Projecting the land cover change and its environmental impacts in the Cedar River Basin in the Midwestern United States

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Abstract
The physical surface of the Earth is in constant change due to climate forcing and human activities. In the Midwestern United States, urban area, farmland, and dedicated energy crop (e.g., switchgrass) cultivation are predicted to expand in the coming decades, which will lead to changes in hydrological processes. This study is designed to (1) project the land use and land cover (LULC) by mid-century using the FORecasting SCEnarios of future land-use (FORE-SCE) model under the A1B greenhouse gas emission scenario (future condition) and (2) assess its potential impacts on the water cycle and water quality against the 2001 baseline condition in the Cedar River Basin using the physically based soil and water assessment tool (SWAT). We compared the baseline LULC (National Land Cover data 2001) and 2050 projection, indicating substantial expansions of urban area and pastureland (including the cultivation of bioenergy crops) and a decrease in rangeland. We then used the above two LULC maps as the input data to drive the SWAT model, keeping other input data (e.g., climate) unchanged to isolate the LULC change impacts. The modeling results indicate that quick-response surface runoff would increase significantly (about 10.5%) due to the projected urban expansion (i.e., increase in impervious areas), and the baseflow would decrease substantially (about 7.3%) because of the reduced infiltration. Although the net effect may cause an increase in water yield, the increased variability may impede its use for public supply. Additionally, the cultivation of bioenergy crops such as switchgrass in the newly added pasture lands may further reduce the soil water content and lead to an increase in nitrogen loading (about 2.5% increase) due to intensified fertilizer application. These study results will be informative to decision makers for sustainable water resource management when facing LULC change and an increasing demand for biofuel production in this area.

Keywords: biofuel production, land cover change, hydrological process, SWAT, water quantity and quality

1. Introduction
Land use and land cover (LULC), which is explicitly linked with carbon, water, and nutrient cycles within ecosystems, have been continuously changing due to natural (climate forcing and change) and anthropogenic (land-use conversion and other management activities) processes. During the past decades, the impacts of LULC change associated with population growth and urbanization, intensified agricultural practices (e.g., improved fertilizer and pest management), the shrinking of grasslands, and deforestation/reforestation have attracted growing concerns on the sustainability of water resources and ecosystems (Jacobson 2011, Schilling et al 2008, Sohl et al 2012a). The nationwide ecological recovery
program in China called ‘conversion of cropland to forest and grassland’ also received much attention due to its potential impacts on the water budget (Qiu et al 2011). In the Great Plains of the United States, LULC change has had dramatic impacts on ecological processes involving water balance, water quality, wildlife habitats, and biodiversity (Sohl et al 2012a).

The Energy Independence and Security Act (EISA) of 2007, which aims to increase the energy efficiency and availability of renewable energy in the United States, requires fuel producers to use at least 36 billion gallons from biofuels by 2022 (US Congress 2007). Corn kernels have been used to produce ethanol for years (CWIBP 2008). But with the implementation of this act, corn stover and perennial herbaceous bioenergy crops such as switchgrass (Panicum virgatum) are being considered as advanced biofuel feedstocks especially because of the latter’s positive energy and environmental advantages (e.g., higher energy production efficiency than other crops, much lower greenhouse gas emission than row crops or prairie, higher water and nitrogen use efficiency than corn, more protection from erosion than row crops, and better biodiversity conservation) (Farrell et al 2006, Le et al 2011, Meehan et al 2010, Renewable and Applicable Energy Laboratory 2007, Robertson et al 2011, Schmer et al 2008, Wang 2001). Thus, it is expected that LULC and management practices may change (e.g., conversion from grasslands or marginal lands to bioenergy crops and increased corn stover harvest) to meet the increasing demand for biofuels production in the Midwest United States (Butterbach-Bahl and Kiese 2013, Gelfand et al 2013, Jain et al 2010, Meehan et al 2010, Solomon et al 2007, Stone et al 2010, Thomas et al 2009). In addition, the population is still growing in 12 Midwestern states, with an average annual growth rate of 3.8%, during 2000–2009 (Eathington 2010). In Iowa, the largest cities and their suburbs are growing while its rural areas are losing residents (Eathington 2010). Hence, increases in population and changes in global living standards are also expected to result in urbanization (expansion of impervious areas) and increased demand for agricultural commodities. In combination, increased demand for agricultural products for both food and fuel are expected in the Midwest United States for the next few decades.

