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Predicting plausible impacts of sets of climate and land use change scenarios on water resources

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A B S T R A C T

Our world is changing at an unprecedented rate in terms of climate and land use, but these changes can affect our water resources. Hence, we need a methodology that can predict both their individual and agglomerative ramifications. Using the Little Miami River (LMR) watershed as a case study, this paper describes a spatial analytical approach integrating mathematical modeling and geographical information sciences to quantitatively examine the relative importance of the separate and combined hydrologic and water quality impacts of climate and land use changes.

The Hydrologic Simulation Program – Fortran (HSPF) model was chosen in this study to simulate stream flow and nutrient transport process. Five hypothetical climate change scenarios were used to cover the possible ranges of variability in the year 2050. An enhanced population-coupled Markov-Cellular Automata (CA-Markov) land use model was developed to predict the 2050 land use pattern. When these scenarios were incorporated into the HSPF model, the future conditions in the LMR basin were postulated. The findings demonstrated that: 1) the LMR watershed would experience an increase in flow and nutrients under the 2050 land use projection, 2) stream flow and water quality impacts would be amplified when both climate and land use changes were simultaneously considered, 3) land use change (and in the case of the LMR watershed, urbanization) could help to alleviate water shortage during the dry years, 4) total phosphorus and nitrogen would increase under all future climate and land use scenarios; the highest increase was found under the combined wettest and future land use scenarios, and 5) the described approach is effective in simulating the hydrologic and water quality effects of climate and land use changes in a basin scale. These results are relevant to planners; they can be useful in formulating realistic watershed management policies and mitigation measures.

Introduction

Within the scientific community, it is generally agreed that our climate is changing, and it will bring significant hydrologic consequences. The Fourth Assessment of the Intergovernmental Panel on Climate Change (IPCC, 2008) reports that with the increasing concentration of greenhouse gases in the atmosphere, there will be a global average temperature increase of 2.3–6.2 °C in this century. In Ohio, the first signs of global warming are appearing. The average temperature between 2000 and 2007 in Cleveland was 0.45 °C above the 30-year average prior to this period, and Cincinnati had experienced 25 days each year with a temperature of at least 32.2 °C, which was six days more than the historical average before 2000. Moreover, since 1900, there has been an increasing trend of precipitation by 10% in northern Ohio, but a decreasing trend by 10% in the south (NCSL & CIER, 2008). The rising temperature and shifting precipitation patterns would have profound hydrologic effects in the Midwest.

In addition to climate, population and land use are also changing. Despite Ohio is not one of the fastest growth areas, it is the seventh most populous state in the nation (Ohio Department of Development, 2010). Moreover, substantial changes in population and land use have occurred in recent decades, especially in the Little Miami River (LMR) watershed in southwestern Ohio. Land use change, such as urbanization, when amalgamated with climate change, would undoubtedly affect both the quantity and quality of water resources. To maintain and sustain our water resources, appropriate watershed management policies and adaptation measures to future changes are necessary (Pielke, Prins, Rayner & Sarewitz, 2007; Yang, 2010). One of the objectives of this research is therefore to ascertain quantitatively the hydrologic and water quality impacts of climate and land use changes.

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Although studies of the combined hydrologic and water quality effects of climate, land use, and population changes are desirable, most published investigations consider only one type of change (climate or land use change) or one type of impact (flow or water quality); while some examine the combined impacts, they only use one or two scenarios. Few studies have investigated both changes and impacts under various scenarios at a basin scale.

In the studies of climate change, most researchers employ the general circulation models (GCMs) or regional climate models (RCMs) to predict the future temperature and precipitation conditions for a study area. By applying a water balance model and/or a water quality model, the projected climatic regimes are used to calculate runoff and simulate pollutant behavior. For example, Gleick (1987) developed a monthly water balance model to examine runoff and soil moisture changes under different climate change scenarios in the Sacramento River Basin. Mimikou, Kouvopolos, Cavadalis, and Vayianos (1991) examined the regional effects of annual temperature increase on the spatial and temporal redistribution of water resources. Guo, Wang, Xiong, Ying, and Li (2002) used a macro-scale and semi-distributed monthly water balance model to predict the impacts of climate change on the magnitude and timing of runoff and assess the vulnerability of the water resource in north China. Most of these studies evaluate only the annual or seasonal stream flow, or the surface or ground water quality.

In land use studies, it is recognized that changes in land use will affect the rates of infiltration, evapotranspiration, and groundwater recharge, as well as the water quality in receiving water bodies, and climate change can further amplify the hydrologic effects. Nonetheless, the current land use modeling applications are often conducted with the assumption that the local climate would remain constant for the simulation period. For example, Jones (1997) used an export coefficient model to simulate the impacts of agricultural land change and catchment management strategies on nitrogen and phosphorus loadings. Zandbergen (1998) developed a conceptual model to demonstrate that the hydrologic impacts of urbanization can be mitigated by changing the amount of impervious areas and the riparian habitats. Bronstert, Niehoff, and Bürger (2002) used WaSiM-ETH model to assess the effects of urbanization and agricultural management on storm runoff.

In the face of impending climate and land use changes, there is a need for new integrative approaches that model not only the separate but also the combined impacts of these changes as they act in tandem with each other. Hence, the second objective of this research was to derive an approach that could be used to examine the hydrologic and water quality effects of population-driven land use change in concert with climate change, highlight the extent to which the combination of climate and land use changes could amplify or ameliorate the hydrologic and water quality effects at a watershed scale, and predict the plausible combined consequences of climate, population, and land use changes under sets of scenarios.

Material and methods

Study area

The LMR watershed

The LMR watershed was selected as a case study in this research (Fig. 1). Originating at the southeast of Springfield in southwestern Ohio, the LMR, a major tributary of the Ohio River, flows 169.78 km from Clark County through several steep-sloped forested gorges to join the Ohio River at the confluence in Hamilton County, near the eastern side of Cincinnati. Draining an area of 5840 sq km, the watershed encompasses Clark, Greene, Warren, Clermont, and Hamilton Counties, and portions of Montgomery, Clinton, Brown, Highland, and Madison Counties.

Lying within the Till Plains section of the Central Lowlands Physiographic Province, the underlying geology of the basin consists of interbedded calcareous shale, limestone, and dolomite from the Upper Ordovician or Silurian (Ohio DNR, 1964). Outwash deposits composed of sand and gravel are usually found at the bedrock valleys and terraces. Due to their high permeability, these glacial materials exert considerable impacts on surface water by absorbing large quantities of rainfall and releasing it throughout the year during the low-flow seasons. Further south where the till cover with impervious shale gradually replaces the glacial drift, the dry-weather flow decreases, and the stream flow is often augmented by wastewater discharges (Schneider, 1957).

The topography of the watershed is influenced by the last three glaciations and the subsequent erosion by rivers. Most of the area is flat to gently rolling with steep-walled river valleys. In many places, outcropping and shale are exposed. The regional topographic gradient is from north to south. The soils in the region belong to the Genesee–Williamsburg Association. Formed from silts, alluvial, and residual materials from the glacial deposits, the soils are deep and highly productive, but susceptible to erosion (Lerch, Hale, & Milliron, 1975). The northern portion of the watershed is characterized by gently sloping land, low gradient streams, and areas of fertile soil. In the southernmost areas, the terrain is more dissected and hilly with a higher stream density and more drainage problems (Debrewer et al., 2000). Soils on the southeast older till plain are less extensively cultivated than the younger till-derived soils in the northwest.

