1-1-2012

The Feasibility of Growing Switchgrass in China for Lignocellulosic Ethanol Production

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THE FEASIBILITY OF GROWING SWITCHGRASS IN CHINA FOR LIGNOCELLULOSIC ETHANOL PRODUCTION

by

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Earth Sciences

The University of Memphis

December, 2012

Dedication

I dedicate this dissertation to my family who has always encouraged me to reach for the stars. I love you all so much. To my wife, Danielle, thank you for all your support and hard work throughout this process. To my children, Zachary and Baby Adkins, you are truly my inspiration. Mom and Dad, there aren't enough words in the world to describe what you mean to me. You instilled in me the importance of a higher education, hard work, achievement, and to never give up when challenges present themselves. Without you this dissertation would not have been possible. Tai, Chris, and Billy, thank you for being the best brothers and sister anyone could ever ask for.

Acknowledgments

I would like to express the deepest appreciation to my advisor, Dr. Gregory Taff, for everything you have done for me throughout this journey. Your uplifting spirit, excitement you bring to teaching, patience, understanding, and genuine care for your students is truly remarkable. To my committee chair, Dr. Hsiang-te Kung, thank you so much for all that you've done for me, especially taking me to China with you and supporting my research there through the Confucius Institute. I would like to thank my committee members, Dr. Daniel Larsen, Dr. Donald Tyler, Dr. Takuya Nakazato, and Dr. Angela Antipova for providing guidance, support, and their expertise throughout this process. I also thank the University of Memphis and the National Science Foundation for funding this dissertation through the Graduate Research Fellowship Program.

Abstract

Adkins, Ronné Allen. Ph.D. The University of Memphis. December, 2012. The Feasibility of Growing Switchgrass in China for Lignocellulosic Ethanol Production. Major Professor: Dr. Hsiang-te Kung.

Switchgrass (*Panicum virgatum* L.) is a perennial plant species native to the United States that is capable of adapting to a wide variety of geographic and climate conditions. There are two ecotypes of switchgrass: lowland varieties which favor areas with higher rainfall and longer growing seasons and upland varieties which favor areas with cooler and drier climate conditions with shorter growing seasons. Switchgrass has the capacity to become a significant bioenergy feedstock for lignocellulosic ethanol conversion. The purpose of this dissertation is to determine which regions in China are suitable for switchgrass production, estimate potential biomass yield, and examine the effects of predicted climate change scenarios at the end of the 21st century on potential yields in China. To accomplish these goals, two ecological niche models (Maxent and GARP) are implemented based on known switchgrass presence data throughout the United States to ascertain which regions in China have suitable habitats for its growth. Multiple linear regression analysis was performed on a comprehensive database of 1,190 switchgrass field trials in 39 separate locations across the United States to build a model that estimates potential switchgrass yields across China. Future climate projections (2070 – 2099) from the Hadley Centre Coupled Model, version 3 (HadCM3) global circulation model (GCM) are employed in the multiple linear regression model to make switchgrass yield estimations for the end of the century. The ecological niche modeling results reveal China has large areas of suitable habitat for switchgrass development. The multiple linear regression analysis demonstrates that China has the potential to produce large quantities of switchgrass, even more so than in the United States; however, analysis of the impact of

climate change by the end of the 21^{st} Century indicates that warmer temperatures will result in lower yields on average, a substantial reduction in suitable habitat for lowlands, and an expanded habitat range for upland ecotypes. This dissertation concludes that switchgrass should be considered a viable plant species to serve as a bioenergy feedstock for lignocellulosic ethanol production in China, and the results herein offer guidelines regarding optimal regions in the country for switchgrass production.

Preface

Chapter 2, "Predicting Potential Switchgrass Distribution across China based on GARP and Maxent Ecological Niche Models," was submitted for publication to the journal, *Ecological Modelling*.

Chapter 3, "Feasibility of Growing Switchgrass as Feedstock for Lignocellulosic Ethanol Production across China: Modeling Potential Yield," was submitted for publication to the journal *Agriculture, Ecosystems, and Environment*.

Chapter 4, "Simulating Potential Switchgrass Yield Response to Climate Change in China," was submitted for publication to the journal *Agriculture, Ecosystems, and Environment*.

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CHAPTER 1

1. Introduction

The purpose of this dissertation is to examine the feasibility of growing switchgrass (*Panicum virgatum L.*) throughout every region of China for the production of lignocellulosic ethanol and soil erosion control under present climate conditions and the end of the 21st century projected climate conditions. The analysis consists of three separate, complementary methods to model switchgrass's potential distribution, predict potential yields, and evaluate the impact climate change could have on switchgrass development throughout China. Switchgrass is a perennial plant species native to the United States and has been researched extensively over the past fifty years, both for soil and habitat rehabilitation and for use as feedstock for biofuel production (i.e. lignocellulosic ethanol). As a result of the accumulated wealth of knowledge regarding where and how much switchgrass can be grown in the United States, the environmental conditions suitable for its development will be analyzed and then projected onto China to determine areas that have similar growing and environmental conditions that could serve as potential sites to cultivate switchgrass for biofuel production or to control and rehabilitate areas of degraded soils.

This research is very important and timely to present energy concerns not only in China, but globally, as more countries are looking to strengthen and reinforce their energy security to meet present and projected future energy needs. China currently leads the rest of the world in population, energy consumption and demand, and has therefore directed many policies and much research toward developing its renewable energy sector. Switchgrass has shown great potential as a relatively low-maintenance energy crop that can produce significant quantities of biomass, as well as play a substantial role in the

United States' Conservation Reserve Program (CRP) that uses switchgrass as a means to enhance degraded soils, improve wildlife habitat and increase biodiversity amongst plant and animal species (McLaughlin and Kszos, 2003).

The regions in China that have suitable climate and environmental conditions necessary for switchgrass to grow, based on information about those conditions in its native habitat in the US are discussed in chapter one. This essentially determines areas in China that meet switchgrass' fundamental niche requirements for growth and long-term survivability. To accomplish this analysis, locations of switchgrass in the United States were used in conjunction with the environmental and climate data from these locations in an ecological niche model. The data were processed using Spatial Analyst tools in ESRI ArcGIS (ESRI, Redlands, CA). Two ecological niche models, maximum entropy (Maxent) and genetic algorithm for rule-making program (GARP), are used to analyze the native presence locations' environmental and climate data and then make projections onto China. The two models are then compared to each other and analyzed for accuracy. The model results will be used to identify areas in China that most reasonably meet switchgrass' development requirements.

Estimates of potential switchgrass yields across China were generated through employing an empirical model built from a multiple linear regression analysis on 1,190 switchgrass field trial observations from 39 locations in the United States and are shown in chapter two. The model uses soil, climate and crop management information for predictor variables and total switchgrass yields from each observation as the outcome variable. Once the model was developed based on the environmental and climate conditions in the United States, it was also then applied to China. A predicted switchgrass potential yield map was produced from the results of the model, indicating estimated potential yields across China. The results show preferential areas for switchgrass production within China, but indicate that China has the potential to produce significant quantities of switchgrass across a vast area of the country.

The final chapter focuses on the effects of predicted climate change at the end of the current century on potential switchgrass yields in China, using the Hadley Centre Coupled Model, vers. 3 (HadCM3), global circulation model (GCM) climate projections. Climate change projections are made based in large part on estimated future global greenhouse gas emissions. Three different emissions scenarios were analyzed, representing high, intermediate, and low greenhouse gas emissions. The regression model developed in chapter 2 was used to predict switchgrass yields in China under these future climate and greenhouse gas scenarios. The objective is to determine the impact of rising greenhouse gas emissions and associated climate change on potential switchgrass yields throughout China.

The results from each chapter complement each other in their representation of switchgrass potential in China, and can be useful to policy makers and energy companies to evaluate the potential large-scale production of switchgrass in China for lignocellulosic ethanol production and for controlling soil erosion problems. Findings from this dissertation represents the first time switchgrass has been analyzed across all of China for potential suitable habitat distributions, yield estimations, and climate change impacts.

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CHAPTER 2

Predicting Potential Switchgrass Distribution across China Based on GARP and Maxent Ecological Niche Models

1. Introduction

Switchgrass (*Panicum virgatum L.*) is a native North American, C_4, perennial grass species that has shown great potential as feedstock for lignocellulosic ethanol production as well as demonstrated success in reducing soil erosion in marginal and degraded soils (Parrish and Fike, 2005). Given China's climate, its growing need for energy, its vast cultivable area, and its struggles with erosion, switchgrass farming may be of significant use in China. Predicting the suitable habitat for switchgrass in China is critical for identifying and mapping these areas for potential ethanol production and rehabilitation and management of eroded soils. Switchgrass's native distribution stretches from the Atlantic coast to the eastern Rocky Mountains and from the southern U.S. border north into Canada (Rinehart, 2006). The growing season is from April through September. The two primary ecotypes of switchgrass are lowland and upland ecotypes. Lowland varieties are taller, coarser, produce more biomass than uplands and generally found in areas that have higher rainfall and longer growing seasons and mild winters (Vogel, 2002). Upland varieties are more adapted to the drier and colder climates that can be found in the Midwestern and Northern states (Bouton, 2007). The ploidy levels for each ecotype are different: lowlands are tetraploids (2n=4x=36) and uplands are primarily octoploids (2n=8x=72) with some tetraploids (Hopkins et al., 1996; Hultquist et al., 1996). Many different cultivars of switchgrass exist within the ecotypes. Cultivars are the different switchgrass varieties within ecotypes that have been selected and reproduced for desirable qualities and characteristics. The most common are Alamo and Kanlow, which are lowlands that are grown in the Southern states and are capable of producing high biomass yields, and Cave-in-Rock, an upland which is best adapted to the Northern states (Parrish and Fike, 2005).

China is currently the largest and fastest growing developing country, the largest automobile market, and the largest energy consumer in the world (CSY, 2008; BP, 2011). Realizing this and facing increasing transportation fuel costs, soaring energy demand, and a diminishing supply of crude oil, China has formulated national policies (i.e. *PRC Law of Renewable Energy* in 2005) that enhance renewable energy research, supply and structure, with the goal of bolstering domestic energy and economic security while protecting the environment (Peidong et al., 2009). China is also home to some of the world's most eroded soils in the Loess Plateau, an area that covers 640,000 km^2 in the upper middle reaches of the Yellow River in northern China. Recent analyses of approximately 20,000 plant species studied for vegetation recovery and soil erosion control in the Loess Plateau concluded that switchgrass functioned the best of all species evaluated (Ichizen et al., 2005). If adopted on a wide scale in China, switchgrass has the potential to be a significant source of biomass feedstock while mitigating the serious environmental concern of soil erosion.

Ecological niche modeling is one approach scientists have used to model the potential geographic distribution of a species. This method analyzes the environmental conditions of a species' known occurrence distribution to predict potential suitable habitats in different locations and is used in a variety of disciplines, including ecology, biogeography, conservation management and many other fields (Peterson et al., 1999; Guisan and Zimmermann, 2000; Guisan and Thuiller, 2005; Peterson et al., 2007; Bombi et al., 2009; Kumar et al., 2009). The predicted distribution is a characterization of the estimated ecological niche of a species. The fundamental niche of a species is comprised of all the environmental conditions necessary for survival; however, its realized niche is a subdivision of the fundamental niche that the species actually occupies (Hutchinson, 1957). It is possible for a species' realized niche to be smaller than its fundamental niche, as a result of anthropogenic impacts, geographic barriers, biotic interactions (such as competition, predation and parasitism), and other factors not easily captured spatially (Phillips et al., 2006; Pearson, 2007). The environmental conditions within a species' fundamental niche is captured in ecological niche models, plotted spatially, hence representing its potential geographic distribution.

While there are many ecological niche models, two commonly used modeling algorithms are the Genetic Algorithm for Rule-set Production (GARP) and maximum entropy (Maxent) (Scachetti-Pereira, 2002; Phillips, 2006). Both are considered presence-only models that use known occurrence data to create pseudo-absences based on locations where the species is not known to occur. Both methods also utilize elevation, temperature, precipitation, soil characteristics and other environmental variables that can potentially affect the species' distribution. GARP uses sets of rules of logic inference to determine the presence or absence of a species in a given area (Stockwell and Nobel, 1992). The occurrence data are divided evenly, with one half (training data) randomly chosen to develop the model rules and the other half (test data) used to evaluate the accuracy of the model rules. GARP uses an iterative process of rule selection, testing, evaluation, rejection or incorporation to select a method from a set of options (logistic regression, atomic rules, range rules, negated range rules) and applies it to the training data to develop or evolve a rule (Stockwell and Peters, 1999). Model output is binary, where 0 represents unsuitable habitat and 1 represents suitable habitat.

Maxent is a recently developed machine learning method based on the principle of maximum entropy (i.e. uniform distribution) (Phillips et al., 2006). It develops the probability distribution for species occurrence by estimating the probability distribution of maximum entropy that is constrained from the environmental parameters in the study area (Phillips et al., 2004). Maxent applies categorical and continuous data, incorporates interactions between different environmental variables, and is effective at avoiding commission errors (Pearson et al., 2007). The Maxent output map is a cumulative probability of occurrence across the study area. Recent studies comparing various ecological niche models found that Maxent performed as good as or better than the other models at predicting a species' potential distribution (Elith et al., 2006; Phillips et al., 2006; Hernandez et al., 2006, 2008).

In this study, GARP and Maxent are employed to predict the potential distribution of switchgrass across every region of China. These two models were selected for this analysis based on their abilities to predict suitable species habitat with presence only data and their consideration of being two of the best ecological niche modeling algorithms (Elith et al., 2006). ArcMap, version 10 (ESRI Inc., Redlands, CA), was used to process environmental data in a Geographic Information Systems (GIS) context and display the projected potential distribution output map. The primary objective of this research is to identify suitable locations in China that can sustain switchgrass development for prospective ethanol production and/or soil erosion control.

2. Materials and Methods

2.1. Occurrence and environmental data

The complete list of occurrence locations for *Panicum virgatum* L. in the United States was collected from the United States Department of Agriculture's (USDA) plants database online (USDA, NRCS, 2010). The database provided switchgrass occurrence data for 1,481 counties in 45 states. Alaska, Hawaii, Washington, Oregon and California are the only states that did not have an occurrence record for switchgrass. Geographic barriers and climate conditions are likely reasons why occurrence records don't exist in those states. The majority of the native distribution lies in the middle of the country between Kansas and Indiana. There is also a large cluster of presence records on the East Coast, stretching from Pennsylvania and New Jersey down the coast to South Carolina. The latitude and longitude of the center of each county where switchgrass has been recorded were obtained by using spatial analyst tools in ArcMap. The USDA's plant database does not differentiate between upland and lowland ecotypes, therefore the occurrence data was divided at the 42°N latitude, where all records above 42°N were considered uplands and those below where labeled lowlands, based upon Casler et al.'s (2004) findings that lowlands lose competitive advantage to uplands at higher latitudes. This analysis yielded 605 lowland ecotypes and 876 upland ecotypes.

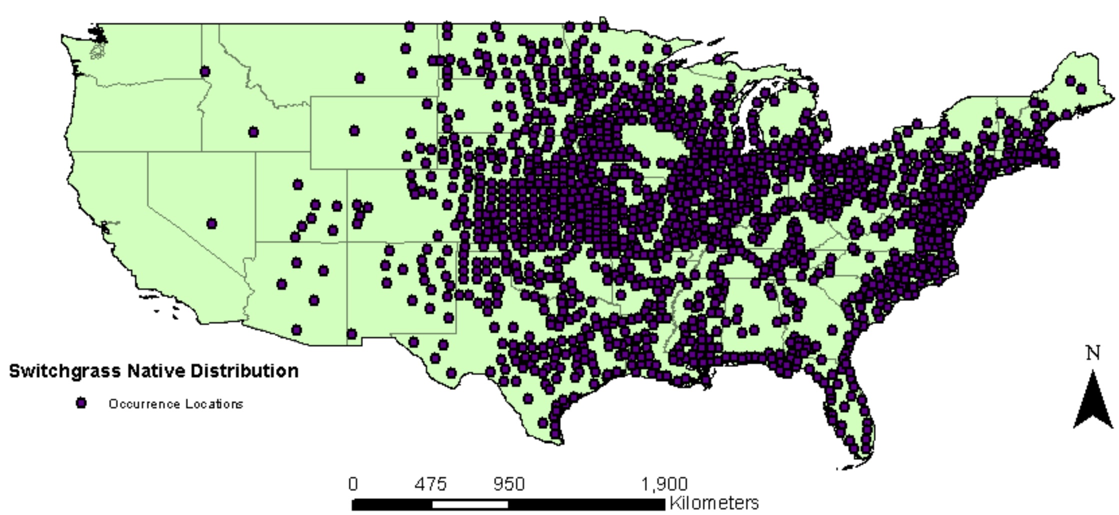

Fig. 1. Switchgrass' native distribution throughout United States (USDA Plants Database).

Switchgrass' adaptability across a wide variety of environmental and edaphic conditions is shown in figure one. Previous studies have found soil type and soil acidity to have minimal effect on switchgrass growth (Sanderson et al., 1999b; Parrish and Fike, 2005; Bona and Belesky, 1992). Soil organic carbon was selected as an environmental variable to use in the model because of its importance to crop production, soil structure, water holding capacity, nutrient availability, carbon sequestration and root growth. It is also a good indicator of the condition of the soils, measured as the percent weight of organic carbon in the top soil, where soils with less than 0.6% organic carbon are considered to be poor in organic matter. The Harmonized World Soil Database (HWSD) provided the soil organic carbon data at 1 km resolution (FAO et al., 2012). Spatial analyst tools in ArcMap were used to extract all of the environmental data used in this study for the United States and China.