A number of studies attempted to investigate the impacts of various LULC (including biofuel production alternatives, disturbance, and management) changes on carbon dynamics (Liu et al 2012a, 2012b, Melillo et al 2009, Zhang et al 2010, Zhao et al 2010, Zhu et al 2012), hydrological cycle (Qiu et al 2011, Schilling et al 2008), and sediment, nutrient and pesticide loadings (Demissie et al 2012, Luo and Zhang 2011, 2010, Ng et al 2010, Thomas et al 2009, Wu and Liu 2012b, Wu et al 2012b, Zhang et al 2011). However, many such studies including our previous work (Wu and Liu 2012b, Wu et al 2012b) depend on a few subjective and hypothetical scenarios such as land cover conversion from one type to another at a certain percentage or increased plant residue removal. This kind of scheme is based on the baseline land cover map only with little or no spatial information. In fact, both the amount and the location of a specific LULC conversion are important factors to the resulting environmental consequences. Therefore, a spatially explicit projection of LULC could be more valuable in predicting the potential impacts with numerical environmental models because LULC projection can take into account the suitability of lands for growing bioenergy crops with a certain spatial allocation (cellulosic-based biofuel stocks are placed in distributed pasturelands in spite of the lack of exact planting locations and acreages due to unknown factors) (see appendix A).

The objectives of this study are (1) to project the future LULC map with high resolution (250 m) for the Cedar River Basin in the Midwestern United States using the FOREcasting SCEnarios of Land-use Change (FORE-SCE) model (Sohl and Sayler 2008, Sohl et al 2007), and (2) to evaluate the potential environmental impacts on water cycles such as evapotranspiration (ET), surface runoff, baseflow, soil water storage, and total water yield and nitrate nitrogen (NO$_3$–N) loadings using the watershed model soil and water assessment tool (SWAT) (Arnold et al 1998, Neitsch et al 2005b), which was modified to facilitate the LULC change implementation (Wu and Liu 2012b).

2. Methods

Because the FORE-SCE land cover model and the SWAT hydrological/water-quality model serve as our modeling approaches, brief descriptions of the two models are given below.

2.1. The FORE-SCE model

The FORE-SCE model was developed by the US Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (Sohl and Sayler 2008, Sohl et al 2007). This model is designed to produce scenario-based LULC projections for large geographic extents with a relatively high thematic resolution. FORE-SCE uses a modular approach to account for both the ‘top-down’ and the ‘bottom-up’ drivers of LULC change. Overall, proportions of LULC change tend to be driven by large-scale driving forces such as demographic change or economic growth (top-down driving forces), while local spatial patterns of change are driven by biophysical site conditions such as soil type, climate, and topography (bottom-up driving forces) (Alcamo et al 2006). Further details about the model and scenario characteristics can be found in appendix A and previous publications (Sleeter et al 2012, Sohl and Sayler 2008, Sohl et al 2007, 2012a, 2012b).

2.2. The SWAT model

The SWAT model was developed by the US Department of Agriculture (USDA) Agricultural Research Service (Arnold et al 1998) for exploring the effects of climate and land cover changes on water, sediment, and agricultural chemical yields. This physically based, watershed scale, continuous model can simulate the hydrological cycle, cycles of plant growth, the transportation of sediment, and agricultural chemical yields on a daily time step (Arnold et al 1998). The hydrological
part of the model is based on the water balance equation in the soil profile with processes, including precipitation, surface runoff, infiltration, evapotranspiration, lateral flow, percolation, and groundwater flow (Arnold et al. 1998, Neitsch et al. 2005b). Additional details about the nutrient transport and transformation have been documented by Neitsch et al. (2005b).

The SWAT model has been widely used for a variety of watershed issues including soil erosion and sediment transport, total maximum daily loads (TMDL), climate and land cover change impacts, and best management practices (BMP) at watershed scales (Douglas-Mankin et al. 2010, Gassman et al. 2007, Jha et al. 2010, Panagopoulos et al. 2011, 2012, Richards et al. 2008, Srinivasan et al. 2010, Tuppard et al. 2010, Wu and Chen 2012, Wu et al. 2012a, Zhang et al. 2011, 2008). Therefore, we selected this well-established model with a land cover change feature (Wu and Liu 2012b) as the modeling approach for our study.

3. Case study

3.1. Study area

The Cedar River originates in Dodge County, Minnesota, and flows roughly southeast to Louisa County, Iowa, where it joins the Iowa River (figure 1). The Cedar River is 483 km long, and the major streamflow gage station (USGS gage No. 05465000) near Conesville has a drainage area of 20 168 km², accounting for 62% of the entire Iowa River Basin. This basin is primarily dominated by agricultural activities, where 77% of the whole basin is identified as cropland. The annual average precipitation in the basin is 875 mm yr⁻¹ and the annual average discharge is about 171 m³ s⁻¹ at Conesville for a 49 year period recorded from 1961 to 2009.