The LMR watershed has a cool temperate climate; summers are warm and humid with a high temperature of 30 °C and a low temperature of 15 °C, while winters are moderately cold with a few annual winter frosts and snowfall. Winter highs are around 0 °C and lows about −10 °C. Average annual air temperature ranges from 10 °C in the north to 13 °C in the south. The average annual precipitation for the area ranges from 90 to 110 cm; about one-third of the precipitation becomes surface runoff. Average snowfall in the watershed is 50–76 cm per year (Debrewer et al., 2000).

Rationale for choosing the LMR watershed as the study area

The LMR watershed was selected to investigate the plausible hydrologic and water quality impacts of climate and land use changes because this predominately agricultural watershed has been undergoing a rapid urbanization process, and its water resources are deteriorating. The LMR was once a pristine river system with minimal anthropogenic impacts. Containing some of the most scenic and diverse riverine habitats in the Ohio River Valley, it is home to more than 340 species of wildflowers, 250 bird species, and over dozens of fish species, some of which are rare, threatened, or endangered (USDA, 1999). Because of its high water quality, diversified aquatic communities of flora and fauna, panoramic setting, and historic sites found along its banks, the Ohio Department of Natural Resources (Ohio DNR) designated the LMR a state scenic river in 1969 and a national scenic river in 1973. It is the first state and national scenic river in Ohio. In addition, the Ohio Environmental Protection Agency (Ohio EPA) listed the river as an Exceptional Warm Water Habitat Stream. It was also designated for Primary Contact Recreation (East Fork LMR Collaborative, 2007).

Historically, most of the land area in the LMR watershed was used for agricultural activities. But in recent decades, the population in the watershed has grown substantially, and the watershed has undergone a rapid urbanization process. As calculated from the land use maps, from 1980 to 2001, the agricultural land use has experienced a drastic decrease of 24.08%, whereas urban land has increased by 6.78% (see Table 1). In the same period,

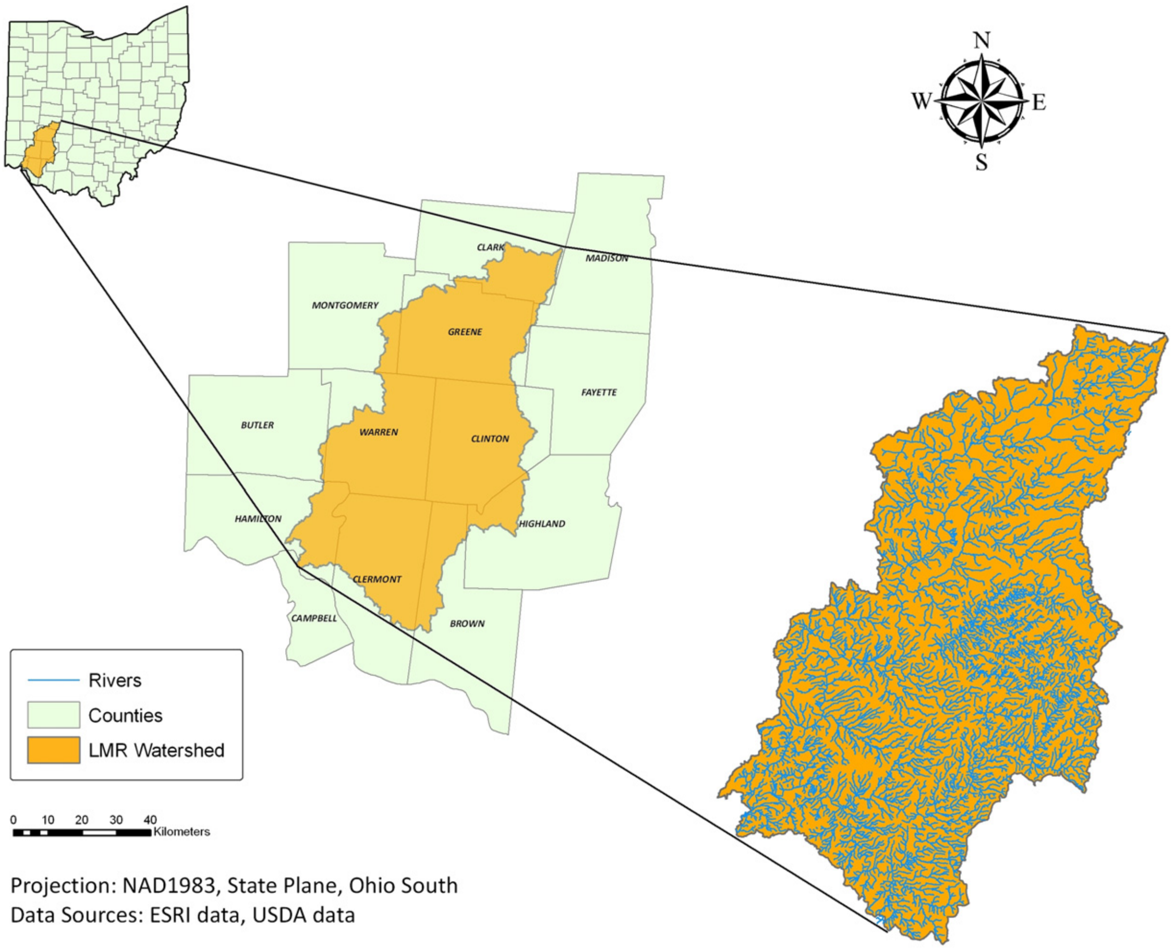

Fig. 1. The Little Miami River watershed study area.

population from the ten counties in the basin has grown from 2,371,943 in 1980 to 2,530,076 in 2000, an increase of 6.67% (US Census Bureau, 2010).

With these recent developments, the water quality in LMR is declining. The northern half of the LMR watershed, still primarily agricultural, is impacted by non-point source pollution. In the south, where there is extensive urbanization and suburban sprawl, the surface runoff is enriched with sediment discharge, rubber fragments, motor oils, nutrients, heavy metals, hydrocarbons, chlorides, conservative solutes, and bacteria. Since the early 1990s, there have been indications that the LMR ecological system is under stress. For instance, the Ohio EPA (2000) has discovered high levels of fish anomalies, as well as widespread presence of *Escherichia coli* and *Fecal coliform* bacteria and pollution-tolerant fish species. Janosy (2003) reported abnormally high levels of arsenic, cadmium, copper, mercury, selenium, and zinc in fish collected from the river. Atrazine, metolacholor, semivolatile organic compounds, and excessive amounts of nitrates were found in many locations of the LMR; some with concentrations at or above drinking-water standards or guidelines for protecting aquatic life (USGS, 2004). As the population increases and urbanization continues, there will be an increase in water demand as well as wastewater discharge and combined sewer overflows, which may further aggravate the conditions in the LMR, reducing water availability and degrading water quality (Ohio EPA, 1996). The likelihood of climate change poses an additional threat to the LMR watershed. In order to conserve the area and to protect our limited and valuable water resources, it is crucial to be able to predict the hydrologic and water quality ramifications of future climate and land use changes so that effective water management actions can be implemented. The LMR watershed therefore is a good study area for this research.

Table 1
Land use categories in the LMR watershed in 1980, 1992, 2001 and 2050 by percentages.

