Modeling Hydrologic and Water Quality Responses to Changing Climate and Land Use/Cover in the Wolf Bay Watershed, South Alabama

by

Ruoyu Wang

A thesis submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Master of Science

Auburn, Alabama
December 13, 2010

Keywords: Climate change, LULC change, SWAT, Flow, Sediment, TN, TP

Approved by

Latif Kalin, Chair, Assistant Professor of School of Forestry and Wildlife Sciences
Hanqin Tian, Alumni Professor of School of Forestry and Wildlife Sciences
Xing Fang, Associate Professor of Department of Civil Engineering

Abstract

Land use/cover (LULC) and climate change are two main factors directly affecting regional hydrology and water quality. In this study, the future potential impacts of LULC and climate change on the hydrologic regimes and water quality in Wolf Bay watershed, South Alabama were explored independently and mutually by using the Soil and Water Assessment Tool (SWAT). Due to lack of measured data, SWAT was calibrated in a nearby watershed, and the calibrated model parameters were transferred to the Wolf Bay watershed. It was shown that using data from nearby watersheds improves the model performance under limited data conditions in the study watershed. The choice of the parameter set, whether it is the default model parameters or those from a donor watershed, has a marginal effect on modeling the impacts of different LULC scenarios.

SWAT with the transferred parameters was then employed to investigate the potential impacts of LULC and climate change on the hydrology and water quality of the Wolf Bay watershed. While four Global Circulation Models (GCMs) under three Green House gas emission scenarios were used to reflect variability in future climate conditions, three future LULC maps generated mainly based on different population growth rate assumptions were used to represent the uncertainty in future LULC conditions. In general, the Wolf Bay watershed is expected to experience increasing precipitation in the future, especially in fall, and temperature is expected to be higher, especially in summer and fall months. Further, the watershed is expected to undergo dramatic urbanization, with percentage of urban areas nearly doubling in future.

Results showed that both climate change and LULC change would cause a redistribution of streamflow. Higher flows were projected to increase, while small flows are expected to decrease. No clear trend of extreme large flow was detected when only climate change was considered. Under combined change scenarios, a more noticeable uneven distribution of streamflow was observed. Monthly average streamflow was projected to increase in spring, fall, and winter, especially during the fall, while no clear trend was observed in summer. LULC change did not significantly affect monthly streamflow, but changed the partitioning of streamflow to baseflow and surface runoff. Surface runoff was predicted to increase every month, while for baseflow an evident decreasing trend was detected. When climate was combined with LULC effect, a more dramatic increasing trend in monthly average streamflows was detected. Furthermore, a visible increasing trend in surface runoff and more dramatic decreasing trend in baseflow were detected.

Monthly distribution of sediment and nutrients are affected by both flow and management practices. Projected variations of TSS, TN, and TP loadings follow the same pattern as flow. No evident difference in annual average N:P ratio was predicted when only climate change was considered. LULC change increased TSS loadings but decreased TN loadings for all months. TP loadings were projected to decrease in summer, but increase in other months. N:P ratio was projected to decrease significantly.

Results of this study indicate that if future loadings are expected/predicted to increase/decrease under either climate or LULC change scenario, then their combined impact is to intensify that trend. On the other hand, if their effects are in opposite directions, that is while one predicts an increase and the other predicts a decrease, then their mutual effect has an offsetting impact. The combined LULC and climate change effect was in general synergistic, i.e. the total effect was greater than the sum of the individual effects.

Acknowledgments

I owe my deepest gratitude to my major professor Dr. Latif Kalin. Without his encouragement this work would not have been possible. In addition, I would like to sincerely thank my graduate committee members, Dr. Hanqin Tian and Dr. Xing Fang for their steadfast support and dedication to the completion of this thesis. Thanks are due to Shufen Pan's group for providing land use/cover map of 2005. I also want to thank Dr. Mingliang Liu for his help in GCM data and Dr. Sabahattin Isik for helping me in programming. I would also like acknowledge my friend and officemate Rewati Niraula for his help during this research, and other colleagues, Amir Sharifi, Andrew Morrison, Harsh Singh and Nishan Bhattarai. Thanks are due to Auburn University's Water Resources Center for funding my project. Finally, to my girlfriend and family who have supported me tirelessly throughout this project, I express my most heartfelt appreciation. Without your love and laughter I would have not been capable of completing this work.

Table of Contents

List of Tables

CHAPTER I

CHAPTER II

List of Figures

CHAPTER I

CHAPTER II

Chapter I

Modeling Effects of Land Use/Cover Changes under Limited Data

ABSTRACT

Watershed models are valuable tools used in the study of impacts of land use/cover (LULC) changes on hydrology. We use the Soil and Water Assessment Tool (SWAT) to study the impacts of LULC changes in a coastal Alabama watershed, where flow data did not exist at the onset of the study. We set up and calibrated the model in the neighboring Magnolia River watershed. Relevant model parameters were then transferred to the Wolf Bay watershed. Impacts of LULC changes on hydrology are studied in the Wolf Bay watershed by running the model with the default parameters, transferred model parameters (from the Magnolia River watershed), and calibrated parameters at the Wolf Bay watershed with limited data that became available later during the study. The relative changes in flow duration curves (FDCs) due to differing LULC showed a similar pattern with each parameter set: There is a clear threshold of around 1% probability of exceedance where the relative change is at its maximum. The relative change in flow due to LULC change drops drastically with increasing probability of exceedance of beyond 2% until it reaches a plateau at p D 20%. Hence, small to medium range flows are less sensitive to the parameter set. Further, the impact of LULC change on flow gradually decreases with the size of the storm for very large events (probability of exceedance <1%).

INTRODUCTION

Quantifying the impacts of land use and land cover (LULC) changes on the hydrologic processes and water balance of river basin has been an area of interest to hydrologists in recent years. Little is known so far if there is a well defined quantitative relationship between the LULC properties and the runoff generation mechanisms. The assessment of future LULC changes with respect to their hydrological impacts is still an unsolved problem (Fohrer, 2002). Several methods were developed to study the implications of LULC changes on hydrologic processes, such as the paired catchments approach, time series analysis (statistical method) and hydrological modeling (Li *et al.* 2009). Among these approaches, hydrological modeling has been widely applied in many different places in the world since it requires less resource and provides more flexibility.

Fohrer *et al.* (2001) assessed the hydrologic response to LULC changes in four meso-scale watersheds in Germany with different LULC distributions. Then the model performance for changing LULC has been tested in an artificial watershed with a single crop at a time and one underlying soil type to eliminate the complex interactions of natural watersheds. Simulation results showed that LULC changes on the annual water balance was moderate. Surface runoff was most susceptible to LULC change at both the artificial and the natural catchment. Hundecha and Bardoosy (2004) simulated the effect of LULC changes on the runoff generation of Rhine River Basin through parameter regionalization of Hydrologiska Byråns Vattenbalansavdelning (HBV) model. Results suggested that increased urbanization leads to an increase in the smaller peak runoffs stemming from summer storms. Increase in the larger peaks resulting from winter rainfall was negligible. A considerable reduction of both the peak runoff and the total runoff volume resulted from intensified afforestation. Savary *et al.* (2009) assessed the effects of historical LULC change on runoff and low-flow using the Gestion Intégrée des Bassins versants à l'aide d'un Système Informatisé (GIBSI) model in the Chaudiere River Watershed, Canada. Simulations showed strong correlations between LULC changes and stream discharge at the outlet of the watershed, especially for summer and fall seasons. Simulated annual and seasonal low flows were also strongly correlated to agricultural and forested land. Guo *et al.* (2008) studied the combined effects of climate and LULC change on hydrological processes using the Soil and Water Assessment Tool (SWAT) in Poyan Lake basin, China. They found that climate effect is dominant to alter annual streamflow; while LULC change may have a moderate impact on annual streamflow. Both of them strongly influences seasonal streamflow and alter the annual hydrograph of the basin. Ma *et al.* (2009) also considered climate change impacts on hydrological responses in a different watershed in southwestern China by SWAT. Contrasting to the results of Guo *et al.* (2008), they found climate having a more profound effect on seasonal variations in streamflow with LULC change having a moderate impact. On the other hand, they observed a much stronger influence by LULC change on mean annual streamflow. Their simulation results also showed that the impact of climate change on surface water, baseflow and streamflow was offset by the impact of LULC changes.

As mentioned above, LULC impacts on hydrologic responses have been thoroughly studied through modeling. However, models are mathematical simplifications of natural processes, with inevitable errors and deficits. Therefore, the reliability of hydrologic models should be evaluated by the fitness between measured flow data and model simulations. In this regard observed data is quite valuable. Hydrologists often need to adjust model variables in order to attain close to optimal parameter values by minimizing the error between model simulations and observed data. However, observed data are sometimes insufficient or not available at all, in which case one can run the model without calibration by estimating parameter values from the literature or rely on regionalization approaches.

The term *regionalization* has its roots in the process of regime classification and watershed grouping. It has later been extended in the rainfall-runoff modeling context to refer to the transfer of parameters from neighboring gauged watersheds (also called donor watersheds) to an ungauged watershed. Nowadays, the concept of regionalization applies to all methods aimed at estimating model parameter values on any ungauged watershed in a definable region of consistent hydrological response. Several methods are available in the literature for the transferring of model parameters. Regionalization based on regression is the most popular method which tries to link parameter values to climate and watershed physical characteristics, such as annual rainfall, temperature, area, slope, and land use/cover (LULC) in a gauged watershed (Yokoo, et.al, 2001; Kim and Kaluarachchi, 2008). Another commonly used approach is regionalization based on physical similarity. Generally information is transferred between neighboring watersheds, not necessarily geographically connected but rather in terms of observable watershed descriptions (Oudin *et al* ., 2008). Parameters are transferred from one or many donor watersheds, whose physical descriptors are similar to the ungauged one, based on one a synthetic rank that reflects the similarity of all physical descriptors between donors and target. The third kind of regionalization is based on spatial proximity. It uses the parameter values calibrated in nearby watersheds, which have sufficiently long data for calibration. The rationale of this method is that physical and climatic characteristics are relatively homogeneous within a small region, thus the neighbors should have similar hydrology.

Over the past few decades, several researchers have attempted to identify the best regionalization approach appropriate for different hydrological models. For example Oudin *et al.*

(2008) applied two lumped rainfall-runoff models to daily data over a large set of 913 French catchments. Their research indicated that the spatial proximity approach provided the best solution and the regression approach was the least satisfactory in France, where a dense network of gauging station is available. Merz and Bloschl (2004) investigated the water balance dynamics of 308 catchments in Austria using the HBV model. They compared regionalization methods for estimating model parameters in ungauged catchments. The method based on multiple regressions with catchment attributes performed significantly poorer than the other two. They found spatial proximity being a better surrogate of unknown controls on runoff dynamics than catchment attributes. Reichl and Western (2009) compared Nash-Sutcliffe efficiency and monthly relative volume error of the SimHyd lumped conceptual rainfall-runoff model by averaging method, spatial proximity approach, local calibration and simple regression in 184 Australian catchments. Averaging method, which selects a number of candidate models from available gauged catchments and weighs them based on likelihood, can be considered as the improvement of regionalization by physical similarity. Their research showed that the averaging method, while inferior to local calibration, is superior to methods based on regression and spatial proximity.

This paper focuses on estimating the impacts of LULC changes on hydrological responses in a coastal Alabama watershed. In particular, it investigates how limited hydrological data affects our understanding of LULC change impacts on hydrology by using the SWAT model. To address this issue, LULC maps corresponding to two different periods (1992 and 2005) are utilized. Model parameters are obtained from a nearby watershed through regionalization based on spatial proximity. Model efficiency is compared through use of time series of flow and flow duration curves (FDC) when transferred parameters and default ones are utilized. The effects of parameter transferring on modeling the impacts of LULC changes on low, medium and high flows are discussed.

METHODOLOGY

Study Area

Wolf Bay is located on the Gulf of Mexico in Baldwin County, Alabama, nestled between Pensacola Bay to the east and Mobile Bay to the west, with a watershed covering about 126 km^2. It is a sub-estuary of Perdido Bay with a connection to the Intracoastal Waterway and includes various freshwater, nutrient and sediment inputs from several sub-watersheds through Wolf, Sandy, Miflin and Hammock creeks (Fig. 1).

The watershed is primarily rural, but several municipalities exist including Foley, Elberta, Gulf Shores, and Orange Beach. Baldwin County's beaches, bays and rivers promote an expanding tourism industry, which exerts substantial influences on water extraction for human uses. Baldwin County experienced a 43% increase in population from 1990 to 2000. As a result of population growth, there is an increased demand for commercial, residential, and infrastructure development, thus bringing growth management issues to the forefront for local elected officials. One of the more visible changes in the landscape of Baldwin County is the rapid transformation of agricultural and forested lands to residential development. These development pressures are threatening the natural resources which make Baldwin County a popular place to live and visit (Stallman et.al, 2005). As a result, detecting the impact of potential LULC changes is urgent and necessary, because it provides policy makers some valuable suggestion which strike a balance between development and the protection of natural resources.

There is only one flow monitoring station in the watershed on the Wolf Creek operated by U.S. Geological Survey (USGS). However, at the commencement of this study no flow data was available yet. USGS essentially monitors flow stage and converts them to discharge through stage-discharge curves only when they have enough flow measurements that cover range of flows. Magnolia River watershed, which is adjacent to Wolf Bay watershed to the northeast (Fig. 1), has 10 years of continuous flow and climate data. Using the regionalization based on spatial proximity, we can setup a model in Magnolia River watershed, calibrate it and transfer the model parameters to Wolf Bay watershed. Besides their spatial proximity, Wolf Bay and Magnolia River watersheds also have quite similar physical characteristics (Table 1). Although it was still partly provisional, almost 2 years of flow data (12/5/2007 to 9/30/2009) later became available from the USGS gauge on Wolf Bay Creek, which provided us an opportunity to assess the feasibility of parameter transferring from Magnolia River watershed to Wolf Bay watershed.

Watershed Model

SWAT is one of the most commonly used watershed models for assessing the impact of management practices and land disturbances on watershed responses. It has a solid track record of applications (Kalin and Hantush, 2006). SWAT has been widely used around the world, such as the Cottonwood River near new Ulm, Minnesota (Hanratt and Stefan, 1998); southern Alberta, Canada (Chanasyk *et al.*, 2003); Jeker river basin, Belgium (Nasr *et al.*, 2005) to assess various impacts of agricultural practices and land use activities on water quantity and quality. SWAT is also suitable for coastal and flat areas, which have more complicated geo-hydrologic conditions (Wu and Xu, 2006). ArcSWAT version 2.3.4 that runs on ArcGIS® was used for preparing the input data and processing the output files.

SWAT is a distributed, process-based watershed model, but with significant number of empirical relationships. The physical backbone of the model facilitates the interpretation of model parameters whereas the empirical simplifications keep data requirements low compared to physically based models (Heuvelmans, 2004). SWAT divides a watershed into several subwatersheds based upon drainage areas of the tributaries. Then, each subwatershed is split into multiple hydrological response units (HRUs) based on LULC and soil types. Each HRU is assumed to be spatially uniform in LULC, soil, topography, and climate. Major hydrologic process that can be simulated by SWAT include evapotranspiration (ET), surface runoff, infiltration, percolation, shallow aquifer and deep aquifer flow, and channel routing (Arnold *et al.*, 1998). Details and the theoretical background of the SWAT is beyond the scope of this paper and can be found in Neitsch *et al.* (2005).

In addition to streamflow, SWAT can also provide baseflow and surface runoff estimates as model outputs. Therefore, we used a baseflow filter to split the observed streamflow into baseflow and surface components to better calibrate the model. The algorithm presented by Arnold *et al.* (1995) is employed for this purpose. In this algorithm, a digital filter, which is borrowed from signal processing, is successively applied to streamflow. Filtering surface runoff (high frequency signals) from base flow (low frequency signals) is analogous to the filtering of high frequency signals in signal analysis and processing. The filter can be passed over the streamflow three times. At each pass, a slower component of streamflow (less baseflow as a percentage of total streamflow) is obtained.

