Current flood and drought prediction systems only provide information on an events with short-term lead times. These warnings are excellent for short-term planning and monitoring of the water system however are not applicable for long-term planning and development for future water resource policy [Johnston and Kummu, 2011]. Furthermore, to effectively plan for any long-term changes in the hydrology of the region, the hydrologic system as is must be fully characterized and changes over time need to be assessed.

Research by Mancosu et al. [2015] has shown that there will be a decrease in water availability worldwide, which has great implications towards food security. Particular regions are at higher risk of climate change and variability. At the regional level, there has been assessments of socioeconomic turmoil due to potential water wars
between countries [Pearse-Smith, 2012] and food security [Mainuddin et al., 2011] in developing countries, much like those in Southeast Asia. Climate variability and land cover change have been identified as major factors contributing to regional vulnerability within the Lower Mekong Basin [Fransisco, 2008]. These changes can have implications on key functions of the river such as aquatic ecosystem productivity [Kummu and Sarkkula, 2008; Lamberts, 2008], transport of sediment and nutrients [Kummu et al., 2006], freshwater supply, and disasters (i.e. flooding). The flow changes are also expected to have an impact on agriculture, including irrigation as well as more traditional agricultural practices such as recession rice [MRC, 2010]. It is therefore important to understand the possible impact climate variability and land cover change have on the hydrology of the system. Many studies to date have characterized how climate change will alter the discharge of the Mekong River [Keskinen et al., 2010; Lauri et al., 2012]. Few studies have attempted to characterize the changes to the hydrologic system as a whole or analyzed how basin development via land cover change will alter the hydrologic regime. Moreover, most analyses have focused on basins as a whole and not considered the spatial aspect of the hydrologic system and have performed their analysis on the whole basin. These approaches do not provide a complete picture of what could be occurring within the basin for effective water resource management within the region.

1.2 Research motivation and objectives

This research effort aims to provide critical information on the spatial and temporal variability of multiple hydrologic parameters within the LMB under climatic and land cover change scenarios. This research will enable decision makers to understand a variety of potential changes to the hydrologic regime in the future. The overarching
goal of the research is to answer the question: *How will climate variability and land cover change affect the spatial and temporal characteristics of the hydrologic system within the LMB?* The research question will be answered through specific objectives including:

1. Develop, calibrate and validate a land cover change model for the LMB
2. Setup, calibrate, and validate a hydrologic model for the LMB
3. Simulate land cover change for different user-defined land cover change scenarios with variable increases in forested, agricultural, and urban areas for the region
4. Develop a climatology dataset for hydrologic variables by simulating the hydrology for observed climate from 1980-2010
5. Simulate hydrologic flow for a projected climate scenario and different land cover change scenarios
6. Compare simulated projected hydrologic variables with climatology to understand changes in the system
7. Discuss these analyses in detail to provide errors and context for decision making

1.3 Hypotheses

The hypotheses of the research are based on the results of the simulations of hydrologic change. The hypotheses are summarized by the following list:

1. Climate scenarios will result in a decrease in *water/streamflow* with increased temperatures and changes in precipitation intensity and pattern
2. Climate scenarios will alter the *timing* of the hydrologic system with changes in precipitation patterns
3. Land cover change scenarios will yield increases in runoff/streamflow associated with increases in agricultural land with decreased evapotranspiration and increased surface runoff.

4. Land cover change scenarios will yield decreases in runoff/streamflow associated with increases in forest land with increased evapotranspiration and decreased surface runoff.

5. The hydrologic system will experience greater changes due to climate variability than land cover change.

1.4 Organization of the thesis

In the remaining chapters of the thesis, the basics of hydrology and land use/land cover change are addressed. Additionally, information on the area of study for this research is discussed. The methods used to address the above objectives are provided along with the results of the research.

Chapter 2 reviews relevant literature on the topics of hydrology, hydrologic modeling and what research has been completed in the region of study. Furthermore, the theory of land use/land cover change is provided with information on the principles, and current land use/land cover modeling studies.

Chapter 3 contains background information for the Lower Mekong Basin, the area of study. The distinguishing features of the basin such as the geopolitical information, climate, land use/land cover, geomorphology and hydrology are discussed. This information will provide the basis upon which the following research builds.
Chapter 4 describes the methods used to address the specific research questions and objectives. An overview of the data, land cover modeling, and hydrologic modeling methods is provided. Additionally, the validation of such methods is provided within the chapter. Lastly, the specific analyses used to quantify the changes to the hydrologic system are also addressed in Chapter 4.

Chapter 5 summarizes the results of the methods discussed in Chapter 4. Interpretation of results and plots are given as well as specific implications of the results in terms of how they can be used. Errors in the results are discussed to provide a realistic expectation of results.

Chapter 6 summarizes the entire research endeavor and address the outcomes of the research. Future directions and how the current research can be improved upon is discussed.
CHAPTER II

LITERATURE REVIEW

The following literature review provides an overview of background information needed for this thesis. A review of hydrology and land cover modeling is given. More specifically, the basic principles of hydrology, hydrologic modeling, types of hydrologic models, the state of hydrology research in the Mekong Basin, and how hydrology fits into water resource management is discussed. Additionally, the principles of land use/land cover change, the state of science, and land use/land cover change efforts in the Mekong Basin are reviewed to provide an overview of land cover modeling.

2.1 Basics of hydrology

Hydrology is broadly defined as the science that describes and predicts the occurrence, circulation, and distribution of water on the Earth and its atmosphere [Dingman, 2002]. Clark and Castellano [1992] defined hydrology as the term that treats water of the earth, their occurrence, circulation and distribution, their chemical and physical properties and their reaction with the environment including their relation to living things. The field of hydrology is motivated by the need to manage water resources
and water-related hazards. Hydrology is an interdisciplinary science that builds upon mathematics, physics, chemistry, and biology, where all of the different fields are combined to answer a fundamental question: how much water is there and where is it?

The field of hydrology has two principal foci:

1. the *global hydrologic cycle* which is the distribution and spatiotemporal variations of water in the global water system and,

2. the *land phase hydrologic cycle* defined as the movement of water on and through the earth’s land surface and the physical, chemical, and/or biological components affecting that movement.

2.1.1 Terminology

To have a complete understanding of hydrology, it is important to define the basic vocabulary of the terms and physical phenomena that provide the foundation for the field. Some common terminology that will be referred to in this text includes: hydrologic cycle, watershed, precipitation, evapotranspiration, runoff, streamflow, discharge, and storage. For a comprehensive explanation of the terms and more hydrologic terminology, see *Dingman* [2002] and *Bedient et al* [2013].

2.1.2 Basic Principles

The concept of hydrology can be related to a system, or cycle, that receives an input, stores a proportion of the quantity, and outputs the rest. The hydrological cycle is the endless circulation of water between the Earth and its atmosphere and is the most fundamental principle of hydrology. A broad representation of the hydrologic cycle is illustrated in Figure 2.1. However simple the representation is, hydrologic phenomena are
extremely complex, highly nonlinear, and exhibit a high degree of spatial and temporal variability.

![Figure 2.1 Pictorial representation of the hydrologic cycle taken from NASA [2010]](image)

The amount of water within the system is governed by the law of conservation of mass where mass is neither created nor destroyed. This law is applied to hydrology in the form of a water balance represented by equation 2.1, which implies that the amount of water coming into a system must equal the amount of water leaving the system along with the change in storage

\[ I - Q - \Delta S = 0 \]  

(2.1)

where \( I \) is the total amount of water coming into the system, \( Q \) is the amount of water leaving the system, and \( \Delta S \) is the total change in storage for the system. The concept of water balance can be applied to an individual watershed to obtain a regional water-
balance used to measure different components of the hydrologic system in a watershed by expanding the inflow and outflow parameters of equation 2.1 as in equation 2.2

\[ P + G_{in} - (Q + ET + G_{out}) = \Delta S \]  

(2.2)

where \( P \) is the total precipitation (both solid and liquid), \( G_{in} \) is the groundwater inflow, \( ET \) is the evapotranspiration, \( Q \) is the stream discharge for the watershed, \( G_{out} \) is the groundwater outflow, and \( \Delta S \) is the change in all forms of storage (both solid and liquid) within the system. The variables described in equation 2.2 are all quantities that vary with time. Thus, the concept of temporal variability is inherently linked to the system. In particular, the discharge rate at a given location is highly variable. Seasonal fluctuations in precipitation and evapotranspiration cause the inter-annual discharge to vary. Moreover, year-to-year variability in weather systems alter the annual mean discharge which reflect the occurrence of floods and droughts. As discharge is dependent on climatic variables such as precipitation, changes in the climate have long term effects on discharge and water availability which in turn have implications for water resource management.

It is not possible to measure all of the variables that are required at specific locations to understand a hydrological system for scientific studies or resource management. Therefore, modeling of hydrological variables becomes one of the most important aspects in the field of hydrology to estimate parameters of the hydrologic cycle. The ultimate aim of predictions, using models, is to assist in decision-making in hydrological problems, such as flood protection and water resources planning.
2.1.3 Hydrologic Modeling

Much of the current research focuses on the application of models to estimate hydrologic variables and their response to specific phenomena such as climate variability. According to Wheater [2008], a model is a simplified representation of a real world system. Models for hydrological studies are mainly used for predicting the system’s behavior and understanding various hydrological processes. The essential function of a simulation model is that it produces an output or series of outputs in response to specific inputs. The two important inputs required for all models are rainfall data and drainage area. Along with these, watershed characteristics like soil properties, vegetation cover, watershed topography, and soil moisture content are also considered.

2.1.4 Type of Hydrologic Models

Hydrologic models can be classified based on the representation of physical processes, space, time, or randomness. The classification of hydrologic models centered on physical process is based on the input and parameters needed for the model and the extent of physical principles represented within the model. Another method for classifying models includes the spatial representation of the basin either modeling the basin as whole where spatial variability is disregarded or by dividing the basin into spatially explicit sub-regions. Further classifications focus on whether randomness is incorporated into the model and if time is represented within the model. Figure 2.2 represents the classifications of the different hydrologic models.
2.1.5 Examples of Hydrologic Models

A physically based hydrologic model is a model that mathematically idealizes the physical processes of hydrology. A physical model is used in this study as the parameters and equations have physical representation and have been developed to address hydrologic response to climate change and land cover change [Paniconi and Putti, 2015]. Two examples are given of commonly used, physically based hydrologic models to compare how each represents the hydrologic system.

2.1.5.1 SWAT Model

The Soil Water Assessment Tool (SWAT) model is an intricate physically based distributed model that was specifically designed to test and forecast the water and sediment transport with a particular focus on agriculture in ungauged systems [Zhang, et al., 2007]. The model breaks the entire catchment into sub-catchments which are further
divided into hydrologic response units (HRU), land use, vegetation, and soil characteristics. Daily precipitation, minimum and maximum air temperature, solar radiation, relative humidity, and wind speed are all meteorological inputs into the model use to drive the water and sediment transport. The model uses the Penman Monteith [Monteith, 1965], Priestly-Taylor [Priestly & Taylor, 1972], and Hargreaves [Hargreaves et al., 1985] methods for estimating evapotranspiration. SWAT also implements the runoff curve number [USDA, 1986], an empirical parameter based on land cover, to estimate surface runoff. SWAT simulates ground water movement as aquifers, where a shallow aquifer contributes to a river channel of the sub-basin and a deep aquifer is assumed to contribute flow outside of the watershed [Arnold et al., 1993]. Manning’s equation is used to define the rate and velocity of flow during the routing process. The water is routed using the variable storage method or Muskingum river routing method, both of which are variations of the kinematic wave model (for more information on the kinematic wave model, see Chow et al. [1988]).

2.1.5.2 VIC model

The Variable Infiltration Capacity (VIC) model is a semi-distributed, grid based hydrology model which uses both water and energy balance equations. The VIC model was developed specifically to simulate land surface hydrologic water and energy fluxes for integration into general circulation models [Liang et al., 1994]. Processes such as infiltration, runoff, and base flow are based on empirical relations. Inputs into the model include precipitation; minimum and maximum daily temperature, and wind speed and land cover. The model characterizes the subsurface into multiple soil layers and allows for sub-grid spatial representation of land cover. Evapotranspiration is represented in the
model as the sum of canopy, vegetation, and bare soil components, each simulated separately using the Penman-Monteith formulation [Monteith, 1965]. Surface runoff is simulated using the Xinanjiang model described in detail by Wood et al. [1992]. The estimation of subsurface flow (i.e. baseflow) is computed using the Arno model [Francini and Pacciani, 1991], which is only applied to the lowest soil layer. The VIC model was not developed with a flow routing component, however, a routing model was later developed by Lohmann et al. [1996a,b] specifically for the VIC model, which applies a unit hydrograph approach [Sherman, 1932] in the form of a linearized Saint-Venant equation [Mesa and Mifflin, 1986; Fread, 1993]. Currently, VIC is applied to a number of river basins study to climate and land cover change effects on the hydrology of a study area [Gayathri et al., 2015].

2.1.6 State of Hydrologic Studies in the Mekong Basin

The initial development of hydrological models and studies for the Mekong Basin was driven by two related goals: to accurately predict flooding to mitigate the human and economic cost of large floods; and to promote development within the region. In particular, the focus of development was on hydropower, irrigation, and flood control [Johnston and Kummu, 2011]. The only operational basin-wide modeling program is MRC’s flood forecasting program. The program has been in operation for 40 years and provides 5-day flood forecasting and flow forecasts along the Mekong mainstream channel which is updated daily during the wet season; and 7-day river monitoring during the dry season, updated weekly. The MRC has implemented the SWAT model to simulate the streamflow for the upper catchment in this framework [Rossi et al. 2009] along with a hydrodynamic models for modeling the flood plain. To date, various
hydrological studies for the Mekong basin have been conducted at different scales to address specific questions regarding the hydrology of the region. For example, Nijssen et al. [2001] evaluated climate effects on the streamflow of the Mekong Basin in context of global watersheds. Additionally, more targeted studies into the effects of climate change on the Mekong Basin have been conducted [Eastham et al. 2008; Prathumratana et al. 2008; Kingston et al., 2011; Lauri et al. 2012] concluding that streamflow is highly dependent on changes in precipitation. Further studies into the hydrology of the Mekong Basin using the VIC model include an investigation into agricultural irrigation effects onto water and energy balances [Haddeland et al. 2006], irrigation effects on water withdraws and surface energy [Tatsumi and Yamashiki, 2015], and land cover influences on soil moisture and surface runoff [Costa-Cabral et al., 2008].

Only a limited number studies focus on land cover effects on hydrologic parameters within the Mekong Basin (e.g. Costa-Cabral et al. [2008]) and how the hydrologic regime will vary with future land cover projections. Other studies have been conducted on the effects of land cover change outside of the Mekong Basin by coupling land cover change models with hydrologic models. For example, Nagaraj & Yaragal [2008] used the Conversion of Land Use and its Effects at a Small regional extent (CLUE-S) model to investigate the impacts of development scenarios on a watershed. Additionally, Wijesekara et al. [2012] coupled a cellular automata model with the MIKE-SHE/MIKE 11 hydrologic model to assess the impact of potential land use changes over next 20 years on the hydrologic process. The integration of land cover change models provide a comprehensive picture of the watershed by incorporating the dominant land use transitions and their impact on the land phase of the hydrologic processes, thus improving
the study over the use of a single scenario such as an increase in deforestation or afforestation [Dwarakish and Ganasri, 2015]

2.1.7 Hydrology in the context of Water Resource Management

To large extent, the field of hydrology has stemmed from the need to solve practical water resource management problems. Water resource management is the process by which governments, businesses and/or individuals reach and implement decisions that are intended to address the future quantity and/or quality of water for societal benefit [Dingman, 2002]. The process at which water resource management is initiated is when a government entity, company, or group of citizens perceives one or more uses of water would benefit from policy change. The management process can be mapped to six specific steps:

1. Establish specific goals for current planning process with consistency to overall goals,
2. Asses resource capabilities and conditions if no action is taken,
3. Frame alternative plans to accomplish objective,
4. Evaluate plans economic cost and its ability to achieve goal,
5. Select best plan (no-action or alternative plan) to implement,
6. Implement decisions.

Hydrologic analyses fit within steps 2-4. The analyses are involved by projecting a scenario of no-action, or baseline scenario, and then used to project alternative plans. The alternative plans are evaluated to understand the beneficial or adverse effects of the alternative plans.
The hydrologic analysis for water resource management can be grouped into four classes, assessment of present and future: (1) supply of water, (2) water quality, (3) flood frequency, and (4) drought frequency. The assessments of flood and drought frequency can loosely be grouped into the assessment of water supply, where floods and droughts are intrinsically linked to the available amount of water in a system. For the purpose of this study, the focus will be on assessing the present and future supply of water with minimal context concerning floods and droughts.