Land use types	1980	1992	2001	Projected 2050
Water	0.68%	0.94%	0.97%	1.55%
Urban	11.01%	17.72%	17.79%	39.22%
Forest	7.60%	20.03%	23.65%	31.28%
Agriculture	80.26%	70.93%	56.18%	26.46%
Others	0.45%	0.38%	1.41%	1.49%

Development of a hydrologic and water quality model

Selection of a hydrologic and water quality model

The Hydrologic Simulation Program – Fortran (HSPF) model (Bicknell, Imhoff, Kittle, Jobes, & Donigian, 2000) was selected in this study to simulate the water quantity and quality. It is a robust, reliable, and comprehensive model commonly applied to flood forecasting, water quality modeling, as well as assessment of best management practices and sensitivity of stream flow to climate change (Bicknell, Donigian, Jobes, & Chinnaswamy, 1996; Chun et al., 2001; Cryer, Fouch, Peacock, & Havens, 2001; Donigian & Huber, 1991; Donigian & Crawford, 1976; Ng & Marsalek, 1992; Tsihrintzis, Fuentes, & Gadipudi, 1997).

As a lumped conceptual model, HSPF uses defined meteorological and watershed conditions to simulate stream flow components and model water quality (Bicknell et al., 2000). There are three basic modules in HSPF: PERLND is the module for pervious lands, IMPLND simulates the hydrodynamics on impervious land segments, and RCHRES is the module for free-flow reaches in streams or lakes, each of which has different water balance equations for the calculation of flow and water quality.

The hydrologic model for the LMR watershed

In order to construct a hydrologic model for the LMR watershed, a base model for the early 1980's conditions was first compiled by delineating the LMR watershed using the hydrologic unit code (HUC) from the U.S. Geological Survey (USGS), stream characteristics and Reach File coverages (RF3) from the U.S. Environmental Protection Agency (USEPA), and digital elevation models at 30 × 30 m resolution (DEMs) from the USGS. Then the daily meteorological data from Jan 1, 1980 to Dec 31, 1984 from the National Climatic Data Center (NCDC) for the climatic station at Dayton Airport, Ohio, the digitized soil layer from the national State Soil Geographic database (STATSGO) collected by the U.S. Department of Agriculture (USDA), and the 1980 land use/land cover layer (LULC) from the USGS Geographic Information Retrieval and Analysis System (GIRAS), as well as the default parameters provided by HSPF were used to run the hydrologic model. The model was calibrated by comparing the simulated flow results with the observed daily discharge records from the USGS gauging station near Milford (gauging number: 03245500) and iteratively adjusting the values of the model parameters to match the local conditions of the river basin by trial-and-error until the error rate, which was calculated as [(simulated value − observed value)/observed value], between simulated and observed stream flow was acceptable. After numerous trials with adjustments of the lower zone nominal soil moisture storage value (LZSN), the index to mean soil infiltration rate (INFILT), the fraction of groundwater inflow entering deep groundwater (DEEPFR), the interflow parameter (INTFW), and the interflow recession parameter (IRC), the error rate was approximately 11.74% (Table 2). According to Bicknell et al. (2000), an error rate below 10% in flow simulation is considered as very good, and a range from 10 to 15% is regarded acceptable (Table 3). The calibration results also showed that the correlation coefficient between simulated and observed flows was 0.88 and the Nash-Sutcliffe model efficiency coefficient, *E* (Nash & Sutcliffe, 1970), a statistic used to indicate how consistently observed values agree with predicted values, was 0.69 (Table 2).

After calibration, the HSPF model was validated to ensure that the model could fairly accurately simulate the real world conditions even under different land use and climate regimes. In the validation, the 1992 land use, 1985–1989 weather data, and the parameter values used in the calibration were utilized. The validation results showed a smaller difference (3.84%) between simulated and observed values. The correlation coefficient between simulated and observed flows was 0.91, and the *E* statistic was 0.72 (Table 2). Since both the calibration and validation results were within acceptable limits, it seemed that the developed hydrologic model was sufficient for flow simulation in the LMR watershed.

Table 3
Calibration/validation targets for HSPF.

	Very good	Good	Fair
Hydrology/Flow	<10[a]	10–15	15–25
Sediment	<20	20–30	30–45
Nutrients	<15	8–12	13–18

[a] The figure shown is the % difference between simulated and observed values according to Bicknell et al. (2000).

The water quality model for the LMR watershed

In this study, nitrates and nitrites as total nitrogen (N) and total phosphorus (TP) were used for water quality simulation because these pollutants are commonly found in the LMR watershed and are considered important water quality indicators. Point source TP and N data from municipal and industrial wastewater treatment plants that discharged to the channel reaches were retrieved from the Permit Compliance System (PCS) from the USEPA and Ohio EPA and added to the model.

As in the development of the hydrologic model, the water quality data from the USEPA's STORET archive from 1980 to 1984 were used in model calibration, and those from 1985 to 1989 were used in model validation. Several parameters, including the storage of phosphorus on the pervious land segment (SQO), the rates of accumulation for phosphorus (ACQOP), and the maximum storage of phosphorus (SQOLIM), were adjusted. The final simulated mean daily TP concentration was 0.402 mg/L. The *E* statistics for the calibration period was 0.42 and that for the validation period was 0.39. Although the *E* values were lower than desired, the correlation coefficient between the simulated and observed TP was 0.83 for the calibration period and 0.80 for the validation (Table 4), indicating that the model could capture most of the variations in TP.

For the N modeling, the correlation coefficients between simulated and observed mean daily concentration were 0.87 for the calibration period and 0.83 for the validation period. The *E* index was 0.54 and 0.46 for the calibration and validation periods, respectively (Table 5). These results were in line with an earlier study (Liu & Tong, 2011), suggesting that the water quality model was acceptable.

Generation of the future climate change scenarios

Despite the continual development in GCMs and RCMs, uncertainty exists on the magnitude of the changes in temperature and precipitation (Wilby et al., 2006). Furthermore, these global and regional models are less reliable in simulating detailed spatial and temporal features (Mailhot, Duchesne, Caya, & Talbot, 2007). Given the difficulties in deducing local climate patterns from regional trends, some scientists, such as Hotchkiss, Jorgensen, Stone, and Fontaine (2000), Stonefelt, Fontaine, and Hotchkiss (2000), Dagnachew, Vallet-Coulomb, and Gasse (2003), Zhu, Jenkins, and Lund (2005), Thomson, Brown, Rosenberg, Srinivasan, and

Table 2
Calibration and validation results for the hydrologic model.

	Mean observed daily flow (m^3/s)	Mean simulated daily flow (m^3/s)	% Error between simulated and observed flow values[a]	Average daily correlation coefficient	Nash-Sutcliffe efficiency coefficient
Calibration Period 1980–1984	37.81	33.37	−11.74%	0.88	0.69
Validation Period 1985–1989	32.51	31.26	−3.84%	0.91	0.72

[a] % error = [(simulated - observed)/observed] × 100.
Source: Bicknell et al. (2000).

Table 4
Calibration and validation results for the mean daily TP concentrations in mg/L.