Model Performance Evaluation

The statistical measures of mass balance error (MBE), coefficient of determination (R^2) and Nash-Sutcliffe (1970) efficiency (E_{NS}) are used as indicators of model performance:

$$MBE = \frac{\sum_{i=1}^{N} Q_{sim,i} - \sum_{i=1}^{N} Q_{obs,i}}{\sum_{i=1}^{N} Q_{obs,i}} = \frac{\overline{Q_{sim}} - \overline{Q_{obs}}}{\overline{Q_{obs}}}$$

$$R^2 = \frac{[\sum_{i-1}^{N} (O_{obs,i} - \overline{O_{obs}})(O_{sim,i} - \overline{O_{sim}})]}{[\sum_{i=1}^{N} (O_{obs,i} - \overline{O_{obs}})^2][\sum_{i=1}^{N} (O_{sim,i} - \overline{O_{sim}})^2]}$$

$$E_{NS} = 1 - \frac{[\sum_{i=1}^{N} (O_{sim,i} - O_{obs,i})^2]}{[\sum_{i=1}^{N} (O_{obs,i} - \overline{O_{obs}})^2]}$$

where $Q_{sim,i}$ and $Q_{obs,i}$ are simulated and observed flows at i^{th} observation, respectively, N is the number of observations. Similarly, $\overline{O}_{sim}$ and $\overline{O}_{obs}$ are average of simulated and observed flows over the simulation period. R^2 describes the proportion of the total variances in the observed data that can be explained by the model and ranges from 0 to 1. E_{NS} is a measure of how well the plot of observed versus predicted values fit the 1:1 line, and can theoretically vary from $-\infty$ to 1, with 1 denoting a perfect model with respect to data agreement. Although R^2 and MBE values have been used often in the past to quantitatively compare model results with data, E_{NS} is a better representative measure for model goodness-of-fit (ASCE 1993, Legates and McCabe 1999).

Modeling LULC changes

LULC changes affect various components of the hydrologic cycle, either directly or indirectly. The infiltration and ET processes are the two vital components of the hydrologic cycle directly affected by LULC changes. SWAT uses SCS curve number method to simulate infiltration process. Each soil/LULC combinations are assigned specific curve numbers, with higher values representing higher surface runoff and less infiltration. Urbanization within a watershed increases the area of impervious surfaces (high Curve Number) which decreases infiltration and increases runoff. As a result, the amount of surface runoff generated from a specific rain event increases. Reduced infiltration results in less groundwater recharge which decreases baseflow contribution to streamflow, eventually causing reduction in low-flows. If change in ET is relatively small, then urbanization in essence redistributes baseflow and runoff components of the streamflow.

SWAT calculates ET from potential ET (PET). One key component in PET calculation is the net radiation, which is a function of the plant albedo (reflectivity). Thus, change in LULC should change net radiation and eventually PET. In SWAT changing LULC has little or no effect on PET depending on the choice of the PET calculation method (Penman Monteith, Priestley-Taylor, and Hargreaves). In calculating the actual ET, SWAT evaporates intercepted water in the canopy first. If water intercepted in the canopy cannot fulfill the PET demand (usually the case), SWAT then calculates transpiration from plants. Transpiration is function of PET, leaf area index (LAI), and soil water content. LAI changes with land cover and plant growing seasons. Higher LAI means more transpiration. Calculation of transpiration and water uptake are described in detail in Neitsch *et al.* (2005).

Two LULC maps representing the years 1992 and 2005 are employed to investigate the impacts of LULC changes on hydrologic responses in Wolf Bay watershed. The 1992 National Land Cover Data (NLCD) is a raster data set with a 30 m resolution. The second LULC map is produced by GIS specialists in Auburn University using circa 2005 as references data. Circa 2005 is a vector dataset attained by trend analysis focused on LULC changes of urban and built-up areas, utilities, and transportation from 2001 to 2005 based on Color Infrared imagery of 2001 and 2005 from Baldwin county commissions. Since these two maps had different LULC classifications, we reclassified them according to SWAT classification to make it consistent with model's own database.

RESULTS AND DISCUSSION

Calibration and validation in the Magnolia River Watershed

SWAT model was first set up in the Magnolia River watershed, then calibrated and validated with a split data set approach. The period from 10/01/1999 to 09/30/2004 of the daily flow data from USGS gauge #02378300 was used for calibration and the period from 10/01/2004 to 09/30/2009 was used for validation. Model validation is defined as the process of demonstrating that model is capable of making accurate predictions for periods outside a calibration period. Usually, calibration of a model is based on 3-5 years of data (Sorooshian *et al.* 1983; Xia *et al.* 2004), and validation on another period of similar length (Tu 2009, Ma *et al.* 2009). Table 2 shows the calibrated model parameters along with their default values. Model simulations actually started from 10/01/1989 with measured precipitation data as input. This corresponds to a warm-up period of 10 years. The idea behind using such a long warm-up period was to minimize the effect of initial unknown conditions such as antecedent moisture, and initial groundwater table height (Kalin and Hantush, 2006).

Model parameters were calibrated first at monthly, then at daily time scales for flow. Fig. 2a shows the observed and simulated monthly flows during the calibration and validation periods. Monthly streamflow values match well to the observed ones. Model performance statistics are shown in Table 3. Note that only *MBE* is shown for baseflow as suggested by Santhi *et al.* (2001). It is difficult to estimate the spatial and temporal distribution of ground water table. Quantifying the impact of deep aquifer system on baseflow response is also challenging (Lee *et al.* 2005). Therefore, it is hard to capture the temporal dynamics of baseflow simulations. Overall SWAT's performance at monthly time scale is good during both calibration and validation periods.

Daily simulations of total streamflow are not as good as monthly simulations, but the E_{NS} of the calibration period is still acceptable. Due to the temporal scale effect discussed in the previous paragraph we only focus on total streamflow at daily time scale. According to Moriasi *et al.* (2007) E_{NS} values above 0.5 with low *MBE* are considered satisfactory. To gain more insight we also compared FDCs of observed and simulated flows in the Magnolia River Watershed from 1999 to 2009 (Fig. 2b). Observed and simulated flows have good agreement for flows having probability of exceedance > 0.2%. For the larger flows model underestimates flow as much as 50%, which is not uncommon in modeling (e.g. Baffaut and Benson, 2009; Larose *et al.*, 2007; Wang and Melesse, 2005).

Note that SWAT is not an event-based model. Although it works reasonably well for long term simulations, it has limitations in extreme events. It cannot capture the dynamics at sub-daily scale. For example, from 31st March 2005 to 6th April 2005, there were series of several very big storms. The total amount of rainfall in this one-week period was 440 mm, which is about one fourth of the average annual precipitation. The model failed to reflect these huge events properly. The *MBE* of streamflow in this period was -53%. The most improper simulation happened on 1st April 2005. Observed daily average flow was 197m^3/s (largest ever recorded), yet SWAT estimated only 35m^3/s of flow. Such extreme events can significantly alter the performance statistics. For instance, if we ignore the event on 1st April, 2005, The E_{NS} for monthly simulation improves from 0.65 to 0.74 (see Table 3). Other than the potential deficiencies of the model in dealing with such huge events, there are two other possible reasons for this. USGS measures stage not discharge; discharge is estimated from stage-discharge relationships (i.e. regression equations) which are known to have problems outside their range. Thus, observed flow during such an extreme event, which is actually estimated from stage, could have serious errors. Spatial variation in precipitation and the rain gauges not being able to capture these accurately is another source of error. Our precipitation data source is a rain gauge located at the watershed outlet. On 1st April 2000, the USGS gauge at Magnolia River recorded a storm event where average daily flow was 6 m^3/s, up from 0.6 m^3/s from the day before. However, no flow is generated by SWAT because the rain gauge did not record any trace of rainfall. The most likely scenario is that it only rained at the upstream portion of the watershed that went undetected by the rain gauge.

We tried different climate data sources to improve model performance. However, current rainfall data offered by the USGS station proved to be the best data source. Two other alternatives to the USGS gauge was a NOAA rain gauge and NEXRAD radar. USGS rain gauge is at the watershed outlet. The NOAA rain gauge is about 16 km away from the Magnolia River watershed outlet and well outside its boundaries. Further, it records daily rainfall from 6:00am to 6:00pm, thus does not represent a calendar day. This may cause problems in daily flow simulations if there is an overnight rain event. The NOAA rain gauge also had extended periods of missing data (e.g. the whole months of November 2002, December 2002, and September 2009 were missing). Like the USGS rain gauge data we observed inconsistencies during big rainfall events in NOAA data. Summer rains in Alabama are dominantly localized pop-up thunderstorms. Capturing these storms requires a very dense network of rain gauges. Radar data seems to be a good alternative but that has its own problems too. We obtained NEXRAD radar data for the Magnolia River watershed for the 2002-2008 period and tried to calibrate the model. Even NEXRAD data did not capture rainfall accurately and we had poorer model performance. The annual average precipitation from 2002 to 2008 based on NOAA rain gauge, NEXRAD and USGS rain gauge were 1794 mm, 1520 mm and 1315mm, respectively, which shows the discrepancies between these three rainfall datasets and the degree of spatial variation in this area.

Once the models were calibrated for flow, they were calibrated subsequently for sediment and nutrients. Since measured sediment and water quality data are discontinuous, USGS's LOADEST (A Fortran Program for Estimating Constituent Loads in Streams and Rivers) is applied to generate continuous loads when given a time series of streamflow, additional data variables and constituent concentration based on regression analysis. By LOADEST, a continuous monthly loadings of TSS and nutrient are generated as observed data.

Due to lack of sufficient measured water quality data, monthly sediment and nutrient was calibrated for year 2000 and validated for year 2001. Model performances are shown in Table 4 and Fig. 3. Calibrated model parameters along with their default values are shown in Table 5 From Fig 3, we found SWAT is able to predict the monthly sediment and nutrient loadings with sufficient accuracy.

Transferability of model parameters from Magnolia River to Wolf Bay watershed

In the previous section, SWAT was manually calibrated for flow in Magnolia River watershed with the calibrated parameters shown in Table 2. The next step is transferring these parameters systematically to Wolf Bay watershed. Table 6 shows the daily model performances with the default and transferred parameter sets. Although SWAT performed better with the transferred parameters, E_{NS} is negative and mass balance error is above 50%. Default parameters resulted in a much lower E_{NS} value (compare -2.07 to -0.21). Although, to some extent we expected low performance with the default parameters, having such low performance with the transferred parameters was surprising since watersheds have similar physical and morphological characteristics and are adjacent to each other. Note that in spite of low E_{NS}, R^2 is high. High R^2 with a low E_{NS} means simulated values have the same trend with observed values in time, but at a disproportionate rate. In other words the model systematically over/under predicts the observed data. In this case, it is an over prediction.

Sometimes when models are run outside their calibration/validation periods, changing LULC may result in poor model performance. Model was set up using LULC map of 2005, but the simulation period was extended to 2009. If LULC changed significantly from 2005 to 2009, then model performance should deteriorate over time. However, LULC didn't change much in that period. We also run SWAT with LULC map of 2008 and compared the daily simulation results to the ones obtained with 2005 LULC. No significant difference was detected between the two daily simulation results.

Based on above findings it is seen that parameter transferring improves the predictable capabilities of the SWAT model in the study area, but not necessarily at the desired level. However, we calibrated and validated the model over a long time period (5+5 years) and tested the model with transferred parameters over a short period (~2 years). Whether the model performs well at the donor watershed during the testing period 10/2007 - 09/2009 is not clear. Note that although the validation period included this period, the length of the validation period (5 years) along with higher flows during the first year (2005) could potentially hinder the model performance in the testing period. If the model cannot accurately predict flow in this specific period at the donor watershed, then the problem is beyond parameter transferability. Indeed, model performance in Magnolia River watershed during this testing period is not good at all. R^2, E_{NS} and *MBE* for daily streamflow are 0.45, -0.21, and 48%, respectively, quite similar to what we attained in Wolf Bay watershed with the transferred parameters. Exchanging the roles of donor and target watersheds, that is calibrating the SWAT model at Wolf Bay watershed and transferring the calibrated model parameters to Magnolia River watershed, resulted in a different story. Daily model performance statistics for the period 10/2007 - 09/2009 was R^2=0.63, E_{NS}= 0.62, and *MBE*=-2.5% at the calibration and R^2=0.54, E_{NS}= 0.51, and *MBE*=12% at the test watersheds. This is a substantial improvement over the previously reported values based calibration at Magnolia River watershed. Therefore, transferring parameters from neighboring watersheds indeed improves the predictive power of the model.

Effect of parameter transferring on hydrologic responses

In previous section we showed that transferred parameters increase model reliability as opposed to using model default parameters. Here we explore the implications of this on hydrological responses. Monthly flow simulation results using default and transferred parameters are shown in Fig. 4. Visually there are no significant differences. The two-sample Kolmogorov–Smirnov (K-S) test, which is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples, is employed to compare the two streamflow time series. The K-S test indicated no significant differences (p=0.482) in simulation results of monthly flow due to use of two separate parameter sets. However, at the daily time scale there are striking differences. As shown in Table 7, two specific years, 2000 and 2005 are selected to represent dry and wet conditions, respectively. The K-S test is employed to check if there are any significant changes in the time series obtained by the two parameter sets, both at daily and monthly time scales. Again, no significant differences exist at monthly time scale, both in dry and wet years ($p=0.518$ and 0.848, respectively). However, if the simulation scale is changed to daily step, significant differences appear in both years ($p<0.0001$ in both).

FDCs for these two years and the whole 10-year-period were also compared (Fig. 5a-c). Differences are evident at high and low flows, regardless of dry or wet year. Note that simulations with default parameters always resulted in higher flows at low exceedance probabilities (<1%). Being in a wet or dry year did not change the fact that if default parameters are used in predicting high-flows we will end up over predicting the flow. Similarly, default parameter set consistently generated lower flows than transferred parameter set when probability of exceedance was larger than 3% during both dry and wet years. Similar results were obtained when the FDC for the whole period was considered. Default parameters always resulted in higher flows at low probability of exceedance and lower flows at high probability of exceedance.

Impact of LULC change on hydrologic responses

Table 8 shows the LULC distributions in 1992 and 2005. From 1992 to 2005 percent forest cover has been reduced by 9%. On the contrary, total urban land has increased by almost 20%. Pasture has been lost to agricultural fields such as sod farming, and low density residential areas. Same climate data and parameter set (the one calibrated in Magnolia River watershed) were utilized as model inputs to run SWAT with both 1992 and 2005 LULC maps. Simulation results for flow for each year are summarized in table 9. For each year, we tabulated annual maximum, minimum and mean daily flow values obtained with LULC of 1992 and 2005. The relative change in mean annual flow due to LULC change shows little variation. Although change in LULC did not have a big impact on streamflow, it affected the partitioning of streamflow to baseflow and surface runoff as evidenced by changes in annual maximum and minimum flows.

In every single year annual minimum flow was predicted to decrease due to LULC change with a range from -16.8% to -36.9%, and an average of -29.7%. Annual maximum flow appears to be most sensitive to LULC changes. It is estimated to increase by 40.6% to 115.3% with an average of 58.0%. Similar results are found in other studies (e.g. Kauffman *et al.* 2009, Rose and Peter 2001). Fig. 6 shows the variation in average monthly streamflows before and after LULC changes. Flow was predicted to increase as much as 12% during the summer months of June through September, which is the growth season with the highest ET rates.

Note that most of the increase in urban land was in form of low density residential areas (Table 8), which are only partially covered by impervious land. SWAT assumes that parts of urban areas not covered by impervious surfaces are bermudagrass. Based on SWAT database, maximum LAI for forest is 5, while for bermudagrass it is 4. Thus, forest to grass conversion does not cause significant change in ET. Over the whole simulation period, SWAT predicted about 20% less ET from grassland compared to forested land. Estimated annual average ET over the whole watershed based on the 1992 and 2005 LULC were 457 and 435 mm, respectively (~ 5% reduction). Low and high density residential areas have on average 12% and 60% imperviousness, respectively, according to the USDA Soil Conservation Service (SCS) classification. Thus, the total increase in percentage of impervious areas from 1992 to 2005 is only 2.95%. Since LULC from 1992 to 2005 did not change uniformly over the whole watershed, it is not reasonable to try to explain the alterations in flow and ET purely by changes in forest cover and urban land use. Note that from 1992 to 2005 pasture had also decreased by 28.3% and agricultural land increased by 15.5%. Therefore, there is a compound effect of all these mixed LULC changes.