3.2. FORE-SCE LULC datasets

The FORE-SCE model runs began in 1992, using a modified version of the 1992 National Land Cover Database (NLCD) (Vogelmann et al. 2001) as the base thematic LULC layer. Modeling proceeded iteratively by year, with patches of ‘new’ LULC placed on the landscape until the demand for a given year was met. Processing then moved on to the next year and the process repeated until all years were simulated for a given scenario. Thus, the final results for the Cedar River Basin were annual LULC maps from 1992 to 2050 at 250 m spatial resolution, and with seven individual LULC classes including cropland, forest, range, pasture, urban, wetland, and water under the four IPCC (A1B, A2, B1, and B2) scenarios (see figure B.1 in appendix B). The A1B scenario is marked by high technological change and strong energy demands, including projected increases in the use of traditional biofuels and widespread adoption of the use of cellulosic feedstocks for biofuels. Further, the A1B scenario assumes moderate population growth, very high economic growth, and a standardization of global living standards, all factors that are likely to increase pressures on agricultural land use in the Midwestern United States. Thus, we selected A1B as a representative scenario for subsequent LULC change analysis (section 4.2) and hydrological modeling (sections 4.3 and 4.4) in our case study. In addition, the annual trend of LULC and the difference between scenarios are not highly distinct (see figure B.1), and this study focuses on LULC change impacts by the middle of the 21st century. Therefore, the derived LULC map under the A1B scenario for year 2050 was used to represent the future LULC map, and is used as the SWAT input for the future scenario. Details about modeling scenarios of SWAT are given in section 3.5.

3.3. SWAT input

The SWAT model requires inputs regarding weather, topography, soils, LULC, and land management (Arnold et al. 2000, Neitsch et al. 2005b). A Geographic Information System (GIS) interface, ArcSWAT (Winchell et al. 2009), was used to automate the development of model input parameters. In this study, the 10 m National Elevation Dataset (NED) was resampled to create 90 m resolution digital elevation model (DEM) data for delineating subbasins, resulting in the definition of 109 subbasins for the Cedar River Basin (figure 1). The 33 year weather data covering 1977 through 2009 from the National Climatic Data Center (www.ncdc.noaa.gov), tile drainage setup (Green et al. 2006), and other management operations (Arnold et al. 2000, Neitsch et al. 2005b) for agricultural lands were used and they were described in our previous studies focusing on the Iowa River Basin (Wu and Liu 2012a, 2012b, 2012c). Considering the spatial heterogeneity of soil fertility and the lack of the recommended amount of fertilizer for a specific area when cultivating switchgrass, the ‘auto-application of nitrogen fertilizer’ built-in the SWAT model was applied as was done in previous studies (Baskaran et al. 2010, Srinivasan et al.
performance, we used a group of widely acceptable criteria, baseline condition and future scenarios. To assess the model in table 1. These optimal parameters are used for both for model calibration. The derived parameters are listed for Modeling Environment (FME) (Soetaert and Petzoldt 2010), 2012a, 2012d), a comprehensive modeling framework for table 1). We then used the R-SW AT-FME (Wu and Liu are sensitive to streamflow and nitrogen simulations (see 2012c, Wu et al (e.g., soil water storage) in the model simulation. used to minimize the impacts of uncertain initial conditions (2000–2009). A 13 year (1977–1989) warm-up period was validated using data collected for the subsequent 10 years collected from the gage near Conesville (figure 1) and then record of the monthly streamflow and NO
3 load data to demonstrate that the model possesses a satisfactory range of accuracy within its domain of applicability (Rykiel 1996). Under the baseline condition (i.e., NLCD 2001), the SWAT model was calibrated using a 10 year (1990–1999) record of the monthly streamflow and NO3–N load data collected from the gage near Conesville (figure 1) and then validated using data collected for the subsequent 10 years (2000–2009). A 13 year (1977–1989) warm-up period was used to minimize the impacts of uncertain initial conditions (e.g., soil water storage) in the model simulation.