2.2 Land Use/Land Cover Change

It is vital for any managerial entity to have adequate information on many complex interrelated aspects of its activities or environment in order to make informed decisions. Land Use/Land Cover (LULC) is an example of a type of information needed for effective management of governments and decision makers at a local to global scale. This information can document how the land is being used (i.e. residential land, protected area, etc.) or what is the dominant feature covering an area of land (i.e. forest, water, etc.). The focus is to map where LULC types are within a landscape, and thus, a land manager is able to understand the location and quantity of specific resources. Moreover, monitoring past LULC change trends can help to understand the arrangement of present LULC and even predict future LULC.

2.2.1 Principles

Land use can be defined as the purpose associated with a given land parcel that can include raising cattle, recreation, or urban living, among other categories. The theory of land use stems from the basic need of land to supply good for economic activities of a
specific location. For example, a market area relies on agricultural goods to supply food to the people, thus the surrounding land must consist of agricultural land driven by the need of the market. The spatial structure of the agriculture and natural environment around a given market center is governed by economic rent. Economic rent is the measure of advantage one parcel of land has over another [Lloyd and Dicken, 1972]. This theory implies that the different areas of land have different values and that value is expressed in either higher or lower returns. In reality, the causes of such difference are much more complex, however, in a simple model of the land, location to the economic center is a key factor making economic rent and location rent analogous. Location rent is the measure of advantage for a land parcel based on location and return on investment from that location Lloyd and Dicken, 1972]. Simply put, a farmer can sell more crops if he is closer to the market center because he will be able to transport more and the crops will not have the opportunity to spoil. The concept of location rent becomes more complex in the event of multiple crops. Each crop will have a different function of location rent relative to a market center leading to different zones being used for different crops. Each zone accommodates the land use with the highest location rent. As shown in Figure 2.3 crop1 has a higher location rent closer to the market making it the land use type for that zone. As the distance from the market increases crop 2 and then subsequently crop 3 have higher location rents making them the land use type.
As noted earlier, location rent in the real world is complex, being influenced by various driving forces, which can be biophysical or anthropogenic in nature. Biophysical forces constitute the natural environment that influences what type of land is where, such as elevation or weather patterns. Anthropogenic forces are influences brought upon the system by humans such as policy or economic demand at either a local or global scale. These drivers can be used to estimate land use at specific locations for use in land management.

Since the advent of satellite imagery, numerous efforts have been undertaken to map the land use and land cover of the Earth’s surface through observations. Land use cannot be determined from satellite or aerial imagery, thus land cover, the physical,
chemical, or biological categorization of the Earth’s surface, is used as a proxy for land use. Land cover maps provide information to help managers best understand the current landscape and see change over time through the use of multiple maps. Land cover maps from different years are used to analyze change over time. This method is commonly used to inform managers how past changes in land cover affected a system for insight into present and future decisions. In efforts to better understand how policy changes or changes to the natural environment affect the natural landscape, studies use LULC change models and to analyze changes to the landscape through time [Agarwal et al., 2001].

2.2.2 State of the Science

Land use change is driven by interaction in space and time between humans and the environment that can be captured by computer simulation models [Veldkamp and Verburg, 2004]. LULC change models can be categorized in multiple ways: by the subject matter of the models, by the modeling techniques or methods used (from simple regression to advanced dynamic programming), or by the applications of the models. A large factor in LULC change models is the human decision making process, which can be classified into levels of complexity ranging from no human decision making - only biophysical variables in the model to multiple types of agents with multiple types of decisions at different scales [Agarwal et al., 2001]. An example of a land cover model using statistical methods with limited human decision making used general additive models and geostatistics to find areas that will most likely be converted to forests [Brown et al., 2002]. Another example of a LULC change model with limited human decision making used a cellular automata approach to identify areas of urban sprawl [Jantz et al.,
Further studies using cellular automata approaches have incorporated socioeconomic data to add a human component to the land cover change [Yang et al., 2014]. Other studies have used a common approach based on suitability maps using either statistical or heuristic modeling methods to find areas best suited for LULC change [Verburg et al., 2002; Rutherford et al., 2007]. In a study completed by Estes et al. [2010] a suitability map was used to find optimal areas for development while anthropogenic factors such as population, transportation, and employment were used to estimate demand for a particular LULC class. Currently, many studies have focused on the use of agent-based modeling to incorporate human decision making in a bottom-up modeling approach [Agarwal et al., 2001]. An example of such studies used agent-based models for land use changes in agricultural systems in Argentina [Bert et al., 2011]. Using an agent-based modeling approach does allow for human interactions to be represented in the model, however, these models are often complex and difficult to implement without expert knowledge.

2.2.3 Land use/Land cover Change in the Mekong Basin

Southeast Asia has experienced major changes in land use and land cover over the last two decades [Fox & Vogler 2005]. All of the countries that contribute to the Mekong Basin, excluding Myanmar, have recently had major economic reforms, resulting in a shift from subsistence farming to market-based agricultural production [Rigg 2006]. Other driving forces contributing to LULC change include: demographic shifts (population growth), agricultural expansion based on market demand, institutional and policy changes, poverty, and small land holdings [ADB, 2000]. Due to the demand, changes in LULC, development in the Mekong Basin, and the importance of LULC for
ecosystem services, many studies have focused on mapping and monitoring LULC in the region.

A particular focus of mapping LULC in the Mekong Basin has been on creating regional land cover maps and mapping agriculture lands. In a study completed by Perera et al. [2010], MODIS data were used to create a land cover map for 2008 with a regional land cover scheme. Another regional land cover mapping study by Leinenkugel et al. [2014] used MODIS data and phenological information to create a regional land cover map for the Mekong Basin with detailed crop information [Leinenkugel et al., 2013]. More focus has been placed simply on mapping agriculture land, most specifically rice. Landsat data have been used widely to map rice paddy areas [Kontgis et al., 2015] as well as synthetic aperture radar data within the Mekong Basin [Nguyen et al., 2015]. Other studies have focused on not only mapping but characterizing the LULC change dynamics [Tran et al., 2015] however these studies have focused on past changes. To the best of knowledge, no studies have attempted to model future land cover in the Mekong Basin.
CHAPTER III

STUDY AREA

This chapter describes the area of study, the Lower Mekong Basin (LMB), including its climate, land use/land cover, geomorphology, and hydrology. The purpose of this chapter is to describe the biophysical conditions of the LMB and its current environmental state.

3.1 The Lower Mekong Basin

The LMB is a water basin located in Southeast Asia that is part of the larger Mekong basin which spans six countries. The main channel of the basin, the Mekong River, is approximately 4,735 km in length and is the twelfth longest river in the world. The Lower Mekong portion of the river accounts for 57% of the total channel length, totaling approximately 2,700 km. The river originates on the Tibetan Plateau in China and flows down through southern Vietnam, discharging about 475 billion m$^3$ of water per year into the South China Sea [van Zalinge, et al., 2004]. The Mekong River Basin has a population of approximately 70 million people and is projected to have a population increase of 60% into 2050 [Pech and Sunada, 2008]. Figure 3.1 displays the geographic
location of the LMB with respect to the countries in Southeast Asia; Table 3.1 tabulates the areal distribution of the LMB for each of the countries within the basin.

**Table 3.1** Percent distribution of countries within the LMB by total area of country and total area of the LMB

<table>
<thead>
<tr>
<th>Country</th>
<th>% Area of Country</th>
<th>% Area of LMB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cambodia</td>
<td>85.9</td>
<td>24.9</td>
</tr>
<tr>
<td>Laos</td>
<td>89.3</td>
<td>32.8</td>
</tr>
<tr>
<td>Myanmar</td>
<td>1.7</td>
<td>1.8</td>
</tr>
<tr>
<td>Thailand</td>
<td>36.4</td>
<td>30.0</td>
</tr>
<tr>
<td>Vietnam</td>
<td>19.9</td>
<td>10.4</td>
</tr>
</tbody>
</table>

**Figure 3.1** Geopolitical map of the LMB displaying national capitals and cities with a population of greater than 50,000 people, including Mukdahan on the border of Thailand and Laos
The LMB has a great economic importance; it is one of the largest exporter of rice in the world along with supporting the largest inland fisheries in the world; both of which bring significant amounts of trade to the region. Thailand and Vietnam are the number one and two, respectively, largest exporters of rice in the world [Sakamoto et al., 2006] estimated to be a total of about US$ 703.68 million from 2000-2004 [Cong Thanh and Singh, 2006]. In addition to farming, fishing is one of the main sources of economic livelihoods in the LMB, with one source reporting portions of the Lower Mekong River averaging 41,740 tons/year of fish and fish products (approximately US$28 million based on per capita consumption of all freshwater fish and other aquatic animal products)[Matsui, et al., 2006; van Zalinge, et al., 2003] Another source conservatively estimates that a floodplain 45 km north of Phnom Penh, Cambodia produces 222-260 kg-ha\(^{-1}\)-year\(^{-1}\) of harvested fish, a large amount, though typical for this region [Poulsen et al., 2002]. The economy is largely driven by the natural system of the basin and rivers as natural phenomena, such as flooding, are vital for the ecological services provided within the region. The Mekong River Basin not only supports a substantial human population, but also over 500 species of fish with many more land vertebrates. This figure places it within the top three rivers systems in the world in terms of fish biodiversity and highlights its importance as an ecologically and economically important river system [Dudgeon, 2000]. The economic and ecological importance of the region create a compelling argument to monitor and manage the LMB environment for regional economic benefit but for the global economy and biodiversity.
3.2 Climate

The LMB climate is classified as a tropical savanna climate and tropical monsoon climate based on the Köppen climate classification [Peel et al., 2007]. The climate is characterized as having monthly mean temperatures greater than 18° Celsius with distinct wet and dry seasons. The wet season is driven by the southwest monsoon from May to October accounting for more than 80% of the annual rainfall in the region [Kite, 2001], driving the natural processes within the basin such as fish migration, fish spawning, and flooding. The temperatures in the region typically range from 15 to 35 °C, however, temperatures outside of this range have been recorded. The annual precipitation for the region is anywhere from 0.5 – 4.0 meters annually. Figure 3.2 displays the seasonality of monthly average precipitation and temperatures for Mukdahan, Thailand (location shown in Figure 3.1). The spatial distribution of annual precipitation, maximum annual temperature, and minimum annual temperature are displayed in Figure 3.3.

Climate variability plays an important role in the LMB. Climate variability in the form of short effects such as the El Niño Southern Oscillation (ENSO) and the Madden Julian Oscillation (MJO) along with long term variability can enforce change on the natural system of the region. For example, the ENSO, and its associated warm period, results in below average precipitation and river discharge whereas cold periods result in above average precipitation and river discharge [Raesenen & Kummu, 2013]. These short-term changes affect the pattern and intensity of precipitation which in turn alter the timing, location, and extent of flooding within the region. Studies into the effects of long term global climate variability have also been conducted and found that the Mekong Basin streamflow will decrease due to climate change [Nijssen et al., 2001a].
Figure 3.2 Climate graph for Mukdahan, Thailand. Monthly average data are from 1981-2010. Data: Thai Meteorological Department [2016]

Figure 3.3 Maps of annual precipitation and minimum and maximum temperature for the LMB. Data: Hijmans et al. [2005]
3.3 Land Use/Land Cover

Particular drivers in the LMB, such as population, agricultural demand, and policies, have shaped the LULC to what is needed for economic prosperity. The land cover of the LMB for 2011 is shown in Figure 3.4 where large expanses of agricultural land can be seen in orange within the basin. Furthermore, fragmented forested areas can be identified near the river system, a pattern which has implications for precipitation runoff for certain areas. The effects of terrain can also be seen in land cover; the mountain range in the east and higher elevations in general are forested lands and the plains area in the west is where most of the agricultural lands are located.

Figure 3.4 Land cover map for 2011 for the LMB. Data: LPDAAC [2016]
Human population growth is linked to deforestation in the LMB through increasing demand for agricultural land, natural resources, and urbanization [Moore et al., 2011]. It is important to monitor land cover changes as it plays a vital role in the local and regional environmental changes. The changes affect the earth-atmosphere interactions within the regional which can consequently affect biodiversity and climate change [Fonji and Taff, 2014].

3.4 Geomorphology

The Mekong Basin can be segmented into the upper and lower portions by the elevation and river characteristics down the basin [Carling, 2009]. Figure 3.5 illustrates the latitudinal profile of the entire Mekong Basin along with segmentation of the basin into the upper and lower stretches. The upper basin has steep, narrow v-shaped valleys and large elevation changes primarily formed from the Tibetan Plateau. The change in elevation in the Mekong Basin (about 4500m elevation change in upper reach alone [Carling, 2009]) makes it an optimal location for hydropower with 261 listed hydropower projects [King et al. 2007] which consequently have implications for the basin downstream [Ziv et al., 2012].
Figure 3.5 Longitudinal profile of the entire Mekong Basin

The LMB’s complex terrain is shown in Figure 3.6; the plains in Thailand on the western side of the basin and the natural mountain range border on the eastern side of the basin can be easily distinguished. The terrain of the basin is linked to the other biophysical parameters of the basin. The spatial characteristics of elevation influence climate, which in turn influences land cover, ecology, and population. Additionally, the elevation slope affects natural land cover and the growth of human populations. Ultimately terrain is the one of the greatest natural driving force within the basin.
3.5 Hydrology

The Mekong River has a catchment area of approximately 800,000 km\(^2\) with hydrology characterized by a large mean annual discharge concentrated in a regular wet season peak. The discharge volume of the wet season peak at the China border is 65 km\(^3\) that increases to 350 km\(^3\) at the Cambodian floodplains [Adamson et al., 2009]. Figure 3.7 displays the mean monthly hydrograph for the Mekong River at Mukdahan, Thailand (16.5426° N, 104.7021° E) from 1960-2004. An easy distinction can be seen between the dry and wet season which is driven by precipitation; however, a large portion of the discharge during the dry season was found to be produced by snowmelt [Cook et al., 2012]. The onset and duration of the seasons is nearly identical for upstream (Vientiane)
and downstream (Stung Treng) gauging stations (see Figure 4.1 for gauge location) despite the upstream portion being dominated by flows from the Tibetan Plateau and the downstream portion being fed by runoff from the lower basin [Adamson et al., 2009].

**Figure 3.7** Hydrograph for the Mukdahan gauging station showing the wet and dry seasons along with the transition periods. Data is from 1960-2004. Data: MRC [2011b]
CHAPTER IV

DATA AND METHODS

The focus of this chapter is on the methods used to model and analyze the simulated hydrologic parameters with a number of different inputs including projected climate data and land cover change scenarios. A description of the data, models and methodology used in this analysis is explained. This includes the development and validation of a land cover change model and calibration and validation of a hydrologic model for the LMB. The data from these two models is used to analyze changes in the quantity and seasonality of streamflow as well as the sensitivity and trends of the hydrologic system spatially within the LMB.

4.1 Introduction

Computer based modeling studies can save time and money because of their ability to perform long-term simulations for a variety of applications. Moreover, computer based modeling studies allow for changes to systems to be studied under a variety of scenarios. Models, however, rely on assumptions and in order to use model outputs for tasks ranging from regulation to research, models should be scientifically
sound, robust, and defensible [U.S. EPA, 2002]. It is equally important to outline data inputs, model assumptions, and any associated errors that could arise from the modeling.

This chapter provides a detailed description of the data and methods used in the modeling and analysis. First, all data used as inputs in the study are summarized with an emphasis on understanding errors that may propagate into model output results. Next, the models used in the study and their setup is described, including assumptions. The validation methods are outlined for the modeling efforts as well the validation results. Lastly, the methods that were used to assess the changes to the hydrologic systems are provided. Figure 4.1 illustrates on overview of steps and organization of the methodologies for this study.

![Flowchart of the methodology for this study](image)

Figure 4.1 Flowchart of the methodology for this study

All of the data processing and analysis were performed using ArcGIS 10.2 software and Python 2.7 programming language. It should be noted that all data were
pre-processed to have the same datum, spatial extent, geographic projection, and align to a template raster. The datum used in this study was the World Geodetic System 1984 (WGS84). The geographic projection used for this study was the Universal Transverse Mercator Zone 48 North (UTM48N). A Geographic Coordinate System (GCS, i.e. latitude and longitude) was used to specify the domain of the hydrologic modeling. The UTM48N system was used for the land cover change modeling and other pre-processing. The UTM48N system was used for the land cover change modeling because a consistent measure of area was needed for areal calculations and the UTM projection provides minimal distortions on a smaller scale.