	Calibration		Validation	
	Observed data	Simulated values	Observed data	Simulated values
	1980–1984	1980–1984	1985–1989	1985–1989
Apr	0.263	0.372		
May	0.392	0.348	0.484	0.449
Jun	0.404	0.383	0.510	0.489
Jul	0.512	0.488	1.845	0.942
Aug	0.442	0.452	1.082	0.916
Sep	0.508	0.529	0.715	0.721
Oct	0.333	0.303	0.838	0.801
Nov	0.370	0.351		
Mean	0.402	0.403	0.912	0.719
Correlation coefficients	0.83		0.80	
Nash-Sutcliffe efficiency coefficient	0.42		0.39	

Izaurralde (2005), and Muzik (2002), preferred to use a range of hypothetical climate scenarios from the estimates of one or more GCMs to simulate the watershed hydrologic responses. Since these hypothetical scenarios cover a wide range of climatic regimes, this approach is simpler and can save considerable time and effort.

Our purpose in this study was not to produce future climate change predictions but to determine the plausible hydrologic impacts from a range of possible future climate change conditions; for this reason, we adopted the latter approach to generate the climate change scenarios. Based on the information provided by Karl, Knight, Easterling, and Quayle (1996) and USEPA (1998), four climate scenarios (W2, W4, D2, and D4) delineating the possible ranges in temperature (+2 and +4 °C) and precipitation (+20% and −20%) in Ohio by the horizon year 2050 were generated (Table 6). These scenarios, together with the base case scenario (BASE CASE) where the climate regime was remained at the 1980–1989 level, were used at a later stage to model the impacts of different climatic conditions on water resources.

Generation of the future land use change scenario

A common approach to derive future land use scenarios is to adopt a land use model to simulate future land use conditions. This method enables one to predict the future conditions under certain known assumptions. In this study, an enhanced land use model coupling the Markov Cellular Automata (CA-Markov) model from IDRISI (2008) with a population variable was developed to generate a 2050 land use scenario. IDRISI is a geographic information system (GIS) and image processing software designed for spatial modeling, decision support application, risk analysis, and spatial statistics computation. Through the Markov chain and/or the cellular automata (CA) modules, IDRISI is capable to simulate future land use conditions.

Table 5
Calibration and validation results for the mean daily N concentrations in mg/L.

	Calibration		Validation	
	Observed data	Simulated values	Observed data	Simulated values
	1980–1984	1980–1984	1985–1989	1985–1989
Apr	2.70	2.42		
May	2.32	2.92	1.88	2.06
Jun	3.71	3.04	2.97	2.37
Jul	3.01	3.15	2.51	2.11
Aug	1.30	1.71	1.66	1.89
Sep	1.95	1.76	2.39	2.2
Oct	1.37	1.77	2.39	2.38
Nov	1.83	2.02		
Mean	2.28	2.35	2.30	2.18
Correlation coefficients	0.87		0.83	
Nash-Sutcliffe efficiency coefficient	0.54		0.46	

Table 6
Hypothetical future climate scenarios.

Climate scenario	Changes in temperature/precipitation
Base case (BASE CASE)	No change in temperature and precipitation
Wettest (W2)	+2 °C, +20% precipitation
Wet (W4)	+4 °C, +20% precipitation
Dry (D2)	+2 °C, −20% precipitation
DRIEST (D4)	+4 °C, −20% precipitation

Markov chain is a stochastic method for generating a series of random values. Their probabilities at a certain time interval depend on the previous values. In land use prediction, Markov analysis uses the historical pattern of land use changes to calculate transition matrices and determine the future land use pattern. Its major drawback is that it does not consider any geographical relationships. But the use of CA in Markov can add the spatial dimension to the model, thereby capturing the temporal-spatial dynamics (Tobler, 1970). In CA, the state of each cell at time t+1 is determined by its neighboring cells at time t according to the pre-defined transition rules (White & Engelen, 1993). By using the Multi-Criteria Evaluation (MCE) in IDRISI, a user-defined variable (such as a population variable) can also be coupled in the CA-Markov model to improve the performance of the original model.

Development of a CA-Markov land use model for the LMR watershed

To build the land use model for LMR watershed, two sets of historical land use records were required to determine the pattern of land use change, and an additional land use map was needed for validation. In this research, the USGS 1980 Land Use and Land Cover (LULC), and the 1992 and 2001 land use maps from the National Land Cover Data (NLCD) data were adopted (Fig. 2). The 1980 and 1992 maps were used as the base maps to develop the model, whereas the 2001 map was employed for validation. This was not ideal as these two datasets had certain differences. The LULC data were derived from aerial photographs from the GIRAS, and the NLCD data were derived from satellite imageries from the Multi-Resolution Land Characteristics Consortium (MRLC). They also differed in terms of mapping units. However, due to the lack of comprehensive historical land use images, it was the only option available. Besides, they were collected by the same agency and were classified using the same method from Anderson, Hardy, Roach, and Witmer (1976). To minimize inconsistence, we further re-sampled and re-classified the land use classes for all three imageries into five categories using Anderson Level I classification method (see Table 1). These maps were also projected into NAD 1983 State Plane Ohio South FIPS 3402 coordinate system and resized to ensure conformity in size and dimension.

The 1980 and 1992 base maps were imported into IDRISI to project the land use pattern for 2001, the validation year. After running the Markov model, the transition probability matrix between each land use class, a transition area file, and a set of five probability images for each land use class were created. When the transition area file and the probability images for each land use class were imported into the CA-Markov model, a projected land use map for 2001 was generated (Fig. 3). Two validation statistics were applied to assess the accuracy of the model. The Relative

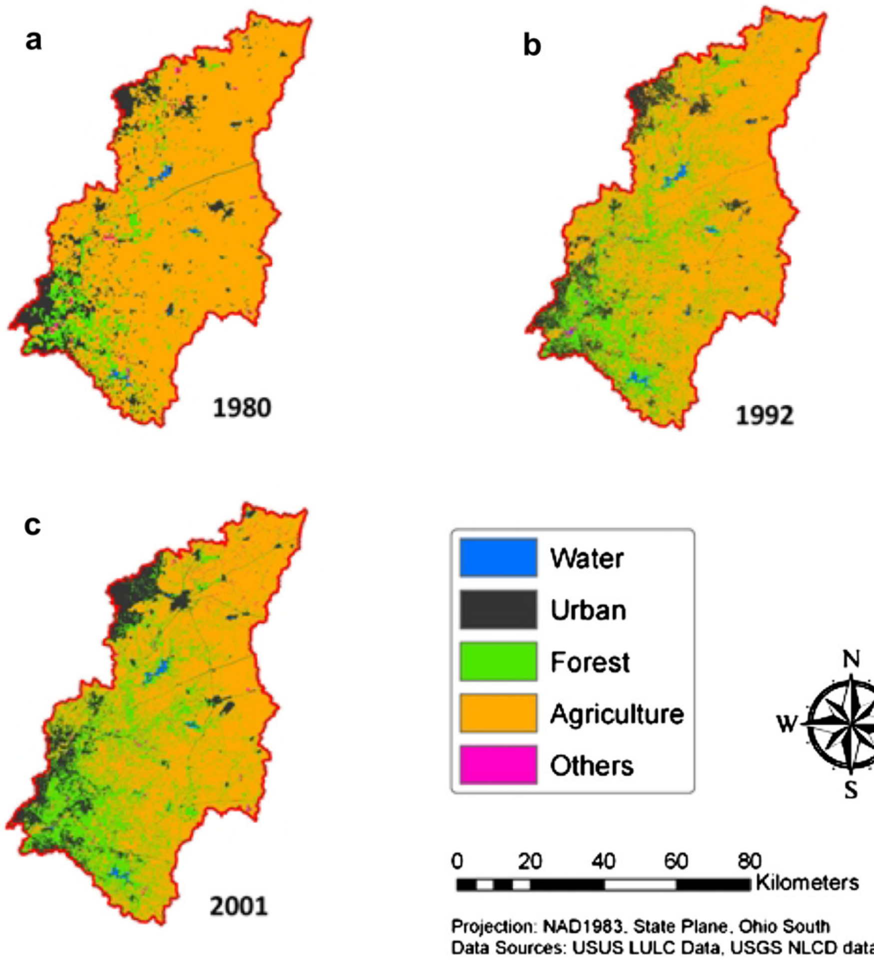

Fig. 2. Land use maps of the Little Miami River Basin acquired from the (a) 1980 LULC, (b) 1992 NLCD, and (c) 2001 NLCD meta-datasets.