Impact of parameter transferring on modeling LULC change

Fig. 7a-c show the FDCs of daily flow simulations in the Wolf Bay watershed obtained with each of the three parameter sets (default, transferred from Magnolia River watershed, and the calibrated set in Wolf Bay watershed) and with the 1992 and 2005 LULC maps. In each figure there are clear differences in FDCs generated from the two LULC maps. Although the scales differ, FDCs with default parameters look similar to FDCs with transferred parameters (Fig. 7a-b). In both cases, the flow with LULC 2005 is higher than the one with LULC 1992 in the exceedance probability below 10%, and the relationship is opposite above 10%.When the calibrated parameters are used, flows based on 1992 LULC never seem to exceed flow based on 2005 LULC (Fig. 7c).

To get a better insight into the effect of parameterization on the differences in FDCs due to LULC changes, relative difference in FDC, i.e. ([FDC of 2005 LULC] – [FDC of 1992 LULC]) / [FDC of 1992 LULC], were depicted in Fig. 8. Trends are similar in all three. Moving from left to right, i.e. from low to high probability of exceedance, the relative differences in flow due to LULC change (from 1992 to 2005 conditions) increase until around 1% and stays at that level until 2%. Thus LULC change has the largest impact on flows with 1% exceedance probability. As flow gets larger (probability of exceedance < 1%) the impact of LULC change is gradually reduced. Beyond 2% all three parameter sets exhibit a sharp drop and reach a plateau again. With the default and transferred parameter sets, the relative change in flow becomes negative around 7-10% exceedance probabilities and stays negative beyond that point, mostly in the -15% to -20% range. On the contrary, with the calibrated parameter set relative change in flow becomes negative around 20% exceedance probability and stays negative until 60% exceedance probability. Except for a short duration, the relative change in flow during this period is around

2%. Beyond 60% exceedance probability all the parameter sets show increase in relative change.

In short, Fig. 8 reveals very interesting facts. First, the choice of the parameter set in simulating LULC changes does not seem to play a big role in relative changes of flow (it does for absolute flows). Although there are differences in the FDCs, trends are mostly consistent and the differences between them are not major. Secondly, LULC change influences most of the flow in a quite steady and moderate manner. Flows with 1-2% probability of exceedance appear to be most sensitive to LULC changes.

SUMMARY AND CONCLUSIONS

In this paper we explored how transferring model parameters from a neighbor (donor) watershed to a target watershed affects modeling LULC changes. The regionalization based on spatial proximity method was employed to transfer the model parameters from the donor Magnolia River watershed to the target Wolf Bay watershed. For this purpose SWAT model was first set up and calibrated in the Magnolia River watershed which has 10 years of continuous measured flow data. Calibrated model parameters were then transferred to the Wolf Bay watershed, which at the start of study had no flow data. Model performances were compared when two different parameter sets are utilized: SWAT default parameters and transferred parameters. About 22 months of measured flow data in Wolf Bay watershed that later became available was used for that purpose. Transferred parameter set resulted in a slightly better model performance than the default parameter set, but not at a desired level (both had negative E_{NS}). The low model performance was due to the fact that when using a long period of data in model calibration the emphasis is on the whole period and the model performance may not be up to the desired level in some subsections of the entire time period. Hence, extension of parameter transfer from donor watersheds through long term calibration to target watersheds for short term predictions requires extra caution, and most likely vice versa.

Flow duration curves (FDCs) are effective tools in visualizing the whole flow range. We created FDCs to get a better insight to the impacts of both LULC change and parameter transferring. Simulations with default parameters always resulted in higher flows at low probability of exceedance (<1%). On the contrary, default parameter set consistently generated lower flows than the transferred parameter set when probability of exceedance was > 3%, regardless of dry or wet year. Similar results were obtained when the FDC for the whole period is considered. Default parameters always resulted in higher flows at low probability of exceedance, and lower flows at high probability of exceedance.

Two LULC maps from 1992 and 2005 were utilized to assess the effect of parameter transferring on modeling LULC changes. The 2005 LULC had about 20% more urban classified land than the 1992 LULC. However, the estimated change in impervious cover from 1992 to 2005 was only 2.95%. Average streamflow was only slightly affected by LULC changes. Maximum and minimum annual streamflows were found to be very sensitive to LULC changes. Annual minimum streamflow decreased moderately and annual maximum streamflow increased substantially due to LULC change. Again FDCs were developed out of model generated daily flows based on 1992 and 2005 LULC maps. This was done for each of the three parameter sets: default, transferred and Wolf Bay calibrated. The relative changes in FDCs due to differing LULC showed a similar pattern with each parameter set: relative change was highest at 1-2% exceedance probability. The impact of LULC change diminished gradually as the event sizes got smaller beyond the 2% probability of exceedance.

This study clearly showed the benefits of using data from nearby watersheds to improve the model performance under limited data conditions in the study watershed. The analysis carried out in this study further suggest that the choice of the parameter set, whether it is default model parameters or transferred from a donor watershed, only has a marginal effect on modeling the impacts of different LULC scenarios.

REFERENCES

Arnold JG, Allen PM, Muttiah R, Bernhardt G. 1995. Automated Baseflow Separation and Recession Analysis Techniques. *Ground Water* **33(6)**: 1010-1018.

Arnold JG, Srinivasan R, Muttiah RS, Williams JR. 1998. Large Area Hydrologic Modeling and Assessment - Part 1:Model Development. *Journal of the American Water Resources Association (JAWRA)* **34(1)**: 73-89

ASCE. 1993. Criteria for evaluation of watershed models. *Journal of Irrigation and Drainage Engineering* **119(3)**: 429-442.

Baffaut C, Benson VW. 2009. Modeling Flow and Pollutant Transport in a Karst Watershed with SWAT. *Transactions of the ASABE* **52(2)**: 469-479.

Chanasyk, DS, Mapfumo E, Willms W. 2003. Quantification and Simulation of Surface Runoff From Fescue Grassland Watersheds. *Agricultural Water Management* **59(2)**: 137-153.

El-Nasr AA, Arnold JG, Feyen J, Berlamont J. 2005. Modelling the Hydrology of a Catchment Using a Distributed and a Semi-Distributed Model. *Hydrological Processes* **19(3)**:573-587.

Fohrer N. 2002. River basin research and management: influence of land cover, land use and soil surface conditions on hydrological processes and water balance of catchment. *Physical and Chemistry of the Earth*. **27**: 617.

Fohrer N, Haverkamp S, Eckhardt K, Frede HG. 2001. Hydrologic Response to Land Use Changes on the Catchment Scale. *Physical and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere* **26**: 577-582.

Guo H, Hu Q, Jiang T. 2008. Annual and seasonal streamflow responses to climate and land-cover changes in the Poyang lake basin, China. *Journal of Hydrology* **355(1-4)**: 106-122.

Hanratty MP, Stefan HG. 1998. Simulating Climate Change Effects in a Minnesota Agricultural Watershed. *Journal of Environmental Quality* **27(6)**: 1524-1532.

Hundecha Y, Bardossy A. 2004. Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model. *Journal of Hydrology* **292(1-4)**: 281-295.

Hevnelmans G, Muys B, Feyen J. 2004. Evaluation of hydrological model parameter transferability for simulating the impact of land use on catchment hydrology. *Physics and Chemistry of the Earth* **29**: 739-747.

Kalin L, Hantush MM. 2006. Hydrologic Modeling of an Eastern Pennsylnania Watershed with NEXRAD and Rain Gauge Data. *Journal of Hydrologic Engineering* **11**(**6)**: 555-569.

Kauffman GJ, Belden AC, Vonck, KJ, Homsey AR. 2009. Link between impervious cover and base flow in the White Clay Creeek Wild and Scenic watershed in Delaware. *Journal of Hydrologic Engineering.* **14(4)**: 324-334.

Kim U, Kaluarachchi J. 2008. Application of parameter estimation and regionalization methodologies to ungauged basins of the Upper Nile River Basin, Ehiopia. *Journal of Hydrology* **362(1)**: 39-56.

Larose M, Heathman GC, Norton DL, Engle B. 2007. Hydrologic and atrazine simulation in the cedar creek watershed using the SWAT model. *Journal of Environmental Quality* **36(2)**:521-531.

Lee D, Kim N, Chung I, 2005. Comparison of runoff responses between SWAT and sequentially coupled SWAT-MODFLOW model. *International SWAT 2005 Conference, Zurich, Switzerland.* http://www.brc.tamus.edu/swat/3rdswatconf/PDF/Session_VII/Lee.pdf. Last access on 07/01/2010.

Legates DR, McCabe GJ. 1999. Evaluating the use of "goodness-of-fit" measures in hydrologic and hydro climatic model validation. *Water Resources Research* **35(1)**:233-241.

Li Z, Liu W, Zhang X, Zeng F. 2009. Impacts of land use change and climate variability on hydrology in an agricultural catchment of the loess Plateau of China. *Journal of Hydrology* **337(1-2)**:35-42.

Ma X, Xu J, Luo Y, Aggarwal SP, Li J. 2009. Response of hydrological processes to land-cover and climate changes in Kejie watershed, South-West China. *Hydrological Process* **23(8)**: 1179-1191.

Merz R, Bloschl G. 2004. Regionalisation of catchment model parameters. *Journal of Hydrology* **287(1-4)**: 95-123.

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulation. *Transactions of the ASABE*, **50(3)**: 885−900.

Nash JE, Sutcliffe JE. 1970. River Flow Forecasting Through Conceptual Models, Part I-A Discussion of Principles. *Journal of Hydrology* **10(3)**:282-290.

Neitsch SL, Arnold JG, Kiniry JR, Williams JR. 2005. Soil and Water Assessment Tool: Theoretical Documentation, version 2005. http://www.brc.tamus.edu/swat/downloads/doc.html. Last accessed on 07/01/2010.

Oudin L, Andreassian V, Perrin C, Michel C, Moine NL. 2008. Spatial proximity, physical similarity, regression and ungaged catchments: A comparison of regionalization approaches based on 913 French catchments. *Water Resources Research* **44**, W03413.

Reichl PC, Western AW, McIntyre NR, and Chiew HS. 2009. Optimization of a similarity measure for estimating ungauged streamflow. *Water Resources Research* **45**, W10423.

Rose S, Peters NE. 2001. Effects of urbanization on streamflow in the Atlanta area (Georgia, USA): a comparative hydrological approach. *Hydrological Processes* **15(8)**: 1441–1457

Santhi C, Arnold JG, Willians JR, Dugas WA, Srinivasan R, Hauck LM. 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. *Journal of the American Water Resources Association (JAWRA)* **37(5)**: 1169-1188.

Savary S, Rousseau AN, Quilbe R. 2009. Assessing the Effects of Historical Land Cover Changes on Runoff and Low Flows Using Remote Sensing and Hydrological Modeling. *Journal of Hydrologic Engineering* **14(6)**: 575-587.

Sorooshian S, Gupta VK, Fulton J L. 1983. Evaluation of maximum likelihood parameter estimation techniques for conceptual rainfall-runoff models: Influence of calibration data variability and length on model credibility. *Water Resource Research* **19(1)**: 251–259.

Stallman C., McIlwain K, Lemoine D. 2005. The Baldwin County Wetland conservation Plan Final Summary Document. Http://www.wetlands.co.baldwin.al.us. Last accessed on 07/01/2010.

Tu J. 2009. Combined impact of climate and land use changes n streanflow and water quality in eastern Massachusetts, USA. *Journal of Hydrology* **379(3-4)**: 268-283.

Wang X, Melesse AM. 2005. Evaluation of the SWAT Model's Snowmelt Hydrology in a Northwestern Minnesota Watershed. *Transactions of the ASAE* **48(4)**:1359-1376.

Wu K, Xu Y. 2006. Evaluation of the applicability of the SWAT model for coastal watersheds in southeastern Louisiana. *Journal of the American Water Resources Association (JAWRA)* **42(5)**: 1247-1260.

Xia Y, Yang Z, Jackson C, Stoffa PL, Sen MK. 2004. Impacts of data length on optimal parameter and uncertainty estimation of a land surface mode. *Journal of Geophysical Research*, **109**: 142-157.

Yokoo Y, Kazama S, Sawamoto M, Nishimura H. 2001. Regionalization of lumped water balance model parameters based on multiple regression. *Journal of Hydrology* **246(1-4)**: 209-222.

Table 1. Physical similarities between Wolf Bay and Magnolia River watersheds

Physical characters	Wolf Bay	Magnolia
Min elevation (m)	0	6
Max elevation (m)	34	36
Mean elevation (m)	16.65	25.31
Area (km^2)	126.04	44.82
Rural area 2005 (%)	72.8	73.65
Urban area 2005 (%)	27.2	26.35
Soil Clay (%)	8.61	12.33
Soil Silt (%)	18.40	24.24
Soil Sand (%)	72.99	63.43
Mean slope	1.88	1.42

Table 2. Calibrated SWAT parameters (flow part) and their default values

	Curve Number	Soil AWC	ESCO	surlag	revapmn	Alpha_BF	Manning's n
Default	Varies*	Varies**	0.95	4	10	0.048	0.014
Calibrated	3	-0.01	1	1	500	0.015	0.114

* Varies by soil type and LULC
** Varies by soil type

Table 3. Model performance (flow part) at Magnolia River watershed

	R^2	E_{NS}	*MBE* (%)
Monthly streamflow			
Calibration	0.84	0.82	-7.1
Validation	0.80/0.78*	0.65/0.74*	-2.0/4.7*
Monthly surface runoff			
Calibration	0.88	0.83	3.6
Validation	0.83	0.68	-4.8
Monthly baseflow			
Calibration	-	-	-13.4
Validation	-	-	0.4
Daily streamflow			
Calibration	0.51	0.50	-7.1
Validation	0.45/0.54*	0.39/0.54*	-2.0/4.7*

* Model performance after removing the extreme event on 04/01/2005

Table 4. Model performance (water quality part) at Magnolia River watershed

	R^2	*Ens*	*MBE (%)*
Monthly TSS			
Calibration	0.90	0.85	8.7
Validation	0.93	0.88	-2.2
Monthly Min-P			
Calibration	0.95	0.86	9.4
Validation	0.87	0.77	-21.3
Monthly Org-P			
Calibration	0.97	0.95	15.7
Validation	0.78	0.76	-1.8
Monthly Org-N			
Calibration	0.93	0.92	-11.6
Validation	0.66	0.61	-7.4
Monthly Min-N			
Calibration	0.74	0.60	-14.8
Validation	0.87	0.85	4.7
Monthly TP			
Calibration	0.96	0.89	11.0
Validation	0.86	0.80	-16.7
Monthly TN			
Calibration	0.75	0.62	-14.5
Validation	0.88	0.86	4.5

TSS: Total suspended solid
Min: Mineral nutrient
Org: Organic nutrient

Table 5. Calibrated SWAT parameters (water quality part) and their default values

	BC4	PSP	PHOSKD	BC1	PPERCO	RS5	AGRRC	Sol_minP
Default	0.35	0.4	175	0.55	10	0.05	0.3	5
Calibrated	0.1	0.7	200	1	17.5	0.1	0.055	3
	PRF	BC3	P_UPDIS	BC2	NPERCO	RS4	RCN	Mgt for AGRR
Default	1	0.21	20	1.1	0.2	0.05	1	Auto fertilize, heat unit
Calibrated	0.6	0.4	100	2	1	0.001	2	Cotton peanut rotation, date

Table 6. Model performance at daily time scale in Wolf Bay watershed

	Default Parameters	Transferred Parameters	Calibrated Parameters
MBE(%)	0.478	0.516	-0.025
R^2	0.536	0.637	0.63
E_{NS}	-2.067	-0.208	0.618

See text for explanation of terms

Table 7. Kolmogorov–Smirnov test for daily and monthly simulated streamflows generated with different parameter sets.

year	Kolmogorov–Smirnov test				Daily average rainfall (mm)	Daily Max rainfall (mm)
	KSa daily	p-daily	KSa monthly	p-monthly		
2000 (dry)	11.421	<0.0001	0.816	0.518	1.1	192.8
2005 (wet)	2.924	<0.0001	0.612	0.848	4.8	50.5