4.2 Datasets

4.2.1 Land Cover Data

The data to be used in this study to represent land cover is the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) combined land cover product version 5.1 (MCD12Q1v5) [Strahler et al., 1999] and the Visible Infrared Imaging Radiometer Suite (VIIRS) surface type environmental data record (ST EDR) [Godin, 2014]. The MCD12Q1v5 dataset is a land cover dataset with five global land cover classification schemes derived from the MODIS sensors onboard both the Aqua and Terra satellites. The dataset contains information on land cover type, land-cover type assessment, and quality-control information. The land cover classes are derived used an ensemble decision tree classification system where BRDF-adjusted surface reflectance, enhanced vegetation index, and land surface temperature are used as inputs along with training data interpreted for Landsat imagery over 2,032 global locations [Cai et al., 2014]. The
accuracy of the MCD12Q1v5 algorithm was found through a cross validation assessment to be 74.8% with a 95% confidence interval of 72.3-77.4% accuracy [Friedl et al., 2010]. The VIIRS ST EDR dataset is a land cover dataset derived from VIIRS moderate resolution imagery using the MODIS heritage C5.0 decision tree classification algorithm. The ST EDR product is in the beta maturity stage and is currently going through rigorous validation; preliminary validation work shows the dataset is below its planned accuracy of 70% [Justice et al., 2013]. Additionally, quality control layers provided within the datasets, which is an assessment data accuracy, were used to mask out poor quality data to preserve the quality of future analysis using the land cover dataset.

The land cover scheme that both datasets are provided in is the International Geosphere-Biosphere Programme (IGBP) classification scheme containing sixteen classes which were specifically identified to capture the physical characteristics of the surface and primarily to surface vegetation at a global scale [Loveland & Belward, 1997]. These classes were reclassified to the International Panel on Climate Change (IPCC) land cover classification using a similar reclassification scheme as Al-Hamdan et al. [submitted, 2016], the only change to the reclassification scheme was for the Woody Savanna class to be remapped as Grassland. Woody Savanna areas have an understory dominated by grasses with large amount of roots in the top layer of soil which is different than a Forests root system [Ratnam et al., 2011] making a difference in the land surface parameterization for hydrologic modeling. This reclassification resulted in six land cover classes that are consistent with other climate modeling efforts [Milne et al., 2003]. Table 4.1 provides an overview of the IGBP classes that were reclassified to the IPCC classes. Additionally, reducing sixteen classes to six limits the complexity of the dynamic
modeling approach used for the land cover change modeling methodology, leading to fewer misclassifications for the projected layers.

**Table 4.1** Description of the IGBP land cover classed and their related IPCC classes

<table>
<thead>
<tr>
<th>IGBP Class</th>
<th>Description</th>
<th>IPCC Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>0: Water</td>
<td>Oceans, seas, lakes, reservoirs, and rivers. Can be either fresh or salt water bodies</td>
<td>3: Water / Wetland</td>
</tr>
<tr>
<td>1: Evergreen Needleleaf</td>
<td>Lands dominated by trees with a percent canopy cover &gt;60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.</td>
<td>0: Forest</td>
</tr>
<tr>
<td>2: Evergreen Broadleaf</td>
<td>Lands dominated by trees with a percent canopy cover &gt;60% and height exceeding 2 meters. Almost all trees remain green all year. Canopy is never without green foliage.</td>
<td>0: Forest</td>
</tr>
<tr>
<td>3: Deciduous Needleleaf</td>
<td>Lands dominated by trees with a percent canopy cover &gt;60% and height exceeding 2 meters. Consists of seasonal needleleaf tree communities with an annual cycle of leaf-on and leaf-off periods</td>
<td>0: Forest</td>
</tr>
<tr>
<td>4: Deciduous Broadleaf</td>
<td>Lands dominated by trees with a percent canopy cover &gt;60% and height exceeding 2 meters. Consists of seasonal broadleaf tree communities with an annual cycle of leaf-on and leaf-off periods</td>
<td>0: Forest</td>
</tr>
<tr>
<td>5: Mixed Forest</td>
<td>Lands dominated by trees with a percent canopy cover &gt;60% and height exceeding 2 meters. Consists of tree communities with interspersed mixtures or mosaics of the other four forest cover types. None of the forest types exceeds 60% of landscape</td>
<td>0: Forest</td>
</tr>
<tr>
<td>6: Closed Shrubland</td>
<td>Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is &gt;60%. The shrub foliage can be either evergreen or deciduous</td>
<td>0: Forest</td>
</tr>
<tr>
<td>7: Open Shrubland</td>
<td>Lands with woody vegetation less than 2 meters tall and with shrub canopy cover is between 10-60%. The shrub foliage can be either evergreen or deciduous.</td>
<td>1: Grassland</td>
</tr>
<tr>
<td>8: Woody Savanna</td>
<td>Lands with herbaceous and other understory systems, and with forest canopy cover between 30-60%. The forest cover height exceeds 2 meters.</td>
<td>1: Grassland</td>
</tr>
<tr>
<td>9: Savanna</td>
<td>Lands with herbaceous and other understory systems, and with forest canopy cover between 10-30%. The forest cover height exceeds 2 meters.</td>
<td>1: Grassland</td>
</tr>
<tr>
<td>10: Grasslands</td>
<td>Lands with herbaceous types of cover. Tree and shrub cover is less than 10%.</td>
<td>1: Grassland</td>
</tr>
</tbody>
</table>
### Table 4.1 Continued

<table>
<thead>
<tr>
<th>IGBP Class</th>
<th>Description</th>
<th>IPCC Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>11: Permanent Wetland</td>
<td>Lands with a permanent mixture of water and herbaceous or woody vegetation that cover extensive areas. The vegetation can be present in either salt, brackish, or fresh water.</td>
<td>3: Water / Wetland</td>
</tr>
<tr>
<td>12: Cropland</td>
<td>Lands covered with temporary crops followed by harvest and a bare soil period (e.g., single and multiple cropping systems. Note that perennial woody crops will be classified as the appropriate forest or shrub land cover type</td>
<td>2: Agriculture</td>
</tr>
<tr>
<td>13: Urban/Built-up</td>
<td>Land covered by buildings and other man-made structures. Note that this class will not be mapped from the AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World.</td>
<td>4: Urban</td>
</tr>
<tr>
<td>14: Cropland/Natural mosaic</td>
<td>Lands with a mosaic of croplands, forest, shrublands, and grasslands in which no one component comprises more than 60% of the landscape</td>
<td>2: Agriculture</td>
</tr>
<tr>
<td>15: Snow/Ice</td>
<td>Lands under snow and/or ice cover throughout the year.</td>
<td>5: Other</td>
</tr>
<tr>
<td>16: Barren/Sparsely vegetated</td>
<td>Lands exposed soil, sand, rocks, or snow and never has more than 10% vegetated cover during any time of the year.</td>
<td>5: Other</td>
</tr>
</tbody>
</table>

### 4.2.2 Meteorological Forcing Data

Meteorological forcing data are required inputs into a hydrological model that are used in the water balance through water and energy calculations. A collection of meteorological reanalysis data and satellite derived precipitation measurements as well as climate projections were used as inputs for the hydrologic model for current conditions and future projections.

#### 4.2.2.1 Current Condition

The maximum and minimum surface air temperatures and the wind speed data used to represent the current conditions needed for the meteorological forcings were collected through the National Center for Atmospheric Research (NCAR) Research Data Archive from the European Centre for Medium-Range Weather Forecasts (ECMWF)
ERA-Interim reanalysis dataset [ECMWF, 2009]. This reanalysis dataset provides global meteorological forcing data on a Gaussian grid at 0.7 degree resolution from 1979 to present at 6 hour intervals [Dee et al., 2011; Berrisford et al., 2011]. The ERA-Interim reanalysis data was chosen for this study because they were found to be slightly more accurate than other reanalysis datasets when compared to global flux tower observations, particularly for near-surface temperatures and wind speed [Decker et al., 2012]. Precipitation errors in the reanalysis data due to premature precipitation onset in the model [Trenberth et al., 2011] and data assimilation methods [Dee, et al., 2011] poses a challenge for using the ERA-Interim precipitation data for hydrologic applications, therefore the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) dataset was used as the precipitation forcing data for this study. The data processing for the CHIRPS dataset uses precipitation estimates from infrared satellite imagery and corrects for biases using observed station data producing a daily quasi-global rainfall dataset at 0.05 degree resolution from 1981-present [Funk et al., 2015]. The CHIRPS dataset was found to outperform other satellite derived rainfall datasets at capturing seasonal cycles and has the lowest mean error of all the datasets compared at -3.21 mm [Tote’ et al., 2015]. Although the CHIRPS dataset underestimates the total rainfall, the dataset tends to overestimate specific rainfall events.

Additional data was used to represent the climatology of the region. The observed climate dataset selected for this study was the WorldClim version 1 created by the Museum of Vertebrate Zoology and the University of California, Berkeley [Hijmans et al., 2005]. This dataset is available globally for maximum temperature, minimum temperature, precipitation, and bioclimatic variables at 30 arc-second resolution. The
data were created by using an interpolation with latitude, longitude, and elevation as independent variables for monthly mean meteorological data from 1960 - 1990, however there are some station records that cover the time period 1950-2000 for data sparse regions. The WorldClim dataset is used primarily for climatic annual averages of meteorological forcing variables such as annual precipitation and average temperature needed for parameterization into the hydrologic model.

4.2.2.2 Climate Projections

Climate projection data from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP) was used as the climate data needed as inputs for hydrologic modeling. This dataset includes twenty-one different Coupled Model Intercomparison Project (CMIP5) Global Circulation Model (GCM) predictions from two different representative concentration pathways (RCP) climate scenarios, RCP4.5 and RCP8.5. These datasets contain three climatic variables, daily surface minimum temperature, daily surface maximum temperature, and daily precipitation rate, at 0.25 degree spatial resolution, and at one day time increments for years 2006-2100. The climate dataset was created using a Bias-Corrected Spatially Disaggregated (BCSD) method which is a statistical downscaling algorithm [Wood et al., 2002; Wood et al., 2004; Maurer et al., 2008; Thrasher et al., 2012]. The algorithm compares the GCM outputs with corresponding climate observations from the Global Meteorological Forcing Dataset (GMFC) for land surface modeling from the Terrestrial Hydrology Research Group at Princeton University [Sheffield, et al., 2006] over a common period and uses information derived from the comparison to adjust future climate projections so that they are (progressively) more consistent with the historical climate records and, presumably,
more realistic for the spatial domain of interest. The algorithm also utilizes the spatial detail provided by observationally-derived datasets to interpolate the GCM outputs to higher-resolution grids. The BCSD algorithm, much like other statistical downscaling methods, was developed to improve the native coarse resolution of GCM for regional impact assessments and applications [Ahmed et al., 2013].

The twenty-one climate models were checked to insure the best quality data was used, from the quality check only fourteen were found to have the correct dates specifically for leap years with 366 days. One of the fourteen quality checked climate models considered was selected from only the RCP4.5 scenario and used in the study as the projected meteorological forcing dataset. This dataset was selected based on three criteria: (1) a climate model that had the least amount of error in the modeled meteorological variables when compared to a validation dataset, (2) was able to capture seasonal trends in meteorological parameters for a validation period, and (3) followed closely to the median projected trend from all twenty-one climate models for each meteorological variable. The methodology for the climate model selection is outlined in Appendix A. The results of the selection found the Beijing Climate Center Climate System (BCC–CSM1.1) [Tongwen et al., 2014] to be the most favorable model to use for this study based on the above criteria. The BCC-CSM1.1 climate projection data used in this study will from here on out be referred to as the NEX climate dataset.

4.2.3 Elevation Data

The United States Geological Survey (USGS) Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) was selected as the digital elevation model (DEM) data set to be used for terrain related variables. This dataset was created through the
collaboration of the USGS and the National Geospatial Intelligence Agency using the latest and most accurate datasets [Danielson & Gesch, 2011]. The GMTED2010 data model aggregates the elevation data used into following products: minimum elevation, maximum elevation, mean elevation, median elevation, standard deviation of elevation, systematic subsample, and breakline emphasis. The products have a geographic coverage of 84°N to 56°S and resolutions of 30-, 15-, and 7.5-arc-second. At 30 arc-seconds, the GMTED2010 root mean square error (RMSE) range is between 25 and 42 meters; at 15 arc-seconds, the RMSE range is between 29 and 32 meters; and at 7.5 arc-seconds, the RMSE range is between 26 and 30 meters [Danielson & Gesch, 2011]. For the purpose of this study the mean elevation dataset at 7.5 arc-second resolution was used as it was found to have the most accurate representation of elevation and has the smallest error range when compared to the other resolutions of the dataset.

4.2.4 Ancillary Data

Ancillary datasets such as major road locations, soil characteristics, and population density was used to derive inputs for more accurate modeling of land use and used as inputs into the hydrologic model. The Global Roads Open Access Data Set version 1 (gROADSv1) acquired from NASA’s Socioeconomic Data Applications Center (SEDAC) was used as the data for major roads. This dataset has been compiled from multiple sources with dates ranging from 1980-2010. The data has a geographic accuracy of 530m-1265m for the African region, it is important to note that the accuracy is assumed to be consistent for other geographic regions [Nelson et al., 2006]. The Harmonized World Soil Database (HWSD) was used as the data to describe soil characteristics within the study area. This dataset is a collection of regional soil
databases that have been harmonized and formatted for the use in a GIS. These data are available at 30 arc-second resolution and contains a plethora of soil characteristics such as pH and drainage. The accuracy of the data is variable across different geographic regions and depends largely on the standard soil data used in the region [Nachergaele et al., 2012]. The HWSD data were used primarily for parameterization of the hydrologic model. Additional ancillary data included LandScan 2014 population density data developed by Oak Ridge National Laboratory. The LandScan data is 30 arc-second resolution dataset of modeled ambient population (averaged over 24 hours) using input data such as census formation, land cover, administrative boundaries, and imagery. The accuracy of the LandScan data is given in percent difference from validation data, where the accuracy of the data was found to be ±14.5% [Dobson et al., 2000].

4.2.4 Validation/Observed Data

4.2.4.1 Observed Meteorological Data

The meteorological station used to analyze the NEX climate data error was the Aranyaphrathet meteorological station in south east Thailand at 13.69° N, 102.51° E latitude and longitude within the LMB study region (see Figure 4.2). This dataset is collected and distributed by the Thai Meteorological Department. The dataset is available from a date range of 2008 to 2015. The dataset included missing data and erroneous data values, therefore bad data were manually removed from the dataset for analysis.

4.2.4.2 Mekong River Commission Observed Streamflow

Observed discharge data was acquired from the Mekong River Commission (MRC) database [MRC, 2011b]. This database consists of hydrometeorological data
including discharge, precipitation, and other variables from ground-based stations distributed throughout the Mekong basin. Four discharge stations were selected for use in the analysis of this study shown in Figure 4.2: Vientiane, Mukdahan, Pakse, and Stung Treng. The Stung Treng gauging station was used for the calibration/validation process as it was found to be the most suitable for calibration being the most downstream observation station with high quality discharge data. The Kratie station, which is located further downstream, was found to be inadequate for the calibration, validation, and analysis in this study. There are issues in the discharge time series data, most likely induced by gradual changes in river cross-section [Lauri et al., 2012].

Figure 4.2 Location of the river gauging and meteorological stations and used in the study overlain a DEM dataset
4.3 Methodology

4.3.1 Land Use/Land Cover Change Modeling

Land cover projections was modeled using a top-down modeling approach to find the dominant land cover type for a given geographic location within the Lower Mekong Basin; this method is based off the Conversion of Land Use and its Effects at Small regional extent (CLUE-S) modeling framework [Verburg et al., 2002]. The CLUE-S model framework was chosen for this study because it allows for land cover trends to be altered simulating policy changes and creating different scenarios of land cover change. This modeling framework is separated into two distinct modules: a non-spatial and spatial module. The non-spatial module calculates the area change for all land-use types for the basin as a whole which is used to drive the spatial module. Within the spatial module of the model the calculated demand for a given land cover type are allocated onto a raster grid based on suitability for a land cover occurring at a given location. This land cover modeling approach is validated against derived land cover data from the MODIS and VIIRS sensors. Lastly, the simulations ran to model future land cover for the hydrologic model input data are explained.