Based on previous studies (Arab et al 2008, Muleta and Nicklow 2005, Santhi et al 2001, Wu and Liu 2012c, Wu et al 2012b), we selected nine parameters that are sensitive to streamflow and nitrogen simulations (see table 1). We then used the R-SWAT-FME (Wu and Liu 2012a, 2012d), a comprehensive modeling framework for the SWAT model inversion with an R package Flexible Modeling Environment (FME) (Soetaert and Petzoldt 2010), for model calibration. The derived parameters are listed in table 1. These optimal parameters are used for both baseline condition and future scenarios. To assess the model performance, we used a group of widely acceptable criteria, including per cent error (PE) (Green and van Griensven 2008), Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970), r2 (r is correlation coefficient), and root mean square error (RMSE)—observation standard deviation ratio (RSR) (Moriasi et al 2007, Singh et al 2005). The corresponding equations of these terms can be found in appendix C.

3.5. Modeling scenarios with SWAT

To assess the potential environmental consequences of LULC change by mid-century, we used NLCD 2001 as the baseline land cover condition (scenario I in table 2) and projected LULC for 2050 with the FORE-SCE model under the IPCC A1B greenhouse gas emission as the future scenario (scenario II in table 2).

Because our study area—the Cedar River Basin—is a highly agricultural area located in the west corn belt ecoregion, corn stover can be expected to be the primary cellulosic bioenergy feedstock; we investigated its water-quality impacts in a previous study (in the Iowa River Basin covering the Cedar River Basin) (Wu and Liu 2012b). Although it is not likely to cultivate bioenergy crops (switchgrass) in large scale in this region using the current croplands, it is still possible to use potential native grasslands. Therefore, it is important to assess and quantify the water-quality impacts of such an alternative for biofuel production. With the FORE-SCE model, however, the bioenergy crops (e.g., switchgrass) are implicitly included in the pastureland due to the LULC classification of the model. The bioenergy crops are more likely cultivated on newly added pasturelands because it will not affect the demand for hay production at the current level. Thus, we proposed one more scenario: using the newly added pastureland for cultivating switchgrass (scenario III in table 2), accounting for 45% of the total pasturelands (i.e., about 3.2% of the basin area). To estimate the long-term environmental impacts at the watershed scale, all the above three scenarios listed in table 2 were simulated with SWAT in the Cedar River Basin for a 20 year (1990–2009) period. Because LULC change is the focus of the study, the climate data and other model input remained the same (i.e., using the baseline condition) among these three scenarios to isolate the LULC change impacts.

Additionally, the cultivar of switchgrass and its crop growth parameters need to be determined. From the

| Parameter | Description | Range | Calibrated value/change |
|-----------|-------------|-------|-------------------------|
| CN2       | SCS curve number for moisture condition II | −8% to +8%a | −3%b |
| ESCO      | Soil evaporation compensation factor | 0.001–1 | 0.98 |
| EPCO      | Plant uptake compensation factor | 0.001–1 | 0.97 |
| SURLAG    | Surface runoff lag coefficient | 0.5–10 | 1.0 |
| CHN2      | Manning’s n for main channel | 0.001–0.2 | 0.014 |
| CHK2      | Effective hydraulic conductivity (mm h−1) | 0–10 | 2.95 |
| RCHG_DP   | Deep aquifer percolation fraction | 0–1 | 0.01 |
| ALPHA_BF  | Baseflow alpha factor (days) | 0.001–1 | 0.079 |
| NPERCO    | Nitrogen percolation factor | 0–1 | 0.98 |

a The relative change (%) of CN2 to its default values. b CN2 decreased 3% relative to the default values based on our previous work (Wu et al 2012a).
Plant Materials Program of the USDA Natural Resources Conservation Service (NRCS), the cultivars of switchgrass such as 'Alamo', 'Kanlow', and 'Cave-In-Rock' are being utilized as biofuel crops in the Northern Great Plains and Southeastern United States (USDA-NRCS 2007b). Among these cultivars, the upland ecotype Cave-In-Rock is recommended for Iowa, Illinois, Missouri and most of the states in the Midwest (USDA-NRCS 2007a). Therefore, this cultivar was selected for use in our modeling, and its required growth parameters can be found in our previous study (Wu et al 2012b), which compiled the parameter values from a number of publications (Baskaran et al 2012b, Parrish and Fike 2005, USDA-NRCS 2010, Ng et al 2010, Neitsch et al 2005a, Parrish and Fike 2005, USDA-NRCS 2007a). Some previous studies (Baskaran et al 2010, Ng et al 2010, Wu et al 2012b, Zhang et al 2011) also demonstrated that SWAT modeling with the current available crop parameters can be acceptable to simulate the plant growth and assess the environmental impacts.

4. Results and discussion

4.1. Model examination

Time series plots (figure 2) and statistical measures (table 3) were used to evaluate the model predictions in simulating streamflow and NO$_3$–N for the 20 year (1990–2009) modeling period with the first 10 yr for calibration and the second 10 yr for validation.