Altitude and climate variables were obtained from WorldClim (version 1.4) (Hijmans et al., 2004) at 1 km resolution. Initially, eight climate variables were selected for analysis in the model, specifically average winter minimum temperature, average growing season maximum temperature, average growing season mean temperature, average annual minimum temperature, average annual mean temperature, average annual maximum temperature, average growing season precipitation and average annual precipitation. SPSS (IBM, Inc., Armonk, New York), a predictive analytics software, was used to test the climate variables for multicollinearity by assessing the cross-correlations between the variables. All of the temperature variables were highly correlated with each other, as were the precipitation variables. Because it cannot be determined exactly which temperature variable is needed to understanding switchgrass' native distribution, average annual mean temperature was selected and all other temperature variables were removed from analysis. Wullschleger et al. (2010) noted the strong correlation of temperature variables when developing a model to predict switchgrass yields in the United States and they also utilized annual mean temperature. While annual precipitation is an important contributor to soil moisture availability, numerous studies have concluded that growing season precipitation is more critical to switchgrass' growth and development (Sanderson et al., 1999; Muir et al., 2001; Berdahl et al., 2005; Lee and Boe, 2005); consequently, average annual precipitation was removed from the model. Therefore, the final set of environmental variables to be applied to the ecological niche models was condensed to four (table 1). Special attention was given during the extraction process to ensure all of the pixels were the same size and that the spatial extent for each environmental layer was the same.

Table 1. Source list for occurrence and environmental data.

	Data Source	
Occurrence Data (categorical)		
(1,481 records)	USDA Plants Database	http://plants.usda.gov/
Environmental Data (continuous)		
Altitude	WorldClim (v. 1.4)	http://www.worldclim.org/
Mean monthly temperature (mean annual temperature variable created from this data source)	WorldClim (v. 1.4)	http://www.worldclim.org/
Mean monthly precipitation (mean growing season precipitation variable created from this data source)	WorldClim (v. 1.4)	http://www.worldclim.org/
Soil organic carbon	Harmonized World Soil Database (v. 1.2)	http://www.iiasa.ac.at/

2.2. GARP model parameters

The Genetic Algorithm for Rule-set Production was implemented in openModeller desktop version 1.1 (available at http://openmodeller.sourceforge.net/; accessed 14 March 2012) (Muñoz et al., 2009). This method of implementation was selected based on Elith et al.'s (2006) findings that openModeller outperformed older desktop GARP versions. The switchgrass occurrence data was randomly separated into two parts, where 50% of the data was used for model training and the remaining 50% was used to test the model. The four environmental predictor variables used in the model were altitude, soil organic carbon, average annual mean temperature and average growing season precipitation. The following parameters were used in the GARP analysis: 400 runs for each experiment, 0.01 convergence limit and up to 2400 maximum iterations. Three of the four (range, negated range and logistic regression) rule types were applied to the model. Atomic rules were omitted because they seem to have little significance compared to the other rules (Stockwell, 1999). The final output from the analysis is a potential distribution map for both ecotypes of switchgrass where pixels are assigned 0 if it is outside the fundamental niche and 1 if the pixel is within a suitable environment. The lowest training presence threshold parameter was selected to determine which pixels would be designated 0 or 1.

2.3. Maxent model parameters

Maxent software, version 3.3.3k, was used in this analysis (Phillips, 2006) along with the same group of climate, elevation and soil variables and occurrence data. Occurrence data were divided randomly in the same equal percentage for training and testing as was implemented in the GARP analysis. A jackknife test was performed to assess each environmental variable's importance to switchgrass's fundamental niche. The logistic output format was chosen, which gives values for each pixel between 0 and 1. The model threshold for Maxent was selected where both the test sensitivity and specificity intersect at their maximum values. This threshold value maximizes the presence of switchgrass in the testing data locations while minimizing false positives (Simon et al., 2010). These values represent the probability of presence of suitable environmental conditions for switchgrass. The rest of the model's algorithm parameters were left at their default values.

3. Results and discussion

The predicted potential geographic distribution of switchgrass from both GARP and Maxent models were projected onto China using the identical environmental variables used to define its fundamental niche in the models (figures 2 and 3). The output maps for China's potential distribution of lowland and upland ecotypes of switchgrass based on GARP analysis were consistent with Maxent's projected distribution. Initially, a 50% probability-of-presence threshold was applied to both models; however the results clearly under-predicted switchgrass distribution based on known climate tolerances of switchgrass. Allowing the models to use a lower threshold, where sensitivity and specificity intersect, produced better results, more in line with expectations. Both models' predicted distribution for lowland ecotypes were in relative agreement with each other, although GARP's suitability areas were slightly thinner than Maxent's lowland ecotype output, meaning Maxent predicted more areas in China for lowland switchgrass. The difference in the upland ecotype potential distribution in China between models was less subtle. Maxent clearly predicted a much larger suitable habitat distribution for upland ecotype switchgrass in China than did the GARP model.

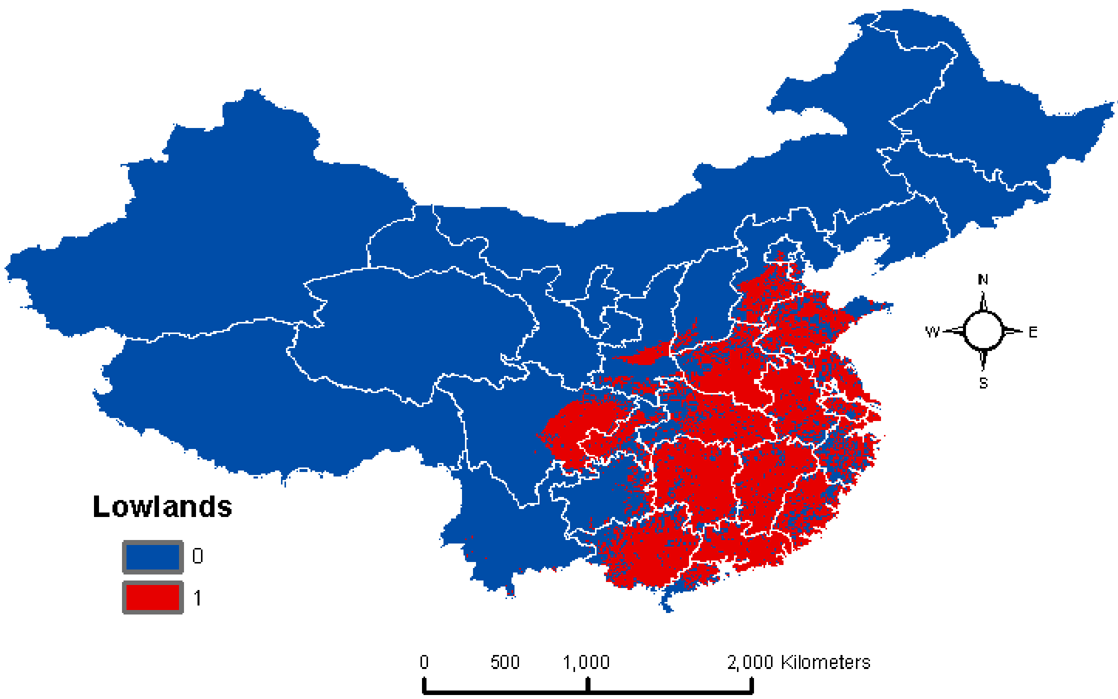

Fig. 2. Potential geographic distribution of lowland switchgrass in China based on GARP.

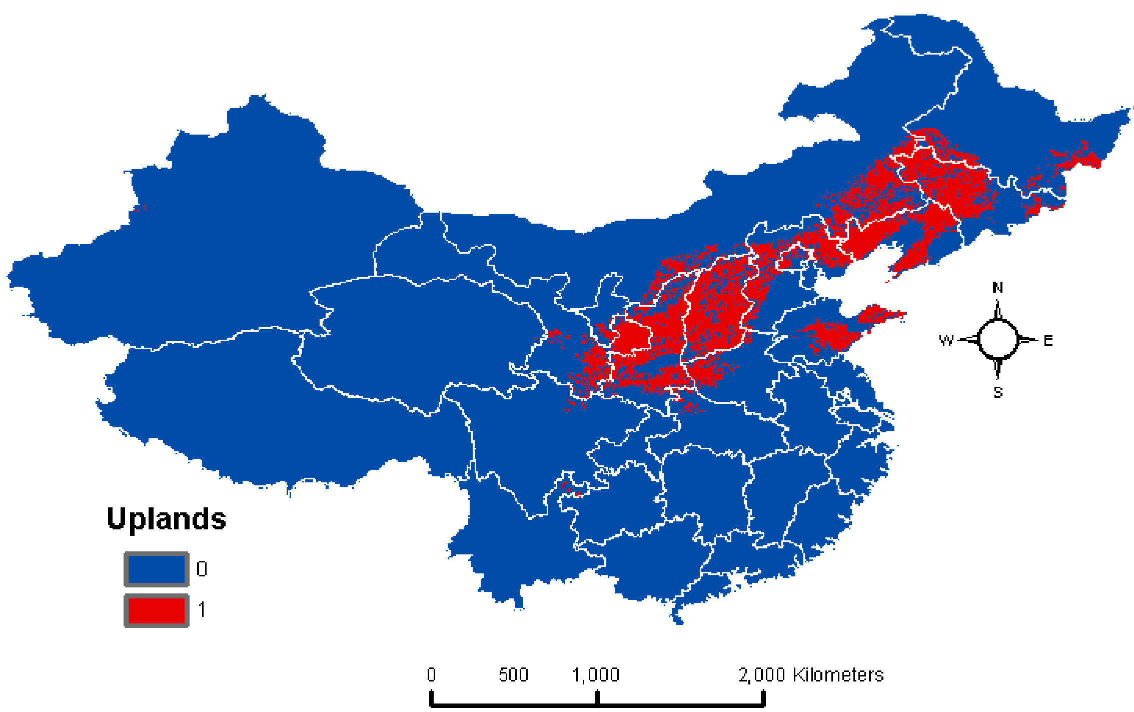

Fig. 2.1. Potential geographic distribution of upland switchgrass in China based on GARP.

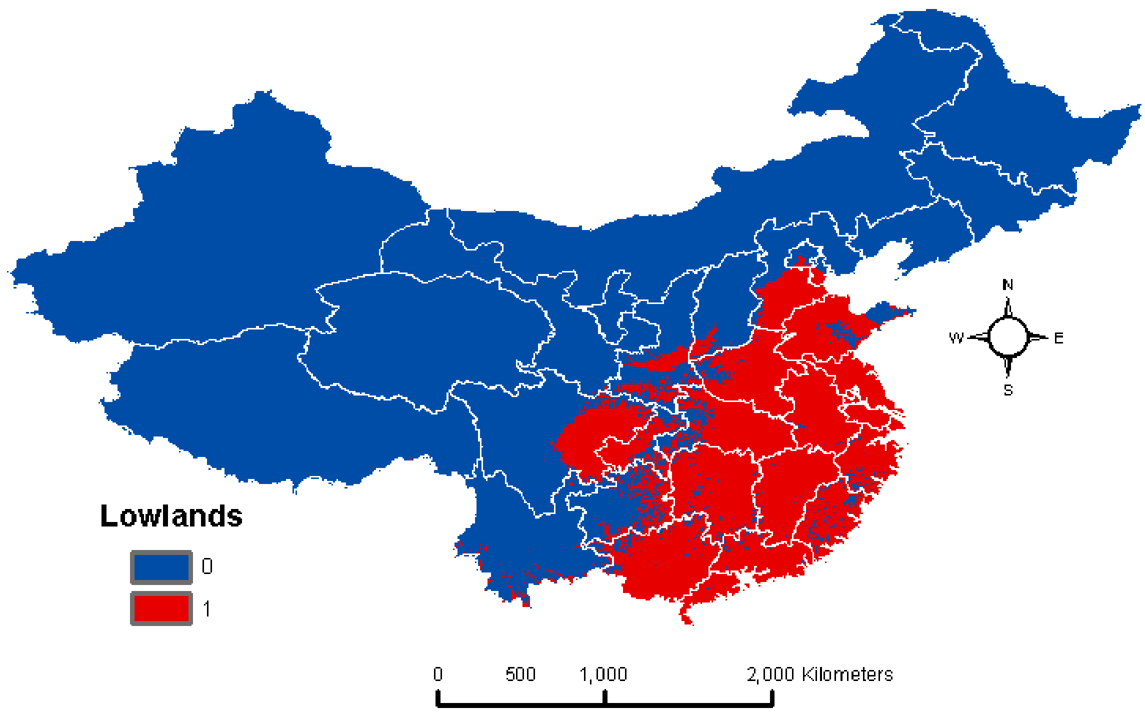

Fig. 3. Potential geographic distribution of lowland switchgrass in China based on Maxent.

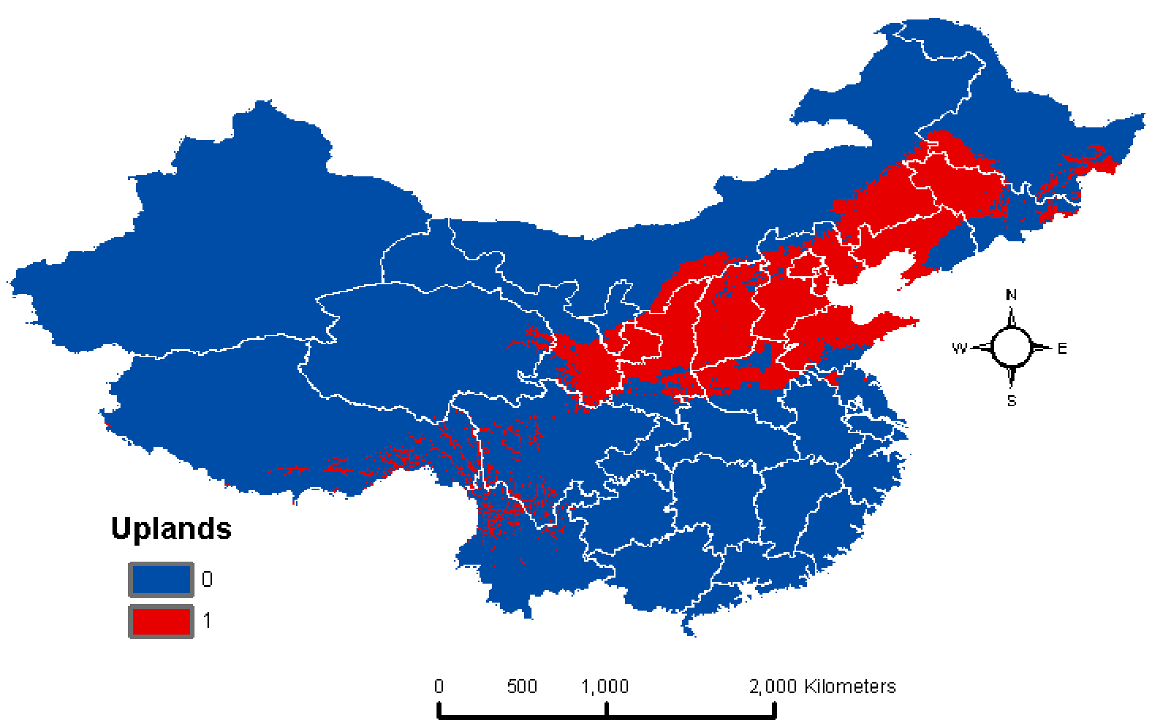

Fig. 3.1. Potential geographic distribution of upland switchgrass in China based on Maxent.

A threshold independent method for evaluating the performance of ecological niche models is to examine the receiver operating characteristics (ROC) curve and calculate the area under the curve (AUC) (Fielding and Bell, 1997). ROC curves are created by plotting the sensitivity, considered the true positive fraction against 1-specificity, the false positive fraction. Thus, the AUC is a calculation of the area under the ROC curve, with ranges between 0.5 and 1, that provides a ranking mechanism to evaluate the differences between ecological niche models and random distribution. Models with AUC values at or near 0.5 are regarded no better than random at predicting potential distribution, whereas values closer to 1 are considered very good models (Phillips et al., 2006).

In this study, AUC values for Maxent where higher than GARP for both ecotypes, indicating that Maxent outperformed GARP at modeling the potential switchgrass distribution in China (table 2). Comparison of the area under curve follows the visual assessment of the output maps between Maxent and GARP, as the values for lowlands are very close to each other, while the upland AUC's display a greater difference between the two models. Maxent estimates, the most suitable provinces in China for upland ecotypes Gansu, Ningxia, Shaanxi, Shanxi, Shandong, Hebei, Tianjin, Beijing, Jilin, and only small parts of Heilongjiang and Inner Mongolia. Lowland ecotypes are predicted to be most suitable in the lower parts of Hebei, Shandong, Henan, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, Hunan, Jiangxi, Hubei, Anhui and Chongqing. This distribution across China is relatively consistent with the known fundamental niche of switchgrass, at least as it pertains to climate. Northern China, which favors upland ecotypes, typically has very dry and cold winters, along with extreme summer heat and precipitation. Southern China, which is more suitable for lowland ecotypes, lies in a subtropical zone and with warm, humid temperatures throughout much of the year. Summer monsoons are also common in this area, providing critical precipitation for the April – September growing season.