4.3.1.1 Non-spatial land cover module

The non-spatial component of the land cover change model was used to calculate the total demand for a given land cover type at a given time for the entire modeling domain. Past trends in land cover change were calculated and used to calibrate what are thought to be future trends in land cover change. This model focused on five year changes; satellite imagery from 2001-2015 in five year increments were used to find the percentage of total area for each land cover class during those times. The future demand
for a given land cover class was calculated using linear extrapolation [Pontius Jr. & Schneider, 2001; Brovkin et al., 2004; Ito, 2007]. An ordinary least squares (OLS) regression model was fit on the past trends using year as the independent variable and the land cover percentages for each class as the dependent variables. The OLS model was used calculate the rates of change through time for each land cover class. The percentages of land cover and linear trends in land cover are shown in Figure 4.3, it should be noted that the trends shown are for the entire LMB and surrounding area within the model domain. Agriculture, forest, and grasslands are the dominant land cover types accounting for more than 95% of the land within the LMB; furthermore, these land cover class have the most variable trends in change from time period to time period. To account for natural variability in future demands of land cover, a demand value was randomly estimated within a range of ±2% around the linearly extrapolated trend line. The estimated demand was then used as input into the spatial component for the total amount of land to allocate for each land cover class at a given time. The framework used for land cover change modeling allows for human influences on the landscape in the form of policy change to be simulated. These influences were represented by developing different land cover change scenarios. For example, a policy change to increase forested area is represented by increasing the trend in forest change, this in turn increases the total amount of forest land to be allocated within the spatial module. The main drivers of land use change in the past decade have comprised of global economic drivers influencing expansion of agriculture and plantation estates, exploitation of minerals and gas, as well as local drivers such as logging, forest fires, high population growth and other economic and demographic changes including poor governance [Costenbader et al., 2015]. It can
be expected that the drivers will influence similar land use change trends in the near future as the region is still experiencing economic growth and with no foreseeable changes in land management policy.

![Figure 4.3](image)

**Figure 4.3** Trends in land cover change for the LMB through time. The dashed lines of the same color are the linear trends calculated by the OLS regression

4.3.1.2 Spatial land cover module

The spatial component of the land cover change model was used to spatially allocate the total demand for a given land cover type at a given time. The spatial allocation process was performed on the LMB and the surrounding area. It was assumed that the LMB was not a closed system and it had outside influences that affected land cover change. The probability of a given land cover type to be a given location at a given
time was used within the spatial allocation process to identify which land cover class was more likely to be found where. For example, a pixel with the highest probability of being forested land is assigned to the forest class. The total probability of a given land cover class occurring within a specific location was calculated using equation 4.1,

\[ P_{\text{total},u} = P_u + ELAS_u + ITER_u \]  

(4.1)

where, \( P_{\text{total},u} \) is the total probability for a given land cover type \((u)\), \( P_u \) is the predicted probability for a land cover type based on predictor variables, \( ELAS_u \) is the land cover type specific elasticity to change, and \( ITER_u \) is an iteration variable for a land cover type and indicative of the relative competitive strength at each time step based on demand.

The predicted probability \((P_u)\), or suitability, for a given land cover type was calculated using a logistic regression model. Predictor variables in the form of slope, elevation, aspect, plan and profile curvature, population density, climatology, distance to road, distance to stream, distance to urban area, distance to protected area, and height above nearest drainage were used to train the logistic regression model for observed land cover change from 2001-2011 [Rutherford et al., 2007]. The logistic regression model was applied to the projected predictor variables at each time step to find the suitability of a land cover class occurring at a geographic location for a given time step using equation 4.2:

\[ \ln \left( \frac{P}{1-P} \right) = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_i x_i + ... + \alpha_0, \]  

(4.2)

where, \( P \) is the predicted suitability for a given class, \( \alpha_i \) are the regression coefficients, and \( x_i \) are the predictor variables. A first-order sensitivity analysis was performed to test the performance of the logistic regression accuracy due to different predictor variables. It
was found that the model was fairly robust and insensitive to changes in input predictor variables with training sample cross-validation scores ranging from 69.49% to 71.52% accuracy; however, a more rigorous sensitivity analysis must be performed to fully understand the model sensitivity.

The elasticity ($ELAS_a$) of a land cover is a static value is a measure of how likely a land cover type is to change [Castella et al., 2005]. The elasticity was calculated by finding the average number of pixels from a land cover class that has changed in five years. An elasticity value of zero means that the land cover is resistant to change, where a higher elasticity value means it is more likely to change.

The iterative value ($ITER_a$) for the probability calculation is based on how well the spatial allocation process captured the demand, or allocated the correct number of pixels, for each land cover class. Initially at each time step, all of the iteration values are equal at 0. If a land cover class did not have enough area allocated for the time step, the iteration value increased, and vice versa if there was too much area. The demand for a land cover class was considered met when the area of a land cover class was within ±2.5% of the calculated demand. A flowchart of the how the iteration value was updated can be seen in Figure 4.4. An example of the evolution of the iteration value throughout the simulation is given in Figure 4.5. It can be seen initially some classes iteration values, in this case the Urban and Forest classes, are adjusted greatly but are corrected as the simulation proceeds.
Figure 4.4 Representation of the iterative procedure for land cover change allocation for each time step.

Figure 4.5 Example of the iteration parameter (ITER) change during the simulation within one time-step.
The land cover change model was further constrained using decision rules. These decision rules were based off of land cover change logic where certain land cover types can or cannot be converted to another (i.e. water converted to urban). By constraining which class can be converted to which, it is assumed that the model represents realistic changes. Table 4.2 summarizes which land cover classes were allowed to change into which within the five-year time steps.

\textbf{Table 4.2} Summary of land cover change possibilities for land cover simulations

<table>
<thead>
<tr>
<th>Class Change</th>
<th>Original Class</th>
<th>Forest</th>
<th>Grassland</th>
<th>Agriculture</th>
<th>Water</th>
<th>Urban</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Grassland</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>

\subsection*{4.3.1.3 Land cover change model validation}

To understand the accuracy and errors associated with the land cover model, a validation process was completed. The validation metrics used in the accuracy assessment included (1) computing a confusion matrix with associated statistics, (2) comparing the area of modeled land cover classes to observed area, and (3) qualitatively comparing the two maps for the modeled land cover against the observed to identify if
The model captured broad land cover patterns within the region. Three land cover simulations were completed for the validation process: (1) a five-year projection for 2011, (2) a five-year projection for 2015, and (3) a ten-year projection for 2015. These simulations were chosen to validate the model because this allowed for two time periods to be modeled with a five-year and ten-year projection providing an understanding of the accuracy under different scenarios.

The confusion matrix and associated statistics were calculated by taking a stratified random sample of 740 points covering all classes to extract the land cover classes from the modeled 2011 and 2015 data as well as the observed MCD12Q1v5 data for 2011 and VIIRS ST data for 2015. The samples were used to create confusion matrices for each simulation shown in Figure 4.6. It can be noted that the land cover change model correctly classified the majority of the classes. The forest class and water classes had the highest accuracy of prediction. The model, however, had difficulty correctly classifying grassland and agriculture; this is common among land cover classifications and land cover change models as the grassland and agriculture classes have been reported to be incorrectly classified between two classes [Clay et al., 2016].
Figure 4.6 Confusion matrices for the validation of land cover change simulations. From left to right are the five-year prediction for 2011, five-year prediction for 2015, and ten-year prediction for 2015. All of the cells were normalized by the observed class.

Additionally, metrics were calculated based on the confusion matrices including overall accuracy, producer’s accuracy, user’s accuracy [Foody, 2002; Olofsson et al., 2014], and the kappa statistic [Stehman, 1996]. These statistical metrics are methods frequently used to assess the agreement between the modeled land cover type and observed land cover type. The overall accuracy statistic is a measurement of agreement between the observed and modeled land cover calculated using equation 4.3

\[
Accuracy_{overall} = \frac{\sum x_{ij}}{n} \cdot 100
\]  

(4.3)

where, \(x_{ij}\) is the number of samples that agree between the observed \((i)\) and modeled \((j)\) classes and \(n\) is the number of samples. For example, an overall accuracy value of 0.75 means that 75% of all of the points evaluated for accuracy agree with each other on modeled and observed land cover class. The producer’s accuracy, or error of omission, is a measurement of the agreement between an observed class and estimated by the model compared to the total number of samples modeled for the class using equation 4.4

\[
Accuracy_{producers} = \frac{\sum x_{ij}}{\sum x_{ij}} \cdot 100
\]  

(4.4)
where, \( x_{i,j} \) is the number of samples that agree between the observed \((i)\) and modeled \((j)\) classes, \( \Sigma x_j \) is the sum of the modeled samples, and \( n \) is the number of classes. A value for producer’s accuracy of 0.75 translates to, on average, 75% of the total number of samples modeled agree between the modeled and observed class. A measurement of user’s accuracy, or error of commission, is the agreement between an observed class and estimated by the model to the total number of observed samples calculated using equation 4.5

\[
Accuracy_{user} = \frac{\Sigma x_{i,j}}{\Sigma \Sigma x_i} \cdot 100 \tag{4.5}
\]

where, \( x_{i,j} \) is the number of samples that agree between the observed \((i)\) and modeled \((j)\) classes, \( \Sigma x_i \) is the sum of the observed samples, and \( n \) is the number of classes. For example, a user’s accuracy value of 0.75 means that, on average, the total number of observed samples for a class agree between the modeled and observed class. Lastly, the kappa coefficient metric reflects the difference between actual agreement and the agreement expected by chance and is estimated using equation 4.6.

\[
Kappa = \frac{\Sigma(x_{i,j}/n) - \Sigma(y_i/n) + (y_j/n)}{1 - \Sigma(y_i/n) + (y_j/n)} \cdot 100 \tag{4.6}
\]

where \( x_{i,j} \) is the number of samples that agree between the observed \((i)\) and modeled \((j)\) samples for each class, \( y_i \) is the total number of observed samples for each class, \( y_j \) is the total number of modeled samples for each class, and \( n \) is the total number of samples. A Kappa statistic value of 0.75 means there is 75% better agreement between the modeled and observed data than by chance alone. The summary of the statistics just described for the 2011, 2015 five-year, and 2015 ten-year simulations are provided in Table 4.3. As seen in the table, the 2011 modeled data had the best agreement with the observed data.
The model was found to be acceptable based on the derived accuracy statistics as the overall accuracy of the model was near 70%. It was found that all simulations’ agreement was over 50% more like to be due to the model than random chance. The user’s accuracy, which is how accurate the data is for a user, was found to be lower than desired, however, the model was still deemed fit. The 2015 five and ten year simulations have similar accuracies, however, the five-year simulation had slightly better agreement. It was expected that both five year simulations will have similar accuracies as the demand calculated would follow the trends more closely, however, this was not the case. The inconsistencies between the two five-year simulations can be explained by uncertainties associated with the input data for model initialization and validation as the MODIS dataset was to calibrate and initialize the model simulation but the VIIRS dataset was used to validate the simulations. An analysis was performed to investigate the agreement between the MODIS and VIIRS land cover dataset over the study area. It was found that the two datasets have poor agreement with each other (57% overall accuracy) which likely caused the decreased accuracy statistics calculated for both of the 2015 simulations. A summary of the analysis performed for the MODIS and VIIRS dataset is given in Appendix B.

Table 4.3 Summary of the error statistics calculated for the land cover validation simulations

<table>
<thead>
<tr>
<th>Simulation Year</th>
<th>Overall Accuracy</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>71.95 %</td>
<td>68.00 %</td>
<td>70.61 %</td>
<td>0.64</td>
</tr>
<tr>
<td>2015 (5 yr. prediction)</td>
<td>67.97 %</td>
<td>59.10 %</td>
<td>55.30 %</td>
<td>0.57</td>
</tr>
<tr>
<td>2015 (10 yr. prediction)</td>
<td>66.08 %</td>
<td>53.40 %</td>
<td>51.32 %</td>
<td>0.55</td>
</tr>
</tbody>
</table>
An assessment of the demand calculation for the validation simulations was performed to understand how well the trend calculations and parameterization of the model performed for the simulations. This analysis simply quantified the difference between the percent area for each land cover class that was modeled and observed within the LMB [Estes et al., 2010]. The summary of difference between each land cover class for the simulations is given in Table 4.4. Absolute and percent difference are given to quantify the offset for the entire LMB as well as relatively for each class. It was found that the demand calculations were acceptable for the model, especially for the three largest land cover classes by area, Forest, Grassland, and Agriculture. The absolute difference in was found to be within 5% of the total land area for a given class, this is expected due to the model parameterization. Additionally, the percent difference for each class was found to be acceptable as no class (aside from Other and Urban) was allocated over 100% of the calculated demand. The Other and Urban classes have larger percent difference values because the number of pixels to be allocated across the entire area were very small compared to the rest of the area (approximately 500 pixels for Other and approximately 5000 pixels for Urban) and any deviation from the calculated demand are relatively larger than if the demand was greater.
Table 4.4 Summary of the differences between the simulated area for each land cover class compared to the observed area

<table>
<thead>
<tr>
<th>Class</th>
<th>Observed %</th>
<th>Simulated %</th>
<th>Absolute Difference</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>31.82</td>
<td>31.66</td>
<td>-0.16</td>
<td>-0.49</td>
</tr>
<tr>
<td>Grassland</td>
<td>17.16</td>
<td>22.28</td>
<td>5.12</td>
<td>29.79</td>
</tr>
<tr>
<td>Agriculture</td>
<td>46.50</td>
<td>41.94</td>
<td>-4.56</td>
<td>-9.81</td>
</tr>
<tr>
<td>Water</td>
<td>4.01</td>
<td>3.50</td>
<td>-0.51</td>
<td>-12.76</td>
</tr>
<tr>
<td>Urban</td>
<td>0.44</td>
<td>0.42</td>
<td>-0.02</td>
<td>-3.36</td>
</tr>
<tr>
<td>Other</td>
<td>0.07</td>
<td>0.20</td>
<td>0.13</td>
<td>182.12</td>
</tr>
</tbody>
</table>

2011

<table>
<thead>
<tr>
<th>Class</th>
<th>Observed %</th>
<th>Simulated %</th>
<th>Absolute Difference</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>37.84</td>
<td>34.36</td>
<td>-3.48</td>
<td>-9.19</td>
</tr>
<tr>
<td>Grassland</td>
<td>21.27</td>
<td>18.93</td>
<td>-2.34</td>
<td>-11.01</td>
</tr>
<tr>
<td>Agriculture</td>
<td>37.79</td>
<td>42.46</td>
<td>4.67</td>
<td>12.37</td>
</tr>
<tr>
<td>Water</td>
<td>2.87</td>
<td>3.82</td>
<td>0.95</td>
<td>32.90</td>
</tr>
<tr>
<td>Urban</td>
<td>0.21</td>
<td>0.41</td>
<td>0.20</td>
<td>97.21</td>
</tr>
<tr>
<td>Other</td>
<td>0.02</td>
<td>0.02</td>
<td>-0.00</td>
<td>-15.19</td>
</tr>
</tbody>
</table>

2015 (5 yr.)

<table>
<thead>
<tr>
<th>Class</th>
<th>Observed %</th>
<th>Simulated %</th>
<th>Absolute Difference</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>37.84</td>
<td>31.48</td>
<td>-6.36</td>
<td>-16.81</td>
</tr>
<tr>
<td>Grassland</td>
<td>21.27</td>
<td>21.96</td>
<td>0.69</td>
<td>3.26</td>
</tr>
<tr>
<td>Agriculture</td>
<td>37.79</td>
<td>42.43</td>
<td>4.64</td>
<td>12.28</td>
</tr>
<tr>
<td>Water</td>
<td>2.87</td>
<td>3.54</td>
<td>0.67</td>
<td>23.06</td>
</tr>
<tr>
<td>Urban</td>
<td>0.21</td>
<td>0.44</td>
<td>0.23</td>
<td>111.89</td>
</tr>
<tr>
<td>Other</td>
<td>0.02</td>
<td>0.15</td>
<td>0.13</td>
<td>613.92</td>
</tr>
</tbody>
</table>

2015 (10 yr.)

The last analysis for the land cover validation was a qualitative analysis into the spatial distribution of the land cover classes throughout the basin for the three simulations (2011, 2015 five-year, and 2015 ten-year). Figure 4.7 shows the land cover data for the observations and simulations. It can be seen that the land cover change model was able to capture the broad geographic structure of land cover for the region, however, the model had particular trouble with the Grassland class. The Grassland class was largely simulated to be clustered together, when, as seen in the observed data, it is distributed. Additionally, there was a larger amount of grassland area allocated to the northern portion of the basin shown in the transition zones between the forested areas. This error
is largely a function of the continuity in the input data used to create the suitability layer for each land cover class that does not capture small scale changes important to land cover. Additionally, the LMB is a large geographic area with different ecoregions that have different suitabilities for different classes. As such, the model created for this study is optimized to capture the general trends, not specific regional trends within the basin.