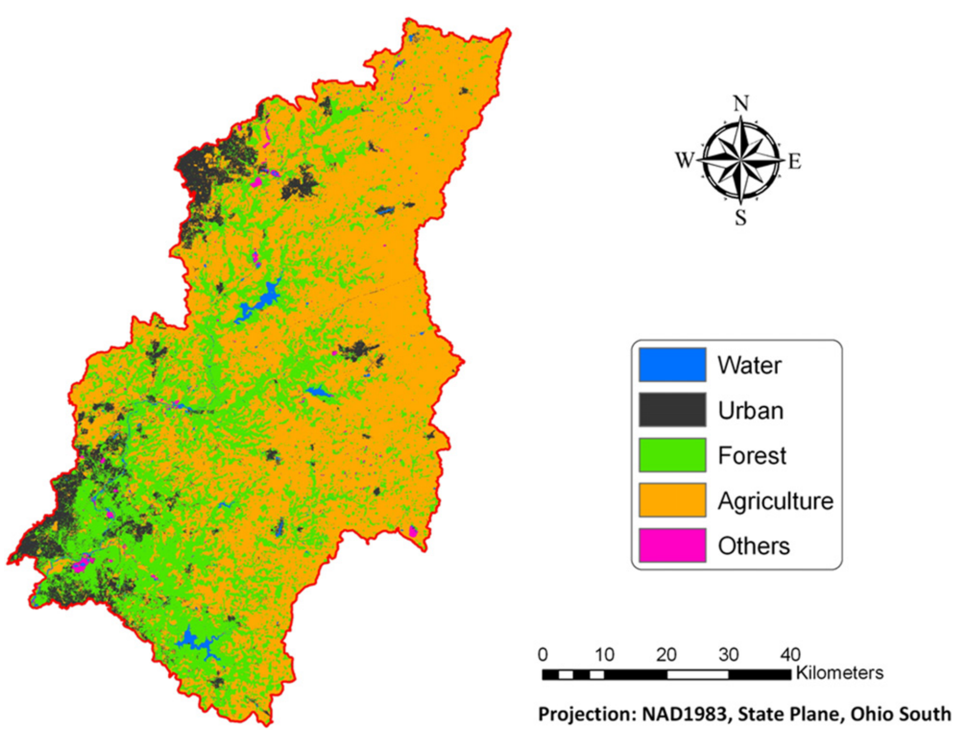

Fig. 3. Projected 2001 land use map generated from CA-Markov.

Operation Characteristic (ROC) examines the validity of a model by comparing a suitability map showing the likelihood of a land use class with a Boolean map showing where that land use class actually exists. A high ROC value indicates a better suitability map and a better prediction result. In this study, the urban suitability map was compared with the actual urban area from the 2001 NLCD map. Another method to validate the accuracy of model is Kappa statistic, which compares the agreement of quantity and location of cells in the categorical image. The ROC and Kappa statistic results (0.957 and 0.9495, respectively; Table 7) showed that the performance of the land use model was adequate.

Prediction of future population growth

The close relationship between population growth, urbanization, and suburban sprawl is well known. It is likely that by introducing a population variant to the CA-Markov analysis, the projection capability of the land use model can be improved. As demonstrated by de Almeida et al. (2003), the incorporation of the population density in the neural network analysis can improve the predictive power of the model. In order to ascertain this concept and to portray the importance of population growth in land use change, a population variable was developed and incorporated into the CA-Markov model by generating another set of a transition area file and a transition probability map with a population variant.

In order to develop the population variable, the trend of population growth has to be determined and the future population estimated. To this end, the 1990 and 2000 census block group population data were abstracted from the U.S. Census Bureau (2008) and projected into the year 2007 with the linear, geometric, and exponential population models. The year 2007 was chosen because of the availability of population data from the Ohio Department of Development (2005). The population projection results from each method were then compared with the 2007 official data (Table 8). A two-tailed t-test was used to examine the statistical differences between the predicted values and the official 2007 estimates (Table 9) and to determine the best model of population growth in the area. This step was to ascertain the accuracy of the population trend for postulating future population growth. Since the t-test results showed that the linear model (Stoto, 1983) had provided the best estimation of the future population trend, it was selected to project the population for the validation year 2001. The projected population was converted into a population density map (Fig. 4a) and a ratio map with population density standardized from low (0) to high (1), the latter was used as the urban suitability map imparting the influence of population growth on land use change (Fig. 4b).

Incorporation of the population variable in the CA-Markov land use model

The urban suitability map was incorporated into CA-Markov through the Multi-Criteria Evaluation (MCE), which is an effective procedure for structuring and aiding complex decision-making processes (Proctor, 2001). The Weighted Linear Combination (WLC) function in MCE was employed to generate the population density mask by assigning a 50% weight for population growth based on the assumption that population growth had an equally important contribution to urban expansion as the transition probabilities. After running the MCE, a new population coupled urban suitability map for 2001 was generated. ROC validation was used again to evaluate whether the new suitability map could provide a better prediction than the original suitability map. The result indicated a higher ROC value with the population coupled suitability map than the one without the population variable. The population coupled urban suitability map was then imported into the CA-Markov model to generate a new land use distribution map for 2001 (Fig. 5). To further ascertain the efficacy of the population coupled CA-Markov model in postulating the future land use pattern, the new projected land use map was compared to the actual land use distribution map in 2001 from NLCD using Kappa statistic (Fig. 2c).

As shown from the results of ROC and Kappa index (Table 7), the projected 2001 land use pattern generated with the population-coupled CA-Markov model displayed a better agreement with the actual 2001 land use than the one without the population variant. The ROC values increased from 0.957 to 0.977, while the Kappa statistics changed from 0.9495 to 0.9507. These results suggested that the method of incorporating the population variable into the CA-Markov model was reasonable; it could improve the model performance and help to better predict the 2050 land use pattern.

Table 7
Validation results for 2001 land use projections.