The significance of KSa is 0.95

Table 8. Land use/cover (LULC) change in Wolf Bay watershed

Land Use	1992(%)	2005(%)	Change(%)
Forest	29.80	20.70	-9.10
Hay	41.20	12.90	-28.30
Wetland	11.20	13.40	2.20
Agricultural	13.30	28.80	15.50
Residential low density	3.50	21.60	18.10
Residential high density	1.10	2.40	1.30

Table 9. Annual statistics of streamflow under different LULC conditions

	Maximum flow (m^3s^{-1})			Minimum flow (m^3s^{-1})			Mean flow (m^3s^{-1})		
Year	1992	2005	Change(%)	1992	2005	Change(%)	1992	2005	Change(%)
1999	7.26	11.74	61.7	0.266	0.194	-27.2	0.835	0.793	-5.01
2000	1.15	2.48	115.3	0.071	0.054	-24.6	0.175	0.193	10.08
2001	1.30	2.67	104.7	0.127	0.105	-16.8	0.255	0.253	-0.65
2002	14.25	21.67	52.1	0.078	0.062	-20.1	0.428	0.509	18.80
2003	8.53	13.63	59.8	0.317	0.243	-23.3	1.003	1.036	3.32
2004	11.30	17.66	56.3	0.438	0.276	-36.9	0.876	0.901	2.85
2005	18.09	25.43	40.6	0.529	0.411	-22.4	1.247	1.213	-2.78
2006	2.81	5.48	95.0	0.196	0.138	-29.3	0.458	0.481	5.19
2007	8.40	13.70	63.1	0.250	0.175	-29.9	0.592	0.620	4.63
2008	4.21	6.94	64.9	0.515	0.331	-35.8	0.855	0.866	1.33
2009	4.84	8.41	73.8	0.510	0.327	-35.9	0.799	0.810	1.38
Mean	7.47	11.80	58.0	0.300	0.211	-29.7	0.684	0.698	1.98

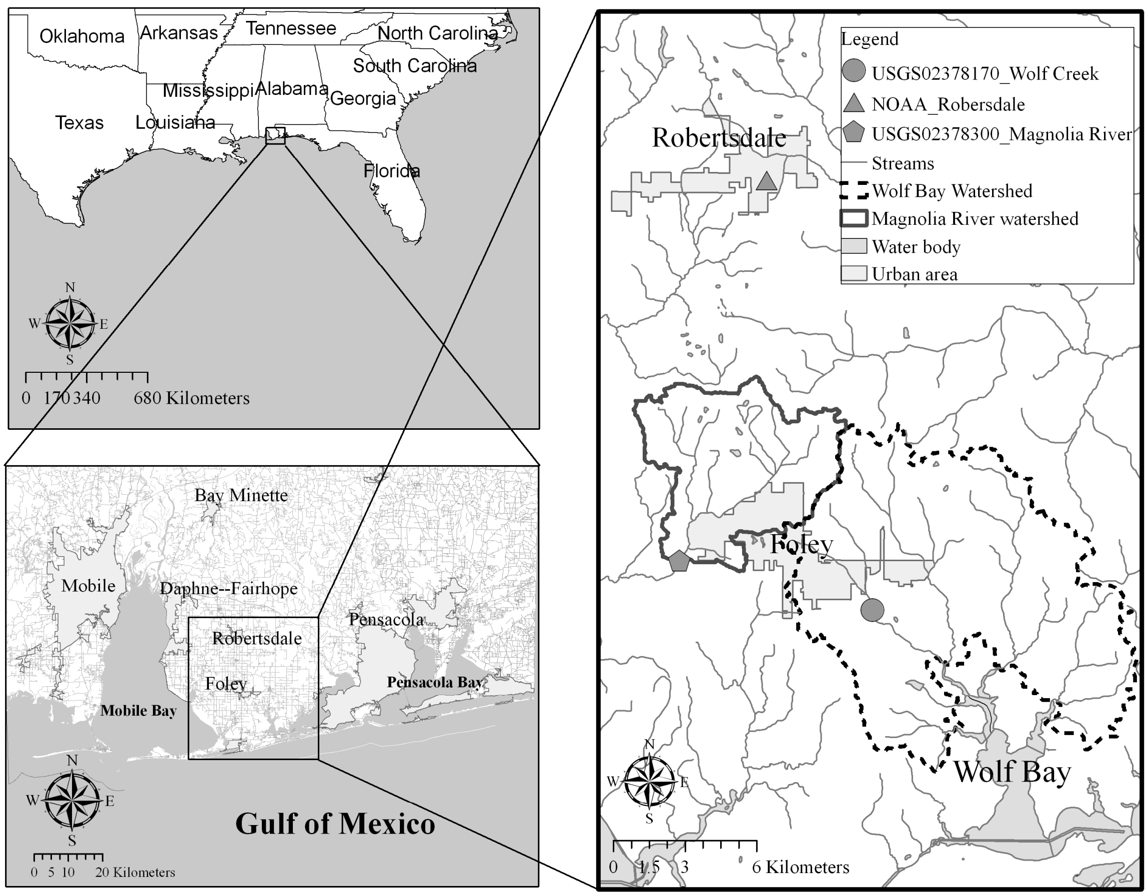

Fig.1 Geographical location of Wolf Bay and Magnolia River watersheds

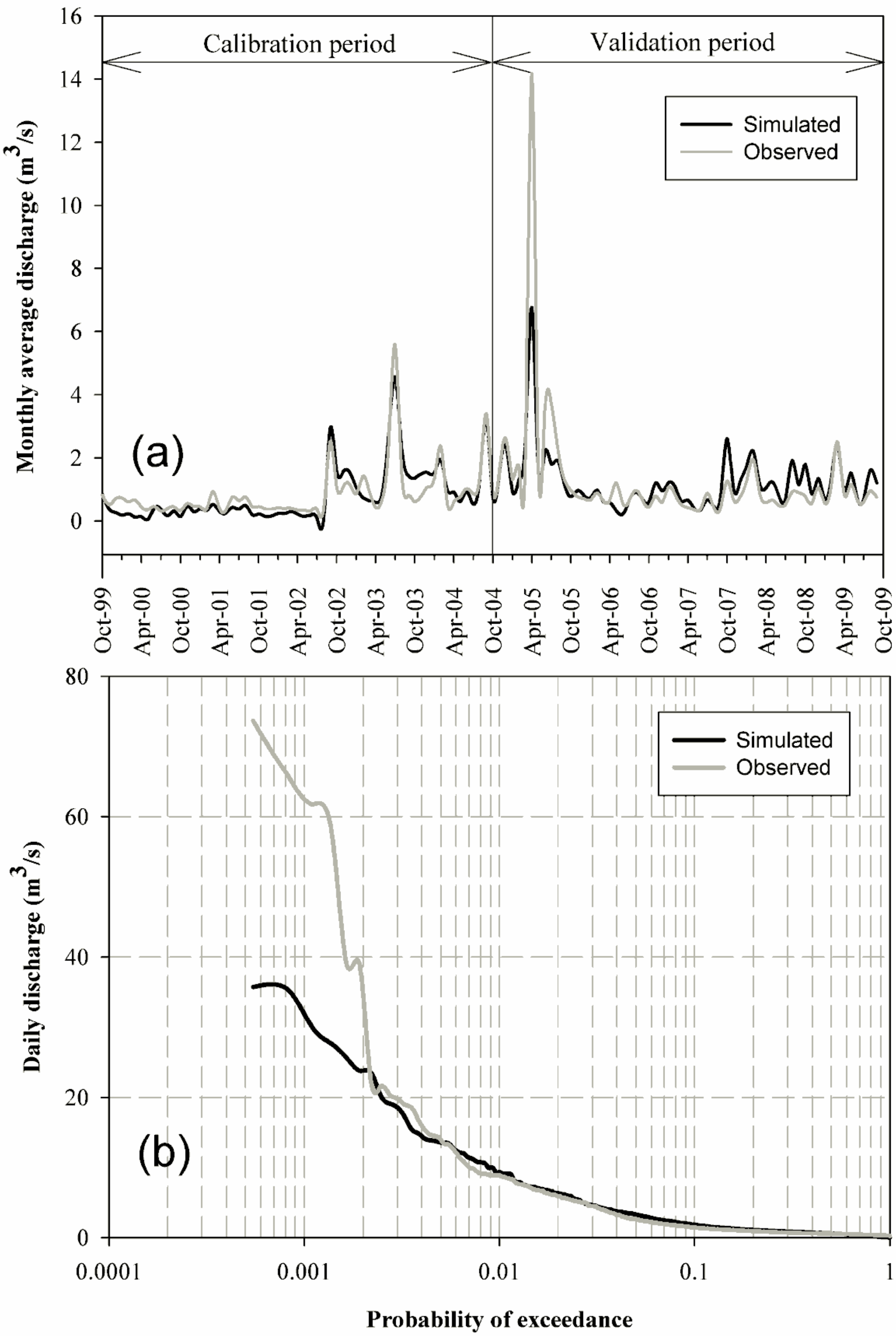

Fig.2 Simulated streamflow compared with observed data from 1999 to 2009 in Magnolia river watershed , (a) monthly time series (b) daily flow duration curve

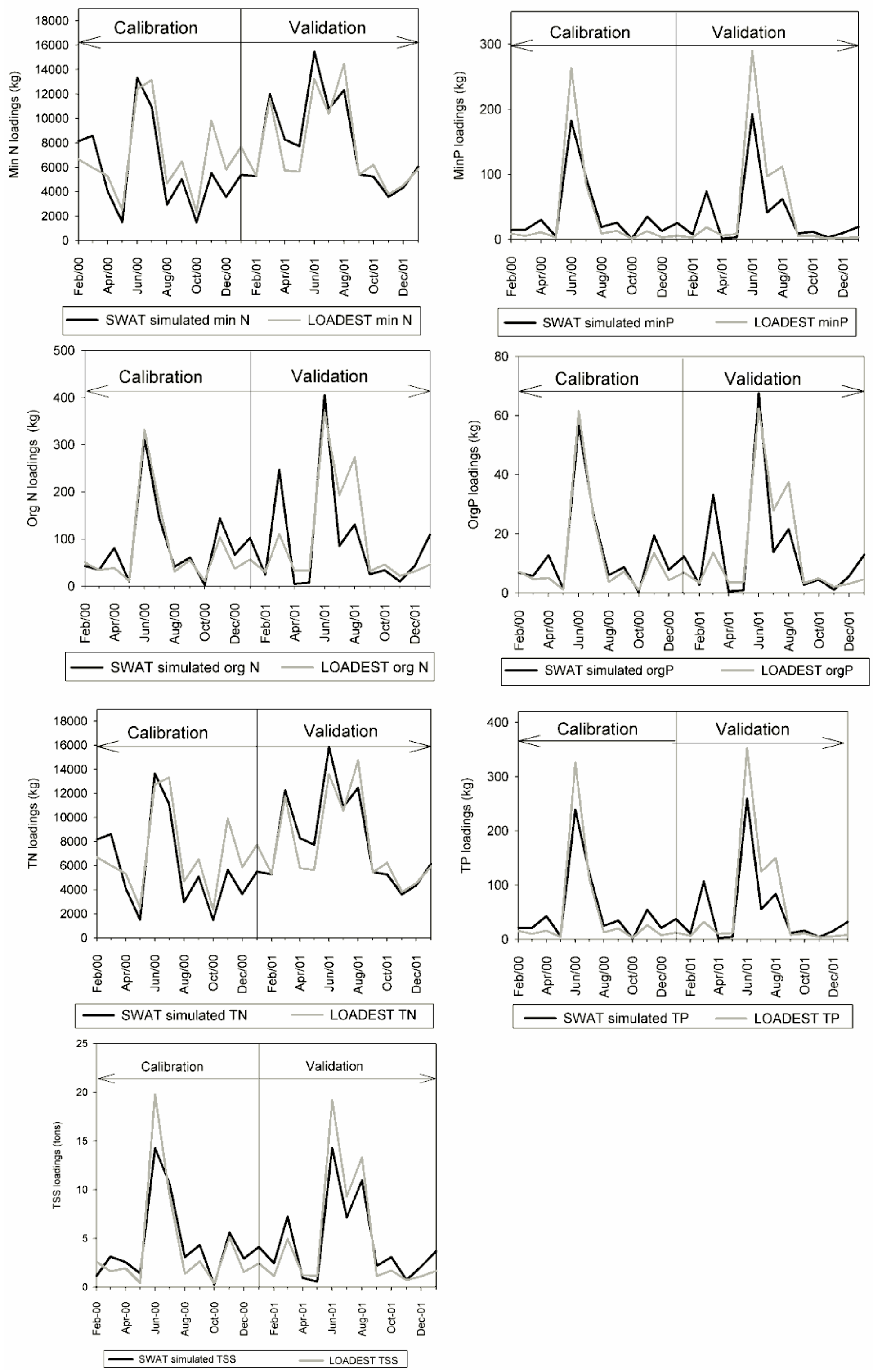

Fig.3 Simulated monthly sediment and nutrient compared with observed data (LOADEST) from 2000 to 2001 in Magnolia River watershed

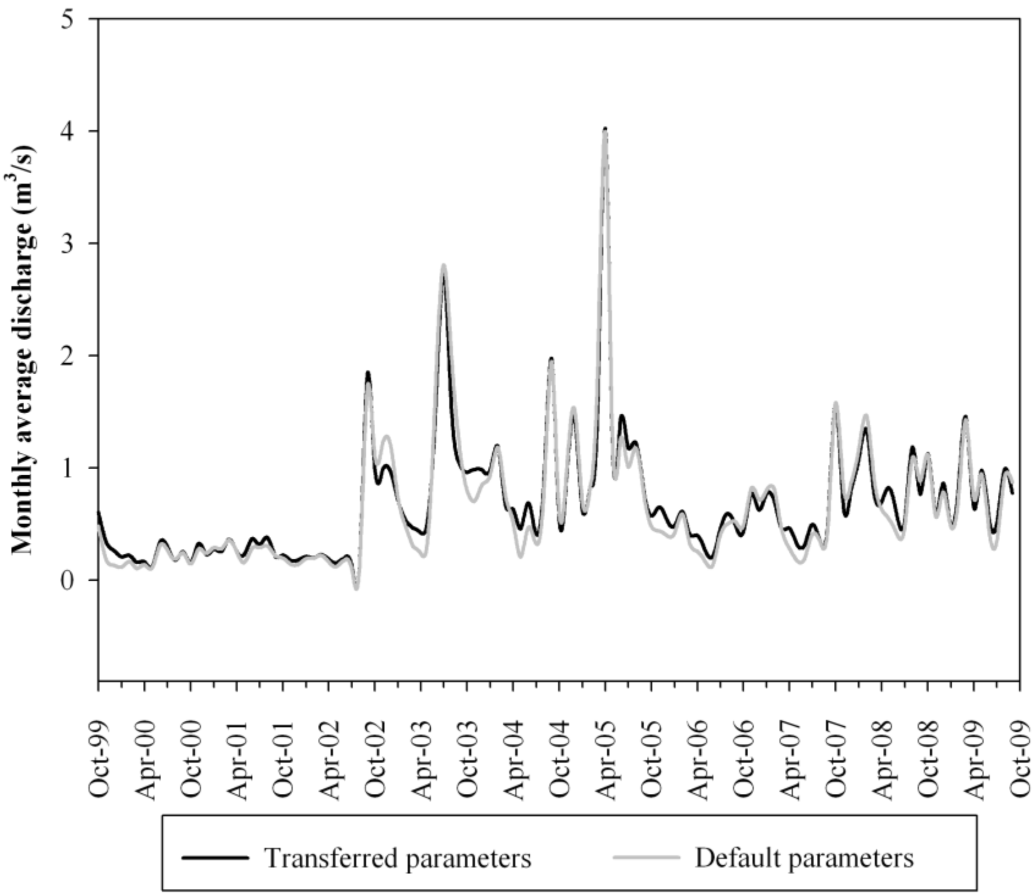

Fig.4 Monthly simulation streamflow for different parameter sets in Wolf Bay watershed