Figure 4.7 Observed and simulated land cover for the 2011 and 2015 land cover change simulations
4.3.1.4 Land cover change simulations

The future land cover simulations were run at 5 year increments from 2015 to 2050. Multiple simulations were run for the time period. The first simulation was a baseline scenario; this simulation used the trend lines calculated from the previous land cover data. The modeled land cover for 2020-2050 are assumed to be representative of the future land cover if the current trends were to remain the same. The next few model runs were set up and executed to simulate changes in land cover policy for the LMB that would alter the trends in land cover change. The trends for the Forest and Agriculture classes were both increased to 5% and 10%; a total of four additional scenarios were completed. The forest and agriculture class trend was chosen to be altered to simulate policy changes of the two classes within the region. The trend increases of 5% and 10% were chosen to understand the sensitivity of larger increases of the land cover type to the hydrologic system. The simulated land cover data was then used as input into the hydrologic model to understand changes in hydrology due to land cover change.

4.3.2 Hydrologic Modeling

The Variable Infiltration Capacity (VIC) model was employed for this study to simulate hydrologic parameters spatially throughout the Lower Mekong Basin. The VIC model is a macroscale semi-distributed model that solves energy and mass balance at each grid cell to simulate evapotranspiration, interception, surface runoff, baseflow, and other hydrological fluxes [Liang et al., 1994]. Each grid cell is simulated independently and able to be partitioned into multiple vegetation heterogeneities, multiple soil layers with variable infiltration rates, and topography layers. The model allows for the time step to update fluxes and for model states to be defined as daily or sub-daily increments. The
VIC model does not represent deep groundwater or water stored in bedrock and this parameter is not considered within this study. The VIC model is coupled with a routing model to simulate discharge using the surface runoff and baseflow parameters. This study uses the routing model described by Lohmann et al. [1996, 1998] to route the streamflow from each grid to a specified outlet.

The VIC model has been successfully implemented in hydrologic studies for major river basins in the US [Abdulla et al., 1996; Bowling et al., 2004; Bowling and Lettenmaier, 2010], the Mekong Basin [Costa-Cabral et al., 2008; Haddeland et al., 2006a,b], and globally [Nijssen et al., 2001a,b,c]. Additional studies have employed the VIC model to study specific aspects of the hydrologic cycle such as changes in evapotranspiration over time [Liu et al., 2013a] and changes to land use change [Cuo et al., 2011; Matheussen et al., 2000] making it a well-established model in hydrological research.

The model was executed at 0.1 degree resolution for the LMB in full energy mode to simulate moisture and energy fluxes. Sub-grid land cover and elevation was defined within each grid cell to account for small scale variability within the large grid cells for a better representation of the land surface. Many other parameters were defined within the model that control the land surface processes of the model; a detailed explanation of the parameterization for different aspects of the model, such as soil and land use classes, are given in Appendix C. The model time step was set up as daily with a spin-up period of one year, as the hydrologic model was found to be stable after one year [Cosgrove et al., 2003]. The routing model was applied at a daily time step and then averaged monthly resulting in simulated monthly average discharge. The VIC model was used to simulate surface runoff, baseflow, and evapotranspiration hydrologic parameters for this study.
from 1982 - 2010 as a baseline climatology and for five year increments from 2020-2050 to assess changes due to climate variability.

4.3.2.1 Model Calibration/Validation

The baseline climatology simulation was partitioned into two additional sections: calibration (1982-1990) and validation (1991-2004). The calibration/validation process was performed by graphically and statistically comparing simulated discharge against observed discharge. The observed discharge dataset was acquired from the Mekong River Commission [MRC, 2011] for the gauge shown in Figure 4.2. The calibration process was performed manually by adjusting the infiltration, $D_s$, $W_s$, and soil depth parameters in the VIC model (information and description of model parameters can be found in Appendix C). The model evaluation guidelines from Moriasi et al. [2007] were followed when assessing the performance of the hydrologic model. The model evaluation guide recommends using the Nash-Sutcliffe Model Efficiency Coefficient (NSE) [Nash and Sutcliffe, 1970], RMSE-Standard Deviation Ration (RSR) and Percent Bias (PBIAS) when evaluating the model [Moriasi et al., 2007]. Additional statistics used in this study to evaluate the model include Pearson correlation coefficient (R) and Mean Relative Error (MRE). Figure 4.8 displays the monthly average discharge for the calibration (a) and validation (b) periods. The hydrographs show an overall good agreement between the simulated and observed discharge, however, the model does slightly over predict baseflow during the dry season. This anomaly becomes less pronounced in the later years, particularly around 2001 which is the date of the land cover data used to parameterize the model. This over prediction of baseflow can be attributed
to the land cover parameterization, which does not affect the overall result of the simulation.

The overall statistical analysis show that the model performance is “good” to “very good” for simulating monthly average discharge based on the Moriasi et al. [2007] performance guidelines. The calculated error statistics, summarized in Table 4.5 for both the calibration and validation periods, are comparable to other modeling efforts for the Mekong Basin. In a study by Thompson et al. [2013], a NSE of 0.791 and 0.858 was calculated for two different gauging stations within the basin, Nakhon Phanom and Pakse, respectively. Additionally, Kingston et al. [2011] obtained a NSE value of 0.770 for the Pakse station. Although the model performance statistics derived from other studies are not directly comparable to the error statistics from this study because of differences in models used, calibration/validation periods, and gauging stations, they provide a baseline for what constitutes an acceptable model within the region.

Table 4.5 Summary of error statistics for the hydrologic model calibration and validation process

<table>
<thead>
<tr>
<th>Statistic</th>
<th>R [-]</th>
<th>NSE [-]</th>
<th>PBIAS [%]</th>
<th>RSR [-]</th>
<th>MRE [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>0.96</td>
<td>0.87</td>
<td>-20.70</td>
<td>0.28</td>
<td>68.13</td>
</tr>
<tr>
<td>Validation</td>
<td>0.95</td>
<td>0.89</td>
<td>-7.40</td>
<td>0.24</td>
<td>41.95</td>
</tr>
</tbody>
</table>
Figure 4.8. Calibration/Validation hydrographs for the discharge gauge in the LMB. The calibration period, 1982-1990, is shown on the top plot (a) and the validation period, 1991-2005, is shown on the bottom (b).

4.3.2.2 Climate data input uncertainty

The hydrologic model was calibrated and validated using an observed satellite derived precipitation data set and the effects of climate portion of this study used climate model data for the analysis, therefore an analysis must be performed to characterize the uncertainty of ingesting a different dataset into the model. To do so, minimum and maximum surface air temperature and precipitation data from the NEX climate reanalysis dataset were used as inputs into the simulation for the same time periods (1982-2010). The results of this analysis show that the NEX climate dataset greatly under predicts discharge during the wet season (Figure 4.9a). Furthermore, the error statistics calculated
by comparing the simulated streamflow to observed streamflow drastically decreased, particularly the calculated NSE (Table 4.6). These values are considered “unsatisfactory” for a hydrologic model. This maybe be due to the resolution of the NEX dataset at 0.25 degree which was found to be too coarse of a resolution to adequately capture small-scale extreme rainfall (i.e. convective storm) events [Le et al., 2014] which frequently occur during the wet season over the LMB. Furthermore, the inconsistencies in total rainfall between the two datasets can be observed when comparing the average yearly accumulated precipitation. The NEX dataset does not only fail to capture the correct amount of precipitation but also contains inconsistencies in the spatial distribution of precipitation within the basin (Figure 4.9b-d). The NEX dataset, on average, underestimated average yearly accumulated precipitation by 341mm with a RMSE of 410 mm. Based on the results of this analysis, it can be expected that the total water availability based on the future predictions will be less than the historic average.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>R [-]</th>
<th>NSE [-]</th>
<th>PBIAS [%]</th>
<th>RSR [-]</th>
<th>MRE [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>0.67</td>
<td>0.17</td>
<td>-44.28</td>
<td>0.55</td>
<td>44.74</td>
</tr>
<tr>
<td>Validation</td>
<td>0.57</td>
<td>0.11</td>
<td>-45.05</td>
<td>0.55</td>
<td>38.56</td>
</tr>
</tbody>
</table>

Table 4.6 Summary of the error statistics for the hydrologic simulations using the NEX climate reanalysis data as inputs
Figure 4.9 Analysis of data uncertainty in input NEX climate data into model showing (a) simulated discharge against observed, (b) CHIRPS observed annual accumulated precipitation, (c) NEX modeled annual accumulated precipitation, and (d) difference between average annual accumulated precipitation.

To account for the biases in the climate model accumulated annual precipitation, a bias correction procedure was performed. The bias correction procedure was applied primarily to adjust the spatial distribution and the accumulation of precipitation at a monthly time step based on the climatology of the region. The power transformation of precipitation bias correction method was used which is a non-linear correction in an exponential form, $a P^b$, that can be used to specifically adjust the variance statistic of the precipitation data [Leander et al., 2008; Teutschbein and Seibert, 2012]. First, the exponential parameter, $b$, is estimated using the methods from Leander and Buishand [2006] with equation 4.7
\[ b(m) = \frac{\log(Q(m)_{p2,o}/Q(m)_{p1,o})}{\log(Q(m)_{p2,c}/Q(m)_{p1,c})} \quad (4.7) \]

where \( Q_{p2} \) and \( Q_{p1} \) is the 99\(^{th}\) and 65\(^{th}\) quantile, respectively, of the basin-wide climatological average precipitation for a given month \( (m) \) for both the observed precipitation \( (o) \) and simulated reanalysis NEX precipitation \( (c) \). Next, the exponential parameter was applied to the reanalysis NEX precipitation using equation 4.8

\[ P_{c}^{*1}(d) = P_{c}(d)^{b(m)} \quad (4.8) \]

where \( P_{c}^{*1} \) is the variance adjusted precipitation for a given day of the year \( (d) \), \( P_{c} \) is the simulated reanalysis NEX precipitation, and \( b \) is the exponential parameter for a given month \( (m) \) which the day is associated with from equation 4.7. Lastly, the bias corrected modeled precipitation is achieved by using a standard linear scaling parameter with equation 4.9

\[ P_{c}^{*}(d) = P_{c}^{*1}(d) \cdot \left[ \frac{\mu_{m}(P_{o}(d))}{\mu_{m}(P_{c}^{*1}(d))} \right] \quad (4.9) \]

where \( P_{c}^{*} \) is the bias corrected precipitation for a given day of the year \( (d) \), \( P_{c}^{*1} \) is the variance adjusted precipitation from equation 4.8, and \( \left[ \frac{\mu_{m}(P_{o}(d))}{\mu_{m}(P_{c}^{*1}(d))} \right] \) is the ratio of long-term mean observed \( (o) \) and variance adjusted reanalysis modeled precipitation \( (c) \). The results of the long-term mean bias corrected precipitation for the entire basin are shown in Figure 4.10. The bias corrected precipitation tends to decrease the interquartile range when compared to the raw NEX climate dataset, however, there are large errors associated with the bias correction particularly during the transition periods (Feb-Mar and Sep-Nov) between the wet and dry seasons. This is to be expected as the seasonal transition periods are the most variable in terms of climatology for precipitation in the region.
Another method used to assess the bias corrected precipitation was to use the data into the hydrologic model to understand how the bias corrected precipitation performs within the hydrologic model. The result of the simulation’s error statistics is summarized in Table 4.7 along with the visual results displayed in Figure 4.11 showing that the simulated discharge using the bias corrected precipitation has a decreased bias when compared with the raw NEX data simulations. The NSE value for the calibration period increased with the bias corrected precipitation and decreased for the validation period; the decrease validation NSE value is primarily due to the 1998-1999 time period where the bias correction was not needed on the raw NEX data. The original NEX dataset predicted
precipitation correctly for 1998-1999, seen in the simulated streamflow data (Figure 4.9a). By applied a bias correction to increase precipitation, the bias corrected precipitation greatly overestimated precipitation and subsequently stream for those years (Figure 4.11a), leading to a decreased accuracy represented in the error statistics.

Table 4.7 Summary of the error statistics for the hydrologic simulations using the bias corrected climate reanalysis data as inputs

<table>
<thead>
<tr>
<th>Statistic</th>
<th>R [-]</th>
<th>NSE [-]</th>
<th>PBIAS [%]</th>
<th>RSR [-]</th>
<th>MRE [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Calibration</td>
<td>0.55</td>
<td>0.24</td>
<td>-20.43</td>
<td>0.57</td>
<td>68.55</td>
</tr>
<tr>
<td>Validation</td>
<td>0.46</td>
<td>-0.08</td>
<td>-22.82</td>
<td>0.57</td>
<td>51.92</td>
</tr>
</tbody>
</table>

Figure 4.11 Same as Figure 4.9 but for the results are shown from the simulations using the bias corrected precipitation
When comparing the spatial distribution of the corrected precipitation climatology to the observed climatology, the annual precipitation in the northern area of the basin have a decreased bias. The bias corrected precipitation continues to underpredict the yearly accumulated precipitation in the southern area of the basin, however, the bias is still less than the raw NEX dataset. The simulated discharge from the hydrologic model follows more closely with the observed hydrograph when compared to the simulated discharge from the raw NEX data. There are some errors in using the bias corrected precipitation for hydrologic applications where the timing of discharge is more variable, and there are some years where the discharge is still underpredicted or overpredicted (seen in Figure 11a for years 1983, 1994, 1996, and 2002). These errors are expected as the bias correction method focused more on the long-term climatology of the precipitation and not individual years.

Based on the results it was deemed that the bias correction method used would limit the uncertainty of using the climate data as input into the hydrologic model. The bias correction parameters calculated were applied to the future NEX climate dataset for 2015-2050, which were used in the hydrologic model to assess the changes on the hydrologic system due to climate variability.

4.3.2.3 Hydrologic Simulations

The hydrologic simulations were run at five year increments from 2015-2050 to analyze how land cover change and climate variability differentially affect the hydrologic system. First, the climate dataset was used as the meteorological forcing data for the specified date ranges. The land cover data used for the climate hydrologic simulations
were the MODIS 2001 data. This dataset remained constant for the climate hydrologic simulations as a control.

Next, the simulated land cover change data outlined in section 4.3.1.4 was used as the land cover data input for the hydrologic model during the specified time periods. In total, there was one scenario to analyze the effects of climate variability on the hydrology and there were five land cover scenarios to analyze the effects of land cover change on the hydrology. The meteorological data used for the land cover change hydrologic simulations was the observed data from 2000-2001. The meteorological data range was chosen to remain constant with the land cover control time frame. The meteorological forcing remained constant for the land cover hydrologic simulations to be confident that the identified hydrologic changes were due to land cover change.

4.3.3 Estimation of variations in hydrology

4.3.3.1 Discharge Changes

An analysis was performed to understand the effects climate variability and land cover change have on the flow regime at gauging stations along the river (Figure 4.2). The analysis comprised of simply finding the percent difference of the hydrologic projection simulations compared to the climatic average from (1981-2010) defined by equation 4.10

\[
\%\Delta = \left( \frac{\mu(D) - \mu(C)}{\mu(C)} \right) \times 100
\]

where \(\%\Delta\) is the percent difference, \(\mu(D)\) is the yearly average streamflow for the simulation \((s)\) and control \((c)\). It should be noted that the control used in this equation is the data from historic hydrologic simulation using the same meteorological inputs. When
applying the equation to understand the change due to climate variability, the control data used were the simulation using the bias corrected climate reanalysis data from 1981-2010. In contrast, when analyzing the change due to land cover change, the control data used was the hydrologic simulation using the observed meteorological data from 1981-2010. The hydrologic simulation data were used instead of the observed streamflow data to limit errors in the results that could emerge from uncertainties in model and data errors.