Comparison	ROC
Original suitability map without population variable *versus* 2001 NLCD urban area	0.957
New suitability map with population variable *versus* 2001 NLCD urban area	0.977
Comparison	Kappa
Projected 2001 land use without population variable *versus* 2001 NLCD	0.9495
Projected 2001 land use with population variable *versus* 2001 NLCD	0.9507

The 2050 land use change scenario for the LMR watershed

Following similar procedures, the 2050 land use scenario was generated using the CA-Markov model in conjunction with the 2050 population density variable generated from MCE. The base maps for 2050 projection were the 1992 and 2001 NLCD land use maps (Fig. 2b and c). According to the linear growth model, the population for the horizon year of 2050 was projected and the population density of the watershed was calculated. The WLC method in MCE was used to generate the 2050 population density variable (Fig. 6a) and the population coupled suitability map of urban area (Fig. 6b). The latter was imported into the CA-Markov model to depict future population and urban growth and to postulate the land use pattern for the 2050 horizon year (Fig. 7). This scenario of land use change therefore was based not only on the information of land cover change from 1992 to 2001, but also on the projected population growth from 2001 to 2050. The projection results showed that there would be substantial urban development in the south-western and north-western portions of the watershed.

Modeling of the hydrologic and water quality impacts of climate, population, and land use changes

To predict the 2050 hydrologic and water quality conditions in the LMR basin under future climate and land use change scenarios, a new model had to be prepared by incorporating the projected 2050 land use map and the four hypothetical climate scenarios for 2050 and the BASE CASE scenario into the validated HSPF model. The model was then used to examine both the separate and the combined impacts of climate change and population-driven land use change under the following scenarios:

(1) The no change scenario (NO CHANGE) where climate was kept at the 1980–1989 BASE CASE level and land use remained as the 1992 pattern;

Table 8
2007 county population projections from the linear, geometric, and exponential models.

County	1990 Population	2000 Population	2007 estimate (official)	2007 projection (linear model)	2007 projection (geometric)	2007 projection (exponential)
Brown	34966	42285	43956	47408	48302	42285
Butler	291479	332705	357888	361563	364986	332705
Clark	147548	144738	140477	142771	142803	144738
Clermont	150167	177450	193490	196548	1994467	177450
Clinton	35417	40543	43071	44131	44567	40543
Greene	136731	147886	154656	155695	156232	147886
Hamilton	866228	845303	842369	830656	830957	845303
Highland	35728	40875	42653	44478	44913	40875
Madison	37068	40216	41499	42420	42577	40216
Montgomery	573809	559062	538104	548739	548965	559062
Warren	113927	159013	204390	190573	200815	159013

Table 9
The *p*-value results from the *t*-tests between 2007 projected population values and the official estimates.

Model	*p*-value
Linear model	0.995
Geometric model	0.982
Exponential model	0.954

(2) The land use change only (LU) scenario where the projected 2050 land use scenario was used in conjunction with the BASE CASE climate condition;

(3–6) the scenarios where only climate was changed –

- The wettest climate change with 2 °C increase in temperature and 20% increase in precipitation only (W2);
- The wet climate change with 4 °C increase in temperature and 20% increase in precipitation only (W4);
- The dry climate change with 2 °C increase in temperature and 20% decrease in precipitation only (D2);
- The driest climate change with 4 °C increase in temperature and 20% decrease in precipitation only (D4);

(7–10) the scenarios where climate change was considered together with land use change –

- The wettest climate and land use changes (W2 + LU);
- The wet climate and land use changes (W4 + LU);
- The dry climate and land use changes (D2 + LU); and
- The driest climate and land use changes (D4 + LU).

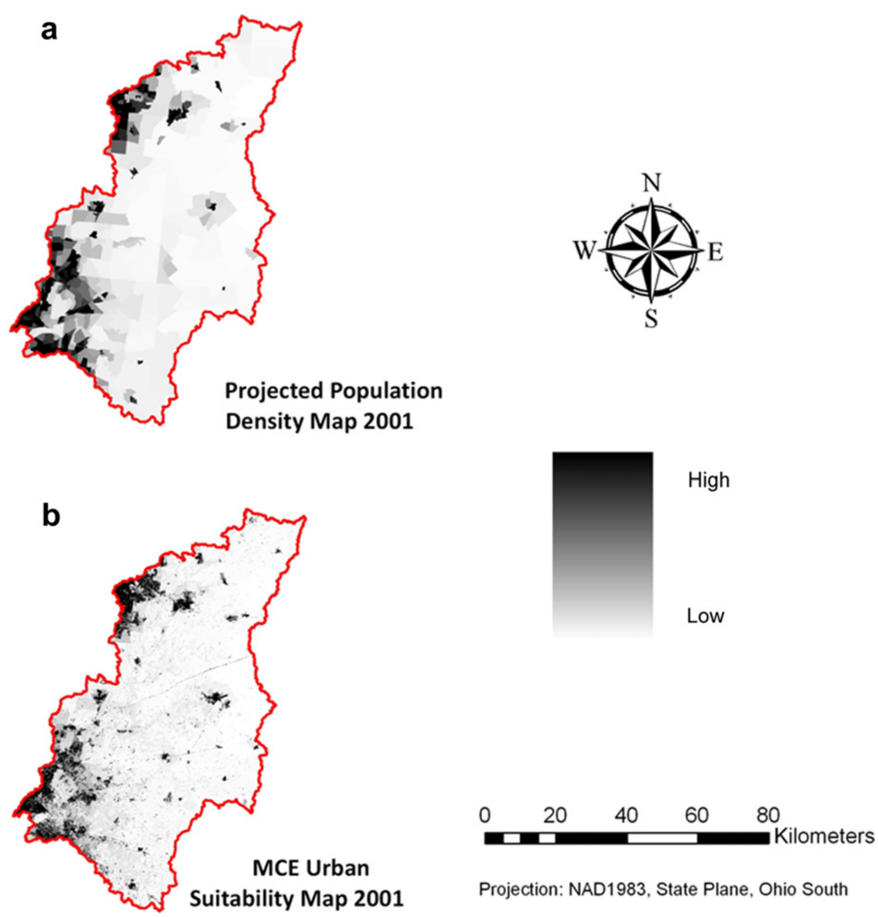

Fig. 4. (a) Projected 2001 population density map, (b) 2001 MCE urban suitability map.

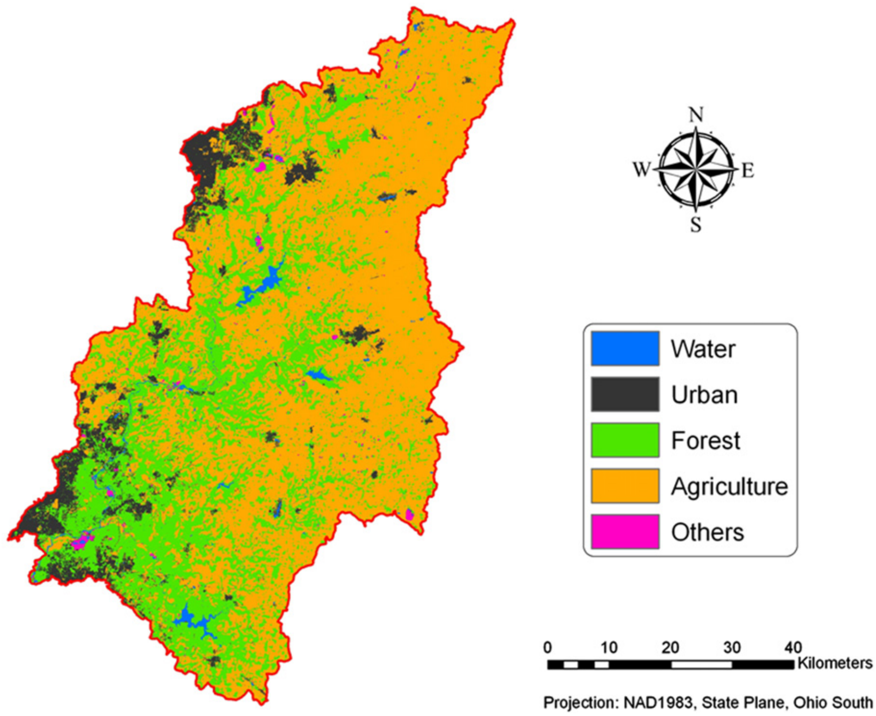

Fig. 5. Projected 2001 land use map generated from the population coupled CA-Markov.