Table 2. Area under curve (AUC) values from Maxent and GARP model runs. AUC >0.9 = very good; 0.7<AUC<0.9 = good; AUC<0.7 = no better than random/model uninformative (Swets, 1988).

	AUC	
	Maxent	**GARP**
Lowlands	0.907	0.89
Uplands	0.863	0.79

Jackknife tests (figure 4) analyzed in Maxent on the environmental predictor variables indicated that average annual mean temperature was the most important environmental predictor affecting the distribution of switchgrass. The jackknife analysis generates a graph of the regularized training gain, which is a measure of the model's fitness, by running several models in order to determine the importance of each variable to the species distribution. One predictor variable is excluded at a time and a model is created with the other variables (turquoise bar). Next a model is created using each predictor variable by itself (blue bar). And finally a model is created with all the variables together (red bar). High values indicate the variable was very important to switchgrass niche modeling, while low values indicate the variable has a low impact on switchgrass's ecological niche. Soil organic carbon was shown to have the least influence on switchgrass distribution.

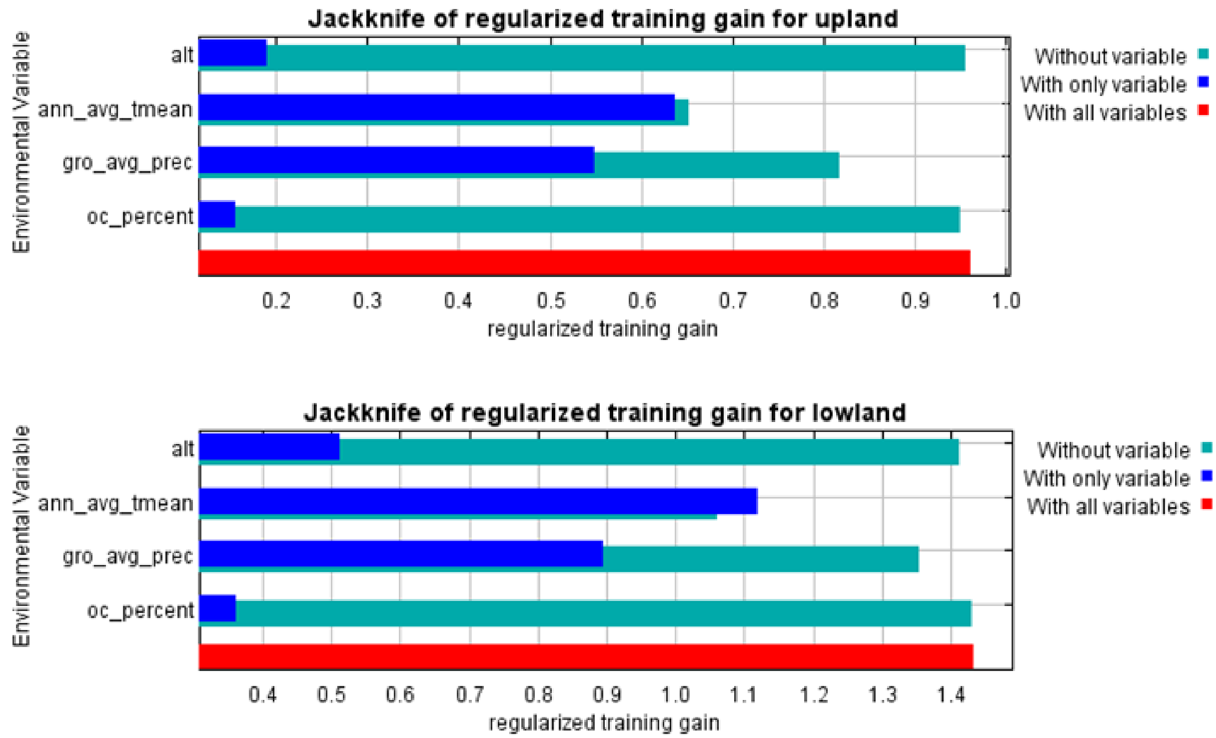

Fig. 4. Jackknife test of individual environmental variables' importance to the Maxent model, in relation to the other environmental variables in the model (red bar).

Analysis of the response curves (figures 5 and 6) also indicate how the logistic prediction for switchgrass changes as each predictor variable is varied while keeping the other predictor variables at their average values. For lowland ecotypes, mean annual temperature has the most effect on switchgrass suitability. For uplands, mean annual temperature and growing season precipitation have the most effect on habitat suitability. Evidence of this can be seen in the parabolic shape of the response curve, indicating an optimal range of precipitation and temperature for upland ecotypes.

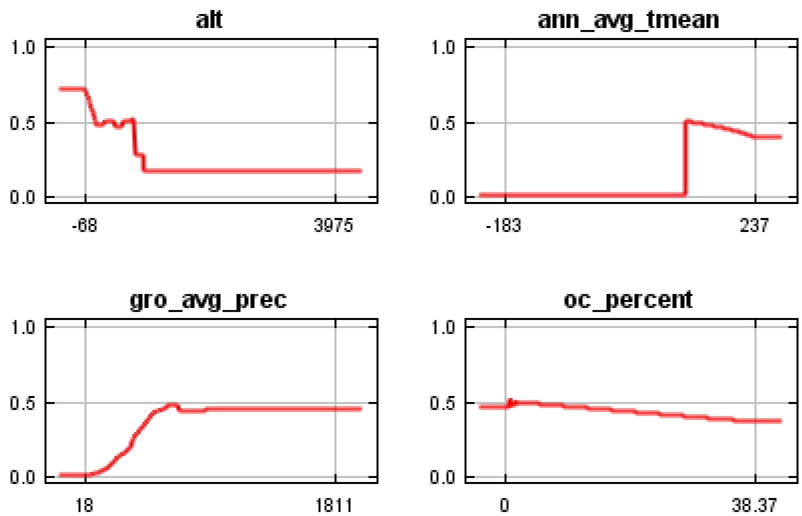

Fig. 5. Response curves for lowland ecotype.

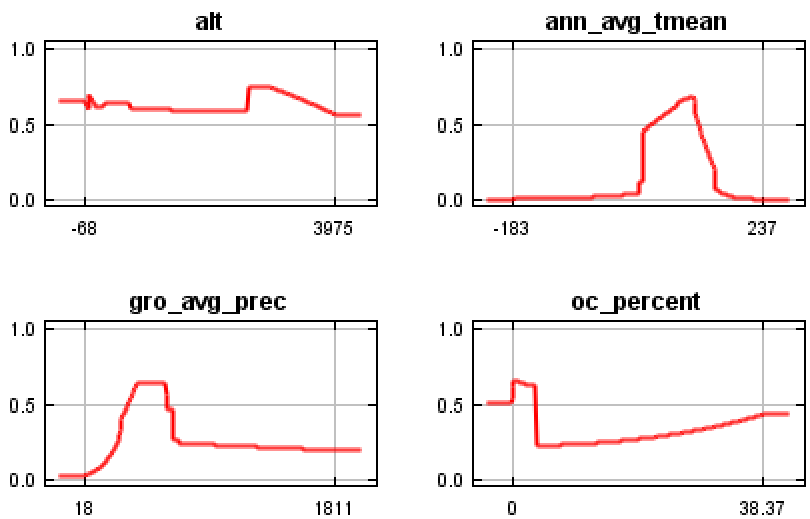

Fig. 6. Response curves for upland ecotype.

Due to switchgrass's high adaptability to a wide variety of environmental conditions, it becomes logical that temperature and precipitation would be a greater factor than soil characteristics in niche modeling, as soil characteristics and qualities change more frequently spatially than do climate variables. Temperature and precipitation's importance to switchgrass's potential distribution, as indicated by the model, is likely due to its C_4 nature. As a C_4 perennial grass, switchgrass is more efficient at utilizing photosynthesis, nitrogen inputs, and water (Parrish and Fike, 2005).

4. Conclusions

This study provides an estimate of the predicted potential distribution of switchgrass across China. Results from these ecological niche models indicate that China has large areas of suitable habitat for switchgrass to grow and survive. Understanding its potential distribution for both ecotypes is significant as China continues to develop its biofuels industry and address soil erosion concerns. Both models predicted potential distribution for upland ecotypes in the Loess Plateau, a region that could benefit from switchgrass' ability to increase biodiversity and improve soil structure. AUC results showed that Maxent had greater predictive power than GARP, consistent with prior research comparing the two models (Elith et al., 2006). The output maps for both ecotypes revealed that switchgrass distribution would be severely restricted in all areas west of Chongqing and Shaanxi provinces. This restriction is most likely due to the contrasting climate in Western China, where growing season precipitation and average annual mean temperatures are considerably lower than other parts of China and the occurrence data in the USA.

The nature of ecological niche models do not allow for one to develop a realized niche of a species, primarily because there are too many macro and micro-interactions that cannot be quantified which could influence a potential species distribution. It is not possible to account for every interaction where a species is known to occur; however, models such as Maxent provide relative straightforward methods for estimating potential distribution, as long as some environmental data based on the known occurrence are collected. The methods and procedures presented here could be used for estimating potential geographic distributions of other bioenergy crops or plant and animal species; however, care should be taken to ensure that the predictor variables selected are significant to the species' fundamental and/or realized niches.

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CHAPTER 3

1. Introduction

Worldwide, population growth, economic and societal advancements over the latter course of the 20th and beginning of the 21st centuries have led to an unsustainable consumption and demand for non-renewable fossil fuel energy sources, leading to rising fuel prices, greenhouse gas emissions and international dependencies on imported fossil fuels. This has encouraged many countries, including China, to develop energy policies that will combat these issues through stimulating growth in domestically produced renewable energy. The passing of the People's Republic of China (*PRC) Law of Renewable Energy* in 2005 emphasized for the first time China's resolute commitment toward developing a strong and sustainable renewable energy industry whose objectives are to enhance energy supply and structure, while ensuring energy and economic security and protecting the environment (Peidong et al., 2009). China is the largest and fastest developing country in the world, with an annual GDP growth rate that has centered around or above 10% on average for the last two decades (CSY, 2008). China turned from a net energy exporter in the early 1990s to become the world's third largest net importer of oil in 2006 (Hengyun et al., 2010). Then, in 2010, China surpassed the United States as the world's largest energy consumer, accounting for 20.3 percent of the global energy demand, compared to 19 percent in the U.S. (BP, 2011). China's population also makes it the largest automobile market in the world.

Rising transportation fuel costs, increasing demand, and diminishing supply of crude oil has spurred the pursuit towards producing renewable biofuels in China. While many plant and herbaceous crop species have been studied as potential biomass feedstock, switchgrass (*Panicum vigratum*) has proven to be one of the best options for developing a non-food crop for biofuel production, and one of the most efficient options of any crop (McLaughlin, 1992). Switchgrass is a native North American perennial grass species that is found from the Atlantic coast to the eastern Rocky Mountains (Rinehart, 2006). In addition to its potential as a feedstock for lignocellulosic ethanol production, it has also demonstrated success in reducing soil erosion in marginal and degraded soils (Parrish and Fike, 2005). Switchgrass adapts to and tolerates a wide variety of environmental conditions, thus enhancing its ability to be adopted as part of a large-scale lignocellulosic ethanol production initiative (Hitchcock, 1951). Another benefit of switchgrass is that it is a non-invasive crop, meaning it will not spread naturally without intentional establishment (Thomson et al., 2009).

The two primary ecotypes of switchgrass are lowland and upland ecotypes. Lowland varieties are taller, coarser and produce more biomass than upland varieties, and are generally found in areas that have higher rainfall and longer growing seasons and mild winters (Vogel, 2004). The shorter upland varieties fare well in drier, colder climates, such as those that are found in the Midwestern and Northern United States (Bouton, 2007). There are also several different types of cultivars for each ecotype. The three most common cultivars are Alamo, a lowland which favors the Southern states and has generated exceptional biomass yields, Kanlow, another lowland that has shown good promise, and Cave-in-Rock, an upland best adapted to the Northern states (Parrish and Fike, 2005).

Switchgrass's perennial nature and ability to be baled similar to hay also makes it a highly desirable bioenergy feedstock, thus being less labor intensive for the farmer and not requiring the purchase or use of specialized farming equipment (Vogel et al., 2002). Switchgrass has also been distinguished for its ability to enhance soils and wildlife in areas where it has been planted, resulting in its robust use in restoring poorly degraded areas across the United States through the Conservation Reserve Program (CRP) (Dunn et al., 1993). Recognizing the need to develop renewable fuels domestically, the U.S. Department of Energy commissioned the Bioenergy Feedstock Development Program (BFDP) at Oak Ridge National Laboratory in 1978. The goal of this program was to test various crop and plant species to determine which showed the most promise as a bioenergy feedstock. Switchgrass demonstrated the most potential of all of the herbaceous crops tested (Bouton, 2007). The results of the BFDP report are particularly interesting in conjunction with the findings of Ichizen et al. (2005) that determined that switchgrass is the best candidate of approximately 20,000 plant species studied for vegetation revitalization and soil erosion control in the Loess Plateau region of China. This area covers 640,000 km^2 in the upper middle segments of the Yellow River watershed in North China and encompasses some of the world's most eroded soils, historically due to natural processes, but more recently exacerbated due to anthropogenic land use change as a result of poor farming and other land management practices (Xinbao et al., 1990). Considering switchgrass's ability to rehabilitate soils and increase biodiversity, planting it in the Loess Plateau and utilizing best practices for crop management could produce vast environmental benefits.

Although switchgrass has been researched on a minor scale at regional levels for use as a bioenergy feedstock in China (Xiong et al., 2008), no effort has been made to quantify potential yield throughout the country. Field testing of the upland cultivar, Cave-in-Rock, in the semiarid climate of Ying Xian in Shanxi Province, near the Loess Plateau, demonstrated switchgrass's adaptability by doubling its yield in the second year, relative to the first, from 9 mg/ha to 18 mg/ha without irrigation (Xiong et al., 2008). The primary objective of this study is to develop a multiple linear regression model that will estimate potential switchgrass yield throughout every region of China. Because there have only been a small number of switchgrass field trials in China, which are mostly concentrated in the North, field trials from the more regionally and climatically diverse United States sites are utilized.

There has been recent interest in the United States to estimate switchgrass yield throughout the country as well. Thomson et al. (2009) simulated potential switchgrass yields in the United States based on seven test locations in the southeast, using the EPIC (Environmental Policy Integrated Climate) model. Wullschleger et al. (2010) developed yield estimates by creating a multiplicative, parametric model for biomass yield from a more regionally diverse database that was compiled from publications that listed switchgrass field trial results from 39 different locations in 17 states, totaling 1190 observations, spanning the Southern, Midwestern, and Northern United States. This was the first published paper written from such a compilation of field trials from across the country and after personal communication with the author, this database was used as the basis for building a regression model to estimate switchgrass yield in the US and applying the model to the entire region of China.

2. MATERIALS AND METHODS

2.1. Dataset and Description

To develop a multiple linear regression model that predicts switchgrass yield in China, the compiled data set of biomass yields used by Wullschleger et al. (2010) was also used in this study (see table 1). To increase the model's predictive performance, it was important that the dataset included a high number of observations from diverse geographic locations with records of biomass yield, ecotype, stand age, nitrogen fertilizer application, growing season precipitation (April-September) and annual mean temperature from the year of harvest for each observation. The latitude and longitude coordinates were used to overlay additional environmental variables in a Geographic Information Systems (GIS) at 1 km resolution, for instance, soil order classifications, soil characteristics, altitude, mean annual maximum and minimum temperature, average growing season mean and maximum temperature, average annual minimum temperature, and annual and growing season average annual precipitation. The U.S. Department of Agriculture's (USDA) Natural Resources Conservation Service (NRCS) provided the soil classification data for China and the United States according to the USDA soil taxonomy. Soil characteristics, such as drainage and soil organic carbon content were added from the Harmonized World Soil's Database (FAO et al., 2012). Drainage was classified into four categories, ranging from 1 for poorly drained soils to 4 for excessively drained soils. Climate data were obtained from the WorldClim global climate database which produced climate grids by interpolating average monthly climate data from weather stations around the globe at 1 km^2 resolution from 1950-2000 (Hijmans et al., 2005). Spatial analyst tools in ArcMap (ESRI Inc., Redlands, CA) were used to extract the site specific data from each of these additional environmental variables at a 1km^2 resolution throughout China.

Table 1. 39 locations of switchgrass field trials along with respective ecotype, climate and soil data.