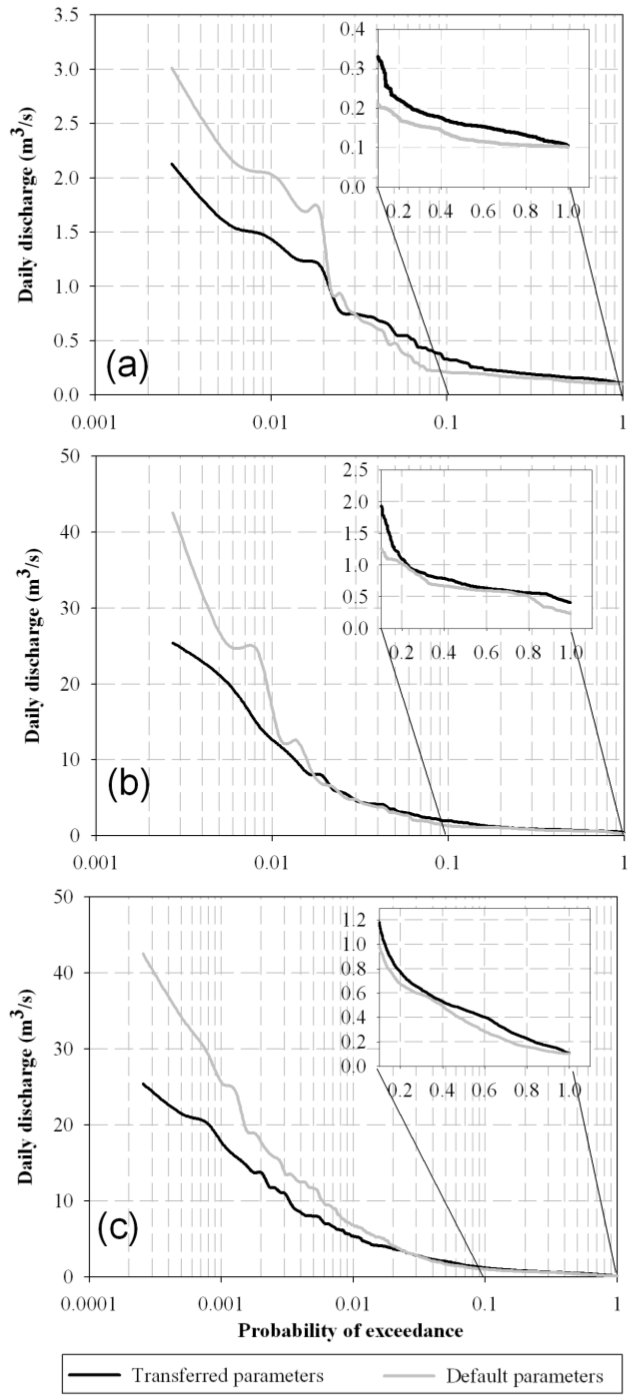

Fig.5 Flow duration curve using different parameter sets in Wolf Bay watershed, (a) dry year 2000, (b) wet year 2005, (c)whole period 1999-2009

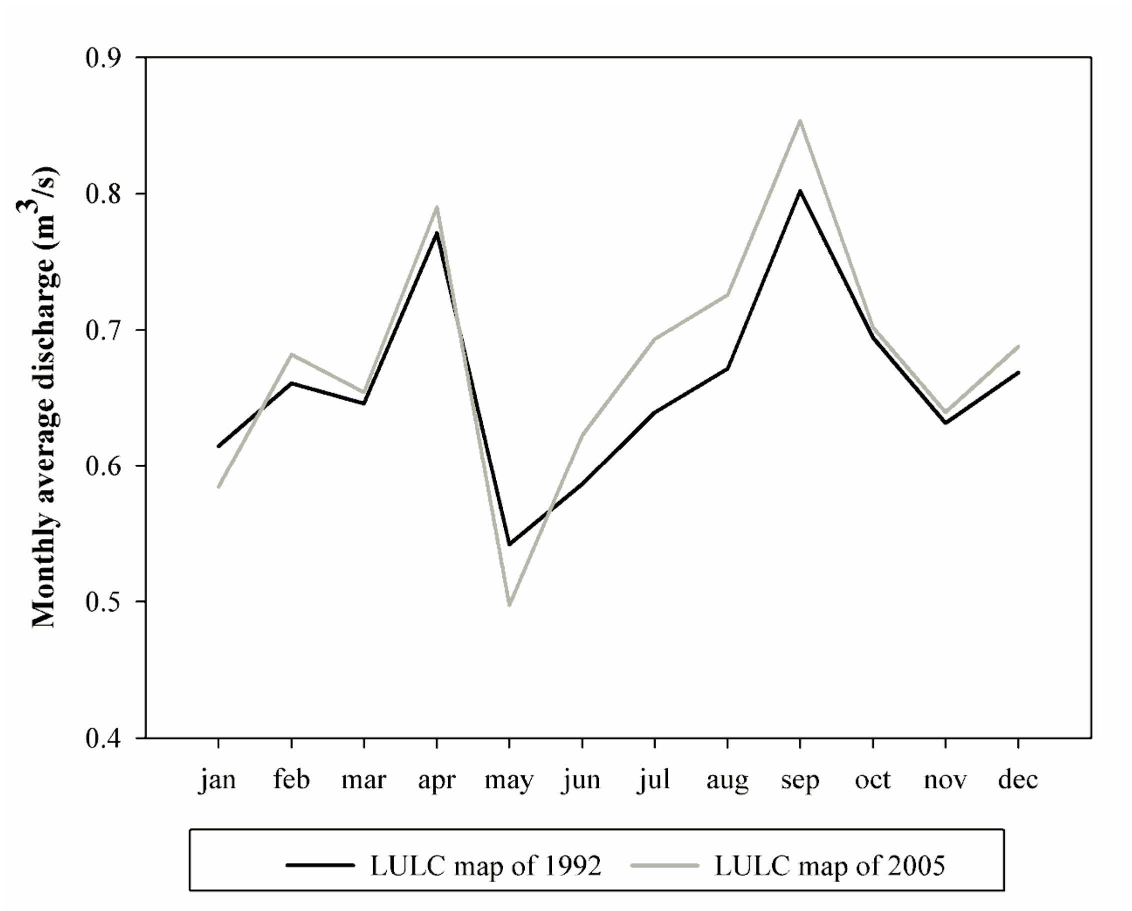

Fig.6 Average monthly flow before and after land use change

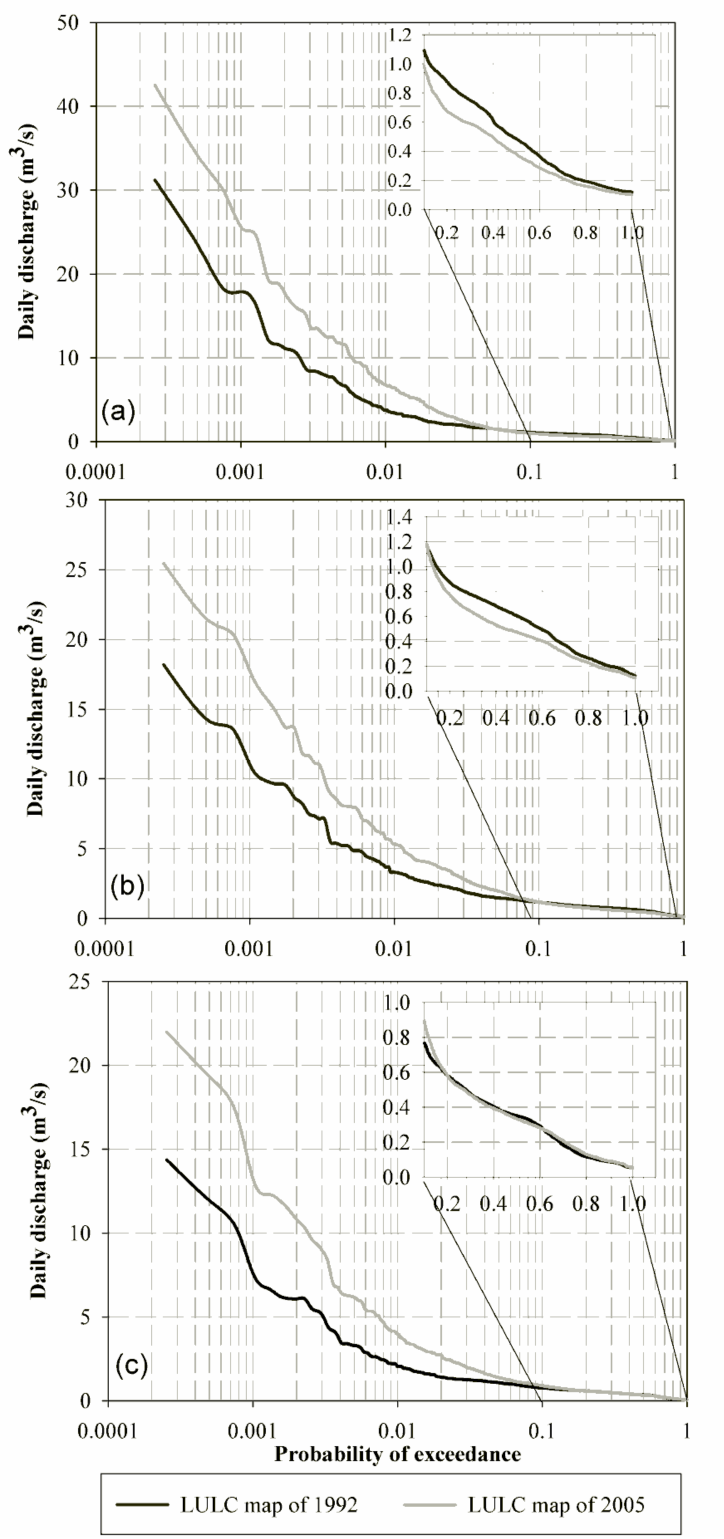

Fig.7 Flow duration curve using different land use maps in Wolf Bay watershed by (a)default (b)transferred (c)calibrated parameters

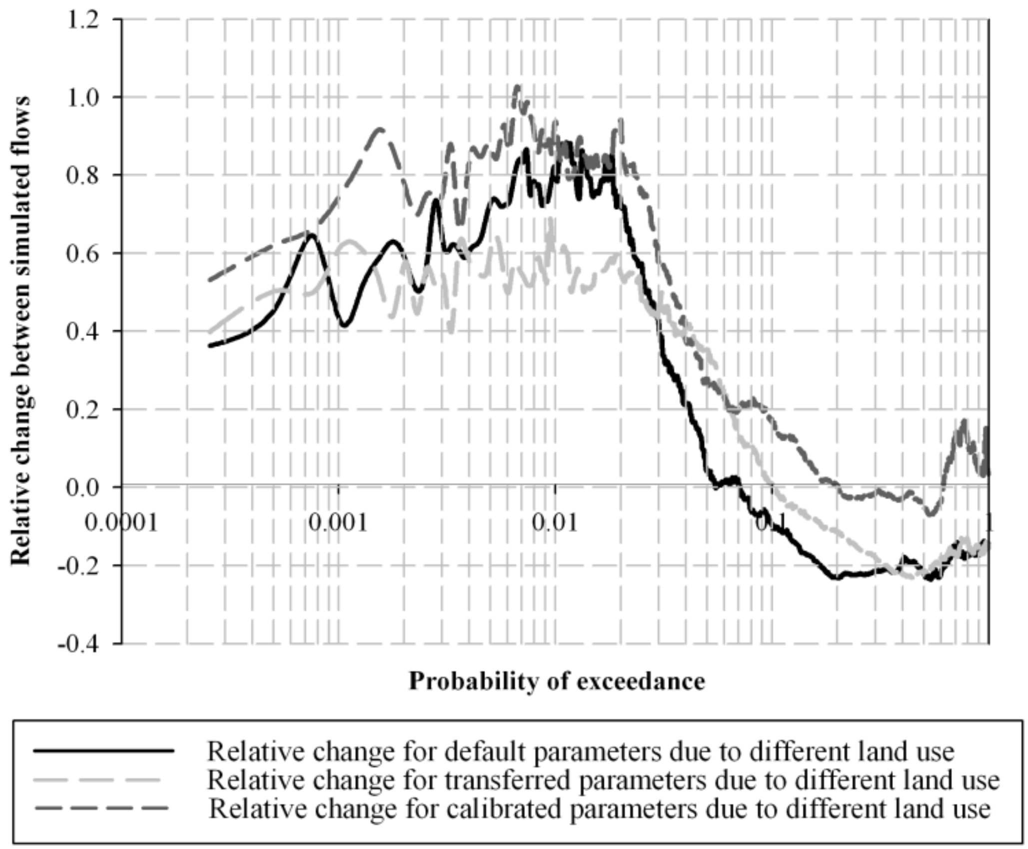

Fig.8 Relative change in simulated streamflows due to different LULC for different parameters in Wolf Bay watershed (1999-2009)

Chapter II

Responses of Hydrological Processes and Water Quality to LULC and Climate Change in Wolf Bay Watershed, Southern Alabama

ABSTRACT

Land use/cover (LULC) and climate change are two main factors affecting watershed hydrology and water quality. In this chapter, the individual and combined impacts of LULC and climate change on flow and water quality were analyzed by SWAT model by simulating the future changes under different LULC and climate change scenarios in the Wolf Bay watershed. Global Circulation Models (GCM) predict slight increase in precipitation in the Wolf Bay watershed, which is projected to experience substantial increase in urban percentage in the future. A redistribution of daily streamflow is projected when either climate or LULC change was considered. High flows are predicted to increase, while low flows are expected to decrease. Combined change effect results in more noticeable uneven distribution of daily streamflow. Monthly average streamflow and surface runoff are projected to increase in spring and winter, but especially in fall, under normal future climate conditions. LULC change does not have a significant effect on monthly average streamflow, but affect partitioning of streamflow, causing higher surface runoff and lower baseflow. Combined effect led to more dramatic increasing trend in monthly average streamflow with a stronger increasing trend in surface runoff and decreasing trend in baseflow. Monthly distribution and projected variation of TSS followed the pattern of flow. Monthly distribution and projected variation of nutrients are complicated, which are

influenced by flow as well as management practices, such as tillage, fertilization and harvesting. Under the climate change scenarios, the variation of TN and TP generally followed the trend of flow. No significant difference in N:P ratio was projected. Under the LULC change scenarios, TN was projected to decrease for all months, which is induced by shrinkage of croplands. TP was projected to increase in fall and winter, since urban areas are also source for TP. The N:P ratio showed a strong decreasing trend with LULC changes. Under the combined change scenario, LULC and climate change effect were considered simultaneously. Results indicate that if future loadings are expected to increase/decrease under either climate or LULC change scenarios, combined change scenario intensifies that trend synergistically. On the other hand, if their effects are in opposite directions, then the combined change has an offsetting effect.

INTRODUCTION

Alteration in flow regimes and water quality deterioration due to land use/cover (LULC) and climate change are of great concern all over the world. LULC changes, mostly caused by human activities including changes in vegetation types, soil properties, land use practices and spatial patterns of interactions among these factors, affect water quantity and quality, often negatively. Many studies have been conducted to explore this strong influence. Zhang and Schilling (2006) found that conversion of perennial vegetation to seasonal row crops in the Mississippi River basin has partly contributed to the increasing trend of baseflow and streamflow. Ouyang *et al.* (2010) studied soil erosion dynamics in response to landscape pattern and found that landscape pattern plays an important role in soil erosion. For instance, smaller patch size and more patch edge led to lower sediment loads in grasslands.

The most commonly observed LULC change is due to urbanization, which has been intensively studied in recent years. Urbanization leads to an increase in impervious areas which decrease the amount of water that infiltrates into the soil. Thus, while baseflow contribution to streamflow reduces, runoff increases, which results in more frequent and intense flooding (Rose and Peter, 2001; Huang *et al.*, 2008). Urbanization also affects water quality adversely. It causes increase in sediment and nutrient loads, heavy metals, blooming of toxic algae which can reduce dissolved oxygen levels in waters (Bakri *et al.* 2008; Susana *et al.* 2008). Kim *et al.* (2002) modeled the changes in average annual runoff due to urbanization in the Indian River Lagoon Watershed of Florida. They found that the average annual runoff increased by more than 113% between 1920 and 1990. Ouyang *et al.* (2006) assessed the impact of urbanization on river water quality in the Peral River delta zone, China. They found that urbanization and urban activities had a significant negative impact on the river water quality with significant increase in nutrient loadings and turbidity.