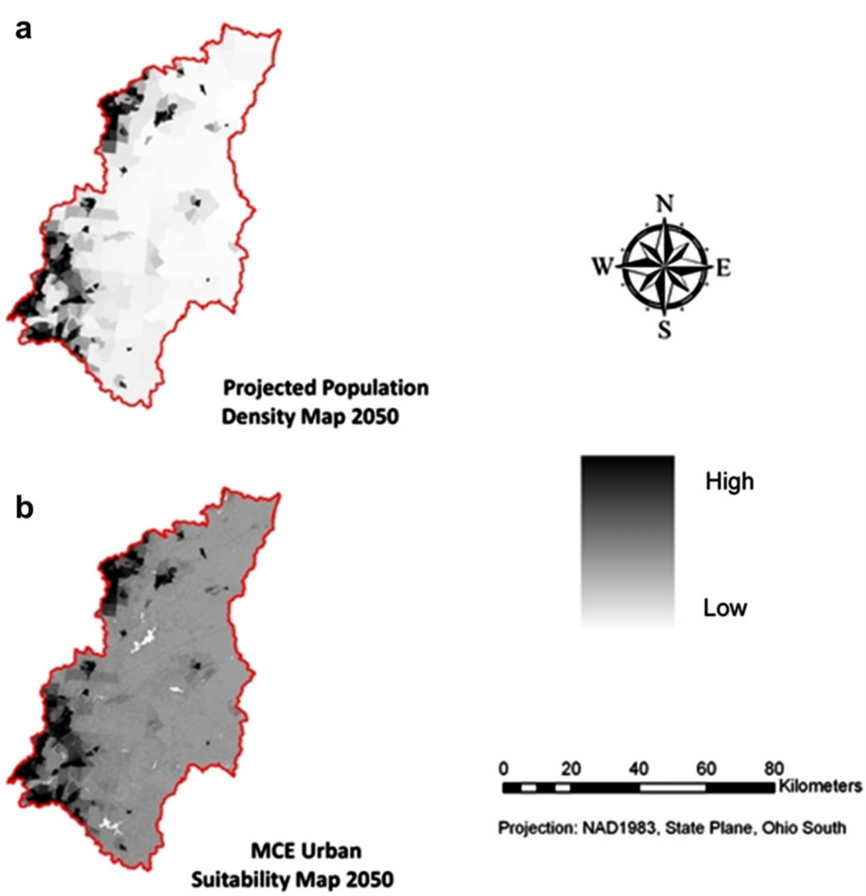

Fig. 6. (a) Projected 2050 population density map, (b) 2050 MCE urban suitability map.

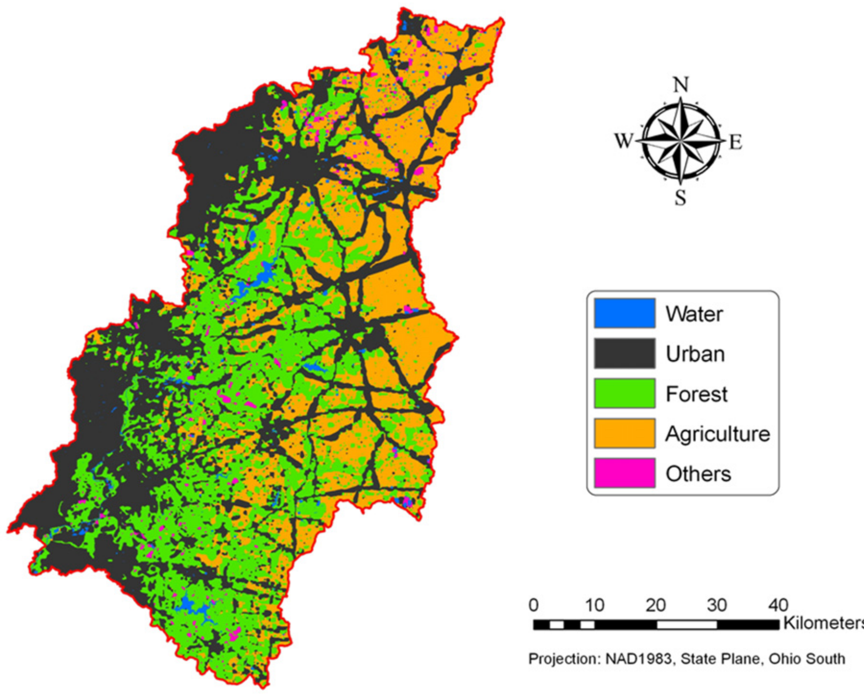

Fig. 7. Projected 2050 land use map generated from the population coupled CA-Markov.

The simulation results from each scenario were compared to assess the individual and combined hydrologic and water quality influences of climate and land use changes.

Results and discussion

Stream flow

When compared to the NO CHANGE scenario, where the climate and land use conditions were kept at the 1980s level, future climate change would alter the flow regime. It would induce an increase of 30.61% flow under the W2 scenario, a 12.84% increase under the W4 scenario, a 50.48% reduction under the D2 scenario, and a 69.05% reduction under the D4 scenario (Table 10). These results showed that under the wet conditions, with a 2 °C increase in temperature, as in the case from W2 to W4, the daily flow would be reduced by 5.74 m^3/s, which would be a 13.60% reduction. Similar situation was found under the dry conditions. A 2 °C increase in temperature would induce a reduction of 6 m^3/s, or 37.50% in daily flow. But with a 40% precipitation change, for example, from W2 to D2, the amount of flow would be reduced by 26.2 m^3/s, or 62.09%.

Using the projected 2050 land use scenario, the simulated amount of daily flow would increase 29.09% (Table 10). This might be attributed to the fact that, according to the projection, there would be more urban areas in the LMR basin in the year 2050. The effect of the projected land use change on stream flow was higher than the W4 climate scenario (12.84%), almost the same as the W2 scenario (30.61%), but much lower than under the D2 and D4 conditions (−50.48% and −69.05%, respectively). Hence, climate change would have a more prominent hydrologic effect than land use change if our environment became dry.

When climate change was considered together with land use change, the impact on discharge was more apparent. More daily discharge (14.16 m^3/s, a 43.83% increase) would be found under the W2 + LU scenario than the NO CHANGE scenario, indicating that by coupling the projected land use and climate changes, the future stream flow could increase an additional 4.76 m^3/s (11.41%) from the LU scenario and an additional 4.27 m^3/s (10.12%) increase from the W2 scenario. A similar case was found under the D4 + LU scenario where land use change could ameliorate the dry condition by increasing the flow regime from 10.00 to 15.16 m^3/s, a difference of 5.16 m^3/s or an increase of 51.60%.

These results implied that the projected land use change could increase the flow, which would be a welcoming relief under dry conditions, mitigating the drought impacts of climate change. On the contrary, if our climate became wetter, than the impending urbanization in the river basin would exacerbate the flow regimes, perhaps causing more floods.