Location	No. of Observations	Lowland	Upland	Mean Annual T (°C)	Mean Growing Season Precip (mm)	Soil Order	% Soil Organic C
Shorter, Al	16	6	10	16.8	674	Ultisol	1
Athens, GA	30	10	20	16.3	595	Ultisol	1
Tifton, GA	30	10	20	18.6	638	Ultisol	1.13
Chariton, IA	60	12	48	9.5	633	Mollisol	1.68
Manhattan, KS	4	2	2	11.5	620	Mollisol	1.83
Princeton, KY	24	12	12	13.9	619	Ultisol	1.45
Clinton, LA	6	6	0	18.7	821	Ultisol	1
Raleigh, NC	24	12	12	15.4	607	Ultisol	1
Dickinson, ND	24	0	24	5.4	328	Mollisol	1.27
Mandan, ND	48	0	48	5.4	329	Entisol	0.48
Munich, ND	3	0	3	2.9	345	Mollisol	1.65
Streeter, ND	3	0	3	4.9	354	Mollisol	2.08
Atkinson, NE	2	0	2	8.7	450	Entisol	0.5
Crofton, NE	3	0	3	8.8	382	Mollisol	0.97
Douglas, NE	3	0	3	10.5	578	Mollisol	1.29
Lawrence, NE	3	0	3	10.4	517	Mollisol	1.27
Mead, NE	4	2	2	10.1	572	Mollisol	1.29
Chickasha, OK	143	115	28	16.2	523	Mollisol	1.27
Haskell, OK	70	28	42	15.6	610	Mollisol	1.05
Perkins, OK	46	46	0	15.4	568	Mollisol	1.27
Stillwater, OK	4	2	2	15.1	601	Mollisol	1.05
Rock Springs, PA	10	0	10	9.3	547	Alfisol	0.86
Bristol, SD	3	0	3	5.8	394	Mollisol	1.74
Brookings, SD	24	0	24	6.2	446	Mollisol	1.27
Ethan, SD	3	0	3	8.3	429	Mollisol	1.27
Highmore, SD	3	0	3	6.7	367	Mollisol	1.27
Huron, SD	3	0	3	7.3	386	Mollisol	1.27
Jackson, TN	24	12	12	15.1	651	Alfisol	0.82
Knoxville, TN	24	12	12	14.3	620	Ultisol	1
Beeville, TX	51	45	6	21.5	493	Alfisol	0.86
College Station, TX	67	46	21	19.9	531	Alfisol	0.86
Dallas, TX	84	74	10	17.9	514	Alfisol	0.86
Stephenville, TX	146	121	25	17.5	469	Alfisol	0.86
Temple, TX	70	59	11	19	475	Vertisol	1.2
Blacksburg, VA	48	24	24	11.1	546	Ultisol	1
Orange, VA	24	12	12	12.9	584	Ultisol	1
Arlington, WI	28	2	26	7.3	550	Alfisol	1.91
Spooner, WI	4	2	2	5.3	554	Spodosol	1.91
Morgantown, WV	24	12	12	10.8	599	Ultisol	1

3. Modeling

A multiple linear regression is a statistical method useful for examining the concurrent relationships between multiple independent variables and one continuous dependent variable (Neter et al., 1996). The model equation for a multiple linear regression is characterized by the following:

$$Y_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots \beta_m X_{im} + e_i \qquad [1]$$

where

Y_i = predicted variable (i.e. biomass yield Mg/ha)
α = regression constant
$\beta_{1\text{-}m}$ = beta coefficient (slope) for independent variables
$X_{i(1,\ldots,m)}$ = independent variables (i.e. environmental and crop management variables)
e_i = error term

The least squares principle is typically used to develop regression parameters and determine the best fit model, which is one that minimizes the sum of squares between the differences from observed and predicted values. The least squares are calculated by the following formula:

$$\hat{Y}_i = a + b_1 X_{i1} + b_2 X_{i2} + b_3 X_{i3} + \ldots b_m X_{im} \qquad [2]$$

where each variable represents the same as in model [1] except $\hat{Y}$ represents the predicted value of Y based on the values of the independent X variables. Since the true model for [1] is unknown, e_i is defined as the residual values from the difference of equations [1] and [2], written as:

$$e_i = Y_i - \hat{Y}_I \qquad [3]$$

where $\Sigma (e_i)^2$ is minimized. A forward stepwise regression procedure was used to determine which independent variables would remain in the model. To build the stepwise regression model, verify the assumptions, and analyze descriptive statistics and bivariate plots, SPSS (IBM, Inc., Armonk, New York), predictive analytics software was used.

4. Data

This analysis is based on a 1 – cut per year harvest management system and makes biomass yield predictions for stand ages greater than 2 years. There are 1,190 observations of switchgrass yield data (Wullschleger et al., 2010) from 39 locations in 17 states covering a time period from 1979 to 2005 are assembled in this database. Lowland ecotypes account for 57.4 percent of the data with 684 observations, whereas uplands make up 42.6 percent of the data with 504 observations. Mean biomass yield was 11.12 Mg/ha. The lowest reported annual yield was 1.03 Mg/ha in Beeville, TX, (Sanderson et al., 1999) during a year that had near average mean annual temperature and growing season precipitation. The highest observed yield was 39.1 Mg/ha, recorded in Temple, TX, (Kirniry et al., 1999) with slightly below average mean annual temperature and above average growing season precipitation. Evaluation of the box plot distribution of biomass yields reveals that the most commonly recorded yields were between 6.9 Mg/ha (25^{th} percentile) and 14.61 Mg/ha (75^{th} percentile) (figure 1). Biomass yields above 26 Mg/ha are few and may be considered outliers (figure 1).

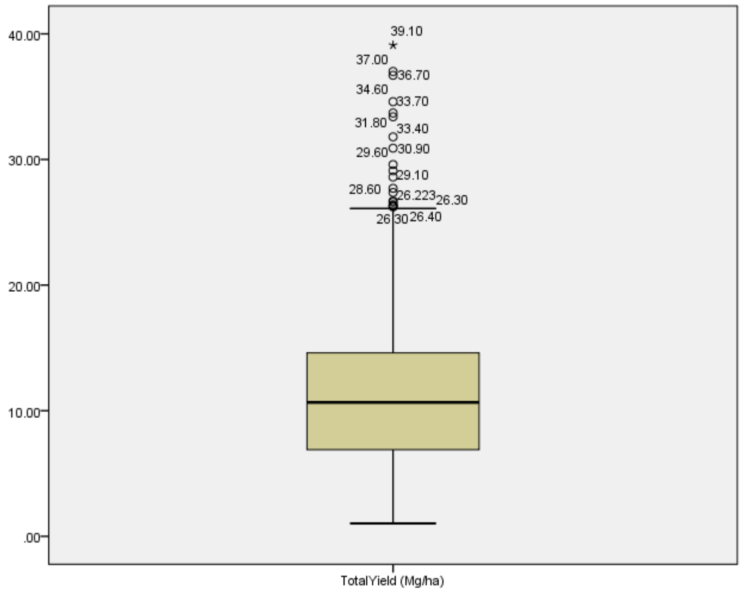

Fig.1. Box plot of all reported biomass yields. The bold horizontal line represents the median yield. The bottom line of the box represents the 25th percentile, while the top represents the 75th. Values above the whiskers are reflected as outliers.

Switchgrass yield generally responded favorably to nitrogen fertilizer application, although some test fields that did not apply N fertilizer produced biomass yields well above the mean yield for all observations. The distribution of N fertilizer application from 0 to 896 kg/ha is shown in figure two. N fertilization above 225 kg/ha was rare and particularly excessive as well (figure 2). The 58 observations that fell into this category were thus treated as outliers and taken out of the regression analysis.

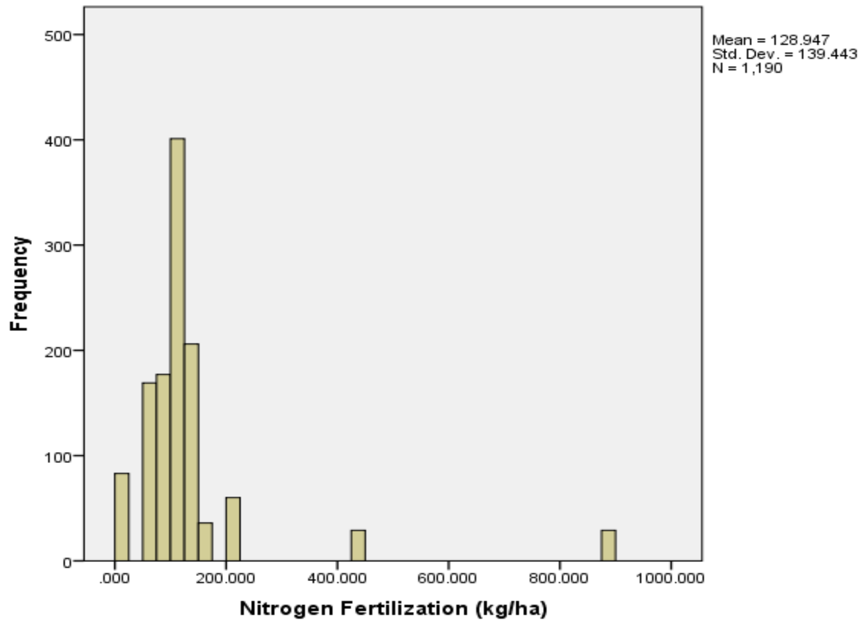

Fig. 2. Frequency distribution of nitrogen fertilizer application for all observations. Application rates above 400 kg/ha were rare and marked as outliers and taken out of the analysis.

Switchgrass yields varied substantially over all values of N fertilization application (figure 3). Other factors such as soil nutrients and climate could account for the high variability, yet this data analysis shows that high N fertilization does not equate to high biomass yields. Switchgrass responds favorably to N fertilization application up to 90-115 kg/ha, and then decreases at higher levels (though there was some increase again as N fertilization levels reached extremely high levels) (figure 3). This indicates that, used in moderation, N fertilization can have positive results on biomass yield. Wolf and Fiske (1995) documented that N fertilization application rates between 80-100 kg/ha for fields 2 years old and greater is considered standard N management procedure. While Nitrogen fertilizer rates at 224 kg/ha in this database generated positive responses, the economics and long-term production sustainability could indicate the need for lower rates (McLaughlin et al., 1999). Wullschleger et al. (2010), in their analysis, found optimal N fertilization rates to be approximately 100 kg/ha, which coincides with the bivariate plot in this study, and therefore will be used as the optimal N fertilizer input for predicting biomass yields in China.

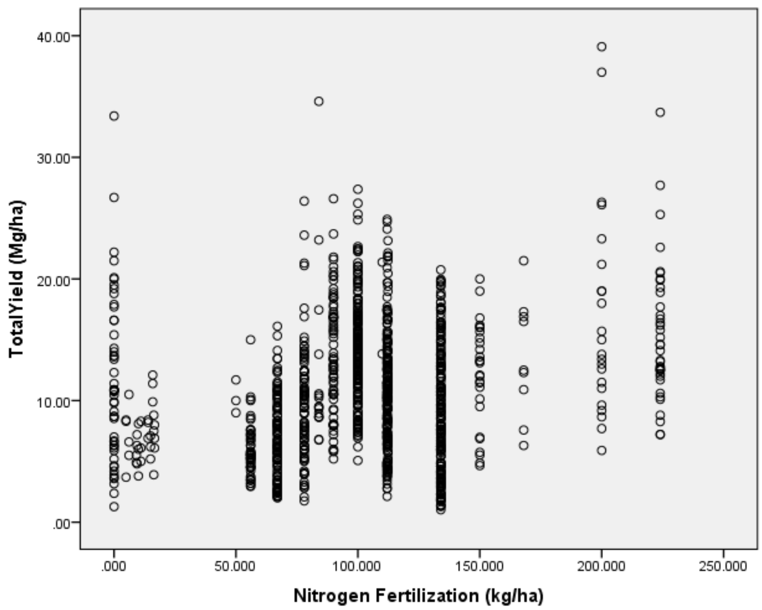

Fig. 3. Bivariate plot of N fertilization and biomass yield from 1,132 observations (58 high N observations were deemed outliers and removed from analysis). Note the biomass yield with zero N fertilization had comparable yields in comparison with other observations.

Switchgrass stand ages in the year of harvest varied in this dataset from 2 to 21 years. Biomass yields were generally greater after the 2nd year (figure 4), corresponding to switchgrass's known biological characteristic of reaching maturity and full yield potential during its third year post-establishment (McLaughlin et al., 1999). Some observations in the second year of harvest had exceptionally high yields, though the reason is likely due to other key parameters. Establishing switchgrass in China for ligno-cellulosic ethanol feedstock is considered a long-term investment, therefore the multiple linear regression analysis will build a yield prediction model with the assumption that biomass yield estimates are for stand ages 3 and greater.

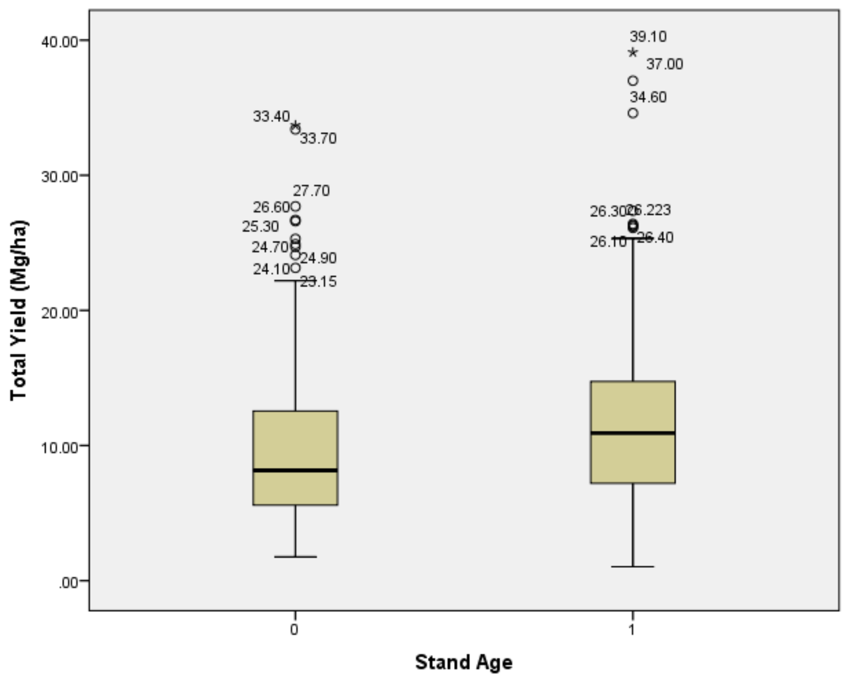

Fig. 4. Boxplot of stand age and total yield. Stand age is represented as a dummy variable, where 0 = all stand ages ≤ 2 years and 1 = all stand ages > 2 years.

There was no obvious correlation between soil characteristics and biomass yield. Switchgrass' native distribution covers much of North America consequently making it well adapted to a wide range of edaphic and environmental conditions. Regression analysis revealed that soil order and drainage were not significant variables in switchgrass production ($p > .10$) and were removed from the model. This finding concurs with research by Sanderson et al. (1999) and Parrish and Fike (2005) that found soil type to have minimal effect on switchgrass yield. Switchgrass has also been reported to be tolerant of strongly acidic soils (Bona and Belesky, 1992). Soil organic carbon also had a p-value greater than .05 and was considered for removal from the model, however it is widely accepted in the agriculture industry that soil organic carbon is a critical element influencing crop production, soil structure, nutrient availability, water holding capacity, root growth and carbon sequestration (Liang et al., 2011). Soil organic carbon is a good indicator of the health of the soils and was therefore included in the model. It is measured as the percent weight of organic carbon in the top soil, where soils with organic carbon < 0.6% are considered to be poor in organic matter (FAO et al., 2012). Switchgrass responds positively to soil organic carbon. Figure 5 shows that the majority of the switchgrass observations occur in soils > 0.6 % and the greatest yields occur in soil organic carbon around 1%. Furthermore, regression analysis yielded a positive estimated *beta* coefficient for soil organic carbon, thus signifying switchgrass's positive response to soil organic carbon content.

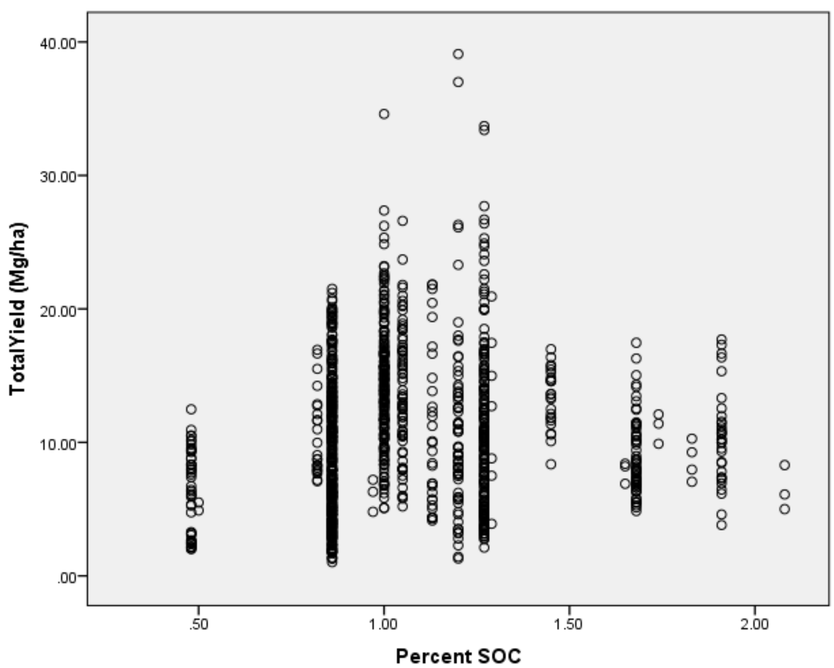

Fig. 5. Bivariate plot of total biomass yield and percent soil organic carbon. Percentages are of total weight of top soil.