Streamflow simulations. Both monthly and annual streamflow simulations matched well with those observed values, including most of the peak and low flows (figures 2(a) and (c)). The model efficiency NSE of monthly and annual streamflow simulations were 0.81 and 0.90 for calibrations, and 0.86 and 0.90 for validations (table 3). The $r^2$ ranged from 0.8 to 0.96 with the absolute value of PE being less than 10% either for calibration or validation. Based on the performance ratings of Moriasi et al (2007), the monthly streamflow simulations can be evaluated as ‘very good’ (NSE > 0.75, |PE| ≤ 10%, and RSR ≤ 0.5) for both calibration and validation periods.

Nitrogen simulations. Based on the comparisons of observed and simulated NO$_3$–N loads at the basin outlet for the 20 year study period at both monthly and annual scales (figures 2(b) and (d)), SWAT performed well in predicting NO$_3$–N loads; the exception (a clear under-estimation) was for an extremely high-water year, 1993. The model performed better in the validation period than the calibration period (table 3) because of the under-estimation in 1993. Nevertheless, NSE and $r^2$ varied from 0.60 to 0.86 during the evaluation periods, with an absolute value of PE of less than 17% either for calibration or validation. Similarly, the model performance in simulating NO$_3$–N loads can be rated as ‘satisfactory’ (NSE > 0.5, |PE| ≤ 70%, and RSR < 0.7) for both calibration and validation periods using the standard of Moriasi et al (2007).

From the above description, the model performance in streamflow and NO$_3$–N simulations are acceptable for assessing long-term environmental impacts.

4.2. LULC change projection

The LULC map for the baseline condition (i.e., NLCD 2001) and its projection for 2050 by the FORE-SCE model under the A1B greenhouse gas emission scenario are shown in figure 3. A visual comparison shows that the Cedar River Basin is a highly agricultural area and that there would be a substantial expansion of urban area by mid-century.

Based on the detailed comparison for each major land cover (figure 4), the croplands occupied 77.8% of the basin area for the baseline condition, and it remained nearly unchanged (77.9% of cropland for 2050). In contrast, the urban areas and the forest areas would increase by 68% and 48%, respectively, accounting for about 5.1% and 3.9%, respectively, of the basin area by 2050. A substantial decrease (62%) in rangelands was projected due mainly to being converted to pasturelands, with its percentage increased from 3.9% to 7.1% (a relative increase of 81%) (figure 4). Based on the NLCD land cover class definition (www.epa.gov/nrmlc/definitions.html), both rangeland (grassland) and pastureland are characterized by herbaceous vegetation, but the latter is planted or intensively managed for the production of food, feed, or fiber; or is maintained in developed settings for specific purposes. Such a significant increase, as stated in section 3.5, is mainly caused by the potential cultivation of bioenergy crops (e.g., switchgrass) to meet the demand for cellulosic biofuel feedstock, which is included in the pastureland category with the FORE-SCE model. That is why we set two potential scenarios—no bioenergy crop (scenario II) and switchgrass (scenario III)—for the newly added pastureland.

Additionally, because the percentages of water surface (0.6%) and wetland (1.8%) are quite small under the baseline condition, the projected relative changes, a 36.5% increase for water surface and a 23.7% decrease for wetland (see figure 4), may have little effect on the hydrological cycle within the

### Table 2. Modeling scenarios with the SWAT model.

| Scenario | Description | Bioenergy crop | Climate$^a$ |
|----------|-------------|----------------|------------|
| I        | Baseline scenario: NLCD 2001 as the land cover input | No$^b$ | Historical climate data (1990–2009) |
| II       | Future scenario: projected land cover for 2050 (A1B) | No$^b$ | Switchgrass$^c$ |
| III      | Future scenario: projected land cover for 2050 (A1B) | | |

$^a$ Weather data (and other model input) remain the same for the three scenarios.

$^b$ No dedicated energy crop is cultivated.

$^c$ Dedicated energy crop (switchgrass) is cultivated on the newly added pasturelands.
basin. However, the substantial expansion of urban areas, pasture areas, and forest areas and the shrinking of the range areas may exert significant impacts on water quantity and quality due to the corresponding land management activities in this basin. The following sections (sections 4.3 and 4.4) give the potential environmental impacts predicted by the SWAT model.