4.3.3.2 Seasonality analysis

A seasonality analysis was employed to complement the previous analysis in identifying the changes to timing of the flow regime at the gauging stations (Figure 4.2). This analysis identified the mean date of the wet season and variability of occurrence of extreme events based on the Burn index [Burn, 1997] which uses circular statistics to identify the mean date or peak of the season and intensity of the season [Parajka et al, 2009]. The mean date of occurrence represents an average position of event occurrences which are plotted in polar coordinate on a unit circle. The position of the event occurrences for each month can be found using equation 4.11

\[ \theta_i = D \frac{2\pi}{12} \]  \hspace{1cm} (4.11)

where \( D \) is the mean date for each month, \( i \), for example \( D \) for January and December is 16 and 350, respectively. The direction of the mean date is calculated using the following sequence of equations 4.12 – 4.14

\[ \bar{x} = \frac{\sum_{i=1}^{n} \cos (\theta_i)}{n} \] \hspace{1cm} (4.12)

\[ \bar{y} = \frac{\sum_{i=1}^{n} \sin (\theta_i)}{n} \] \hspace{1cm} (4.13)

\[ \bar{\theta} = \tan^{-1}(\bar{y}/\bar{x}) \] \hspace{1cm} (4.14)
where $\bar{\Theta}$ is the direction of the average vector from the origin representing the mean date of occurrence of extreme events. The variability or intensity of the season is characterized by a length parameter defined in equation 4.15

$$r = \sqrt{x^2 + y^2}/n$$

(4.15)

where $r$ ranges from zero to one, with zero representing a uniform distribution and one representing all of the extreme events occur in the same month. This analysis provides an understanding into how the mean date and intensity of the wet season of the LMB changes due to climate variability and the changes in land cover.

**4.3.3.3 Runoff elasticity**

In this study the effects of precipitation changes and land cover change on runoff were estimated with the concept of elasticity. Numerous studies have documented the sensitivity of streamflow to climate change by estimating the precipitation elasticity of streamflow. Schaake [1990] introduced the concept of elasticity for evaluating the sensitivity of streamflow to changes in climate. Climate elasticity of streamflow is defined by the proportional change in streamflow $Q$ divided by the proportional change in a climatic variable such as precipitation $P$, defined in equation 4.16

$$\varepsilon_P(P, Q) = \frac{dQ/Q}{dP/P} = \frac{dQ}{dP} \frac{P}{Q}$$

(4.16)

If the elasticity coefficient is greater than 1, a 1% change in annual rainfall would result in more than 1% change in annual streamflow. For example, an elasticity of +5 indicates that a 1% increase in annual rainfall would lead to 5% increase in annual streamflow.

Sankarasubramanian et al. [2001] introduced a specific nonparametric estimator of elasticity represented by equation 4.10 that employs the mean value of the climatic variable in the sensitivity analysis defined by equation 4.17
\[ \varepsilon_r = \text{median} \left( \frac{Q_t - \bar{Q}}{P_t - \bar{P}} \right) = \text{median}(U) \] (4.17)

where \( \bar{Q} \) and \( \bar{P} \) represent the mean annual streamflow and precipitation, respectively. A value of \( U \) was calculated for each pair of \( Q_t \) and \( P_t \) for the climate time series. This relates how a change in precipitation will produce a change on streamflow. In percentage terms, the percentage change in streamflow will be times the percentage change in precipitation. For this particular analysis, the term \( Q \) was substituted with runoff (surface and subsurface), \( R \), as these two quantities become identical when integrated over a sufficient time period [Nijssen et al., 2001a].

The principle of elasticity was also applied to the hydrologic simulations with the land cover change scenario data. The same concept is used where the land cover elasticity, \( \varepsilon_L \), was defined as a ratio of the annual runoff to the percentage of a land cover change. If the elasticity parameter is greater than 1, a 1% change in the land cover type will result in a greater than a 1% change in annual runoff. The elasticity parameter for land cover change was calculated using equation 4.18 following the methods outlined by Zheng et al. [2013]

\[ \varepsilon_L = \frac{(R_{t+1} - R_t)/R_t}{(L_{u,t+1} - L_{u,t})/L_t} = \frac{\Delta R_t/R_t}{\Delta L_t/L_t} \] (4.18)

where \( \varepsilon_L \) is the sensitivity of annual runoff, \( R \), to changes for a given land cover class, \( L_u \), for two consecutive time periods \( t \) and \( (t+1) \). The values of elasticity with respects to both the climate and land cover were calculated at the time steps coinciding with the simulations.
4.3.3.4 Spatial Hydrologic Trends

A trend analysis was conducted to understand the changes of yearly accumulated water balance terms throughout time due to either climate variability or land cover change. Furthermore, this analysis was applied spatially throughout the LMB to characterize the geographic variations of the variables. The magnitude of trends was calculated using a nonparametric slope estimator proposed by Sen [1968] where the median slope is calculated among all lines through pairs of two-dimensional sample points. The Sen slope estimator has been used widely to assess trends in climatological [Romanić et al., 2015], hydrologic [Kibria et al., 2016], and remote sensing [Fernandes & Leblanc, 2005; Liu et al., 2015] studies by applying equation 4.19

\[ \beta = \text{median} \left( \frac{Y_j - Y_i}{X_j - X_i} \right) \]  

(4.19)

where \( \beta \) is the median for all possible combinations of pairs of any two data points \( (i) \) and \( (j) \) in the entire dataset. The median slope is then used to calculate the percent change trend using equation 4.20 as explained by Liu et al. [2013]

\[ \% \Delta = \frac{\beta_{x \xi} n}{\mu_{x \xi}} \]  

(4.20)

where \( \beta \) is the trend line for the hydrologic variable \( (x) \) at pixel \( (i) \), \( n \) is the number of years for the trend period (for this study it was 40 years, 2011-2050), and \( \mu \) was the climatological mean for the variable at a given pixel. The trend estimation was applied to each time series for all of the pixels within the basin and for each hydrologic parameter which included change in storage, runoff ratio and evapotranspiration. These hydrologic parameters were chosen as they further define the nature of water balance within the system. Characterizing the trends in these parameters will further elucidate how much and where the climate variability and land cover changes alter the hydrologic system. A
simple water balance model is used to calculate the change in storage parameter \((\Delta S)\) at each grid cell defined as

\[
P = E + R + \Delta S
\]

(4.21)

where \(P\) is precipitation, \(E\) is evapotranspiration, \(R\) is runoff, and \(\Delta S\) is the change in storage. The \(\Delta S\) term is understood to include all of the water stored as soil moisture, snow, and canopy infiltration. Over a long period of time (i.e., 10 years+), it is reasonable to assume that the term \(\Delta S\) approaches zero based on conservation of mass [Liu et al., 2013b], however, the short term water balance and trends are variable. Runoff ratio is defined using equation 4.22

\[
\alpha = \frac{R}{P}
\]

(4.22)

where \(\alpha\) is the runoff ratio, \(R\) is runoff, and \(P\) is the precipitation. Runoff ratio represents the long-term water balance separation between water that is released from the catchment as streamflow or as evapotranspiration, assuming there is no net change in storage. A high value for runoff ratio relates to region where large amount of water exits as runoff, where as a low runoff ration relates to large amount of water leaving as evapotranspiration. The last hydrologic parameter, evapotranspiration, was output directly from the hydrologic simulations.

4.3.3.5 Climate variability/Land cover change effects comparison

The final goal of this study is to understand how the hydrologic system responds to climate variability and land cover change as well as quantify the degree of change on the hydrology within the LMB. The changes on the hydrology due to climate variability and land cover change are compared to identify which factor will potentially cause the greatest changes and where those changes occur. This information can provide valuable
information into which country will experience the most detrimental effects due to which changes. This information has implications towards policy where decision makers can form.

4.4. Summary

The methods used to address the response to the hydrologic system of the LMB were described in this chapter. First, all of the data and sources were outlined including errors associated with the data to better understand how the data may affect future results. Next, the methods used to simulate land cover and the specific change scenarios were discussed. The land cover change model accuracy was found to be sufficient for this study at around 70% accurate. The VIC model was used for the hydrologic modeling to simulate the changes to the hydrologic system due to climate variability and land cover change. The resulting hydrologic data was analyzed for changes compared to the historic mean or analyzed for trends in the changes.
CHAPTER V

RESULTS AND DISCUSSION

This chapter summarizes the results of the thesis and discusses further implications of the research. It lists the advantages and limitations of the final results and describes how these results can be used in the future.

5.1 Land Cover Change Simulations

The land cover simulations were run specifically to create land cover scenario data as inputs into the hydrologic model. First, before discussing the results of the hydrologic simulations, it is important to discuss the land cover data models to better understand the results of the hydrologic simulations. Specific scenarios were simulated with the land cover model: (a) Baseline land cover change (LCC), (b) forest increase of 5%, (c) forest increase of 10%, (d) agriculture increase of 5%, and (e) agriculture increase of 10%. Figure 5.1 displays the results of the land cover change simulations, showing the percent area of each class within the LMB for each time step for all of the simulations. The baseline simulation showed little changes throughout time, however, the other simulations showed rapid increases in the class projected to increase where
grassland and the other majority class (forest or agriculture) decreased. Figure 5.2 shows the spatial distributions for each class under all scenarios for 2050. It can be seen in the maps that the large scale spatial patterns are consistent, however, with forest increases large patches of forest can be noted where agriculture typically was located and vice versa for the agriculture increases. This shift between the two classes are largely identified in the Cambodia region. It may seem that the scenarios with 10% increases in either forest or agriculture are not feasible but it is important to simulate the hydrologic response to these changes to understand the sensitivity to large shifts in land cover.

Figure 5.1 Summary of land cover change simulation areal changes for each class.
The resulting maps and information from the land cover change simulations can be used by land managers and policy makers to help create manageable and advantageous policies for land cover change. Based on the modeling, it can be expected to see the greatest land cover change in the lower portions of the basin in and around Cambodia.
These changes can have implications for flooding within the flood plains in the region but will not have much contribute to the streamflow in the upper reaches of the basin.

### 5.2 Discharge Changes

The first analysis in addressing changes of the hydrologic system were to evaluate changes to discharge for the gauging stations. Figure 5.3 displays the simulated monthly discharge for 2050 from all of the simulations. The simulation with the climate data showed the greatest change with the peak discharge occurring in July with comparatively minimal wet season discharge following July. The land cover change scenarios showed little changes from the historic average, however, it can be seen that increases in agriculture land increase discharge and increase in forest land decrease discharge.

![Hydrographs for Stung Treng stations showing changes to discharge for 2050 from all of the scenarios](image)

*Figure 5.3* Hydrographs for Stung Treng stations showing changes to discharge for 2050 from all of the scenarios
Additional data was compiled for each gauging station at each year. Figure 5.4 displays the percent difference from mean annual discharge for each scenario. The climate scenario has the greatest impact on the discharge for all stations. Additionally, the land cover simulations show similar trends with agriculture increases resulting in an increase in discharge and forest increases resulting in decreases in discharge. The decreases in discharge due to increases in forest area is likely due to the fact that increasing the forest area also increases the evapotranspiration for the region. Controversially, by increasing agricultural areas there is a decrease in plant water uptake and vegetation canopy interception which leads to a decreased evapotranspiration and increased runoff. Showing that increases in forest can decrease discharge throughout the basin has implications for reducing the annual flood waters. The offset in simulated discharge from the land cover scenarios compared to the mean discharge for 2015 at the Vientiane station is most likely due to errors in the spatial allocation of land cover class within the land cover change model upstream from that gauging station, the other stations seem to not have any uncertainties from the hydrologic simulations using land cover scenario data. Additional uncertainties in the discharge separation could be attributed to the upper catchment having an increase in precipitation for 2001 as compared to the climatological average.
5.3 Seasonality Analysis

A seasonality analysis was used to derive additional information about the discharge at the gauging stations, specifically information on the timing of the mean date of peak discharge (i.e. wet season) and the intensity of the season. Figure 5.5 displays the results of the seasonality analysis for the hydrologic simulations using the climate data. As seen in the figure, the date of peak season becomes sporadic with most simulated years showing a shift in peak season to an earlier date between July and September. Likewise, the intensity of the season is irregular. There appears to be no noticeable

Figure 5.4 Percent changes in mean annual discharge from all scenarios through time
temporal trend in seasonality changes due to climate variability leading to the conclusion that the resulting changes to discharge are unpredictable.

**Figure 5.5** Seasonality results for the simulated streamflow with climate projections. Large variations, on the order of one month, in the intensity and peak wet season

![Graph showing seasonality results for different locations and years.](image)

The discharge is dependent on the precipitation, therefore, a seasonality analysis was performed on accumulated monthly precipitation as well to confirm that the shift forward in peak season discharge dates were due to change in precipitation. Figure 5.6 displays the results of the seasonality analysis for precipitation. There is coherence between the discharge and precipitation parameters, although there are inconsistencies between the predicted discharge seasonality and the precipitation seasonality. Most notably, the 2030 discharge has a large seasonality signal, just shy of 1, that is not present for precipitation. Additionally, the 2020 wet season timing at the Vientiane station shows the peak of the season occurring in late July, in contrast, the precipitation seasonality
does not show that signal. These inconsistencies suggest that the signature of seasonality may not be as dominated by precipitation as initially hypothesized.

Figure 5.6 Seasonality analysis for accumulated precipitation from the projected climate data. Variations in rainfall peak season align with the variations in streamflow, however, not the intensity of wet season.

The seasonality analysis was also applied to the simulated discharge from the hydrologic simulations using the land cover change scenarios. The results of the analyses are found in Figures 5.7 – 5.11. As shown in the figures, there was no noticeable difference in seasonality for all land cover change simulations. There is a slight shift forward in the mean date of season, however that shift can be attributed to using meteorological data from 2001 and comparing the discharge from 2001 to a climatological mean. It can be deduced from these results that land cover does not have a significant role in seasonality, which is driven primarily by climatic variables.
Figure 5.7 Streamflow seasonality analysis using the baseline land cover change scenario data. Almost no changes in seasonality can be observed due to baseline land cover change scenario.

Figure 5.8 Streamflow seasonality analysis using the 5% increase in forest area scenario.
Figure 5.9 Streamflow seasonality analysis using the 10% increase in forest area scenario

Figure 5.10 Streamflow seasonality analysis using the 5% increase in agriculture area scenario
5.4 Runoff Elasticity

The elasticity parameters due to climate variability and land cover change were calculated to understand how changes in precipitation and land cover change will alter the surface runoff. The spatial distribution of runoff elasticity to precipitation within the basin are displayed in Figure 5.12 along with the temporal evolution of elasticity through time. Overall, the runoff elasticity for the LMB due to climate variability shows that an increase in precipitation will result in an increase in runoff. The elasticity parameter averaged for the basin is, on average, approximately 2%, meaning a 1% increase in precipitation will result, on average, in a 2% increase in runoff. The temporal evolution of runoff elasticity seemingly has an upward trend from 2040-2050. This upward trend shows that the average runoff elasticity may increase greater than a value of three, which
would greatly increase the runoff. When analyzing the spatial characteristics of elasticity for the basin, it can be seen that areas of Thailand and northern Laos have the highest elasticity values, implying that they will experience the greatest increases in runoff due to increases in precipitation. There are small areas of negative elasticity in Cambodia showing there is some capacity of decreasing runoff, however, this negative area is only a small portion in comparison to the entire basin which largely has a positive elasticity value. Increases in runoff also have implications for flooding. Increases in precipitation alone can induce floods, however, coupling increases in precipitation with a near double increase in runoff can potentially increase the flood frequency, duration, and distribution for the region. Spatial information from these results can assist land managers in effectively managing areas that will experience greater amounts of runoff, thus helping limit water available for flooding further downstream.

![Spatial and temporal representation of runoff elasticity for the LMB](image)

**Figure 5.12** Spatial and temporal representation of runoff elasticity for the LMB
The runoff elasticity due to land cover change for the basin as a whole is summarized in Figure 5.13. The elasticity calculations due to land cover change could not have a spatial component to the results as the analysis is based on total basin-wide changes for each land cover. For each scenario and land cover class, there is little change in basin-wide runoff. These results align with the findings from the discharge change analysis, where little changes were found in discharge due to land cover change. Conceptually, this is logical as changes in runoff will result in changes in discharge.

There is a small signal (less than 1% change) from both water bodies and urban areas. Interestingly, the urban signals for the 10% increases in forest and agriculture scenarios have similar curves; more research is needed to understand if these curves are actual signals or noise due to the modeling methodologies.

![Figure 5.13](image.png)

**Figure 5.13** Runoff elasticity values for each land cover class for each land cover scenario. Almost no changes can be seen for each land cover variable through time with small signals (<1%) for the Urban class.
5.5 Spatial Hydrological Trends

The hydrologic trends analysis was performed on a cell-by-cell basis to analyze where and how much specific variables of the hydrologic system changed due to climate variability and land cover change. The hydrologic variables assessed included: (a) storage, (b) runoff-precipitation ratio (RP), and (c) evapotranspiration (ET). Figure 5.14 displays the trends for each hydrologic variable throughout the basin due to climate change. The most notable trend is in the change of storage, where the majority of the basin have negative trends near negative 25% - 100% change. These changes have a stronger signal as the historic storage value for water storage is near zero based on the theory of water balance. This shows that the total water availability within the basin is decreasing relative to the climatological average. The RP ratio also displays some areas with decreasing trends. The decrease in RP ratio can be due to various factors including increased ET, decreased rainfall intensities, and changing rainfall patterns. Regardless of the factors contributing to the decrease in RP ratio relates to decrease in effective precipitation (i.e. the amount of precipitation that is converted to runoff). The ET variable is shown to have an increase due to climate variability, most likely due to the projected rising temperatures in the region.
Figure 5.14 Trends in hydrologic variables in the LMB due to climate variability. Large changes (25-100%) can be seen for the $\Delta S$ variable with smaller changes (1-5%) for the R/P ratio and ET due to climate variability.