In general, lowland ecotypes outperformed uplands with an average biomass yield of 12.59 Mg/ha and 8.74 Mg/ha, respectively. To account for this difference in yield in the prediction model, it was necessary to create a dummy variable for ecotype, where 0 = lowlands and 1 = uplands (figure 6). This caused the estimated *beta* coefficient for the binary ecotype variable to be negative, an expected result given that lowlands produced greater biomass yield. Accordingly, a method was required to assign pixel values in

China that identified whether or not they would be classified as 1 for upland or 0 for lowland ecotypes when the prediction model was applied. Scientific studies have indicated that in the United States lowland ecotypes exhibit a competitive advantage over uplands in southern latitudes up to 42^{o}N (Casler et al., 2004). Because both ecotypes can grow in many locations throughout the United States, they are also likely to be viable in areas with similar climates in China.

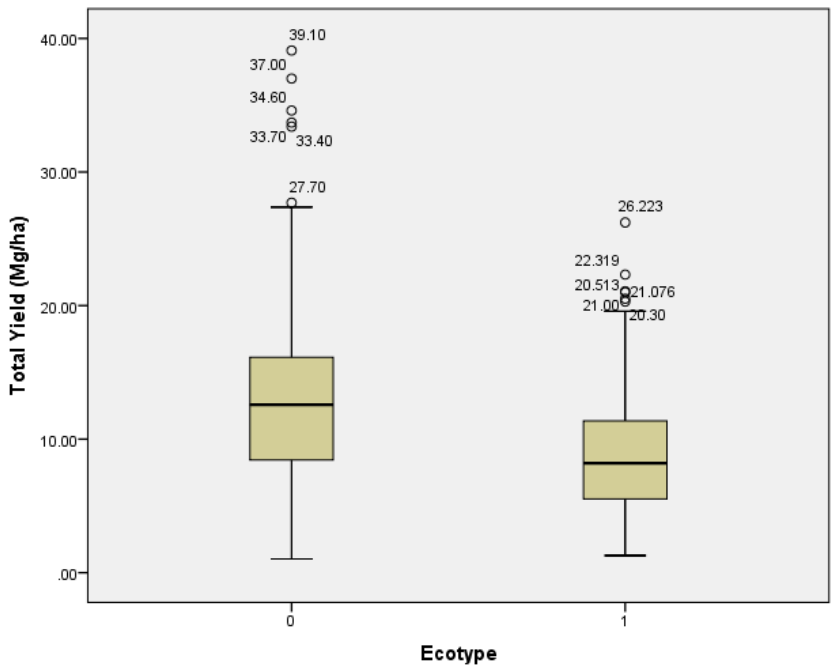

Fig. 6. Boxplot of ecotype (lowland = 0, upland = 1) and total yield. Plot shows that lowlands produce greater yields on average compared to uplands.

Rather than allowing the 42 ^{o}N latitude to be the dividing line for uplands and lowlands when predicting biomass yields in China, climate was used to determine this dividing line instead, by running a logistic regression in SPSS on the ecotype variable. When the dependent variable is binary, logistic regression analysis is a good method for determining the absence or presence of a species at a particular location relative to climactic or other environmental variables, thus making it possible to predict its potential occurrence in regions outside of its native range (Pearce and Ferrier, 2000). In this case, the logistic model was built using the climate data from the observations that had the highest yield at each of the 39 locations (n = 39 and 22 lowlands, 17 uplands). These observations were selected because they produced the greatest yields under the present climate settings, thereby providing key information regarding how each ecotype performs under those conditions. Growing season precipitation and mean annual temperature from the years of harvest were the independent variables and ecotype of the highest-yield crop was the outcome (dependent) variable. Running the logistic regression produces the estimated constant and *beta* coefficients required to model $Logit(p) = \alpha + ß_1X_1 + ß_2X_2 + \varepsilon$, where Logit(p) = the probability that Y = 1. Once the model was developed, it was applied to the United States and China in ArcMap, using growing season precipitation and average mean annual temperature raster grids for each country.

The subsequent map output (figure 7) for the United States showed that optimum locations for lowland ecotypes were constrained to the majority of the Southeast, while being extremely restricted in the West, and extended North up to nearly 40^{o}N. These findings are comparable to the results of Casler et al. (2004) and Wullschleger et al. (2010) that found lowland ecotype production decreases at a rate of 12.5% per degree at latitudes above 38^{o}N and lose all competitive advantage to upland ecotypes at 42^{o}N.

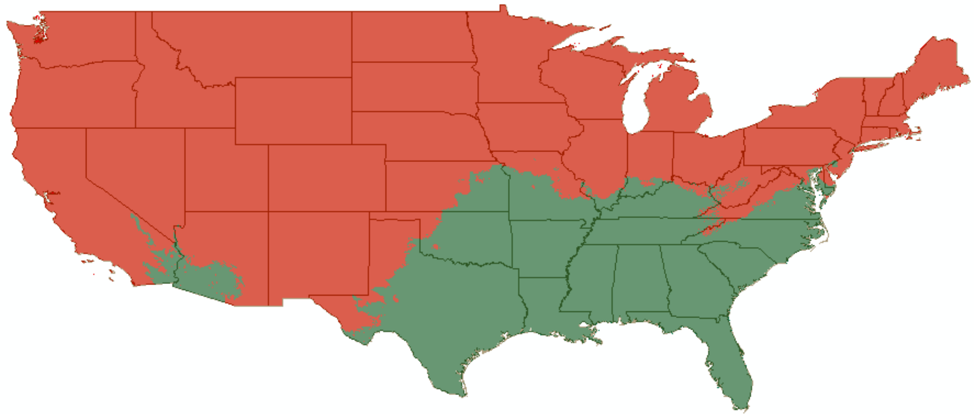

Fig. 7. Here the logistic regression model results, which predict optimal yields for lowland (green) or upland (red) ecotypes, are presented.

Climate variables are significant environmental variables for the production of switchgrass (Schmer et al., 2005). Biomass yields fluctuated across all mean annual temperatures and growing season precipitation (figures 8 and 9). Yields were lowest between 5-8^{o}C and highest between 12-16^{o}C, emphasizing switchgrass's proclivity to produce higher biomass yields in warmer regions with longer growing seasons. Wullschleger et al. (2010) found that biomass yield increases up to 14^{o}C and then decreases as temperatures increase, suggesting a parabolic effect on temperature, as can be observed in the bivariate plot (figure 8). To account for this effect in the model, a squared mean annual temperature variable was created. In order to do this, mean annual temperature had to first be increased by 30^{o}C for each location to eliminate the outcome of squared negative values becoming positive as there are negative average mean annual temperature values in some locations within China. As a result, the model was able to depict this parabolic effect with a positive estimated *beta* coefficient for annual mean temperature and a negative estimated *beta* for the squared term.

Growing season precipitation had a positive effect on biomass yield across all precipitation amounts (as can be seen from the regression results below and a slight upward trend in the graph in figure 9), though there were both high and low biomass yields recorded for high and low precipitation values (figure 8). Growing season precipitation has been considered to be one of the most important factors in determining biomass yield (Sanderson et al., 1999b). The bivariate plot also depicts that growing season precipitation values above 600 mm do not necessarily enhance productivity. Soil water holding capacity is essential to how switchgrass manages and responds to periods of low rainfall, droughts and imbalanced rainfall distribution (Stout et al., 1988).

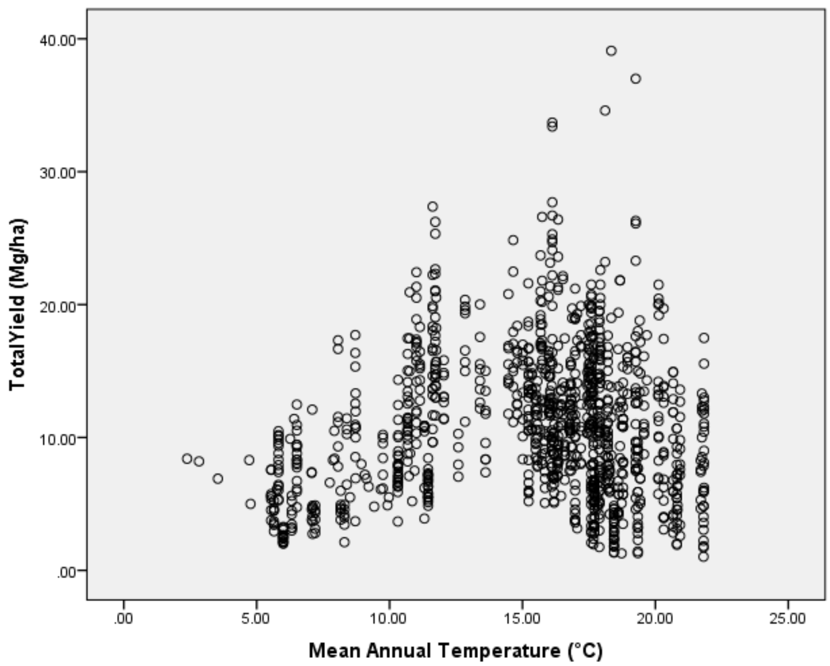

Fig. 8. Bivariate plot of mean annual temperature and total yield. Plot indicates parabolic effect on temperature, as yield increases to a point and then decreases.

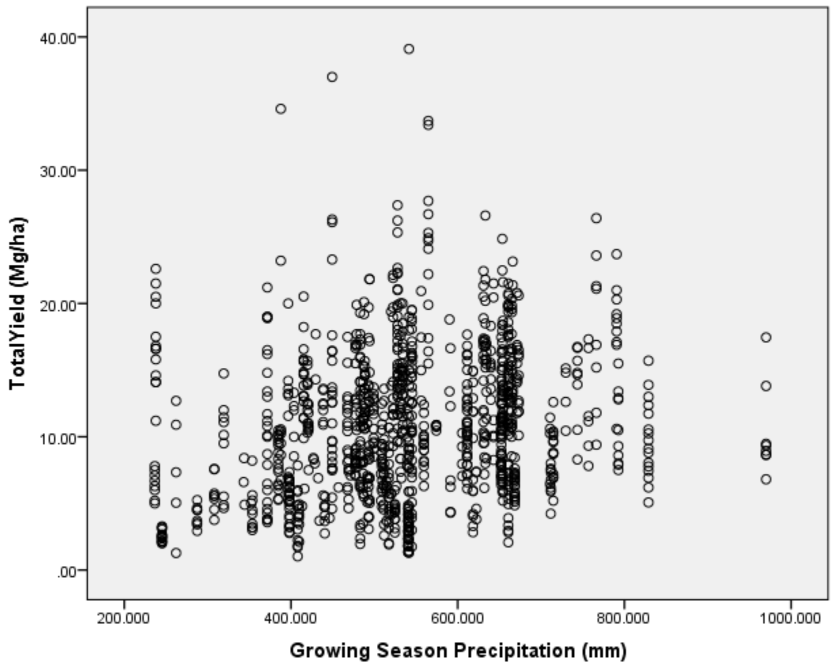

Fig. 9. Bivariate plot of growing season precipitation and total yield. Plot shows how yields vary across all values of precipitation.

5. Multiple Linear Regression Results

Initially, the stepwise regression procedure was run with yield as the outcome variable, and the following independent variables: soil order classifications, altitude, average annual mean, maximum and minimum temperature, average growing season mean and maximum temperature, average annual minimum temperature, annual and growing season average annual precipitation, ecotype, stand age, nitrogen fertilizer application, growing season precipitation and annual mean temperature from the year of harvest. The final model produced by the stepwise regression procedure contained seven independent variables (growing season precipitation, annual mean temperature, annual mean temperature squared, a binary ecotype, a binary stand age variable, N fertilization, and soil organic carbon) when modeled against yield as the outcome variable.

Residual analysis revealed a heteroskedastic association in the model and that the square root transformation on yield provided a better fit to linearize the relationships. The modeling process revealed that annual mean temperature had a nonlinear effect on the outcome variable (square root of yield), so various transformations were tested on the annual mean temperature variable, and it was found that the inclusion in the model of annual mean temperature squared (in addition to annual mean temperature) did the best to linearize the relationship. Altitude was tested in the model; however it was not at all significant and taken out of the model. An explanation for this could be that climate, in many ways, is affected by altitude and the climate variables selected for this analysis accounted for changes in altitude. After deleting the 58 high N fertilization observations and inspecting the studentized deleted residuals, Cook's D and leverage values, no other observations needed to be removed as statistical outliers. Analysis of the residual plots against predicted values and predictor variables indicated agreement with linearity and homoskedasticity regression assumptions. Tests for normality of the residual values showed that the residuals adhered to normality (figure 10).

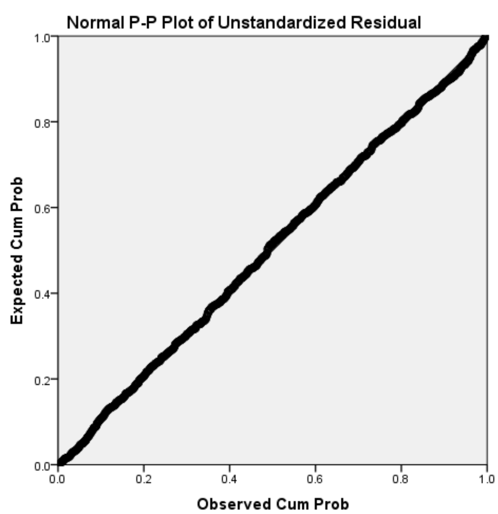

Fig. 10. P-P Plot of residuals follows a straight line, indicating the data does not significantly deviate from normality.

Six out of the seven (soil organic carbon being the exception) independent variables were all very significant (table 2). Adjusted r^2 was .291, indicating the model accounted for roughly 30% of the variation seen in the square root of biomass yield. . Since this study was completed on such a broad scale with a relatively small sample size of input locations, there are likely many more variables and interactions that could not be accounted for, such as field management methods, timing of rainfall, and more soil characteristics. Therefore, even this modest R-square is a significant accomplishment.

Table 2. Regression analysis output from final model run.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-21.988	2.314		-9.503	.000		
	ann_tmean_YoH_30	1.167	.109	5.914	10.723	.000	.002	485.280
	Ecotype_Bin	-.614	.050	-.361	-12.241	.000	.722	1.386
	gro_prec_YoH	.001	.000	.120	4.243	.000	.777	1.286
	Ntotal	.002	.001	.113	4.077	.000	.821	1.217
	Percent_OC	.051	.078	.018	.662	.508	.834	1.200
	sq_ann_tmean_YoH_30	-.014	.001	-6.027	-10.945	.000	.002	483.717
	StandAge_Bin	.151	.054	.073	2.826	.005	.937	1.068

a. Dependent Variable: sqrt_Yield

Examination of the estimated *beta* coefficients revealed the annual mean temperature was the most important predictor variable, positively affecting yield when holding all other variables constant. On the other hand, the squared temperature term indicated that when mean annual temperatures are too high, biomass yields are negatively affected. Keeping all other variables constant, the data show that biomass yields increases up to 13^{o}C and then decreases at temperatures above that threshold, although there is not much difference in predicted yield between 12-14^{o}C (table 3).

Table 3. Effect of mean annual temperature (X_{i1}) and squared mean annual temperature (X_{i2}) variables on biomass yield. The maximum effect is at 13°C.

Mean Annual T (°C)	$\mathbf{b_1X_{i1} + b_2X_{i2}}$
10	24.86672
11	24.928943
12	24.963876
13	24.97152
14	24.951872
15	24.904935
16	24.830708

Stand age had a positive effect on biomass yield; however its overall contribution to the prediction model was relatively small. Predicted biomass yields in China are made assuming stand ages are 2 years or greater. Growing season precipitation and N fertilization increased biomass yields as well, although more modestly than the other predictor variables. Biomass yield responded very positively to soil organic carbon, which was expected given the importance organic carbon is to plant growth. The *beta* coefficient for the binary ecotype variable was negative, implying that biomass yield decreases when the ecotype is upland and all other variables held constant.

This model predicts biomass yield based on raw predictor variables and does not take into account micro-level interactions that occur within seasons, above and underground dynamics of soil organic carbon and N fertilization and the method in which each of these acts on each ecotype. Wullschleger et al. (2010) found that plot size and harvest year were not significant factors in switchgrass production. Research has also shown that harvest management (1 or 2 cut systems) along with whether or not surface litter residue is removed, is critical to below ground carbon and nitrogen availability and switchgrass production (Garten et al., 2010). Mean growing season, winter and annual temperatures are all too correlated for linear regression analysis, however any of these variables, as well as other temperature correlations such as mean diurnal range and isothermality could influence switchgrass production. Annual precipitation was not reported for the observations, yet it may influence soil water holding capacity and other aspects of soil texture throughout the year that could not be accounted for. The amount of precipitation switchgrass receives during the growing season is important for its growth, but the effect of precipitation during the fall and winter months could have implications as well. Edaphic conditions are another area that could boost r^2 and help with the understanding of switchgrass production. Because switchgrass grows in a variety of geographic areas with different soil types and textures, it is difficult to develop significant relationships to biomass yield. Future switchgrass field trials could benefit from the collection of more underlying soil, climate, nitrogen and carbon data.

6. Results and discussion

Prior to predicting biomass yields in China, the model was first applied to the United States (figure 11) to compare the results to Wullschleger et al.'s (2010) multiplicative, parametric model for estimating switchgrass yield. Key model assumptions are that stand ages are > 2years and, for the China model, that N fertilization use across all of China would be 100 kg/ha. Mapped output from Wullschleger et al.'s (2010) model and this paper's model revealed differences in ecotype distribution and biomass yield estimates. Wullschleger et al.'s (2010) output map implies that lowland ecotypes extend up to 42^{o}N, and are capable of producing high biomass yields in the latitudes between 40 – 42^{o}N. Their research also indicates high biomass yields extending from the Southeast west into the majority of New Mexico, the eastern half of Colorado, all of Kansas and parts of Nebraska. They predict the highest biomass yields (23 Mg/ha) throughout the middle section of the country in the Southeast.