4.3. LULC change impacts on the water cycle

Based on the long-term averaged monthly hydrological variables including ET, water yield, surface runoff, baseflow, and soil water for scenario I (baseline) and scenario II (2050) (figures 5(a)–(e)), we can derive the annual average amounts of these variables and their relative changes (figure 6). Overall, ET decreased due to the LULC change, and the monthly relative changes varied from −1.9% in March to 0.66% in August (figure 5(a)), with an annual average of −0.8% (figure 6). This percentage appears to be slight, but the absolute annual reduction of 4 mm may not be negligible. The decrease in ET can be attributed to the declined soil water content, whose monthly relative decrease ranged from 1.2% to 2.5% (figure 5(e)), and the annual average amount

Figure 2. Monthly ((a) and (b)) and annual ((c) and (d)) time series comparison of simulated versus observed streamflow at the gage (near Conesville) during the 10 year (1990–1999) calibration and 10 year (2000–2009) validation periods.
declined by 2% (figure 6). This prediction (ET decreases due to the declined soil water content) can be explained by the substantial urban expansion, which means the increase in impervious areas and produces the increase of surface runoff and the decrease of infiltration (Neitsch et al. 2005b). The monthly quick-response surface runoff may increase significantly from 2.9% to 14.9% (figure 5(c)), with an annual averaged increase of 10.5% (figure 6). However, the reduced infiltration would not only cause lower soil water availability but also trigger the declined seepage from the bottom of the soil profile to the shallow aquifer, which is why the monthly baseflow decreased from 5.7 to 10.5% (figure 6). Both surface runoff and baseflow are the major pathways contributing to the water yield. The positive effect on surface runoff overwhelmed the negative effect on baseflow, resulting in an increase of 1.8% in the annual average water yield (figure 6), with the monthly relative changes varying from -0.2% to 3.4% (figure 5(b)).

As we stated previously, there is no bioenergy crop cultivation in scenario II. In contrast, if switchgrass is proposed to be cultivated on the newly added pastureland (scenario III in table 2), how will the above hydrological components respond? The switchgrass cultivation may further reduce soil water and baseflow due to its larger biomass production and higher water consumption, and the annual average amounts would decrease by 2.3% for soil water and 10.1% for baseflow compared to the baseline condition (scenario I) (figure 6). The increase in surface runoff under scenario III was attenuated because switchgrass is a perennial plant that is resistant to overland flow generation. As a result, both reductions in surface runoff and baseflow led to a smaller increase in water yield than scenario II.

4.4. LULC change impacts on water quality

Surface-water quality is also sensitive to LULC changes, especially due to the intensive nitrogen fertilizer application for boosting crop production. The multi-year averaged monthly NO$_3$–N load for the baseline condition (scenario I) and projection scenario (scenario II) (figure 5(f)) illustrates an increase in NO$_3$–N load in each calendar month, ranging
from 0.7% to 2.8%. Based on the annual average NO$_3$–N load for the baseline condition (scenario I), we can derive the relative changes for projection scenarios (scenarios II and III) (figure 6). The NO$_3$–N load would increase from 32.5 kg ha$^{-1}$ for scenario I to 32.9 kg ha$^{-1}$ for scenario II (no bioenergy crop cultivation), a slight relative increase of 1%. However, if the newly added pastureland is used to cultivate switchgrass, the NO$_3$–N load can reach 33.3 kg ha$^{-1}$, which is a relative increase of 2.5%. This percentage does not seem high, but it should be given our attention when considering that switchgrass is cultivated on 3.2% of the basin area (i.e., the newly added pastureland). To meet the increased biofuel production target in the next decades, this quantification of nitrogen load can be helpful for watershed managers to estimate potential impacts when developing bioenergy in this basin.

4.5. Implications

This study demonstrates that the projected land cover change of the Cedar River Basin is substantial, characterized by

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**Figure 4.** Areas of major land covers for 2001 and 2050 and their relative changes. NLCD 2001 and FORE-SCE projected land cover map for 2050 under the A1B greenhouse gas emission scenario were used to represent the land covers for 2001 and 2050, respectively.

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**Figure 5.** Multi-year averaged monthly ET (a), water yield (b), surface runoff (c), baseflow (d), soil water (e), and NO$_3$–N (f) for 2001 (scenario I in table 2) and 2050 (scenario II in table 2) at the basin scale and their relative changes.