The trends for the simulated hydrologic variables due to land cover change are shown in Figures 5.15-5.19. There are few geographically isolated trends within the basin due to different land cover change scenarios, however, the basin as a whole shows minimal changes to the hydrologic variables through time due to land cover change. The baseline land cover change scenario shows there is a decreasing trend in storage near the northwestern portions of the basin, additionally, there are small increasing trends in storage in southeastern portion of the basin. There are no large (greater than 10%) trends for in RP and ET for the baseline land cover change scenario. The increases in forest areas show more of a signal for trends where increases in storage and ET can be seen in both forest scenarios. There is a larger geographic area with increasing trends in storage and ET for the 10% increase scenario due to increased forest area. The scenarios with increases in agricultural areas show decreasing trends in storage and ET. The findings align with the hypothesis that forested areas in this region would increase overall ET and
hold more water and increases in agricultural areas would decrease overall ET and storage. There were no notable changes to the RP variable due to land cover change. Additionally, there seemed to be more intense, 5-25% as opposed to less than 10% change, for increasing trends due to increases in forest area than the decreasing trends of agriculture area, leading to believe that the hydrologic system of the LMB is more sensitive to increases in forest area.

**Figure 5.15** Trends in hydrologic variables in the LMB due to land cover change for the baseline scenario. Minimal changes (both 5-10% increase and decrease) can be seen in ΔS variable across the basin with almost no change in R/P ratio and ET due to the baseline land cover change scenario.
Figure 5.16 Trends in hydrologic variables in the LMB due to land cover change for the 5% forest increase scenario. Increases in $\Delta S$ and slight increases (2-5%) ET can be seen in the southern portions of the basin with the increases in forested area.

Figure 5.17 Trends in hydrologic variables in the LMB due to land cover change for the 10% forest increase scenario. Large increases (25-75%) in $\Delta S$ and increases (2-5%) ET can be seen in the southern portions of the basin with the increases in forested area; areas increasing are larger for a 10% increase in forest than with a 5% increase in forest.
Figure 5.18 Trends in hydrologic variables in the LMB due to land cover change for the 5% agriculture increase scenario. Slight decreases (-3—10%) in ΔS can be seen, however, almost no change in R/P ratio and ET are seen.

Figure 5.19 Trends in hydrologic variables in the LMB due to land cover change for the 10% agriculture increase scenario. Slight decreases (-4—25%) in ΔS can be seen with minimal decreases (-1—3%) in ET are seen as well.
5.6 Summary

The hydrologic system was found to be more sensitive to climate variability than land cover changes. This is a logical finding as the hydrologic system is driven by meteorological variables (precipitation input and temperature), whereas the land cover plays a more passive role in the hydrologic system by being reactive to the meteorological inputs. Climate variability had the largest effects by altering the annual discharge amount and seasonality as well as altering the storage, RP, and ET for the entire basin. Changes to the hydrologic system were identified for land cover change, however, the effects were less than the changes climate had. The changes in hydrology due to land cover found that increases in forest decreased annual streamflow, increased ET, and increased storage. Increases in agricultural land had the opposite effect where discharge increased and there were decreasing trends in ET and storage. The scenarios with 10% increase for forest and agriculture were found to have the most amplified effects on the system.
CHAPTER VI

SUMMARY AND CONCLUSION

This chapter summarizes the major findings of this research and explains how the errors and uncertainties associated with the analyses. A list of results from the research is given which can benefit ongoing research in the region. Future directions of research will also be discussed.

6.1 Overall Conclusions

This study aimed to investigate the spatial and temporal change to the LMB hydrologic system due to climate variability and land cover change. A land cover change model was developed to simulate how land cover will change through time within the basin under a variety of scenarios. A hydrologic model was setup for the LMB using the VIC hydrologic model. The land cover data from the simulations and climate projections were used to simulate future hydrologic variables. The hydrologic variables were then compared to the past climatological averages to analyze for change.

The results of the analyses showed that climate variability will result in variable river discharge with different onset and durations of the wet season. The mean annual
discharge was found to increase and the mean date of the wet season is to shift forward by approximately one month (from beginning of Sep. to Aug.). Surface runoff was found to be sensitive to changes in precipitation with about 2% increases in surface runoff to a 1% increases in precipitation. The total water storage showed a decreasing trend across most of the basin and evapotranspiration was found to have a small increasing trend across the entire basin due to climate variability. The hydrologic system was found to be sensitive to climate variability based on the modeling efforts.

The changes in land cover shown to have minimal impacts on the discharge for the entire basin. Although the changes were small, there was a notable separation between the simulated discharge from the forest and agricultural area increases for the land cover change simulations. The forest increases shown to have a decrease in discharge whereas increases in agriculture areas increased discharge. There was no notable change to the seasonality of discharge due to land cover change. The basin was also found to have almost no sensitivity of surface runoff to land cover changes, making the argument that another variable was controlling the changes in discharge. The spatial trends in hydrologic variables show that storage and evapotranspiration had the most changes. There was an increasing trend in storage and evapotranspiration with increase in forested area and a decreasing trend in storage and evapotranspiration with increases in agricultural area. The hydrologic system was found to be insensitive to changes in land cover.

6.2 Additional outcomes of research

A few additional results have come from completing this research. First, a 30-year dataset of hydrologic variables including surface runoff, evapotranspiration, and soil
moisture were created. This dataset was used within this study as the control environment for the LMB to analyze changes against. These data can be used in other studies to analyze past and future changes to hydrology. Additionally, other data outputs from the hydrologic model, such as energy budget variables, can be created for a more comprehensive outlook on the hydrology and climatology for further climate studies.

A more significant contribution of this study is the modeling framework that was developed. A calibrated and validated land cover change and hydrologic model have been developed for the LMB which can be used and expanded for other studies. The land cover change model can be applied by land managers to analyze different land cover change scenarios for the basin to understand how policy changes may affect the landscape of the basin. The hydrologic model can also be used for future hydrologic research and other weather and climate studies that have a need for the implementation of a land surface model. Furthermore, with the increasing accuracy of data inputs, such as climate projections, and more accurate parameterization and representation of physics within models, a more precise depiction of hydrologic changes can be concluded from the modeling efforts.

6.3 Errors, uncertainties, and caveats

There are many ways that errors and uncertainties can arise from this study. For example, the main sources of errors can be from parametrization of the VIC model, parameterization of the land cover model, and data inputs can cause errors. The uncertainty within the models used, both the hydrologic and land cover change model, were characterized through the validation of both models, resulting in statistically valid models.
Another source of error from this study comes from the approach of analysis, particularly in characterizing future changes. This study used projected land cover within the analysis to test changes to the system due to land cover change. The effects of land cover change on the hydrologic system could be characterized by analyzing past observed data, however, the modeling approach used allowed for more scenarios, such as the 10% increase in forested area, to be analyzed for changes to the hydrologic system. The use of different scenarios could not be achieved using part observed data, however, using past observed land cover change information would have eliminated the errors in results from using modeled data as inputs.

The largest uncertainty associated with this study can be attributed to the input data used, particularly the use of climate model input data. Predictions and projections of weather and climate from time scales of days to centuries usually come from numerical models that rely on inputs of initial condition information, boundary conditions, and the parameterization or mathematic representation of relevant processes [Telbadi and Knutti, 2007]. The input conditions into projections primarily affect short-term time scales, however, parameterizations within the models result are the largest source of uncertainty through computationally constraining small-scale, but important, physical processes. These assumptions within climate models and their resulting uncertainties make the modeling of the Earth’s climate system practically impossible [Telbadi and Knutti, 2007]. It was found there is a large uncertainty in climate model data used for this study (see section 4.3.2.2) which can propagate into the output of resulting models using the data. Van Griensven and Meixner [2006] report that the uncertainty in outputs from models are mainly affected by the model’s structure uncertainty, including input data.
With the high uncertainty associated with this study, particularly within the
cclimate model data inputs and how it affects the results of analysis, *the results of this
study should not be used for any decision making or policy formulation within the region.*
This study provides a first-order analysis of how the hydrologic system can change due to
land cover change and future climate variability, however, it does not give a definitive
depiction of hydrologic change within the basis for water resource management. The aim
of this study was to give insight on the possible effects of land cover change and climate
variability on the water resources and the results should be taken as provisional
outcomes.

More work and more accurate climate model data is needed to provide the precise
results needed for decision making. With the advent of new climate modeling techniques
and models, more accurate climate predictions can be provided for analyses such as this
study. The modeling framework as a result of this study can use the improved climate
projection for more accurate results. The results of increased accuracy from both climate
projections and the applications using the projects can then be used for enhanced decision
making and water resource management.

### 6.4 Integration of research into the SERVIR program

The Regional Visualization and Monitoring System (SERVIR) program, a joint
initiative between the U.S. National Aeronautics and Space Administration (NASA) and
the U.S. Agency for International Development (USAID), focuses on building the
capacity of developing countries to use information provided by Earth observing
satellites and geospatial technologies to manage climate risks and land use. The work
presented is in direct alignment with SERVIR’s goals by addressing issues of climate
change and land cover change within a geographic region of focus, the LMB. This research touches upon multiple key themes addressed in the SERVIR-Mekong’s need assessment for the region including: (a) land cover mapping and monitoring, (b) water resource management, and (c) climate change adaptation for the region [SERVIR-Mekong, 2015]. Through the SERVIR-Mekong project implemented by the Asian Disaster Preparedness Center (ADPC) based in Bangkok Thailand, the modeling framework stemming from this study and future work can be disseminated to land use planning and water resource management departments within the region for their use while also building the capacity within the region to manage climate risks and land use changes. Furthermore, other projects being implemented by the SERVIR-Mekong project are using the VIC model for flood management and drought monitoring. The calibration factors and model setup used in this study can be shared to support the SERVIR-Mekong efforts in using the VIC model.

6.5 Future Work

The work presented can be expanded through future work on the technical and analytical aspects of the work to provide more information for enhanced decision making. First, the future work will include updating the technical aspects of the land cover change model. The updating of the land cover change model will include taking into account spatial autocorrelation into the spatial allocation module to simulate how distance plays a role into related land cover features. Furthermore, spatial disaggregation of the demand trend calculations and spatial allocation procedures to administrative boundaries, such as at the country level, can provide a means of accounting for the different land management policies in place spatially within the modeling domain.
Another means to represent different policies and decision making is through modeling the small-scale human decision taking into account local-level change to produce a bottom-up modeling approach. Incorporating agent-based modeling will help produce a more realistic representation of human decision making and policy changes within the model. Additionally, future work on the land cover model will include making the model more dynamic so that it can be implemented for other geographic regions for such studies.

Further future work in terms of hydrologic modeling will include performing the same analysis as in this thesis but for liberal (high) and conservative (low) climate projections. Additionally, using climate model ensemble data can provide a probabilistic outlook into the future hydrology under an array of scenarios [Telbadi and Knutti, 2007]. The need for such an analysis is to have a range of scenarios for hydrologic change so that water resource managers can plan for a worst-case scenario while also having a “best-guess” scenario from probabilistic model outputs.

Hydropower development through the building of dams has also been identified as a major concern within the Mekong Basin. Figure 6.1 displays the locations of current, planned, and commissioned dams within the region, where many dams can be seen along the tributaries of the Mekong River with many more planned or under construction. Dams alter the flow regime which have major implications for downstream water availability, ecology, and delta development. Research is currently being conducted on the hydrologic effects of dams in the region. Future work for this study will incorporate the effects of dams, climate, and land cover change for a more comprehensive analysis on alterations to the LMB hydrological system.
Lastly, the same work flow and research from this thesis can be applied to other basins within Southeast Asia. The modeling framework can be transitioned to other regions with minimal effort. The same analysis will provide critical information regarding the hydrologic system of other Southeast Asia basins such as the Irrawaddy and Chao Phraya basins. The expansion of the hydrological analysis framework can and will provide insight into variations of hydrology within Southeast Asia, particularly with the arrival of more accurate models and predictions for both land cover change and climate change.
APPENDIX A: Selection of climate model methodology

The selection of one climate model from the fourteen was constrained by three criteria: (1) a climate model that had the least amount of error in the modeled meteorological variables when compared to a validation dataset, (2) was able to capture seasonal trends in meteorological parameters for a validation period, and (3) follow closely to the median projected trend from all twenty-one climate models for each meteorological variable. Although all variables were considered to be important, more weight was given to how the precipitation variable for each model performed as it has been found that hydrologic models are sensitive to the spatial patterns and intensity of precipitation inputs [McMillan et al., 2011]. These three criteria for the selection of a climate model attempt to find the most accurate model that has the least error when compared to an observed dataset and captures seasonality of the region for past conditions assuming the ability to represent past conditions will translate to future prediction [Knutti et al., 2010]. Furthermore, selecting a climate model that represents the median trends is based on the evidence that multimodel averages tend to yield a better prediction than a single model [Knutti et al., 2010]. Only one climate model was selected because different climate models are structured differently with diverse systems for modeling the atmospheric system which leads to biases in the dataset. If an equally weighted average of the models were to be taken, it would assume that individual model biases will partially cancel and the resulting multimodel average is more likely to be correct [Knutti et al., 2010], however this is not always the case and creating an accurate multimodel average dataset is beyond the scope of this thesis.
The NEX climate datasets were first compared with observed data from one meteorological station in the southern western portion in the LMB described in section 4.2.4.1 to find a dataset with the least error of all three meteorological variables. The error metric used to evaluate the models was the relative error [Gleckler et al., 2008]. This metric assumes that all datasets being compared will have errors and the resulting information will be the error of each model compared to each other. First, the daily root mean square (RMS) error was calculated for each climate dataset and for each variable. Next, the ‘typical’ model error was defined as the median of the of the RMS errors; the median values were used rather than the mean values to prevent models with unusually large errors (outliers) from influencing the results. The calculation for relative error is defined by equation A.1:

$$RE_{i,v} = \frac{(RMS_{i,v} - RMS_v)}{RMS_v}$$  \hspace{1cm} (A.1)

where, $RE_{i,v}$ is the relative error for a given climate model and variable, $RMS_{i,v}$ is the RMS error for a given model and variable, and $RMS_v$ is the median RSE error for a given variable. By normalizing the error calculations in this manner, it provides a measure of how well a given model (with respect to the reference data set) compares with the typical model error of all the datasets. For example, if the relative error is a value of -0.1, then the model’s RMS error is 10% less than the typical model. Conversely, if the relative error has a value of 0.1, the model’s RMS error is 10% greater than the median RMS error [Gleckler et al., 2008]. The results of the relative error calculations are displayed in Figure A.1. Only six of the fourteen models had favorable relative errors for precipitation. Of those six models, only two had a relative error of less than -0.1, the bcc-csm1-1 model and the BNU-ESM model. Despite having the least error for precipitation,
the BNU-ESM model had a positive relative error for both minimum and maximum temperature resulting in a higher relative error for those two variables than the bcc-csm1-1 model.

Figure A.1 Relative error of all 14 climate models compared to the observed station data

The fourteen NEX climate datasets were then analyzed to find which model best represented the median trend from all climate models. The median trend was found by finding the median values of each variable from all fourteen climate models at a yearly time step (for this case a full year was used) then a linear least-square regression was applied to find the trendline. A linear least-square regression was also performed for each climate model to find the trend lines. Next, the RMS error for each climate model trend
line was calculated compared to the median trend line. The resulting information shows which model has a trendline closest to the median projection trend. The results of this analysis is shown in Figure A.2 where the mean offset from the median trend for precipitation, minimum temperature, and maximum temperature for each climate model is shown. It was found that the bcc-csm1-1 and BNU-ESM models are best representative of the median projection trend for all three variables combined. The two models have almost identical offsets from the median precipitation trend, however the bcc-csm1-1 model is more representative of the median projected trend from minimum and maximum temperature and was therefore favored over the BNU-ESM model. Figure A.3 displays the trend of the bcc-csm1-1 projected climate variables compared to the median trend from all fourteen datasets. Both the minimum and maximum trend begin higher than the median trend but become less as time proceeds whereas the projected precipitation trend is somewhat less than the median trend.
Figure A.2 Offset of each climate model trend line compared to the median trend line for all models
The last analysis implements to identify if the bcc-csm1-1 model was to be used for this study was to check if the past climatology modeled by the climate model represents the actual observed climate. This analysis found the mean precipitation, minimum temperature, and maximum temperature observed from the Aranyaphrathet station for each month as well as from the bcc-csm1-1 model. The climatology from both datasets as well as error statistics are displayed in Figure A.4. The climate model overestimates the minimum temperature for the entire year and overestimates the minimum temperature by approximately 1.2 degree Celsius. The maximum temperature underestimated on average by about 0.4 degree Celsius; the model specifically was found
to overpredict the maximum temperature during the dry season and underpredict the maximum temperature during the wet season.