The model analysis in this paper used climate to estimate the distribution of upland ecotypes and lowland ecotypes, rather than using latitude as a parameter of the model itself, and appears to have produced results more in line with the climactic niche for each ecotype. For instance, there is a 2 – 3^{o}C difference in average mean annual temperature between locations at 42^{o}N versus those at 39 – 40^{o}N. According to these model results, the cooler temperatures are likely to favor uplands rather than lowlands in latitudes between 39° and 42°N, which also imply lower yield estimates. Additionally, average growing season precipitation is generally lower at 42^{o}N than at 39 – 40^{o}N and is considerably lower from the middle half of the country out to the Pacific coast. Absent of irrigation systems, the reduced rainfall in the higher latitudes coupled with cooler temperatures favor uplands as well and also imply reduced yield estimates from the lower, warmer latitudes. Biomass yield estimates were much lower in this analysis, with the highest yielding region predicted to produce 13-16 Mg/Ha as opposed to 23 Mg/ha in Wullschleger et al.'s (2010) model. The differences in biomass yield estimates are most likely because they are based on different empirical modeling techniques. Areas in figure 10 that show yields above 16 Mg/ha, including stretches in Minnesota with yields above 10 Mg/ha should be considered anomalies because those yield predictions are all (with the exception of the area in northern Georgia and South Carolina) influenced by exorbitantly high soil organic carbon content as opposed to the data used to build the model. The region in northern Georgia and South Carolina appears to predict high biomass yields due to an extraordinary amount of precipitation during the growing season in that region, well outside the bounds in the training data.

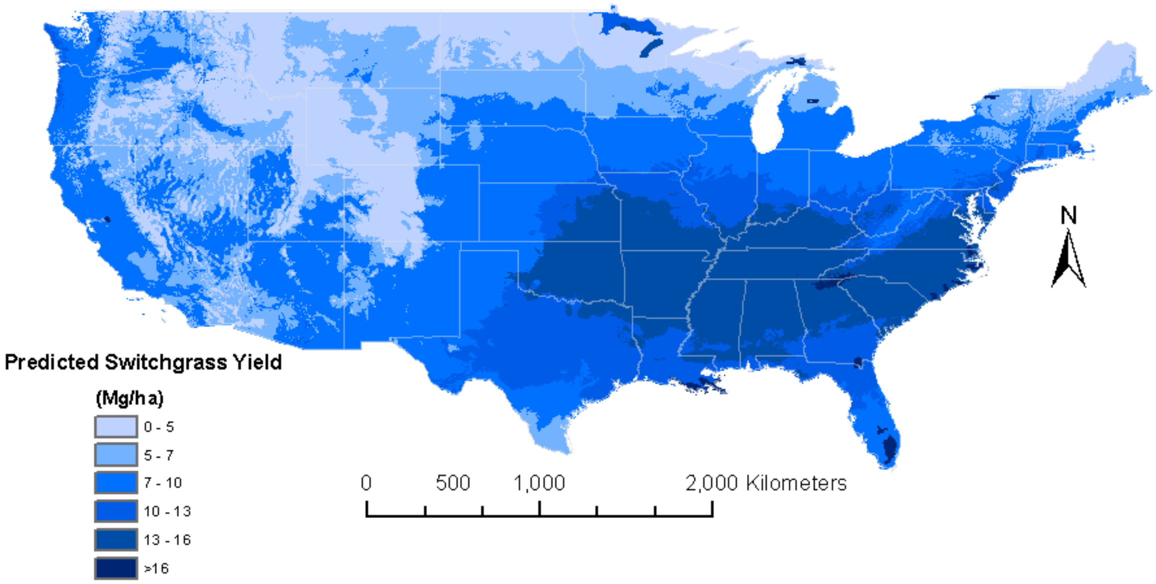

Fig. 11. Predicted switchgrass biomass yield for the United States.

Projecting the model onto China (figure 12) revealed that switchgrass can grow exceptionally well in many areas throughout China. The model projected lowland and upland ecotypes well within their known climatic niches. Unexpectedly, the model shows that China has the capability of producing higher biomass yields per unit area on average than the United States. The highest switchgrass yields were predicted in the southeastern part of China, primarily consisting of the North China Plain, Sichuan Basin, and the Chang Jiang Downstream Plain, where growing season precipitation is the highest, largely due to the summer monsoon season. It is of no coincidence that these areas consist of China's largest and most important agricultural regions.

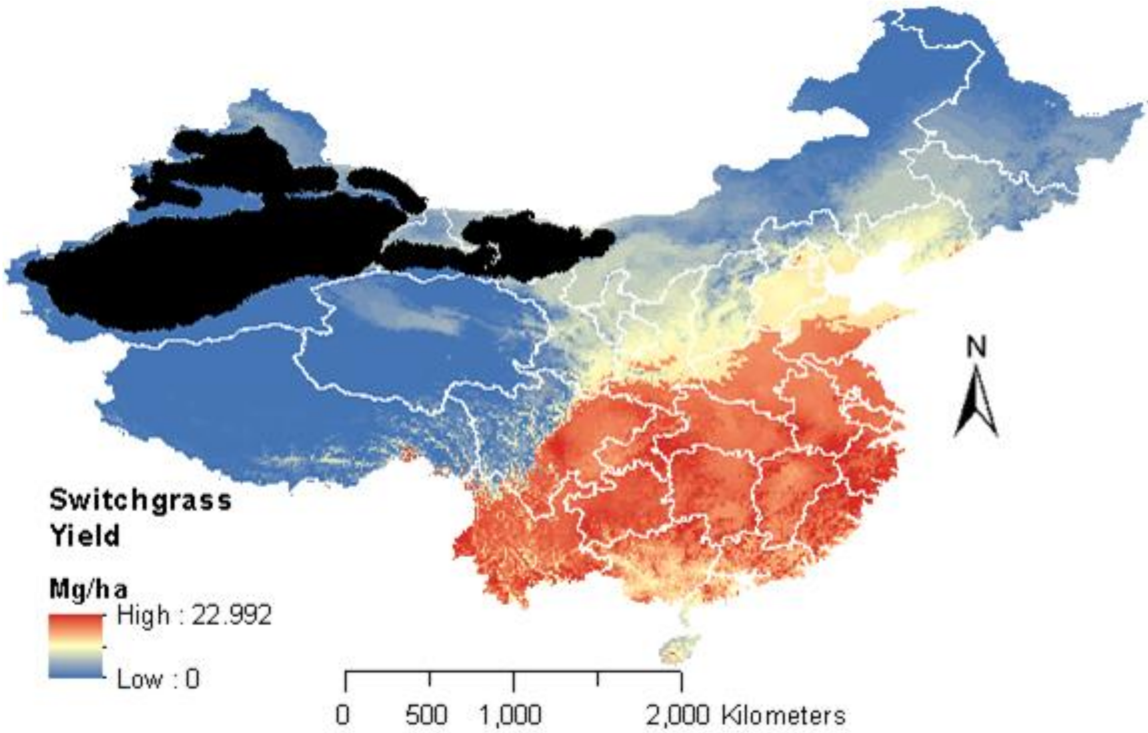

Fig. 12. Predicted switchgrass biomass yield for China. Areas in black represent regions that have environmental data that far exceed the training data.

The model output map also implies that switchgrass would grow well in the Loess Plateau, an area of pronounced soil erosion, and produce respectable yields between 7 – 10 Mg/ha. An initial hypothesis held prior to conducting this research was that while switchgrass may grow in the Loess Plateau, it would not produce enough to make it economically feasible to be harvested for biofuel feedstock and would have to be used instead solely for soil and vegetative recovery. To the contrary, the model shows that upland ecotypes can produce harvestable amounts of biomass in the Loess Plateau. This analysis, of course, does not take into account other factors behind crop management, such as storage, transportation and biofuel conversion, or difficulties of growing switchgrass in an area where wind or water erosion may carry away sewn seeds – one or more of these factors may make harvesting switchgrass difficult or not economically feasible in this area as well as more rural parts of China. Switchgrass biomass yield is predicted to be lowest in western and northern China, consisting of the Plateau of Tibet, Takla Makan Desert and the Gobi Desert. The region shaded in black represents a region of China that had environmental data outside the data range used to build the model, and could not be used to accurately predict biomass yield.

The purpose of this research was to estimate yield on a broad scale for switchgrass as a function of climate, soil organic carbon, N fertilization and ecotype selection across all of China, rather than individual locations or regions, and thus does not account for all of the intricacies and nuances of managing bioenergy crops on the ground level where individual differences, such as plot sizes, N fertilization amounts, irrigation, till or no-till farming, cultivar selection and other factors can influence biomass yield. However based on the training data, this model represents a relatively accurate assessment of potential switchgrass yields across China.

7. Conclusions

In this research, a large pre-published database of switchgrass field trials was used to estimate potential biomass yields across China based on climate, ecotype, N fertilization, soil organic carbon and stand age. The model showed that switchgrass yield is heavily influenced by climate conditions along with ecotype. In general, switchgrass responded positively to N fertilization, but also produced strong yields without any. N fertilization use in China for switchgrass growth should vary based on soil conditions throughout the different regions. China has the potential to produce significant switchgrass yields; however, the majority of the high producing agricultural areas is currently being farmed for food crops and, given China’s high population, switching to a bioenergy crop may not be socially and economically feasible in many areas. This leaves marginal lands and regions such as the Loess Plateau as potential sites for switchgrass production. Under this scenario, a double benefit can be realized, both for biofuel feedstock and soil and biodiversity recovery. In addition, more switchgrass field trials for biofuel production throughout different climate regions in China are needed to provide more spatially accurate data for predicting biomass yields across China. The database used in this analysis is the best and largest compilation of switchgrass field trials available to spatially extrapolate estimated potential switchgrass biomass yields. However, when utilizing a database of this nature, a pre-published compilation of multiple published studies, limitations exist that may constrain the level of analysis that can be achieved with the data. For instance, the analyses are not repeatable and there may have been different management techniques between studies. The timing of rainfall, warm temperatures, first frost and solar receipt could have differed between times and places of studies. Different studies may also have different levels of error associated with their measurements. Though a better understanding of soil interactions and nutrient cycles could increase the model's performance, this model can be spatially extrapolated to any country or region based on climate, however, the limitations that exist within this type of database should be considered.

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CHAPTER 4

Simulating potential switchgrass yield response to climate change in China

1. Introduction

Climate change and its effects on crop production, water availability, energy resources, and social and economic development are just a few of the important issues facing China and the rest of the world in the twenty-first century. In its Fourth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) found that global temperatures have increased by 0.74 (± 0.18)°C during the 100-year study period (1906 – 2005), up from 0.6 (± 0.2)°C (1901 – 2000) reported in the Third Assessment Report in 2001 (IPCC, 2007). Mean surface temperature across China mirrored the global rate, increasing significantly over the past 100 years on average between 0.5 – 0.8°C (Ding e al., 2006). The IPCC report also concluded that increased concentrations of greenhouse gases in the atmosphere are expected to influence global climate by lengthening the summer agricultural growing season, increasing worldwide averaged mean precipitation, evaporation and severe rainfall event frequency (i.e. flooding and more intense thunderstorms, monsoons and hurricanes), while also prolonging droughts in other regions. Mitigating ground level impacts of increased severe rainfall events are of great importance, as intermittent severe storms have been shown to increase soil erosion and loss, leading to a reduction in agricultural productivity and air quality from rising concentrations of particulate matter (Edwards and Owens, 1991; Zhang and Liu, 2005; Zhang and Garbrecht, 2002).

If no mitigating actions in China against climate change are taken by 2030, total crop productivity is expected to decrease by 5 – 10%. By the latter half of the 21st century, wheat, rice, and maize harvest will reduce by 37%, in conjunction with thinning water resources necessary to irrigate farmlands (Erda et al., 2007). In 2010, China became the world's largest automobile market and energy consumer, accounting for 20.3 percent of the global energy demand (BP, 2011). While all living organisms give off greenhouse gases, the rising concentrations experienced over the past 100 years and those predicted in the future are largely due to the combustion of fossil fuels for energy usage. Therefore, there is an urgent effort in China to develop non-fossil based renewable fuels capable of supplementing current and future energy demands as well as reducing the buildup of greenhouse gases in the atmosphere.

Switchgrass is a perennial grass species, native to North America that could be grown in China to provide biofuel feedstock, enhance soils and reduce soil erosion. It has shown great potential as a highly efficient bioenergy feedstock and has proven success at reducing soil erosion, increasing biodiversity, and sequestering carbon (McLaughlin et al., 1999; Parrish and Fike, 2005). Many studies have documented switchgrass's deep root system's abilities to store carbon and increase soil organic matter (McLauglin and Walsh, 1998; Romm et al., 1998; Ma et al., 2000; Ma et al., 2001; Lemus and Lal, 2005; Garten et al., 2010). Because switchgrass is a perennial crop and the root system is so vast, it is likely to provide superior carbon sequestration versus other annual energy crops, such as corn or soybeans (Zan et al., 2001). Zhou et al.'s (2009) analysis in China demonstrated that low-input high-diversity grasslands should be the preferred bioenergy feedstock of choice for producers because they are more economical and have greater environmental benefits than do annual biofuel crops. Annual biofuel crops lose significant quantities of soil organic matter through respiration and soil erosion (Garten and Wullschleger, 1999; Hallam et al., 2001). Switchgrass' tolerance to drought and flooding, two issues of significant concern with future climate change, also makes it an appealing biofuel feedstock (Rinehart, 2006).

The two primary ecotypes of switchgrass consist of lowland and upland ecotypes. Lowlands are taller, coarser and produce more biomass than uplands, and are generally found in areas that have higher rainfall and longer growing seasons and mild winters (Vogel, 2004). The shorter uplands fare well in drier, colder climates, such as those that are found in the Midwestern and Northern United States (Bouton, 2007). There are also several different types of cultivars for each ecotype. The three most common cultivars are Alamo, a lowland ecotype which favors the Southern states and has generated exceptional biomass yields, Kanlow, another lowland ecotype that has shown good promise, and Cave-in-Rock, an upland ecotype best adapted to the Northern states (Parrish and Fike, 2005).

Ichizen et al. (2005) and Xiong et al. (2008) demonstrated switchgrass's potential in China as an important option in mitigating severe soil erosion in the Loess Plateau and its ability to produce significant biomass yield for bioenergy conversion, respectively. A multiple linear regression analysis on switchgrass yield data from 1,190 observations provided by Wullschleger et al. (2010) from 39 different locations in the United States was used to build a model to estimate potential switchgrass yield across China. This paper estimates future yields in China using climatic conditions estimated from global circulation models (GCMs). GCMs simulate climate patterns at the continental level; however, the coarse resolution of the models requires them to be downscaled to higher spatial resolutions (Arnell, 2004) for some applications. The IPCC's Special Report on Emissions Scenarios (SRES) from its fourth assessment (IPCC, 2007) provides the most recent future greenhouse gas projections, which influences future climate, and is applied in this analysis. The purpose of this analysis is to assess the impact of climate change at the end of the 21st century (2070-2099) under three different IPCC SRES greenhouse gas emission scenarios (high, intermediate and low) on potential switchgrass yields and distribution across China. To accomplish this goal a model is built from switchgrass field trial observations based on present climate and environmental conditions in the United States and then projected onto China with the 2070-2099 climate projections.

2. Materials and Methods

2.1. Dataset description

1,190 field trials of switchgrass production from 39 different locations in the United States (table 1) were used to build a multiple linear regression model to predict potential switchgrass yields across China (Wullschleger et al., 2010). The data were compiled from switchgrass field trials presented in 18 publications by Wullschleger et al. 2010. The 39 locations represented diverse climate regions and the data included GPS coordinates, biomass yield, stand age, nitrogen fertilizer application, ecotype selection, growing season (April – September) precipitation and mean annual temperature from the year of harvest. Latitude and longitude coordinates of each field test site were used to determine soil organic carbon, obtained from the Harmonized World Soil Database (FAO et al., 2012) at 1 km resolution. Table 2 provides a summary of the data sources. Spatial analyst tools in ArcMap 10 (ESRI Inc., Redlands, CA) were used to extract the site-specific data from each of these additional environmental variables, at a 1km^2 pixel resolution for the whole country of China.

Table 1. 39 locations of switchgrass field trials along with respective ecotype, climate and soil data.