Studies show that climate change leads to intensification of the global hydrological cycle and has a major impact on regional water resources, which affects both the distribution and availability of water resources and in turn influences processes controlling water quality, such as erosion, sediment transport and deposition, settling of nutrient and pollutions (Dam, 1999; Oki and Kanae *et al.*, 2006; Konikow and Kendy, 2005). Not only deterioration in water quality is a problem by itself, but also it contributes to the problem of water scarcity. Ficklin *et al.* (2009) assessed the climate change effect on San Joaquin Valley watershed in California and found that under future scenarios, streamflow will increase by 23.5%. Marshall and Randhir (2008) investigated the effect of climate change in the Connecticut River watershed, New England, by employing two downscaled GCM model outputs. They found that due to warming in climate water storage will decrease during the winter months. They further predicted increased sediment loadings in summer months in spite of a decline in surface runoff rate. This was because of antecedent moisture conditions, variability in sediment transport capacity resulting from soil characteristics, and detachment process caused by higher precipitation. N:P ratio was projected to increase, resulting in the watershed becoming more nitrogen limited. Cruise *et al.* (1999) coupled the United Kingdom Hadley Center climate model with a regional stochastic approach and a physically based soil moisture model in the southeastern U.S. Results of their study revealed that several basins located in regions of intense agricultural activity or in proximity to the gulf coast are projected to have reduction in streamflow over the next 30-50 years, thus exacerbating water quality problems, such as high nitrogen concentration levels.

From the past studies it is obvious that both LULC and climate change play key roles for water resources and water quality, yet their combined effect and relative importance is still not very clear, difficult to separate empirically, and varies from case to case. Several studies (Qi *et al.*, 2009; Liu *et al.*, 2010; D'Agostino *et al.*, 2010) explored the combined effect from both LULC and climate change. Mango *et al.* (2010) used modeling to determine the impacts of LULC and climate change scenarios on the water flux of the upper Mara River, Africa. They found that deforestation resulted in a slightly more erratic discharge while rainfall and air temperature changes had a more predictable impact on the discharge and water balance components. Guo *et al.* (2008) studied the combined effects of climate and LULC change to hydrological processes in Poyan Lake basin, China. They found that climate change is more likely to alter annual streamflow, while LULC change may have a moderate impact. Both of them strongly influenced seasonal variation in streamflow. Olivera and Defee (2007) studied urbanization effects on a 223 km^2 watershed located in the northwest suburbs of Houston, TX.

They found that runoff depths and peak flows have increased by 146% and 159%, respectively, since early 1970s. Urbanization was responsible for 77% and 32% of the increase, respectively, while variation in precipitation accounted for the remaining increase of 69% and 127%.

As a valuable tool for studying the processes governing impacts of climate and LULC change on water quantity and quality, modeling is an inherently probabilistic exercise (Praskievicz and Chang, 2009). Generally, there are three different aspects of uncertainty in assessing impacts on hydrology and water quality. The first source of uncertainty is from future climate. This could come from (i) choice of the Global Circulation Models (GCMs) and future greenhouse gas emissions scenarios, and (ii) representation of climatology at regional scales, including differences between dynamical and statistical downscaling methods. The second source is associated with future LULC conditions, which are quite hard to predict and are often affected by land use policy, economic development, population increasing rate and natural environment. The third source of uncertainty stems from hydrologic models, such as model parameter estimation and model structure, like mathematical representation of the physical processes, which require many assumptions and simplifications. When projecting the impacts from potential future changes, uncertainty is inevitable and amplifies at each stage of the modeling process. Therefore, addressing uncertainties stemming from modeling potential LULC and climate change impacts and their combined effect is essential.

Although there are several studies in the literature focusing on the combined effects of LULC and climate change on water quantity/quality, the following research gaps remains still exist:

1. Most of the previous studies are confined in the aspect of water quantity (Ma *et al.*, 2009; Li *et al.*, 2009; Cuo *et al.*, 2009), with few studies addressing the effect on both water quality and quantity. Those studies concerned with the combined effects of climate and LULC change on

sediment or nutrients involved very limited water quality indices. For example, Tu (2010) assessed the seasonal distribution and annual averages of nitrogen loadings in eastern Massachusetts, USA. Similarly, Asselman *et al.* (2003) estimated the potential effects of climate combined with LULC changes on the mobilization of fine sediment and the net transport of wash load from the upstream basin to the lower Rhine delta. However, influences on nutrient were not stated in their paper.

2. Compared to future climate change scenarios, which usually contain various GCM outputs under different green house gas emission scenarios, LULC change scenarios are too simplistic and do not consider the factors affecting LULC changes, such as land use policy, economic development, and natural environment. For example, Montenegro and Ragab (2010) explored the hydrological response of a Brazilian semi-arid catchment to combined effect of LULC and climate change. However, their land use change scenario was hypothetical and overly simplified, replacing different amounts of catinga forest with castor beans.

3. The uncertainties of model results are not satisfactorily addressed in most of the studies. As stated before, the uncertainty in the model output originates from many sources. Some studies only acknowledged the uncertainty caused by climate inputs. For example, Wilby *et al.* (2006) studied climate change impacts on water resources and water quality in a British lowland catchment by 3 GCMs and 2 green house emission scenarios. Their results confirmed the large uncertainty in climate change scenarios and freshwater impacts due to the choice of GCM. However, there are limited studies dealing with the uncertainties from climate combined with LULC change.

In this study, a process-based hydrologic and water quality model, Soil and Water Assessment Tool (SWAT) was utilized to simulate flow, sediment and nutrient (N and P) loadings under future climate and LULC conditions in Wolf Bay watershed, which drains to the Gulf of Mexico. The specific objectives are: (1) to explore the hydrologic and water quality responses to combined effects of climate and LULC change, (2) to examine whether climate change exacerbates or offsets the impacts of LULC change and vice versa. Uncertainties caused by climate and LULC change are also analyzed for both objectives.

METHODOLOGY

Study Area

Wolf Bay and its watershed (Fig. 1) is located on the Gulf of Mexico in Baldwin County, Alabama, nestled between Pensacola Bay to the east and Mobile Bay to the west, with a watershed covering about 126 km^2. As an estuary where freshwater and saltwater mix, it creates a diverse environment that fosters a rich array of plant and animal life, including several federally listed species, such as bald eagles, sea turtles, Gulf sturgeons, American alligators and Eastern indigo snakes. Wolf Bay and its surrounding waters are the most pristine estuarine waters in Alabama, which was granted "Outstanding Alabama water" status by Alabama Department of Environmental management in April, 2007. The beautiful waters attract many people to coastal Baldwin County, contributing greatly to the economic base of coastal communities through tourism, commercial and recreational fishing and aquaculture.

Wolf Bay watershed is primarily rural, but several municipalities exist including Foley, Elberta, Gulf Shores, and Orange Beach (Fig. 1). The basin generates various nutrient and sediment inputs from several sub-watersheds through Wolf, Sandy, Miflin and Hammock creeks, which finally drain to the Wolf Bay. Alteration in vegetations, management practices of the watershed can change hydrology and water quality, and in turn can significantly affect the water resource and ecologic health of the bay.

Baldwin County experienced a 43% increase in population from 1990 to 2000. As a result of this population growth, there has been an increased demand for commercial, residential, and infrastructure development, thus bringing growth management issues to the forefront for local elected officials. One of the more visible changes in the landscape of Baldwin County is the rapid transformation of agricultural and forested lands to residential development. Such LULC change is deemed to affect water quantity and quality, usually negatively. Considering the potential climate change effects, the situation becomes more complicated. Their potential effects can be reflected in:

(1) Water quality: Increased soil erosion can change the shoreline from sandy to muddy, which could destroy the fish stock and damage the benthos and habitats. Increased turbidity also degrades the ecosystem by decreasing the light available for photosynthesis. Further, excessive nutrients can lead to water quality degradation, which reduce dissolved oxygen, causing hypoxia or anoxia. This may destruct the whole ecosystem by blooming harmful algae and therefore causing massive fish kills.

(2) Water quantity: Due to climate and urbanization, it is anticipated that peak flows will increase and dry season flows will decrease, thus exacerbating flooding in wet seasons and droughts in dry seasons. This will also affect water quality indirectly. For example, if the estuary is slowly flushed, the extra load of nutrients and pollutants will cause degradation in water quality, ecological services and biodiversity. Also, fluctuations in freshwater discharge to the bay affect the salinity of water, which affects the health and incubation of fishes. For example, a

slight change in salinity can cause fish, frog or shrimp eggs to float too much (high salinity) or not enough (low salinity), thus reducing or eliminating their chances of development into adults.

Because of all these, we found a unique opportunity to study the potential impacts of LULC and climate changes on hydrologic responses and water quality in the Wolf Bay watershed. Findings from this study should benefit local stakeholders and decision makers in the Wolf Bay area.

Watershed model

The Soil and Water Assessment Tool (SWAT) version 2005 (Neitsch et.al, 2005) was used in this study. SWAT is one of the most widely used models for assessing the impact of management practices and land disturbances on watershed responses, and has a solid track record of applications (Kalin and Hantush, 2006 ; Gul and Rosbjerg, 2010; Pisinaras V *et al.*, 2010). SWAT has been widely used around the world, such as Nzoia catchment, Kenya (Githui *et al.*, 2009), Rocky Mountain Watershed, Montana, USA (Ahl *et al.*, 2008), Kielstau catchment in North German lowlands (Lam *et al.*,2010), etc., to assess various impacts of agricultural practices and land use activities on water quantity and quality. SWAT is also suitable for coastal and flat areas, which has more complicated geo-hydrologic conditions (Wu and Xu, 2006). SWAT is a distributed, process-based watershed model. It is partly physical-based with number of empirical relationships. The physical backbone of the model facilitates the interpretation of model parameters whereas the empirical simplifications keep data requirements low compared to fully physical based models (Heuvelmans, 2004). SWAT divides a watershed into several subwatersheds based upon drainage areas of the tributaries. Each subwatershed is split into multiple hydrological response units (HRUs) based on LULC and soil types. Each HRU is assumed to be spatially uniform in LULC, soil, topography, and climate. SWAT simulates eight major components: hydrology, weather, sediment, soil temperature, crop growth, nutrients, pesticides, and agricultural management (Neitsch *et al.*, 2005). Major hydrologic process that can be simulated by the model include evapotranspiration, surface runoff, infiltration, percolation, shallow aquifer and deep aquifer flow, and channel routing (Arnold *et al.*, 1998). Erosion and sediment yield are estimated for each HRU with the Modified Universal Soil Loss Equation (MUSLE) (Williams, 1975). Sediment routing is also considered based on deposition and degradation processes. SWAT also tracks the movement and transformation of several forms of nutrients (phosphorus and nitrogen) in the soil. Nutrient may be introduced to the main channel by surface or subsurface runoff, nutrient routing in the stream is then controlled by the in-stream water quality component adapted from QUAL2E (Brown and Barnwell, 1987). Detailed description of processes modeled in SWAT can be found in Neitsch *et al.* (2005).

LULC data

In order to explore the LULC change effect on hydrology and water quality in the Wolf Bay watershed, present and projected LULC maps are needed. LULC map circa 2005 is used to represent the current period. It is a vector dataset attained by trend analysis from Baldwin County Planning Commission. This vector dataset is focused on changes in urban and built-up areas, utilities, and transportation from 2001 to 2005 based on Color Infrared imagery 2001 and 2005 for the whole Baldwin County. Using this trend map as a reference, GIS specialists at Auburn University improved its accuracy and produced LULC map of 2005. This map is a product of an interdisciplinary project “Impact of Human Activities and Climate Change on Water Resources and Ecosystem Health in Wolf Bay Basin: A Coastal Diagnostic and Forecast System (CDFS) for Integrated Assessment". Based on this map, Wolf Bay watershed is dominated by agricultural land (30%) followed by urban area (26.4%) and forest (20.9%). High percentage of urban area and crop land is due to conversion from forest and pasture land in the past 10-15 years.

Future LULC of the Wolf Bay watershed was projected by members of the same interdisciplinary project at Auburn University. They developed an advanced LULC model by linking GIS techniques and remotely sensed images creating a hybrid model. The predicted LULC change is driven by land demands, physical properties such as topography and distance to major facilities, and disturbances such as extreme climate events (hurricanes, storms and droughts). The LULC prediction model can simply be described as:

$$LULC = f(land\ demand, spatial\ allocation, random)$$

$$Land\ demand = f(population, economy, land\ policy, energy\ price)$$

$$Spatial\ allocation = f(topography, land\ price, distance\ to\ highways, shoreline, roads, rivers, the\ city\ proper)$$

$$Random\ =\ f(hurricane, storm, rising\ sea\ level)$$

Based on this modeling framework, historical LULC data sets and the derived spatial data sets from DEM and survey data were used to generate preliminary simulation results on the projected urban distributions from 2008 to 2040. With the validated LULC model and relevant data sets, projected urban expansions with different population growth scenarios are provided. Three LULC scenarios (Fig. 2) were generated for 2030 assuming high, medium and low population increasing rates (HPR, MPR and LPR). Higher population increase rate causes higher urban fraction and vice versa. Compared with the most recent land use map of 2005, there is a clear trend of urban sprawl. Even with the least aggressive growth scenario, 50% of the watershed is projected to be urban land in 2030 (Table 1). Other LULC types are projected to decline by 2030 owing to the urbanization effect. For example, by comparing LULC map of

2005 with LPR future projected map of 2030, the evident increase of urban area (around 25%) is mainly contributed by decreases of forest, agriculture land, wetland and pasture. The percent reduction in forest cover is around 5%, which does not represent a typical deforestation trend in future. The disparity in some of the LULC types among the three projected LULC maps of 2030 is not so significant, especially for forest, pasture and wetland. The main difference is in percentages of urban and agricultural land. Higher population increase rate causes higher urban fraction and lower cropland percentage. For example, the increase of urban fraction is 25%, 32% and 39% for LPR, MPR and HPR, respectively while the reductions in cropland are 5%, 10% and 15%, respectively.

Climate data

Monthly precipitation and temperature for future scenarios

In order to demonstrate the variability of future climate, outputs from four Global Circulation Models (GFDL_cm2_0 (Delworth *et al.*, 2006), GISS_model_e_r (Russell *et al.*, 2000), NCAR_ccsm3_0 (Collins *et al.*, 2006), UKMO_hadcm3 (Gordon *et al.*, 2000)) under 3 green house gas emission scenarios (A2, A1B, B1) were utilized to attain potential monthly precipitation and temperature estimates in the Wolf Bay watershed for the period 2016-2040. This corresponds to a 25 year period, which is long enough to explore the potential responses due to climate change. Further, the future LULC map of 2030 roughly falls in the middle of this time period, which presents a more realistic set up for exploring the combined effects of climate and LULC change.

All climate projections were provided by "the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset" which was referenced in the Intergovernmental Panel on Climate Change Fourth Assessment Report. CMIP3 data is bias-corrected and spatially downscaled by Maurer *et al.* (2007) to a finer spatial resolution (1/8 degree). Spatially downscaled monthly rainfall and surface air temperature data (available at: http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections/) were further downscaled to daily time scale as explained below.

Since there is no observed data for future scenarios, ensuring the reliability of GCMs projection is quite important. Generally, GCMs also provide simulated precipitation and temperature for historic periods, which should compare well with observed climate data. In most of the cases, those historic GCM outputs match well with observed data at large spatial scales (e.g. global or continent scale). However, once spatially downscaled, those products could become quite different from historic data at smaller scales, such as watershed level, which is often the required scale for hydrologic modeling. Therefore, even spatially downscaled climate projections cannot be directly utilized as climate input for hydrologic modeling. Refinement of those spatially downscaled data is often necessary.