Figure A.4 Comparison of monthly climatology and time series calculated from the climate model against the station data. Breaks within the time series plots indicate no data recorded by the meteorological station.

Based on the criteria selected, the bcc-csm1-1 model was the best suited model for this study. The model was able to loosely capture the climatology for the region based on Figure A.4. This model will be referred to as the NEX dataset throughout the text.
An inter-sensor accuracy assessment was completed for the MODIS and VIIRS sensors. This analysis was conducted to identify how well the MODIS MCD12Q1v5 land cover data and the VIIRS ST EDR land cover data agree to understand errors in the land cover change models performance drop from 2011 to 2015.

The latest MODIS land cover data from 2012 and the earliest VIIRS land cover data from 2013 was used in this analysis. There was no direct overlap between land cover product creations. To accommodate no overlap in data, only the last yearly quarter (Oct. – Dec.) land cover information retrieved from MODIS was extracted using the QA layers. The VIIRS data product currently does not have a yearly product, thus, a pseudo-level 3 data product was created by gridding the daily level 2 land cover product for the first yearly quarter (Jan. – Mar.) and taking the land cover that appeared the most for each pixel. A set of data samples were created using a stratified-random sampling method; a total of 580 sample points were created. The land cover classes for each dataset at the sample were extracted and used to create a confusion matrix and calculate error statistics.

The resulting confusion matrix is displayed in Figure B.1. The confusion matrix shows that there is poor agreement between the MODIS and VIIRS sensors. The VIIRS land cover classification classified more forest than MODIS. Additionally, there is some discrepancies between the grassland and agriculture classes for the two sensors. There is poor agreement for the water class where the MOIDS land cover classification has more water pixels classified as other. The resulting error statistics calculated from the confusion matrix are summarized in Table B.1. The overall accuracy between the two sensors is poor as well as the user’s and producer’s accuracies. Lastly, the kappa statistic
shows there is only a 47% chance that the agreement is due to the classifications rather than random chance. The results of this analysis show that there is poor agreement between the MODIS and VIIRS sensor land cover classifications. The poor agreement is possibly due to differences in sensor characteristics, such as spectral resolution and spatial resolution, and the inputs into classification algorithms used.

**Figure B.1** Confusion matrix for MODIS and VIIRS land cover classes

**Table B.1** Error statistics for the MODIS to VIIRS comparison

<table>
<thead>
<tr>
<th></th>
<th>Overall Accuracy</th>
<th>Producer’s Accuracy</th>
<th>User’s Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>VIIRS Class</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>56.72 %</td>
<td>67.72 %</td>
<td>57.01 %</td>
<td>0.47</td>
</tr>
<tr>
<td>Grassland</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>MODIS Class</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest</td>
<td>56.72 %</td>
<td>67.72 %</td>
<td>57.01 %</td>
<td>0.47</td>
</tr>
<tr>
<td>Grassland</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
APPENDIX C: Parameterization and setup of the hydrologic model

This section outlines the parameterization and setup for the VIC hydrologic model used in this study. All of the variable descriptions can be found at the VIC documentation webpage (vic.readthedocs.io); for simplicity, Table C.1 summarizes all of the parameters in this appendix and its description.

Table C.1 Description of variables parameterized in model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>b</td>
<td>n/a</td>
<td>Variable infiltration curve parameter</td>
</tr>
<tr>
<td>Ds</td>
<td>fraction</td>
<td>Fraction of $D_{s_{\text{max}}}$ where non-linear baseflow occurs</td>
</tr>
<tr>
<td>Ws</td>
<td>fraction</td>
<td>Fraction of maximum soil moisture where non-linear baseflow occurs</td>
</tr>
<tr>
<td>$D_{s_{\text{max}}}$</td>
<td>mm·day$^{-1}$</td>
<td>Maximum velocity of baseflow</td>
</tr>
<tr>
<td>$K_{\text{sat}}$</td>
<td>mm·day$^{-1}$</td>
<td>Saturated hydrologic conductivity</td>
</tr>
<tr>
<td>expt</td>
<td>n/a</td>
<td>Exponent in Cambell’s equation for hydraulic conductivity</td>
</tr>
<tr>
<td>$W_{\text{c,r}}$</td>
<td>fraction</td>
<td>Fraction of soil moisture content at the critical point</td>
</tr>
<tr>
<td>$W_{\text{wpw}}$</td>
<td>fraction</td>
<td>Fraction of soil moisture content at wilting point</td>
</tr>
<tr>
<td>$R_d (i)$</td>
<td>m</td>
<td>Root zone thickness for each zone $(i)$</td>
</tr>
<tr>
<td>$R_f (i)$</td>
<td>fraction</td>
<td>Fraction of root in the zone $(i)$</td>
</tr>
<tr>
<td>$R_{\text{arc}}$</td>
<td>s·m$^{-1}$</td>
<td>Architectural resistance of vegetation type</td>
</tr>
<tr>
<td>$R_{\text{min}}$</td>
<td>s·m$^{-1}$</td>
<td>Minimal stomatal resistance of vegetation type</td>
</tr>
<tr>
<td>LAI</td>
<td>m$^2$·m$^{-2}$</td>
<td>Leaf-area index of vegetation type</td>
</tr>
<tr>
<td>Veg</td>
<td>fraction</td>
<td>Vegetation cover fraction</td>
</tr>
<tr>
<td>Alb</td>
<td>fraction</td>
<td>Shortwave albedo for vegetation type</td>
</tr>
<tr>
<td>Rou</td>
<td>m</td>
<td>Vegetation roughness length</td>
</tr>
<tr>
<td>Dis</td>
<td>m</td>
<td>Vegetation displacement height</td>
</tr>
<tr>
<td>RGL</td>
<td>W·m$^{-2}$</td>
<td>Minimum incoming shortwave radiation at which there will be transpiration</td>
</tr>
</tbody>
</table>

The spatial resolution of the model grid was specified at 0.1 degree resolution, for all of the sub-grid spatial variability the resolution was set at 0.01 degree therefore, for each model grid there was 100 pixels. The fraction of each land cover class was used
within each model grid cell for sub-grid variability in land cover. The elevation variability for a grid cell was represented by partitioning the entire basin into eight elevation bands; then the fraction for each band within a given grid cell was used. The elevation of the basin was segmented into eight elevation bands by using a quantile mapping method. Sub-grid areal precipitation was also defined for the elevation bands by using yearly accumulated precipitation climatology data from Hijmans et al. [2005].

Parameterization of soils was an important factor that controls how water behaves in the soils. Drainage of soils was one variable within the soil database, this information was used to parameterize the infiltration of water in the soils. Table C.2 summarizes the drainage classes and to parameters set for each class.

<table>
<thead>
<tr>
<th>Drainage Class</th>
<th>b</th>
<th>D_s</th>
<th>W_s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Poor</td>
<td>0.23</td>
<td>0.001</td>
<td>0.80</td>
</tr>
<tr>
<td>Poor</td>
<td>0.22</td>
<td>0.00105</td>
<td>0.81</td>
</tr>
<tr>
<td>Imperfectly</td>
<td>0.21</td>
<td>0.00115</td>
<td>0.84</td>
</tr>
<tr>
<td>Moderately Well</td>
<td>0.205</td>
<td>0.00125</td>
<td>0.85</td>
</tr>
<tr>
<td>Well</td>
<td>0.20</td>
<td>0.0013</td>
<td>0.86</td>
</tr>
<tr>
<td>Somewhat Excessive</td>
<td>0.19</td>
<td>0.0014</td>
<td>0.88</td>
</tr>
<tr>
<td>Excessive</td>
<td>0.18</td>
<td>0.0015</td>
<td>0.9</td>
</tr>
</tbody>
</table>

The USDA soil classes were used for further parameterization of the soils. Table C.3 summarizes all of the parameter values for each USDA soil class. The $D_{\text{max}}$ parameter was estimated by taking the average slope of the grid and multiplying it by the saturated hydrologic conductivity. The grid slope was calculated using the methods described by [Lauri and Kummu, 2014]. The initial moisture conditions were estimated by multiplying the depth of the soil layer by the fraction of soil moisture content at
critical point \((W_{cr})\). The remainder of the soil parameters were used based off of suggested parameters from the VIC documentation.

**Table C.3** Soil variable parameterization based off of USDA soil class

<table>
<thead>
<tr>
<th>USDA soil class</th>
<th>(K_{sat})</th>
<th>expt</th>
<th>(W_{cr})</th>
<th>(W_{pwp})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>9218.4</td>
<td>11.2</td>
<td>0.19</td>
<td>0.07</td>
</tr>
<tr>
<td>Loamy sand</td>
<td>2608.8</td>
<td>10.98</td>
<td>0.36</td>
<td>0.14</td>
</tr>
<tr>
<td>Sandy loam</td>
<td>1257.6</td>
<td>12.68</td>
<td>0.53</td>
<td>0.22</td>
</tr>
<tr>
<td>Silt loam</td>
<td>950.4</td>
<td>10.58</td>
<td>0.70</td>
<td>0.26</td>
</tr>
<tr>
<td>Silt</td>
<td>2061.6</td>
<td>9.1</td>
<td>0.54</td>
<td>0.15</td>
</tr>
<tr>
<td>Loam</td>
<td>472.80</td>
<td>13.6</td>
<td>0.67</td>
<td>0.33</td>
</tr>
<tr>
<td>Sandy clay loam</td>
<td>576.0</td>
<td>20.32</td>
<td>0.69</td>
<td>0.44</td>
</tr>
<tr>
<td>Silty clay loam</td>
<td>1096.8</td>
<td>17.96</td>
<td>0.75</td>
<td>0.44</td>
</tr>
<tr>
<td>Clay loam</td>
<td>424.80</td>
<td>19.04</td>
<td>0.74</td>
<td>0.46</td>
</tr>
<tr>
<td>Sandy clay</td>
<td>585.6</td>
<td>29.0</td>
<td>0.76</td>
<td>0.56</td>
</tr>
<tr>
<td>Silty clay</td>
<td>708.0</td>
<td>22.52</td>
<td>0.76</td>
<td>0.51</td>
</tr>
<tr>
<td>Clay</td>
<td>763.2</td>
<td>27.56</td>
<td>0.77</td>
<td>0.57</td>
</tr>
</tbody>
</table>

The next parameterization was based on the land cover types. These parameterizations included the soil profile for each land cover class and land cover characteristic such as albedo and leaf-area index (LAI) for each class. Table C.4 summarizes the parameterization for each land cover soil profile, the parameters included rooting depth (Rd) and rooting fraction (Rf) for each rooting depth. Three rooting depths were specified in meters for the model were the total rooting depth is the sum of all the rooting depths. The total rooting fraction equals 1 through all three rooting depths.
Table C.4 Soil profile parameterization for the land cover classes

<table>
<thead>
<tr>
<th>Land cover class</th>
<th>$R_d$ (1)</th>
<th>$R_d$ (2)</th>
<th>$R_d$ (3)</th>
<th>$R_f$ (1)</th>
<th>$R_f$ (2)</th>
<th>$R_f$ (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>0.45</td>
<td>0.75</td>
<td>1.8</td>
<td>0.23</td>
<td>0.75</td>
<td>0.02</td>
</tr>
<tr>
<td>Grassland</td>
<td>0.15</td>
<td>0.25</td>
<td>0.6</td>
<td>0.85</td>
<td>0.14</td>
<td>0.01</td>
</tr>
<tr>
<td>Agriculture</td>
<td>0.075</td>
<td>0.125</td>
<td>0.3</td>
<td>0.85</td>
<td>0.14</td>
<td>0.01</td>
</tr>
<tr>
<td>Water</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.98</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Urban</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.9</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Other</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.8</td>
<td>0.15</td>
<td>0.05</td>
</tr>
</tbody>
</table>

The remainder of the parameterization focuses on the land cover characteristics for the land surface. Table C.5 summarizes the parameterization used for the land surface characteristics. The LAI parameter in particular was estimated from remote sensing datasets where monthly values of LAI were used summarized in Table C.6, all other parameters were static.

Table C.5 Summary of land surface parameterization for each land cover classes

<table>
<thead>
<tr>
<th>Land cover class</th>
<th>$R_{arc}$</th>
<th>$R_{min}$</th>
<th>Veg</th>
<th>Alb</th>
<th>Rou</th>
<th>Dis</th>
<th>RGL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>30.0</td>
<td>95</td>
<td>0.85</td>
<td>0.125</td>
<td>3.69</td>
<td>20.1</td>
<td>30</td>
</tr>
<tr>
<td>Grassland</td>
<td>3.5</td>
<td>80</td>
<td>0.68</td>
<td>0.165</td>
<td>0.62</td>
<td>0.62</td>
<td>100</td>
</tr>
<tr>
<td>Agriculture</td>
<td>2.0</td>
<td>100</td>
<td>0.75</td>
<td>0.170</td>
<td>0.13</td>
<td>0.13</td>
<td>100</td>
</tr>
<tr>
<td>Water</td>
<td>0.5</td>
<td>70</td>
<td>0</td>
<td>0.080</td>
<td>0.0001</td>
<td>0.005</td>
<td>30</td>
</tr>
<tr>
<td>Urban</td>
<td>0.5</td>
<td>200</td>
<td>0.10</td>
<td>0.150</td>
<td>1.85</td>
<td>10.1</td>
<td>999</td>
</tr>
<tr>
<td>Other</td>
<td>0.5</td>
<td>999</td>
<td>0.01</td>
<td>0.380</td>
<td>0.01</td>
<td>0.05</td>
<td>999</td>
</tr>
</tbody>
</table>

Table C.6 Summary of monthly LAI values used for land cover parameterization for each land cover class

<table>
<thead>
<tr>
<th>Land cover class</th>
<th>Jan</th>
<th>Feb</th>
<th>Mar</th>
<th>Apr</th>
<th>May</th>
<th>Jun</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>6.50</td>
<td>6.40</td>
<td>5.90</td>
<td>5.60</td>
<td>5.40</td>
<td>5.40</td>
</tr>
<tr>
<td>Grassland</td>
<td>3.60</td>
<td>4.00</td>
<td>3.50</td>
<td>3.20</td>
<td>2.90</td>
<td>2.30</td>
</tr>
<tr>
<td>Agriculture</td>
<td>1.70</td>
<td>100</td>
<td>0.75</td>
<td>0.170</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>Water</td>
<td>1.70</td>
<td>1.90</td>
<td>1.90</td>
<td>1.70</td>
<td>1.40</td>
<td>1.25</td>
</tr>
<tr>
<td>Urban</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Other</td>
<td>0.75</td>
<td>0.75</td>
<td>0.62</td>
<td>0.49</td>
<td>0.36</td>
<td>0.23</td>
</tr>
<tr>
<td>Land cover class</td>
<td>Jul</td>
<td>Aug</td>
<td>Sep</td>
<td>Oct</td>
<td>Nov</td>
<td>Dec</td>
</tr>
<tr>
<td>------------------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Forest</td>
<td>5.20</td>
<td>5.40</td>
<td>5.60</td>
<td>6.20</td>
<td>6.30</td>
<td>6.40</td>
</tr>
<tr>
<td>Grassland</td>
<td>2.00</td>
<td>1.50</td>
<td>2.00</td>
<td>2.20</td>
<td>2.20</td>
<td>3.00</td>
</tr>
<tr>
<td>Agriculture</td>
<td>1.20</td>
<td>1.10</td>
<td>1.20</td>
<td>1.30</td>
<td>1.40</td>
<td>1.50</td>
</tr>
<tr>
<td>Water</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Urban</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Other</td>
<td>0.10</td>
<td>0.10</td>
<td>0.23</td>
<td>0.36</td>
<td>0.49</td>
<td>0.62</td>
</tr>
</tbody>
</table>
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