Location	No. of Observations	Lowland	Upland	Mean Annual T (°C)	Mean Growing Season Precip (mm)	Soil Order	% Soil Organic C
Shorter, Al	16	6	10	16.8	674	Ultisol	1
Athens, GA	30	10	20	16.3	595	Ultisol	1
Tifton, GA	30	10	20	18.6	638	Ultisol	1.13
Chariton, IA	60	12	48	9.5	633	Mollisol	1.68
Manhattan, KS	4	2	2	11.5	620	Mollisol	1.83
Princeton, KY	24	12	12	13.9	619	Ultisol	1.45
Clinton, LA	6	6	0	18.7	821	Ultisol	1
Raleigh, NC	24	12	12	15.4	607	Ultisol	1
Dickinson, ND	24	0	24	5.4	328	Mollisol	1.27
Mandan, ND	48	0	48	5.4	329	Entisol	0.48
Munich, ND	3	0	3	2.9	345	Mollisol	1.65
Streeter, ND	3	0	3	4.9	354	Mollisol	2.08
Atkinson, NE	2	0	2	8.7	450	Entisol	0.5
Crofton, NE	3	0	3	8.8	382	Mollisol	0.97
Douglas, NE	3	0	3	10.5	578	Mollisol	1.29
Lawrence, NE	3	0	3	10.4	517	Mollisol	1.27
Mead, NE	4	2	2	10.1	572	Mollisol	1.29
Chickasha, OK	143	115	28	16.2	523	Mollisol	1.27
Haskell, OK	70	28	42	15.6	610	Mollisol	1.05
Perkins, OK	46	46	0	15.4	568	Mollisol	1.27
Stillwater, OK	4	2	2	15.1	601	Mollisol	1.05
Rock Springs, PA	10	0	10	9.3	547	Alfisol	0.86
Bristol, SD	3	0	3	5.8	394	Mollisol	1.74
Brookings, SD	24	0	24	6.2	446	Mollisol	1.27
Ethan, SD	3	0	3	8.3	429	Mollisol	1.27
Highmore, SD	3	0	3	6.7	367	Mollisol	1.27
Huron, SD	3	0	3	7.3	386	Mollisol	1.27
Jackson, TN	24	12	12	15.1	651	Alfisol	0.82
Knoxville, TN	24	12	12	14.3	620	Ultisol	1
Beeville, TX	51	45	6	21.5	493	Alfisol	0.86
College Station, TX	67	46	21	19.9	531	Alfisol	0.86
Dallas, TX	84	74	10	17.9	514	Alfisol	0.86
Stephenville, TX	146	121	25	17.5	469	Alfisol	0.86
Temple, TX	70	59	11	19	475	Vertisol	1.2
Blacksburg, VA	48	24	24	11.1	546	Ultisol	1
Orange, VA	24	12	12	12.9	584	Ultisol	1
Arlington, WI	28	2	26	7.3	550	Alfisol	1.91
Spooner, WI	4	2	2	5.3	554	Spodosol	1.91
Morgantown, WV	24	12	12	10.8	599	Ultisol	1

Table 2. Data Sources

Switchgrass Field Trial Data		
(1,190 observations)		Wullschleger et al., 2010
Environmental Variables		
Mean annual temperature	WorldClim (v. 1.4)	http://www.worldclim.org/
Mean growing season precipitation	WorldClim (v. 1.4)	http://www.worldclim.org/
Climate data (2070 - 2099)	CCAFS	http://www.ccafs-climate.org/
Soil organic carbon	Harmonized World Soil Database (v. 1.2)	http://www.iiasa.ac.at/

2.2. Regression model and analysis

The independent variables used to build this model were mean annual temperature, growing season precipitation, nitrogen fertilizer application, soil organic carbon percentage, and binary ecotype and stand age variables. These variables explained more variation in yield than did other environmental variables. To build the stepwise regression model, verify the assumptions, analyze descriptive statistics and plots, SPSS (IBM, Inc., Armonk, New York) predictive analytics software was used (table 3).

Table 3. Regression analysis output from final model run.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-21.988	2.314		-9.503	.000		
	ann_tmean_YoH_30	1.167	.109	5.914	10.723	.000	.002	485.280
	Ecotype_Bin	-.614	.050	-.361	-12.241	.000	.722	1.386
	gro_prec_YoH	.001	.000	.120	4.243	.000	.777	1.286
	Ntotal	.002	.001	.113	4.077	.000	.821	1.217
	Percent_OC	.051	.078	.018	.662	.508	.834	1.200
	sq_ann_tmean_YoH_30	-.014	.001	-6.027	-10.945	.000	.002	483.717
	StandAge_Bin	.151	.054	.073	2.826	.005	.937	1.068

a. Dependent Variable: sqrt_Yield

Adjusted r^2 was .291, indicating the model accounted for roughly 30% of the variation seen in the square root of biomass yield. This linear regression analysis assumes a 1 – cut per year harvest management system and makes biomass yield predictions for stand ages older than 2 years. 1,190 observations of switchgrass yield data (Wullschleger et al., 2010) from 39 locations in 17 states over the period from 1979 to 2005 are assembled in this database. There are 684 observations of lowland ecotypes and 504 observations of uplands. Mean biomass yield for the database was 11.12 Mg/ha. The lowest reported annual yield was 1.03 Mg/ha in Beeville, TX, (Sanderson et al., 1999) during a year with normal mean annual temperature and growing season precipitation. The highest observed yield was 39.1 Mg/ha, recorded in Temple, TX, (Kirniry et al., 1999) with slightly below average mean annual temperature and above average growing season precipitation. The most commonly recorded yields were between 6.9 Mg/ha (25th percentile) and 14.61 Mg/ha (75th percentile) and biomass yields above 26 Mg/ha were considered outliers. Residual analysis revealed a heteroskedastic association in the model and that the square root transformation on yield provided a better fit to linearize the relationships.

While some switchgrass stands without applications of nitrogen fertilization produced biomass yields well above the average, the data indicate that switchgrass responds favorably to nitrogen fertilizer. Nitrogen fertilizer rates across the database varied from 0 to 896 kg/ha, although applications greater than 225 kg/ha was rare and especially excessive. There were 58 observations that fell into this category and were thus treated as outliers and taken out of the regression analysis.

Switchgrass yields varied considerably over all values of nitrogen fertilization application, yet data analysis indicated that high nitrogen fertilization does not always produce high biomass yields. Further analysis revealed that switchgrass responds favorably to nitrogen fertilization up to 90-115 kg/ha, and then declines at higher quantities. This implies that switchgrass is not nitrogen fertilization dependent; however, if used in moderation, it can have positive results on biomass yield. Nitrogen fertilization application rates between 80-100 kg/ha in stands 2 years and older are considered standard nitrogen management procedure (Wolf and Fiske, 1995). Wullschleger et al. (2010) found optimal nitrogen fertilization rates to be approximately 100 kg/ha. This rate coincides with bivariate plot analysis of nitrogen and biomass yields (data not shown) and therefore will be used as the optimal nitrogen fertilizer input for predicting biomass yields in China.

Switchgrass stand ages varied from 2 to 21 years and biomass yields were generally greater after the 2nd year, which corresponds to switchgrass' known biological trait of reaching maturity and full yield potential during its third year post-establishment (McLaughlin et al., 1999). Some observations with exceptionally high yields were in the second year of harvest; however, the reasons were unclear and beyond the scope of this study. Model results showed that while stand age had a positive effect on yield, its overall contribution to the prediction model was relatively minor. Establishing switchgrass in China for bioenergy feedstock is considered a long-term investment; therefore, the model will make the assumption that biomass yield estimates are for stands > 2 years.

The percentage of soil organic carbon in the soil profile is considered one good measure of the quality of the soil and was therefore included in the model. It is measured as the percent weight of organic carbon in the topsoil, where soils with organic carbon < 0.6% are considered to be poor in organic matter (FAO et al., 2012). The majority of the observations occurred in soils > 0.6 % and plot analysis suggests that switchgrass responds well to soil organic carbon.

In order to determine the potential distribution of the two switchgrass ecotypes in China and develop a more accurate yield model, it was necessary to create a binary variable for ecotype, where 0 = lowlands and 1 = uplands. Lowland ecotypes outperformed uplands with an average biomass yield of 12.59 Mg/ha and 8.74 Mg/ha, respectively. Past studies on the optimal ecotype distribution in the United States have indicated that lowland ecotypes exhibit a competitive advantage over uplands in the southern regions up to 42^{o}N (Casler et al., 2004). Since both ecotypes can grow in many locations throughout the United States, they are also likely to be viable in areas with similar latitudes and climates in China.

Instead of simply using the 42 ^{o}N latitude as the threshold determinant for uplands and lowlands when predicting biomass yields in China, climate indicators were used by running a logistic regression on the ecotype variable. With a binary dependent variable, logistic regression analysis becomes a good method for determining the absence or presence of a species at a particular location relative to climate or other environmental variables, thus making it feasible to predict its potential distribution in regions outside of its native range (Pearce and Ferrier, 2000). The logistic model was built using the growing season precipitation and mean annual temperature from the observations that had the highest yield at each of the 39 locations (n = 39 and 22 lowlands, 17 uplands). These observations were selected because they produced the greatest yields under the present climate settings, thereby providing key information regarding how each ecotype performs under those conditions. Growing season precipitation and mean annual temperature from the years of harvest were the independent variables and ecotype was the outcome variable. Running the logistic regression produces the constant and *beta* coefficient required to model Logit(p) = $\alpha + ßX + \varepsilon$, where Logit(p) = the probability that

Y = 1. Once the model was developed, it was applied to China's growing season precipitation and mean annual temperature variables in ArcMap 10.

Climate is a significant environmental variable for the production of switchgrass (Schmer et al., 2005). Biomass yields varied across all mean annual temperatures and growing season precipitation. Yields were lowest between 5-8^{o}C and highest between 12-16^{o}C, emphasizing switchgrass' proclivity to produce higher biomass yields in warmer regions with longer growing seasons. Wullschleger et al. (2010) found that biomass yield increases up to 14^{o}C and then decreases with further temperature increase, suggesting a parabolic effect of temperature on biomass yield. To account for this effect in the model, a squared mean annual temperature variable was created. In order to do this, mean annual temperature had to first be increased by 30^{o}C for each location to eliminate the outcome of squared negative values becoming positive as there are negative mean annual temperature values in some locations within China. With all other variables constant, the model shows that switchgrass yields increases up to approximately 13^{o}C and then decreases at greater temperatures, although not much difference is predicted in biomass yield between 12-14^{o}C. Growing season precipitation had a positive effect on biomass yield across all precipitation values. Growing season precipitation is considered to be one of the most important variables in determining biomass yield (Sanderson et al., 1999b). The data also suggest that growing season precipitation amounts above 600mm does not automatically enhance biomass yields.

2.3. China climate data and emission scenarios

Baseline (present) climate data were obtained from the WorldClim global climate database, which produced climate grids by interpolating average monthly climate data from weather stations around the globe at 1 km resolution from 1950-2000 (Hijmans et al., 2005). Future climate projections for the time period 2070 – 2099 were obtained from the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) database available for download at http://www.ccafs-climate.org/data/. CCAFS climate projections are downscaled from very coarse resolution (between 100 – 300 km) to 1 km resolution from the IPCC fourth assessment GCMs.

The climate change scenarios used in this study were derived from the Hadley Centre Coupled Model, version 3 (HadCM3) GCM, which employed the delta method downscaling technique. The delta method, developed by Ramirez-Villegas and Jarvis (2010), is a statistical downscaling technique designed to be used for crop modeling, ecological niche modeling and measuring impacts of climate change on agriculture at high resolutions. Two key assumptions this method makes are that relationships between variables in the baseline data (1950-2000) are probable to be sustained into the future and climate differences vary only over large distances (Ramirez-Villegas and Jarvis, 2010). This method is also designed to minimize inconsistences with the data when downscaled. The original dataset is simply too coarse to be useful for these types of studies, rendering downscaling a necessary step.

The IPCC (2007) report provides new projections of greenhouse gas emissions, contained in four emission scenario families, A1, A2, B1 and B2. Each scenario is based on a combination of future economic development, global population flux, technological advances, environmental stewardship and social welfare. The A1 emission family consists of three sub-families, whereas the others have one each, and project a future of very rapid economic growth, more efficient technology, improved cultural and social interactions, considerable reductions in regional disparities in per capita income, and a global population that peaks in the mid-century and declines afterwards. The sub-families are represented by the fossil fuel reliant A1F1, non-fossil fuel A1T, and A1B which represents a balance across all energy sources (meaning the use of a mixture of fossil and renewable energies).

A2 represents a more heterogeneous, self-reliant world, with emphasis on preserving local cultures and traditions. Technological and economic growth is assumed to be less than in A1 and more regionally fragmented; however, the convergence of fertility rates across regions yields a higher and steady population growth rate throughout the century. A2A is considered the “business as usual” scenario and the one most often predicted to unfold in the future; hence it is the recommended choice for future modeling if only one climate change emission scenario is to be analyzed (White et al., 2010). B1 and B2 scenarios represent a more globalized world with increased focus on sustainable environmental, economic, technological and social development with greater social equity. B1 is even more environmentally oriented than B2, and therefore has lower greenhouse gas emissions and the least effect on predicted climate change. Population growth increases steadily in B2, but less than A2, while B1’s global population growth rate is the same as A1. The emission scenarios employed here are A2A, A1B and B2A, which were selected to represent high, medium and low greenhouse gas emissions, respectively, by the end of the 21st century.

For each climate scenario, including baseline, mean annual temperature and mean growing season precipitation variables in China were created from monthly mean temperatures and monthly total precipitation at 1 km resolution using spatial analyst tools in ArcMap 10 (table 3).

Table 4. Comparisons of present and future climate data. Table summarizes all pixels in China for both present and future climate.

	Growing Season Precipitation (mm)				Mean Annual Temp (°C)			
	Min	Max	Mean	St. Dev.	Min	Max	Mean	St. Dev.
Present Conditions	7	2345	455.9	359.67	-21.6	25.8	6.4	7.91
A2A	0	472	87.2	70.7	-17.3	29	11.1	7.7
A1B	1	462	90.3	70.5	-17.7	29.2	11.2	7.74
B2A	0	456	83.9	67.5	-18.8	28.2	9.8	7.71

3. Results and discussion

3.1. Climate and ecotype threshold

Logistic model results restrict lowland ecotypes to southern China in both present and future projections; however, the distribution becomes smaller and more fragmented in future conditions (figure 1). The B2A scenario predicts the most scarce distribution of lowland ecotypes, presumably because it has the lowest growing season precipitation along with temperatures higher than the optimal range for lowlands. A2A and A1B emission scenarios had very similar distributions for lowland and upland ecotypes, likely due to almost identical maximum mean annual temperatures. It is clear, however, that climate change is expected to alter suitable habitat for lowlands and uplands, as both ecotypes have a southern migration trend in the future.

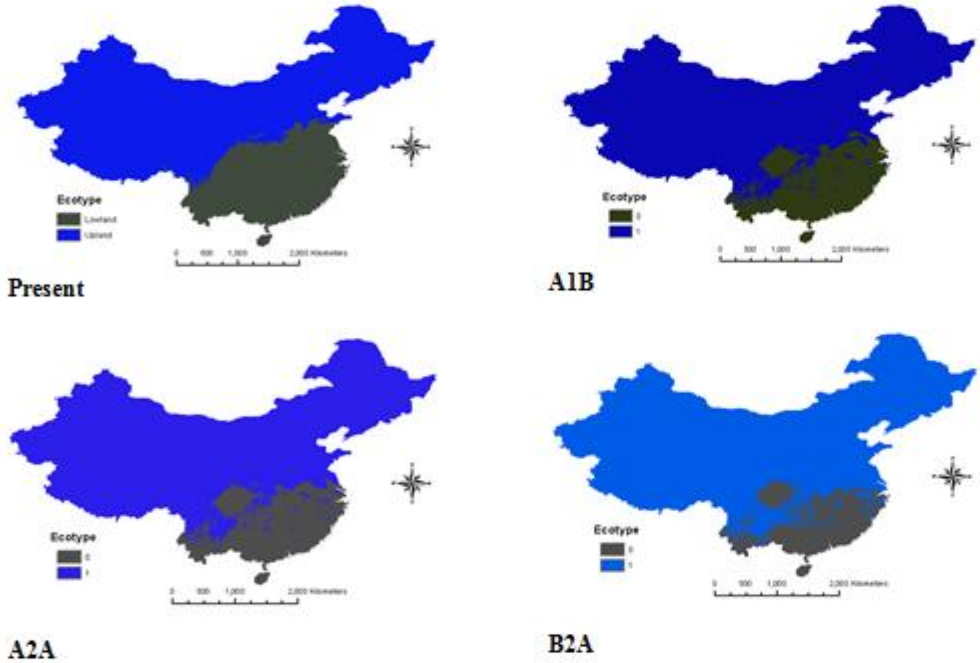

Fig.1. Predicted upland and lowland threshold based on mean annual temperature and growing season precipitation for present and future time periods.

3.2. Current Predicted Switchgrass Yield

The present-day regression model results indicate that switchgrass has a strong productivity potential in China, particularly in the southern regions (figure 2). The climate in Southern China favors lowland ecotypes, with compliant mean annual temperatures and plentiful precipitation due to the summer monsoon season. As a result, the model predicts a considerable amount of biomass production (13 – 19 Mg/ha) in the region. In Sichuan province, there is a clear decline to nearly 0 Mg/ha of switchgrass productivity from the western half of the province all the way through Qinghai and Xizang provinces. The division is caused by a drastic change elevation in the region by the Qionglai Mountains, leading to much lower temperatures and precipitation, both of which combinations are unfavorable for switchgrass development. To the north and northeast, switchgrass potential is effectively zero in Inner Mongolia and provinces north of Liaoning. Switchgrass is even expected to grow well in the Loess Plateau, with predicted yields between 7 – 10 Mg/ha. This is a harvestable amount that could be very beneficial for not only biofuel production but also for the soils in the region. On the whole, the model indicates that the current climate conditions in China are more than adequate to allow wide scale switchgrass production for biomass feedstock as well as soil erosion control.