When all the scenarios were compared, the greatest increase in daily flow occurred under the W2 + LU scenario (43.83%), while the greatest decrease took place under D4 scenario (−69.05%).

Table 10
Modeling results of the effects of future climate and land use changes on stream flow.

Scenario	Mean daily flows (m^3/s)	% Difference from NO CHANGE[a]
No change (NO CHANGE)	32.31	
Land use change only (LU)	41.71	29.09%
Wettest climate change only (W2)	42.20	30.61%
Wettest climate and land use changes (W2 + LU)	46.47	43.83%
Wet climate change only (W4)	36.46	12.84%
Wet climate and land use changes (W4 + LU)	37.55	16.22%
Dry climate change only (D2)	16.00	−50.48%
Dry climate and land use changes (D2 + LU)	18.12	−43.92%
Driest climate change only (D4)	10.00	−69.05%
Driest climate and land use changes (D4 + LU)	15.16	−53.08%

[a] % Difference = (current scenario − NO CHANGE)/NO CHANGE.

Water quality change

Compared to the NO CHANGE scenario, the simulation results of TP showed an increase in the mean daily concentration under all scenarios (Table 11). The greatest increase in the mean daily TP concentration was found under the W2 + LU scenario (21.35%). According to the USEPA Ambient Water Quality Criteria Recommendations (USEPA, 2005), the level for phosphorus in freshwater systems is limited to 0.2–0.3 mg/L, beyond which there would be a negative effect on aquatic ecosystems. The concentration of 0.415 mg/L found under this scenario would exceed this limit. The smallest increase of phosphorus occurred under the D4 scenario (2.63%); however, the concentration level under this scenario (0.351 mg/L) would still be higher than the USEPA standard.

Land use change alone, the LU scenario, would produce a 4.09% increase of TP concentration from the NO CHANGE scenario, which would be less than the effects of climate change under W2, D2, and W4 scenarios (14.33%, 7.60%, and 5.85%, respectively). These results indicated that climate change and, in a slightly lesser extent, land use change, would increase daily TP concentration.

The results from N modeling also revealed a moderate increase in the mean daily concentration under all scenarios (Table 12). Under the wet conditions, an increase of only 2 °C in temperature (in the case of W2) would induce an increase of the mean daily N concentration of 7.94% from the NO CHANGE scenario, whereas an increase of 4 °C (in the case of W4) could cause an increase of 5.05%. Under the dry conditions, the effects of temperature increase were not as apparent, as the mean daily N concentration only increased 1.44% (under D2) to 2.17% (under D4) from NO CHANGE.

When climate change was combined with land use change, the simulated mean daily N concentration increased somewhat. The largest effect of land use in such a combination was found under the W2 + LU scenario, where the N concentration increased from 2.99 under W2 scenario to 3.09 mg/L, a difference of 0.10 mg/L. This signified that when the agglomerate effects were considered, the effects of land use change alone could only contribute a slight increase in N concentration.

When compared with all the scenarios, the W2 + LU had the highest increase of nitrogen from NO CHANGE (11.55%), while the D2 scenario generated the least increase (1.44%).

Judging from these results, it was evident that both climate change and land use change could have negative impacts on water quality. When the climate and land use changes occurred simultaneously, the joint impacts could be intensified. In this study, both TP and N simulations showed an increase in concentrations under all climate and land use change scenarios. These two water quality parameters are critical to the integrity of ecosystem and human health. An increase in nutrient levels would likely cause more incidences of algae blooms and eutrophication, degrading water quality. Hence, with the impending global warming and urbanization, it seemed that the LMR basin would experience more nutrient enrichment problems.

Table 11
Modeling results of the effects of future climate and land use changes on TP.

Scenario	Mean daily concentration (mg/L)	% Difference with NO CHANGE[a]
No change (NO CHANGE)	0.342	
Land use change only (LU)	0.356	4.09%
Wettest climate change only (W2)	0.391	14.33%
Wettest climate and land use changes (W2 + LU)	0.415	21.35%
Wet climate change only (W4)	0.362	5.85%
Wet climate and land use changes (W4 + LU)	0.370	8.19%
Dry climate change only (D2)	0.368	7.60%
Dry climate and land use changes (D2 + LU)	0.383	11.99%
Driest climate change only (D4)	0.351	2.63%
Driest climate and land use changes (D4 + LU)	0.365	6.73%

[a] % Difference = (current scenario−NO CHANGE)/NO CHANGE.

Table 12
Modeling results of the effects of future climate and land use changes on N.

Scenario	Mean daily concentration (mg/L)	% Difference with NO CHANGE[a]
No Change (NO CHANGE)	2.77	
Land use change only (LU)	2.86	3.25%
Wettest climate change only (W2)	2.99	7.94%
Wettest climate and land use changes (W2 + LU)	3.09	11.55%
Wet climate change only (W4)	2.91	5.05%
Wet climate and land use changes (W4 + LU)	2.97	7.22%
Dry climate change only (D2)	2.81	1.44%
Dry climate and land use changes (D2 + LU)	2.85	2.89%
Driest climate change only (D4)	2.83	2.17%
Driest climate and land use changes (D4 + LU)	2.88	3.97%

[a] % Difference = (current scenario−NO CHANGE)/NO CHANGE.

Conclusion

This research attempted to derive an integrated spatial analytical methodology capable of postulating the possible hydrologic and water quality ramifications of future changes in terms of climate, population, and land use. Using the approach outlined in this paper, the separate as well as the combined impacts of climate and land use changes on water resources in the year 2050 in the LMR basin were examined.

The hydrologic and water quality modeling results in the LMR basin revealed that stream flow would change in accordance with climate change, although land use modification might be able to mitigate some of the effects. In general, simulations under the dry conditions paired with future land use change scenario (D2 + LU and D4 + LU) produced an increase in daily flow in the LMR and a slight increase in the daily concentrations of TP and N than under the climate change only (D2 and D4) scenarios. The results from the combined wettest climate scenario and land use change scenario (W2 + LU) showed a much larger increase in daily flow as well as a higher level of nutrients in the water. However, regardless of the future scenarios, it was predicted that the mean daily phosphorus (TP) and nitrates and nitrites (as N) concentrations in the receiving water bodies would increase. Thus, nutrient enrichments would be a problem in the future, especially under the wet conditions.

By examining not only the separate but also the combined impacts of climate and land use changes on water resources, it would help us to further our understanding of the dynamics of the physical system in a watershed. The scenario results from this study depicted a possible range of future flow and water quality conditions, which could be of values to the decision-makers in their development of adaptation and mitigation strategies in preparation for future climate and land use changes. Using this information, better comprehensive and sustainable watershed protection programs, including erosion and sediment control, storm water management, and best management practices, could be devised to minimize the adverse impacts of flow and non-point source pollution in the face of these impending changes.

The results also demonstrated the efficacy of HSPF in modeling water quantity and quality under a watershed scale. The application of CA-Markov model coupling with a population variable also proved to be more effective than the one without the population variant in simulating future land use changes, providing a more realistic land use pattern for the year 2050. This comprehensive approach seemed to be reliable and might provide a reasonable tool for predicting the long-term impacts of land use and climate changes on water resources, useful to environmental scientists, state and local agencies, watershed managers, and regional planners.

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