The method recommended by Tung *et al.* (2006) was used to determine monthly temperature and precipitation for different climate scenarios:

$$\bar{T}_k = \bar{T}_k^b + \left(\bar{\tau}_k^f - \bar{\tau}_k^b\right) \qquad (1)$$

$$\bar{P}_k = \bar{P}_k^b + \left(\bar{\rho}_k^f - \bar{\rho}_k^b\right) \qquad (2)$$

where $\bar{T}_k$ and $\bar{P}_k$ are mean monthly temperature (^{0}C) and precipitation (mm) for future periods (2016-2040); $\bar{T}_k^b$ and $\bar{P}_k^b$ are observed historic mean monthly temperature (^{0}C) and precipitation (mm) for the baseline period (1984-2008); $\bar{\tau}_k^b$ and $\bar{\rho}_k^b$ are mean monthly temperature and precipitation coming from GCM predictions for the baseline period ; and $\bar{\tau}_k^f$ and $\bar{\rho}_k^f$ are GCM projected mean monthly temperature and precipitation for appropriate future periods. The subscript k in each term represents the month. Note that future period spans from 1/1/2016 to 12/31/2040 and the baseline period spans from 1/1/1984 to 12/31/2008. Therefore, while k =1 represents Jan 1984 in the baseline period, it represents Jan 2016 in the future period. In other words, there is a one to one correspondence between the months of baseline and future periods. For example, May 2020 in the future period corresponds to may 1988 of the baseline period. Equations (1) and (2) assume that the difference in monthly averages of GCM projections between the future and baseline periods are the same as the change between observed historic monthly averages and the future monthly averages. Finally, since there are 4 GCMs and 3 green house gas emission scenarios, 12 groups of future monthly precipitation and temperature data were generated.

Daily precipitation and temperature

Since SWAT simulates flow and nutrients at daily time scale, monthly climate projections still need to be downscaled to daily time scale in order to study the climate change effects on hydrology and water quality. Hence, SWAT model's stochastic weather generator, WXGEN (Sharpley and Williams, 1990) was used to generate daily rainfall from monthly statistics, such as mean monthly rain and number of wet days in that month, etc, to downscale monthly precipitation data to daily time scale. Those statistics are often estimated from historic weather records. SWAT has a built in database for such statistics compiled from long term NOAA rainfall data. For the same monthly parameters, weather generator may produce hundreds of different daily rainfall patterns, which reflects the variation of daily rainfall. In general, 20 sets is the minimum number to obtain a representative distribution of possible weather scenarios given the predicted probabilities (Neitsch et al., 2005). Therefore 21 sets of daily rainfall patterns were generated by WXGEN.

For a given month *m*, future daily precipitation was calculated as follows:

$$P_{m,i} = \frac{r_{m,i}}{\frac{1}{n} \times \sum_{i=1}^{n_m} r_{m,i}} \times \bar{P}_m \tag{3}$$

Where n_m is the number of days in a given month *m*, in this study the total number of months is 25*12=300; *i* is any day in the given month; $P_{m,i}$ reflects projected daily precipitation of day *i* in the given month *m*; $r_{m,i}$ is the generated daily rainfall for day *i* in the given month *m* by WXGEN; $\sum_{i=1}^{n_m} r_{m,i}$ is the total precipitation in the given month *m*; $\bar{P}_m$ is the future mean monthly precipitation coming from equation (1). Since there are 12 groups of $\bar{P}_m$ for each month *m* reflecting different combinations of GCMs and green gas emission scenarios, and 21 sets of $r_{m,i}$ generated by WXGEN, in total, 12*21=252 sets of daily precipitation data were generated.

Compared with daily variation of precipitation, which may substantially affect flow and water quality, daily temperature does not fluctuate substantially in a given month. In this study, daily patterns of daily temperature were not generated; rather daily maximum and minimum temperatures for future were estimated as follows:

$$T_{m,i}^{max} = T_{m,i}^{b,max} + \left(\bar{\tau}_m^f - \bar{\tau}_m^b\right) \tag{4}$$

$$T_{m,i}^{min} = T_{m,i}^{b,min} + \left(\bar{\tau}_m^f - \bar{\tau}_m^b\right) \tag{5}$$

where $T_{m,i}^{max}$ and $T_{m,i}^{min}$ are respectively daily maximum and minimum temperatures for future period (2016-2040) of a given day *i* in a given month *m*; $T_{m,i}^{b,max}$ and $T_{m,i}^{b,min}$ are daily observed maximum and minimum temperatures, respectively, for the baseline period (1984-2008); $\bar{\tau}_m^b$ is the mean monthly temperature from GCM predictions for the baseline period; and $\bar{\tau}_m^f$ is the GCM projected mean monthly temperature for the future period. Obviously, the number of daily temperature patterns is consistent with the number of GCM and green house gas emission scenario combinations, which is 12 as stated before. Lastly, although each GCM under a specific green house gas emission scenario have 21 sets of daily precipitation patterns, it has only one set of daily temperature pattern as SWAT input. For instance, SWAT simulated the GFDL_cm2_0 under A1B scenario 21 times with different daily precipitation, but with the same daily temperature data.

Model experiment set up:

The SWAT simulations were performed for two 25-year time periods. First one was the baseline period, 1984-2008, for which calibration and validation for flow, sediment and nutrient were performed. Since there was no sufficient measured data in the Wolf Bay watershed, SWAT was calibrated and validated in the nearby data rich Magnolia River watershed. Relevant model parameters were then transferred to the Wolf Bay watershed (Wang and Kalin, 2010). This method is called regionalization approach based on spatial proximity and is widely used when there is no enough observed data in a target watershed to ensure model reliability (Merz and Bloschl, 2004; Oudin *et al*., 2008; Reichl *et al.*, 2009). The second period is to simulate future climate from 2016 to 2040, for which the 3 projected LULC map and the 4 downscaled GCM under 3 green house gas emission scenarios for climate conditions were used. Parameter set was assumed to be the same as the one used for the baseline period. In order to detect the marginal and joint effects of LULC and climate change, the approach of one factor at a time was used (Li *et al.*, 2009). This approach changes one factor at a time while holding others constant. We designed the model experiments based on that, as outlined below:

i) *Baseline run*: Most recent LULC map of 2005 and daily measured climate data (1984-2008) from NOAA station at Robertsdale (Fig. 1) was used as SWAT input.

ii) *Only climate change effect*: Current LULC map of 2005 and future daily climate data (2016-2040) downscaled from 4 GCM under 3 green house gas emission scenarios were used. Model had 4*3*21=252 ensemble of outputs.

iii) *Only LULC change effect*: Three projected LULC maps for year 2030 and historic climate data (1984-2008) from NOAA station at Robertsdale were used as input.

iv) *Combined change effect*: Three projected LULC maps for year 2030 and future daily climate data (2016-2040) downscaled from 4 GCM under 3 green house gas emission scenarios were used. Model had 252*3=756 ensemble of outputs.

RESULTS AND DISSCUSSION

Climate change effects on precipitation and temperature.

Fig. 3 shows variations in average seasonal precipitation and temperature for the future period (2016-2040) relative to the baseline period (1984-2008). The horizontal axes in each panel indicate changes in average precipitation, while vertical axes denote changes in average temperature. The 12 dots in each panel correspond to 12 different future scenarios (4 GCMs*3 emission scenarios) with the cross indicating the average of 12 scenarios. It is clear that future climate predictions are quite different from each other, and the uncertainty range exhibit a seasonality behavior. Based on Fig. 3, all future projections indicate a rising trend in temperature, but distinct magnitudes are detected according to seasons. For summer and fall, the range is from +0.4 to +2.0 ^{0}C, while for spring and winter, the range is from +0.2 to +1.6 ^{0}C. Annual increase of mean temperature varies from +0.4 to +1.4 ^{0}C. Precipitation has a different pattern than temperature. Although there is no clear trend of increase or decrease in average monthly precipitation for spring, summer and winter, in fall, 11 of the 12 scenarios show increase in precipitation, with an average of 10% for fall months. This is potentially a good thing as fall is typically the driest season in the Southeast U.S. At the annual scale, 8 of the 12 future projections predicted increase in precipitation, approximately 4% on average. Generally, based on Fig. 3, Wolf Bay watershed will more likely experience increased precipitation in future, especially in fall months. Temperature is expected to increase for all seasons, especially in summer and fall.

Fig. 3 provides some general information about the potential changes in precipitation in the future in the Wolf Bay watershed, such as averages and seasonal differences. However, the change in frequency and magnitude of daily rainfall is not shown. Fig. 4 reflects exceedance probabilities for daily precipitation, which provides more insight. Probability of exceedance (PE) in the figure reflects the possibility of having rainfall amount of that magnitude or higher in a given day. Therefore, what is shown in the figure are complimentary cumulative distribution functions (CCDF). Out of the 252 complimentary CDFs generated from 252 sets of future daily precipitation data, Fig. 4 shows only the 95th and 5th percentiles (90% confidence interval). Median of the CCDF's is also shown in the figure. It can be seen that the relative positions of projected precipitation curves and baseline curve differs with PE. Baseline fluctuates around the median curve when PE< 0.001, then falls below the 90% confidence interval from around PE=0.0015 to around PE=0.03. After PE=0.03, relative position of baseline is rising again until it becomes higher than the upper limit around PE=0.15. This means large rain events will be more intense in the future. On the contrary, the rainfall intensity of smaller events (PE<0.15) will be reduced. Combining Fig. 3 with Fig. 4 one can conclude that in the future there will be a shift in rainfall pattern with large events getting more intense and smaller events becoming less intense.

Climate change effects only

SWAT was run at annual, monthly and daily time scales 252 times to simulate flow, sediment and nutrient loadings under future scenarios. From this ensemble of model outputs 5th and 95th percentiles were calculated to represent dry and wet conditions, respectively, in future. Median of the ensemble of model outputs was also used to represent normal conditions. Results are discussed below.

Annual and monthly flow

The projected annual average daily streamflow for the future period was 3.19, 4.87, and 6.81m^3/s, under dry, normal and wet conditions, respectively. Compared to average daily streamflow in the baseline period, which was 4.57 m^3/s, it is hard to judge if there is an increasing trend in average daily streamflow under normal conditions. We conducted a t-test for two independent samples between baseline group and future normal condition group. One-sided p-value (pooled) of 0.16 indicates no significant difference between the two groups. Therefore, the projected increase in annual average daily streamflow is statistically insignificant. For baseflow and surface runoff, the projected daily average values under the normal condition were 2.55 m^3/s and 2.29 m^3/s, respectively. For baseline, the corresponding annual average daily discharges were 2.33 and 2.24 m^3/s, respectively. The t-test resulted in p-values of 0.07 and 0.37 for surface runoff and baseflow, respectively. Therefore, no trend was detected for baseflow under the normal condition. On the other hand, the p-value of 0.07 obtained for surface runoff is not that big. Although at 5% level there is no statistical difference, at 10% there is an increase in surface runoff.

Compared with Cruise's (1999) study, our results doesn't reflect strong decreasing trend in streamflow. Since Cruise's conclusion was only based on the United Kingdom Hadley Center climate model and focused on the whole Southeast U.S., it is not surprising to have different predictions in streamflow.

Fig. 5 shows the 5th and 95th percentiles along with the median of average monthly streamflow, surface runoff and baseflow by running SWAT with the 252 climate inputs. Under wet conditions, streamflow, direct runoff and baseflow are all showing a rising trend for all months when compared to the baseline. For dry conditions, all three reflect a declining trend, though in September and October the difference is marginal. Under the normal conditions, consistent with the rainfall, streamflow and surface runoff are projected to increase in fall months (September, October and November). Winter (December, January, and February) and spring (March, April, and May) will experience moderate increase in streamflow and surface runoff. In summer (June, July, August), no significant difference is predicted in streamflow and direct runoff. Baseflow is projected to decrease slightly in spring and summer, while increase marginally in winter.

Daily flow for the whole period

Fig. 6a shows the 90% confidence interval along with the median of the FDCs generated from daily streamflow by running the SWAT model with the 252 precipitation inputs. In the figure, upper and lower limit represents the wet and dry conditions, while median reflects the normal conditions in the future. According to different probability of exceedance, future daily discharge illustrates substantial differences when compared to baseline. Furthermore, positions of future FDCs relative to the baseline FDC are quite similar to the precipitation CCDFs shown in Fig. 4. This is not quite surprising as precipitation is the main driver for flow.

To get a better insight into the effect of climate change on daily flow responses, the relative difference of future conditions from the baseline, i.e. ([FDC of future conditions] – [FDC of baseline situation]) / [FDC of baseline situation], were generated and depicted in Fig. 6b. Based on this figure, under wet conditions (upper confidence limit), the relative change of flow is always a positive value. It fluctuates between 75% and 10% when PE<0.01. It reaches at a plateau at 40% until PE arrives at 0.1, and then reduces to 10%. Under normal condition (median of 90% confidence interval), relative change fluctuates around 0 when PE<0.001, and reaches a maximum of about 30% around PE=0.01. It then decreases gradually from 30% to 5%, until PE=0.9. After PE=0.9, it drops drastically all the way to -30%. The shapes of these two curves are quite similar, only shifting in relative positions. Under dry conditions, as PE increases from 0 to 0.01, the relative change grows consistently from -40% to 20%. The relative change is 0 when PE is around 0.002. After PE=0.01, it decreases gradually from 20% to -15% until it reaches PE=0.85. From PE=0.85 till the end it drops drastically to -60%. When 0.002<PE<0.3, the relative changes are always positive, which indicates great possibility (90% confidence) of increasing trend in daily flow even under dry conditions in the future. Flows in that range are moderate to large (return period from 3 days to 500 days).

Seasonality effect

From the earlier discussions, it was evident that responses of rainfall and temperature to climate change show strong seasonality. Therefore, it is believed that seasonality exists in the responses of streamflow as well. Similar to FDC for the whole period, 252 sets of daily flows were categorized by seasons, and then sorted. Upper limit, lower limit, and median for the 90% confidence interval were calculated. Comparing with the baselines in different seasons, relative changes were also attained to detect seasonal responses of daily streamflows. As shown in Fig. 7, under wet conditions in future, all seasons, especially winter and fall, indicate increase in flow. Under normal conditions, variation of high and medium flows in winter differs from those in other seasons. Large (0.001<PE<0.1) and extreme large flows (PE<0.001) show a significant increasing trend only in winter. While for spring, summer, and fall, decrease in extreme large flows were predicted. When PE is larger than 0.1, relative change from baseline in winter becomes zero when PE is around 0.15, then becomes negative till the end, while the threshold of PE is around 0.3 for flow in spring, it is around 0.6 for both summer and fall. When PE is bigger than ~0.75, relative change from the baseline become negative for all seasons under normal conditions, which means reduction of low flows in the future. Under dry conditions, spring and summer are predicted to experience lower flows for all range of flows, while in fall, large flows will increase, indicating that fall is going to have higher large flows in the future, even under extreme dry conditions.

Water quality

Monthly distribution of TSS, TP and TN (Fig. 8a,b,c) are consistent with surface runoff, with higher loadings in March, April, July and September. The consistent pattern between flow and TSS can be linked to the MUSLE equation used in SWAT to simulate erosion and sediment transport. In MUSLE runoff volume and peak runoff rate are utilized to calculate sediment yield. During channel routing, deposition or degradation may happen depending on the maximum concentration of sediment that can be transported by flow. Monthly distribution pattern of TN and TP follow the average monthly surface runoff trends as well. For example, TN and TP peaks occur in March, June, July and September like flow.

In terms of projected variation (Fig. 8d,e,f), TSS, TP and TN also reflect similar patterns to flow. Loadings are expected to decrease for all months under dry condition, while all show increasing trend under wet conditions. The magnitude of increase or decrease is bigger in spring and fall, while smaller in summer. Under normal condition, TN has an increasing trend in all months; the magnitude of increase in summer is smaller than those in other seasons. TP is projected to decrease in summer, while increase in other seasons under normal condition.

SWAT has a comprehensive nutrient cycling component. It calculates and provides as output the organic and mineral forms of nutrients. In order to get a better insight on nutrient loadings, we analyzed the monthly distribution and projected variation of organic and mineral forms of N and P (Fig. 9). From the figures it is apparent that Min-N is the dominant component of TN, therefore monthly distribution and projected variation of TN is mainly decided by Min-N. For phosphors, loadings of mineral and organic forms are comparable. Thus, TP is influenced by both Min-P and Org-P.