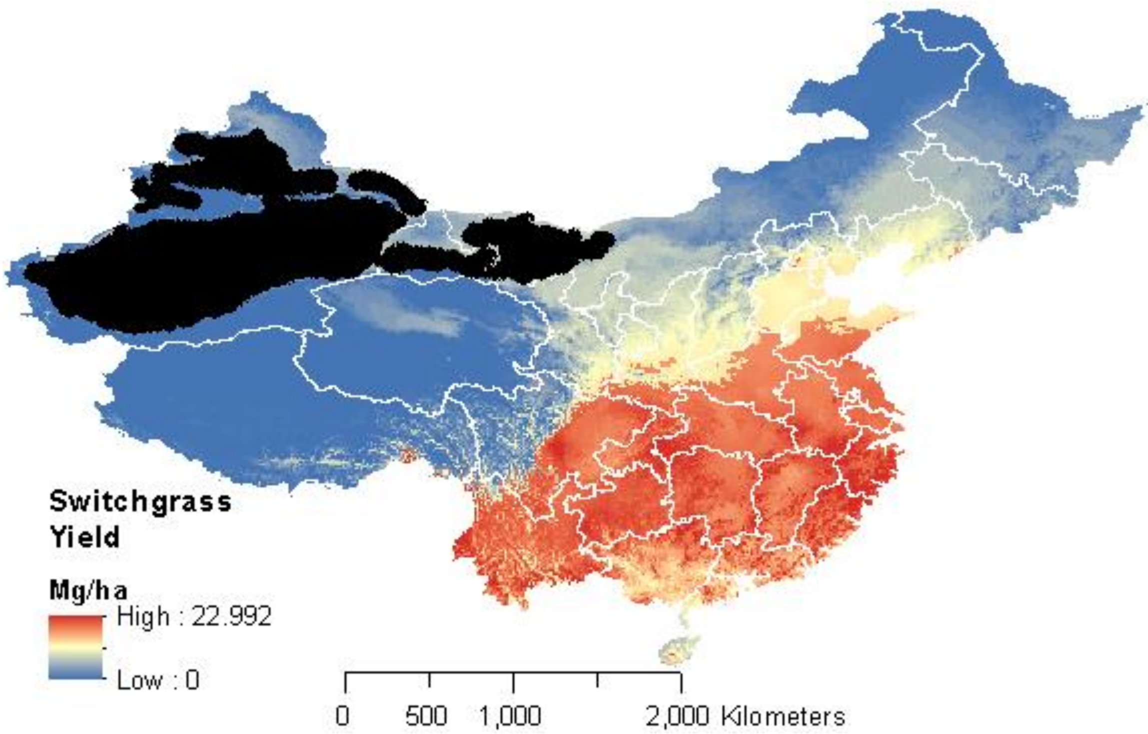

Fig. 2. Predicted switchgrass yield across China under present climate conditions.

3.3. Projected climate change impact

According to Table 3table 4, climate change will have a profound effect on China across all scenarios. The predicted precipitation and temperature values in all scenarios were very similar to each other. Mean annual temperatures are nearly 4° higher than now in each model and growing season precipitation is predicted to be considerably less than under current conditions. In addition, while future maximum temperatures are all higher than baseline conditions, the corresponding minimum temperatures are all nearly just as high above the current low. Mean precipitation values further illustrate the vast disparity in future precipitation values. This amounts to prolonged drought-like conditions, compared to the present time period. The social and economic effect these climate conditions could have on China could be very significant. Projected mean growing season precipitation during 2070 – 2099 decreases by an average of 368.7 mm, 365.6 mm and 372.0 mm for A2A, A1B and B2A emission scenarios, respectively. While switchgrass is generally water efficient and drought tolerant, this significant decrease in precipitation is undoubtedly a reason future switchgrass yield estimates are considerably lower than present conditions (figure 3).

Despite the reduction in biomass yield, the future increase in temperature has a profound impact on upland distribution, particularly in Inner Mongolia and Northeast China. The warmer temperatures in the northern regions are creating suitable habitats for upland switchgrass. On the other hand, the temperatures become even warmer in the southern regions where lowlands dominated in present climate conditions, becoming potentially too excessive for lowlands to produce high yields. The expansion of the upland ecotypes and the reduction of the lowlands distribution exhibited in the model could be because uplands are thought to be more tolerant of drought conditions than lowlands (Porter, 1966). Uplands also exchange CO_2 at higher rates, utilize water more efficiently, and improve faster than lowlands under drought stress (Nickell, 1972). Areas along the southern coast were productive in present conditions, but exceedingly unproductive in the future predictions. All emission scenarios reflect a significant decline in switchgrass production by the end of the century.

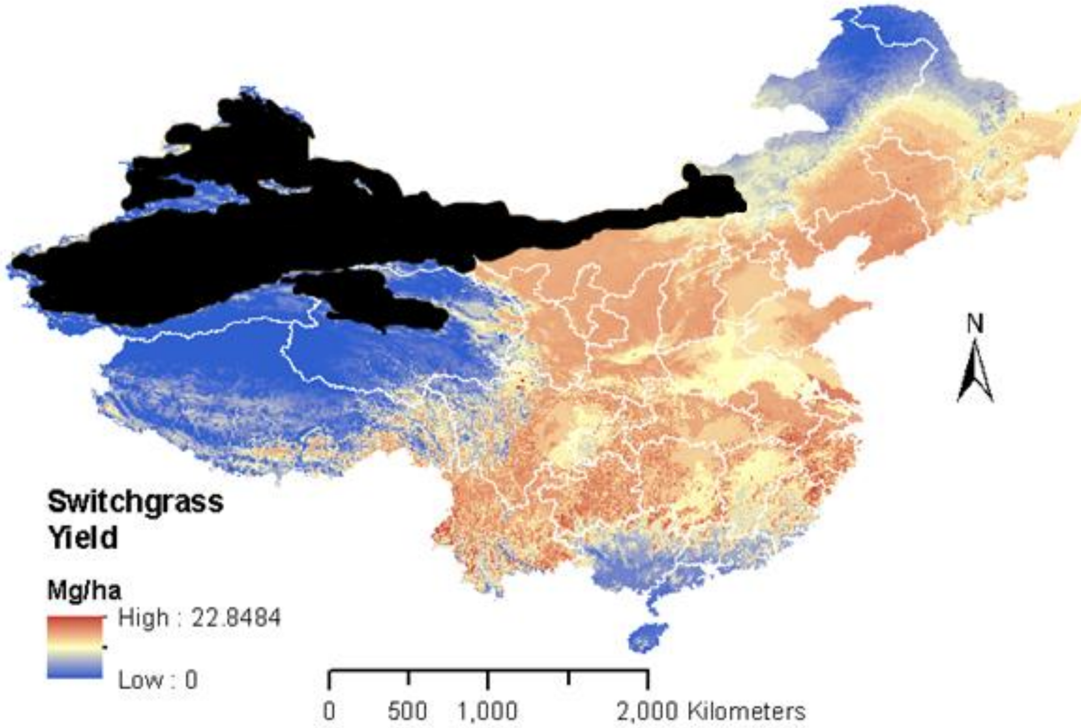

Fig. 3.1. Switchgrass yield predictions for future A2A climate conditions.

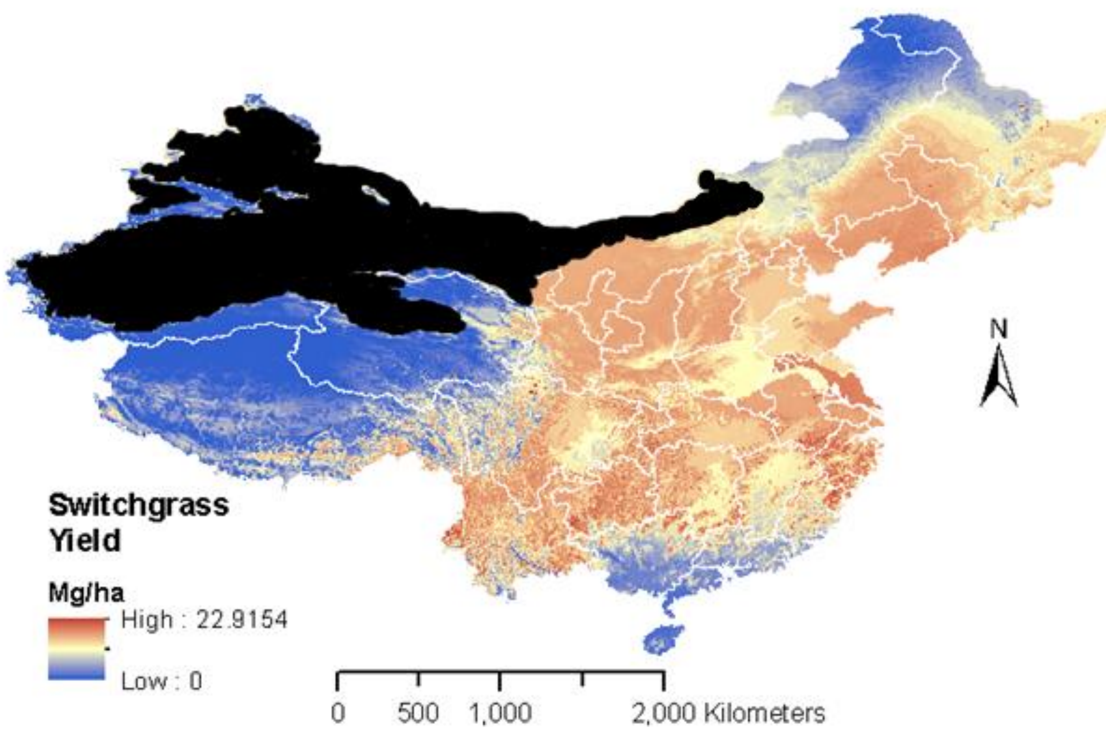

Fig. 3.2. Switchgrass yield predictions for future A1B climate conditions.

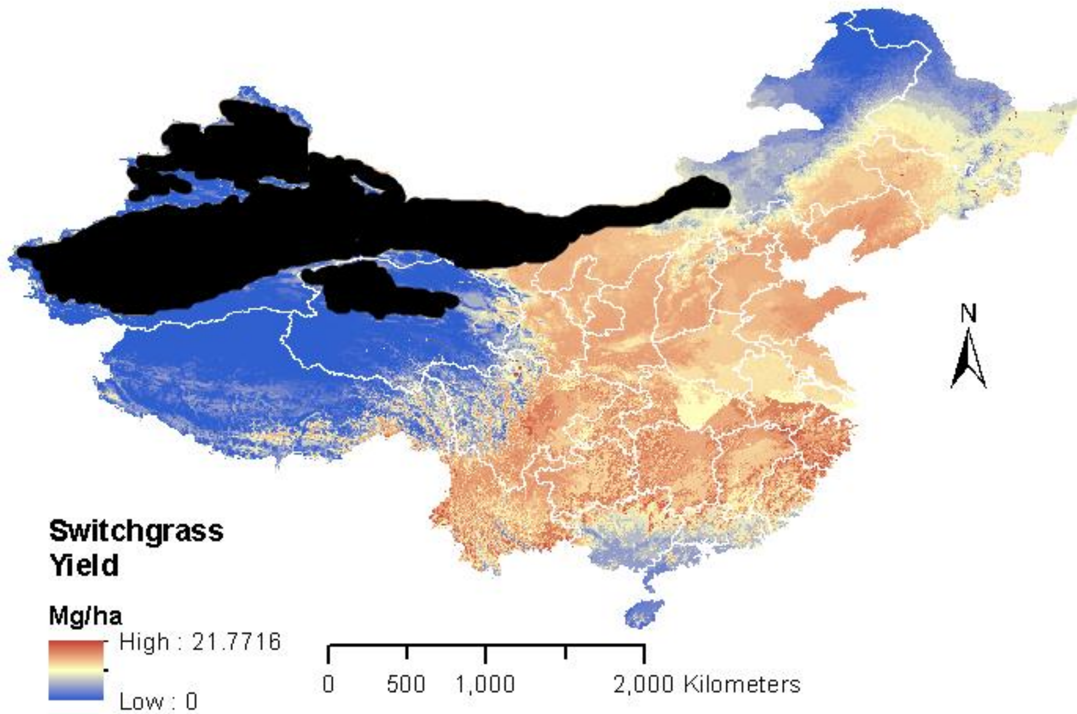

Fig. 3.3. Switchgrass yield predictions for future B2A climate conditions.

4. Conclusions

Switchgrass yield estimates in the years 2070 – 2099 were modeled in this study using three emission scenarios derived from the Hadley Centre model (HadCM3). It should be noted that the choice of this model was subjective, essentially due to data availability, as there are other GCM models with different emission scenarios available for analysis, however, not all of the models have been down-scaled. The HadCM3 model provided down-scaled data for all three target scenarios. The future climate scenarios depict a changing agricultural landscape in China, where regions can become unsuitable or cost ineffective for production absent some forms of agricultural engineering. While B2A is the most environmentally friendly scenario and has the lowest greenhouse gas emissions, mean annual temperature is still significantly higher than present conditions and presents a diminished outlook on switchgrass production in China compared to projections under present conditions. Though yield estimates are lower on average in the future climate projection scenarios than in the present, a large portion of China is estimated to produce switchgrass yields between 7 – 10 Mg/ha, which is significant enough to make switchgrass a viable option in the future for China's renewable energy production.

This regression model was built using mean annual temperature from the years of harvest at each location. Previous regression analyses revealed that all temperature variables, mean annual, growing season, winter, minimum and maximum temperatures were all very correlated in relation to switchgrass production (Wullschleger et al., 2010), resulting in the need to exclude the others from the regression model due to multicollinearity. The vast difference in climate between the two research periods could decrease correlation amongst temperature variables and should be considered in future studies. Soil changes as a result of climate change could also impact future yield predictions and should be further explored; however, future soil projections are currently not available.

The end of the 21st century temperature projections in China results in a southerly shift and reduction in switchgrass productivity yet provides a good demonstration of switchgrass's adaptability. The lower precipitation estimates will lead to more difficulty in producing substantial yields in both biofuel and food crops. Results suggest that switchgrass is a viable candidate for bioenergy feedstock development, under present and future climate conditions. Switchgrass's positive environmental benefits may help improve its viability despite the rising temperatures and decreasing precipitation predicted in the future. It should be kept in mind that these climate scenarios are only forecasts and substantial uncertainty exists between projections and models. Developing reasonable measures to mitigate against future climate change will be very critical for

China in order to meet their future energy needs while protecting the environment and to remain a harmonious society.

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CHAPTER 5

1. Conclusion

The primary research objective of this dissertation was to determine where switchgrass could be grown in China based on its known climate and environmental constraints in the USA, and if so provide estimates on yield so that policy makers in China can assess if this is a feasible feedstock for bioenergy production and controlling soil erosion. Three research questions were addressed using a variety of geographic, biogeographic, ecological and spatial statistics tools to analyze the feasibility of growing switchgrass in China.

In the first chapter, two ecological niche models were created that projected potential suitable habitats for switchgrass in China. The models determined switchgrass' fundamental environment and climate requirements based on a set of independent variables produced from switchgrass's habitats throughout the United States where it is native. Results reveal that the climate in much of China is very favorable for growing switchgrass and that a large portion of the country is quite suitable for growing switchgrass, even in some areas of serious soil degradation.

The second chapter utilizes a multiple linear regression model to estimate switchgrass yields across China. Developing the model allowed for the analysis of individual predictor variables on switchgrass yield. Annual average temperature proved to be the most significant variable for switchgrass growth, followed by growing season precipitation. Since so much of China's climate is so favorable for switchgrass, the results indicate that China has the potential to produce a considerable amount of switchgrass, even more so than in the United States where switchgrass is native. This research improved upon current methods of determining latitudinal thresholds for switchgrass ecotypes by developing a logarithmic regression model on climate variables based on yield results from switchgrass field trials.

In the final chapter, the effects of climate change under three greenhouse gas emission scenarios at the end of the 21st century were modeled to estimate potential future switchgrass yields. In all of the emission scenarios, which represent high, intermediate, and low emissions, the average annual temperatures are all considerably higher than present conditions and total precipitation values throughout the growing season are much lower as well. Due to the importance of these climate variables, estimated switchgrass yields are all much lower than the present yield estimations. Climate change could have not only a staggering affect on switchgrass in China, but also on its entire agroeconomy. Although there are a variety of farm management tools that can be used to help combat the changing climate, mitigation of these future conditions should begin now to ensure China’s sustainable development of agriculture in the future. This chapter also represents the first time potential switchgrass yields have been modeled across China or any country for the end of the 21st century time horizon.

In summary, this dissertation demonstrated that switchgrass is capable of growing well throughout a large area in China and should be considered a meaningful option for bioenergy feedstock input and soil erosion control. In addition, the model performance can be improved if data become available from switchgrass field trials in China, or more field trials elsewhere in the world. Policy makers and agribusinesses in China could also utilize and benefit from the findings in this research. Not only has it been demonstrated that switchgrass can grow well in China, but yield estimates indicate that switchgrass production for biofuels are significant enough to warrant further economic analysis and potential adoption to address goals to increase domestic biofuel production. A useful next step would be to create a water urban mask to eliminate areas in China not available to grow or convert switchgrass production. In addition, further analysis may allow these map outputs to help identify underutilized agricultural or vacant land areas in China suitable for growing switchgrass. Such underutilized lands are generally found in rural areas, suggesting that switchgrass production could help boost the rural economy and economically motivate improvement of infrastructure in those regions to allow for the efficient production and processing of biofuels. Future research on switchgrass in China is needed to study the environmental and economic feasibility of growing and converting switchgrass into lignocellulosic ethanol. Furthermore, these research methodologies can be adapted to other countries to determine switchgrass feasibility for present and future climate conditions.