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**Figure 6.** Annual average ET, water yield, surface runoff, baseflow, soil water, and NO$_3$–N for the baseline condition (scenario I) and their relative changes for two projection scenarios: no bioenergy crop (scenario II in table 2) and switchgrass (scenario III in table 2) cultivation on the newly added pastureland. Relative change refers to change relative to the baseline conditions (scenario I in table 2). Circles are used to show the absolute values for the baseline condition, and bars represent relative changes of scenarios II and III against scenario I. The units on the primary vertical axis are mm for the first five variables and kg ha$^{-1}$ for the last one (NO$_3$–N).
a substantial increase (68%) of the urban areas due to population growth and economic development by mid-century. The notable predicted impacts of land cover change on water cycle is the increase of quick-response surface runoff (10.5%) and reduction of infiltration accompanied with decreased soil water content (−2%) and baseflow (−7.3%). In contrast to the baseline period, apparently, there would be a much higher temporal variability with more water in the wet season and less in the dry season. Therefore, this may intensify the risks of flooding in the wet season and drought (water shortage in both stream channel and soil profile) in the dry season. Furthermore, climate change-induced increase in rainfall intensity (torrential and brief precipitation) may pose increased threats of flooding and drought (Zhou et al. 2011). Hence, it is important to quantify the impacts of both land cover and climate changes on water cycle in this area. This topic is, in particular, a subject of further studies.

Our study also indicates that the projected LULC change may exacerbate the water quality: 1% increases in NO3−N load without bioenergy crop cultivation (scenario II) and 2.5% increase with cultivating bioenergy crops on the newly added pasturelands (scenario III). This finding indicates that even growing bioenergy crops on lands, which are currently rangelands and accounting for only 3.2% of the basin, can lead to a higher nitrogen flux to local waterways due to fertilization and may ultimately deteriorate the hypoxic conditions in the Gulf of Mexico. It is clear that the energy and water interdependence (i.e., a drive and drink issue) can play a key role in planning and development of bioenergy in the Midwest of the United States (Dominguez-Faus et al. 2009). Therefore, evaluating the potential water-quality impacts of bioenergy crop cultivation in small- or large scale is a critical step because it can be valuable and informative for decision makers to seek a robust and environmentally sustainable biofuel program.

5. Conclusions

In this study, we analyzed the potential LULC changes by mid-century using two sets of LULC maps for the Cedar River Basin in the Midwestern United States: NLCD 2001 for the baseline condition and projected LULC for 2050 by the FORE-SCE model under the A1B greenhouse gas emission scenario. Our results suggest substantial expansions of urban area (68%) and pastureland (including the land for bioenergy crops) (81%), a decrease in rangeland (−62%), and a slight increase in the agricultural land by 2050. Then, these LULC changes were modeled to generate the long-term environmental impacts on the water cycle in this basin by substantially enhancing surface runoff (10.5%) due to the increase in impervious areas and reducing the baseflow (−7.3%) due to the declined infiltration. The net effect on the total amount of water yield seems positive, but the increased variability may reduce water availability for public use. Furthermore, flooding and drought may be exacerbated simultaneously under the projected LULC in this region regardless of the climate. Additionally, the cultivation of bioenergy crops such as switchgrass may further reduce the water yield because of its higher water consumption for higher biomass production and may degrade the water quality because of fertilization. Overall, the quantification of these environmental consequences could be useful for decision makers to take precautions and seek sustainability of water resources in this region.

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Appendix A. Other details of the FORE-SCE model

The FORE-SCE model uses a scenario-based ‘demand’ component to develop future proportions of LULC change at aggregated regional scales, based on top-down driving forces. A ‘spatial allocation’ component uses input from ‘demand’ to produce spatially explicit LULC maps annually, with spatial patterns driven up by bottom-up driving forces. The demand component simply provides proportions of LULC at the aggregate, regional level for each modeled year. Scenarios based on the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions scenarios (SRES) including A1B, A2, B1, and B2 (Nakicenovic et al 2000, Strengers et al 2004, Van Vuuren and O’Neill 2006) were the basis of constructing LULC demand for this work. Scenarios were constructed using a combination of an existing, integrated modeling framework, regional land-use histories for the United States, and an expert-driven scenario construction workshop. The integrated modeling framework—Integrated Model to Assess the Global Environment (IMAGE) version 2.2 (IMAGE Team 2001, Strengers et al 2004)—models both biophysical and socioeconomic drivers of land-use change, and was used to provide basic proportions of land use for the conterminous United States for future scenarios. The Agricultural Economy Model within IMAGE 2.2 provided ‘demand’ for agricultural land use in this area, including explicit modeling of demand for both ‘traditional’ and ‘non-traditional’ (i.e., cellulosic-based) biofuel production. IMAGE model results and land-use histories from the USGS Land Cover Trends project (Loveland et al 2002) were used in a workshop setting to disaggregate United States estimates of land-use demand to a regional level (Sleeter et al 2012). Qualitative storylines, and quantitative future proportions of LULC change were constructed for each of 84 USEPA Level III ecoregions in the
United States (Omernik 1987, USEPA 1999). The quantitative proportions of future LULC change were produced at 5 yr increments for each of the four SRES storylines, through 2050, for each level III ecoregion in the United States, information that fed into the spatial allocation component of the FORE-SCE model. A more comprehensive discussion of the scenario construction process and scenario downscaling results for this work can be found in Sleeter et al (2012).

The spatial allocation component of the FORE-SCE model ingests ‘demand’ from the scenarios and uses a patch-based modeling approach to produce spatially explicit maps, placing individual patches on the landscape until ‘demand’ for a scenario is met for a given year. Patch characteristics are determined from regional, historical LULC patterns as mapped by the USGS LULC Trends project (Loveland et al 2002). An approximation of historical patch characteristics for each modeled LULC class ensures the generation of realistic landscape patterns for a given region. The placement of patches is dictated by suitability surfaces produced by statistically examining relationships between existing LULC type and spatially explicit ancillary data, using logistic regression. Suitability surfaces are constructed individually for each modeled LULC class and for each USEPA Level III ecoregion. A ‘dispersion’ variable is used to control how dispersed or clumped new patches of an individual LULC class are by defining the range of suitability values on which a new LULC patch may be placed. For example, for a LULC class such as ‘developed’, where new patches of urban development are likely to occur in close proximity to each other and to existing urban land, the dispersion variable was set to only allow the placement of new urban patches in areas with suitability values at the far upper end of the suitability histogram. A Protected Area Database (PAD-US Partnership 2009) was used to control LULC change within protected areas, with protection status dependent upon LULC being mapped. Protection status rules were also dependent upon scenario, with the economically oriented ‘A’ scenarios having fewer restrictions on LULC change in protected areas than the environmentally oriented ‘B’ scenarios. More details of the spatial modeling component of the FORE-SCE model that was used for this work can also be found in previous studies (Sohl et al 2012a, 2012b).

Appendix B. Projected land cover trend

Based on the FORE-SCE land cover model projections, the annual proportions of land cover classes during 2001–2050

Figure B.1. Annual time series of land cover class proportions in the Cedar River Basin from 2001 to 2050 under the four scenarios (A1B, A2, B1, and B2).
under the four IPCC scenarios (A1B, A2, B1, and B2) was presented below.

Appendix C. Criteria to assess model performance

In order to assess model performance compared to observations, the following popular criteria were used in this study.

(I) The per cent error (PE) (Green and van Griensven 2008) measures the average difference between measurements and model simulations. The optimal value of PE is 0.0, with low-magnitude values indicating accurate model simulation, while positive or negative values indicate over-prediction or under-prediction bias, respectively,

\[
PE = \frac{\bar{Y}_{\text{sim}} - \bar{Y}_{\text{obs}}}{\bar{Y}_{\text{obs}}} \times 100\%.
\]

(II) The Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970) measures the goodness of fit and approaches unity if the simulation is satisfactorily representing the observation. The NSE describes the explained variance for the observed values over time that is accounted for by the model (Green and van Griensven 2008). If the efficiency becomes negative, model predictions are worse than a prediction performed using the average of all observations.

\[
\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (Y_{i,\text{sim}} - \bar{Y}_{\text{sim}})^2}{\sum_{i=1}^{n} (Y_{i,\text{obs}} - \bar{Y}_{\text{obs}})^2}.
\]

(III) The \( r^2 \) (\( r \) is correlation coefficient) evaluates how accurately the model tracks the variation of the observed values. It can reveal the strength and direction of a linear relationship between the simulation and observation. The difference between the NSE and the \( r^2 \) is that the NSE can interpret model performance in replicating individually observed values, while the \( r^2 \) does not track the variation of the observed values (Green and van Griensven 2008).

\[
r^2 = \frac{\sum_{i=1}^{n} (Y_{i,\text{obs}} - \bar{Y}_{\text{obs}})(Y_{i,\text{sim}} - \bar{Y}_{\text{sim}})^2}{\sum_{i=1}^{n} (Y_{i,\text{obs}} - \bar{Y}_{\text{obs}})^2 \sum_{i=1}^{n} (Y_{i,\text{sim}} - \bar{Y}_{\text{sim}})^2}.
\]

where \( n \) is the number of observation/simulation data points for comparison, \( Y_{i,\text{obs}} \) and \( Y_{i,\text{sim}} \) are observed and simulated data, respectively, on each time step \( i \) (e.g., day or month), and \( \bar{Y}_{\text{obs}} \) and \( \bar{Y}_{\text{sim}} \) are mean values for observation and simulation, respectively, during the examination period.

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