Org-P and Org-N illustrate similar patterns as expected: peaks appear in March and November, and lowest loadings happen in summer. This is related to agricultural management practices. Tillage and harvesting, usually applied in spring and fall, provide large amounts of organic matter. Lower loadings of organic matter in summer are due to higher vegetation cover, which retain the organic matter, and also due to higher temperatures, which convert organic matters into mineral forms. Mineral forms of N and P follow the monthly pattern of flow. Mineral forms of nutrients are also affected by management practices. For example, higher values of mineral N, and P in June are due to fertilization of mineral N, P as well. In terms of projected variation, the relative change of four forms (Org-P, Min-P, Org-N, Min-N) follow the flow variation. If flow is projected to increase, they show increasing trend and vice versa. For example, in fall, under wet condition, the relative change of streamflow is +40%. Accordingly, the relative change is around +80% for Org-N, +40% for Min-N, +70% for Org-P, and +50% for Min-P.

Since shift in the N:P ratio of the loads entering coastal waters can contribute to an alteration in species dominance in the phytoplankton population, N:P ratio under climate change scenarios was also studied. Through simulation, the expected N:P ratio was found to vary from 46 to 50. Compared to the baseline N:P ratio of 47.6, this does not indicate any shift in N:P ratio.

Land use change effects only

Annual and monthly flow

The projected average daily streamflow for the future period were 4.67, 4.70 and 4.73 m^3/s, under LPR, MPR and HPR growth scenarios, respectively. Compared to the baseline period value of 4.57 m^3/s, there is an increase in streamflow under any future conditions. For baseflow, the projected average daily values are 2.12, 2.11 and 2.10 m^3/s for LPR, MPR and HPR. Future projected baseflow under different LULC scenarios are quite similar to each other, yet the decreasing trend is apparent when compared to the baseline baseflow, which was 2.33 m^3/s. Future predicted surface runoff values are also quite close to each other: 2.54, 2.59 and 2.63 m^3/s for LPR, MPR and HPR. Compared with the baseline value of 2.24 m^3/s, there is an evident increasing trend.

Fig. 10 displays average monthly distribution and projected variation of streamflow, surface runoff, and baseflow from the Wolf Bay watershed. Due to LULC change, they exhibit different or similar responses from each other. The total volume of future streamflow does not change appreciably compared to the baseline period, but significant differences are detected in some months with high flows, like July. Monthly streamflows for three future scenarios are quite close to each other. The partitioning of streamflow to baseflow and surface runoff is significantly affected as shown in Fig. 10. Surface runoff shows an increasing trend while baseflow decreases for all months. Although average monthly surface runoff and baseflow are quite close to each other for the three different future LULC scenarios, the trend is clear: urbanization results in higher direct runoff and lower baseflow, and vice versa.

Daily flow

Fig. 11 illustrates the daily FDC for baseline period (pre-urbanization) and 3 different future land use scenarios (post-urbanization). Although not significant, differences exist between baseline FDC and future FDCs. Compared to the FDC in the pre-urbanization period, future FDCs are a little steeper. When $PE<0.3$, baseline flows are always lower than future flows. After $PE=0.3$, future flows become lower. That means medium to high flows are projected to increase, while medium and low flows are projected to decrease. No evident differences are detected in FDCs among different future scenarios, which is due to quite similar urban percentages (see Table 1) for the three future LULC scenarios. Consistent with other researches (e.g. Rose and Peter, 2001), this indicates one important effect of LULC change in the future: the hydrologic regime is altered, which increases large flows and reduces small flows. However, this redistribution trend is not so evident if the extent of urbanization is not so serious.

Relative change curves for different future scenarios to baseline are also shown in Fig. 11 bottom panel. All three curves reflect the same trend. Moving from left to right, the relative change is a positive value and increase from 2% to 7% till PE reaches around 0.01. Then it stays in a stable status around 7%, until PE=0.1. After that, the relative change drops to zero when PE reaches 0.3. The dropping trend continues and relative changes stay negative till the end, with the maximum negative relative change around -8% when flows are extremely small. It seems that urbanization has more evident effect on extremes, both at the high and low flow end. Differences among the three future curves are not evident when PE is extremely small, but visible when PE is between 0.05 and 0.3. This indicates large flows show different sensitivities even LULC change rates are close.

Water quality

Variations in average monthly TSS loads (Fig. 12) are closely related to monthly distribution of direct runoff. Peaks for TSS are found in April, July and September, which is consistent with surface runoff. Tillage loosening the soil and breaking up large aggregates to fine particles, and harvesting providing residues, contribute to TSS peaks in spring and fall. In general, TSS is projected to increase in future, and the amounts of increases are quite close to each other for different future LULC scenarios.

In terms of nutrient loads, the situation is quite different. TN loadings were predicted to decline for all months under all future LULC scenarios. Differences among future average monthly loads are evident. TP was projected to increase in spring, fall and winter, but decrease in summer. Fig. 13 shows average monthly loads of Org-N, Min-N, Org-P and Min-P. Higher predicted Org-N and Org-P loadings found in spring and fall are due to increase of surface runoff after urbanization. Since the management practices in spring and fall provide enough sources of organic matters, surface runoff, which picks up nutrients along its way, becomes the main driver to affect average monthly loadings. The larger the volume of surface runoff, the bigger the organic loadings in spring and fall is. Some of the organic matter gets mineralized in time; especially at increased rates in summer due to high temperatures. This process converts organic N and P to mineral forms resulting in higher min-N and min-P in summer, but lower org-N and org-P. Therefore, organic N, and P loadings are projected to decrease in summer months, with the largest decrease predicted under the high population growth scenario, which has the lowest fraction of croplands.

Min-N is projected to decrease in all months. The largest decrease is projected under HPR, while smallest decrease is expected under the LPR scenario. This variation is again due to diminishing cropland and consequently decreases in Min-N fertilization, which is an important source of Min-N loadings. Based on future LULC scenarios, the percentages of crop land are 29.9%, 23.1%, 19.6% and 15.3% respectively for baseline, LPR, MPR and HPR scenarios, which shows a gradually decreasing trend consistent with the decline in average monthly Min-N loadings.

The projected variation in average monthly Min-P follows Min-N in summer, but is quite different in fall and winter, where increasing trend in Min-P was predicted. The LULC scenario based on HPR is expected to result in higher increase of Min-P loadings in those months. Increasing trend of Min-P after urbanization in fall and winter months is due to the increase of urban areas, because urban is an important source as Min-P. Unlike other land use types, SWAT employs USGS linear regression model (Driver and Tasker, 1988) to calculate loadings in urban areas. Loadings generated by urban areas are positively related to the fraction of the total area that is impervious. Therefore, urbanization results in increase of Min-P loadings. Mineral nitrogen is projected to decline for the whole period, because usage of N fertilizer is expected to decrease due to reduction in cropland in future.

Due to land use change, N:P ratio also changes. Projected N:P ratios are 39.5,38.1 and 36.7 for LPR, MPR and HPR, respectively. Compared with the baseline value of 47.6, this indicates towards an evident decrease in N:P ratio. Scenarios with higher urban fractions causes largest drop in N:P ratio and vice versa. Compared to the climate change effect, LULC change have a more dramatic influence on the N:P ratio.

Combined change effects

Based on 252 climate inputs and 3 future LULC scenarios, SWAT was run in annual, monthly and daily time scales 756 times, to obtain model outputs of flow, sediment and nutrient loadings. Again, from the ensemble of model outputs the 95th and 5th percentiles were determined to obtain a 90% confidence interval, as upper and lower limit for future conditions. Median of 90% confidence interval reflects normal condition in future. Results are discussed below:

Annual and monthly flow

The projected average daily discharges for the future period were 3.26, 5.01 and 7.03 m^3/s, respectively for the lower limit, median, and upper limit. To simplify the analysis only median flows will be compared to baseline flows under the combined change effect. Compared to the average daily streamflow of 4.57 m^3/s during the baseline period, an increasing trend in streamflow is expected, which corresponds to 9.6%. When compared to the median value (4.87

m^3/s) obtained from the only climate change scenario, which correspond to a relative change of 6.6%, higher streamflow is expected under the combined change scenarios. For baseflow and surface runoff, the median of the projected average daily values are 2.06 m^3/s and 2.92 m^3/s, respectively. Compared to the baseline values of 2.33 m^3/s and 2.23 m^3/s these represent substantial increase for surface runoff and decrease for baseflow. The relative change from the baseline is +31% and -12%, respectively for surface runoff and baseflow. We conducted t- test for two independent samples between annual baseline data and future normal condition data for surface runoff and baseline. Under the combined change scenarios both show significant differences, where p values are 0.002 and 0.004, respectively, for surface runoff and baseflow. Therefore, under the combined change effect scenarios, higher annual streamflow is expected/predicted relative to the baseline. When compared with the scenarios where only climate change was considered, that increasing trend is more evident The partitioning of annual streamflow is significantly affected under combined change scenarios, which substantially increase surface runoff and decrease baseflow.

Fig.14 shows the average monthly distribution of flow, caused by climate combined with LULC change. For streamflow, the monthly distribution is quite similar to Fig.5, which only reflects climate change effect. Peaks occur in April, July and September, but shift a little bit upwards, which indicates stronger increasing trend of streamflow for all months. Baseline stays between the median and lower limit of 90% confidence interval, closer to median curve in winter, spring and summer, but gets closer to the upper limit in fall, which again indicates higher possibility of streamflow increase in fall.

In terms of surface runoff and baseflow, monthly distribution is again quite similar to the one shown in Fig. 5, but the gap between the future predicted values and the baseline values are widened. Baseline for surface runoff is closer to the lower limit of 90% confidence interval, and is outside the band in fall, which indicates a very strong increasing trend. On the contrary, baseline for baseflow is quite close to the upper limit for future prediction, indicating reduction in baseflow in the future is highly likely under the combined effect scenario.

Daily flow

Fig. 15 shows the 90% confidence interval along with the median of the FDCs generated from the ensemble of daily streamflow time series obtained by running SWAT with 252 climate inputs and 3 future LULC scenarios. According to different probability of exceedance, future daily discharge for combined change scenario reflects substantial differences compared to the baseline. When PE is less than 0.001, baseline fluctuates along the median curve, and then it falls below the 90% confidence band until PE reaches 0.3. Baseline stays between the median and the lower limit until PE reaches 0.5. Beyond that point, baseline is always above the median curve getting closer to upper limit till the end. Compared to Fig. 6, which only captures the climate change effect, one can see that the general trends of these two are quite similar, but FDCs in Fig. 15 are somewhat steeper, which means large flows increase and small flows decrease more. For example, from Fig. 15, upper limit for the 90% confidence interval varies from around 310 to 1.0 m^3/s. However, if only climate change effect is considered, the range is from 300 to 1.3 m^3/s. Similar circumstances occur for median FDC and the lower limit as well.

Fig. 15 also depicts the relative differences in flow between the future and the baseline conditions. Similar to Fig. 6, extreme large flows fluctuate until PE=0.01. When PE is between 0.01 and 0.1, they reach at a stable status, where the relative change is around 55%, 40% and 30%

for the upper limit, median and the lower limit, respectively. When PE exceeds 0.1, all three curves go down and finally arrive at values around 0%, -35% and -65% when PE is near 1.

Based on the FDCs and the relative changes of flow from the baseline, combined change effect results in more noticeable uneven distribution of streamflow, when compared to “only climate change” or “only LULC change” scenarios (Fig. 6 and Fig. 11). The combined effect increases high flows and decreases low flows, which caused steeper FDCs.

Seasonality effects on daily flow

Fig. 16 illustrates the seasonal FDCs and relative changes between FDCs from future and baseline scenarios. When compared to seasonal FDCs only reflecting climate change effects, these FDCs are all steeper due to the combined effect, which again means large flows will get even larger, while small flows will become smaller. Such a trend is also clear when relative changes (lower panels in Fig. 16) for combined effect are compared to the ones reflecting only climate change in Fig. 7. When PE is smaller than 0.1, it is clearly seen that the relative positions of all three curves in Fig. 16 shift a little bit upwards compared to those in Fig. 7, which indicates seasonal higher flows due to the combined effect. For small flows, the curves shift downwards. Those shifts are detected in all four seasons, pointing out to the fact that more uneven distribution of streamflow caused by combined change is not confined in any specific season, but dispersed over all seasons.

Water quality

Monthly distribution of TSS is compatible with variation of surface runoff (Fig.17). Compared to Fig. 8, the 90% confidence band shift upwards, making the baseline stay between the median and the lower limit. This indicates a stronger trend in TSS increase for all months, even in summer. No clear trend was detected when only climate change effect was considered in summer. Comparing the relative change in TSS for each month, it is evident that the combined change effect leads to a larger relative change than the LULC or climate change alone scenarios (Fig. 8, Fig. 12 and Fig. 17).

Monthly distributions of nutrients are more complex when combined effect is considered (Fig. 17). Nutrients were again divided into organic and mineral parts as shown in Fig. 18, for in debt discussion. Org-N and Org-P represent similar behavior for monthly distribution. Compared to Fig. 8, which only reflects climate change, the 90% confidence bands of predicted Org-N and Org-P shift upwards in spring, fall and winter, which is mainly caused by strong increase in direct runoff. However, there is a downward shift in summer, which is primarily due to the decrease of agriculture land that serves as the source of organic matters.

Future predicted Min-P shift upwards in spring, fall and winter, but downwards in summer. When compared to Fig. 8, which only reflects the effect of climate change, the increasing trend in spring, fall and winter under the combined effect is intensified by LULC change, while the decreasing trend in summer shows offsetting effect.

Under combined scenarios, min-N was projected to decrease in all months. The baseline values were above the median of the 90% confidence interval in summer, which indicates a big possibility for decrease in min-N. The decreasing trend of min-N is caused by the shrinking of agriculture land. Since N fertilization is applied in early summer, diminishing crop land results in less input of min-N.

The annual average N:P ratio, under the combined change scenarios, is projected to decrease under all conditions. The projected N:P ratio was 35.1, 37.7 and 39.8 for the upper, median and lower limit of 90% confidence, respectively. Compared to the baseline value of 47.6, they all indicate toward reduction in the N:P ratio, which are smaller than both the climate change only and LULC change only scenarios.

In summary, under the combined change scenarios, since LULC and climate change effect were considered simultaneously, water quality was affected by both. If future loadings are expected to increase/decrease under either climate or LULC change scenarios, combined change scenario intensifies that trend. On the other hand, if their effects are in opposite directions, then the combined change has an offsetting effect.

Relative importance of LULC and climate change effects

We have shown that both climate and LULC change affect watershed hydrology and water quality, not only the annual averages loadings but also their seasonal, monthly and daily distributions. When LULC was combined with climate change, the compound effect was either intensification or offsetting of the effects caused by either climate or LULC change. Projected variations in flow and water quality loadings due to the combined change effect are not simply the summation of the results caused by the individual factors. In other words, the marginal effects are not additive. To identify the relative importance of LULC and climate change when they act jointly, average monthly percentage change in streamflow, TSS, TN and TP loadings were compared (Fig. 19). For convenience, we only focused on the results under normal condition (median of the 90% confidence interval). The relative increase/decrease caused by the combined effect is contributed by three factors: Effect of LULC change only, effect of climate change only and the synergistic effect. The synergistic effect, thus, can be determined as follows:

$$\begin{aligned} Synergistic\ effect \\ &= (combined\ effect) - (climate\ change\ effect\ only \\ &+ LULC\ change\ effect\ only) \end{aligned}$$

From Fig. 19a, it is seen that average monthly percentage change in streamflow is mainly due to climate change in spring, fall and winter. In summer, the effect of LULC and climate change on streamflow is close to each other. In July they have opposite effects. Compared with LULC and climate effect, synergistic effect has very slight influences on streamflow, which can be ignored. From Fig. 19b, the relative importance of climate and LULC change effect on TSS follows the flow pattern. Climate change is still the dominant factor for all seasons except summer. Another interesting observation is that the synergistic effect on TSS is more evident compared to the synergistic effect on flow. The synergistic effect on TSS even exceeds LULC effect in several months. Therefore, unlike streamflow, there is a nonlinear interaction between LULC and climate for TSS, and the combined change effect intensifies the increase in TSS loadings. Figures 19.c and 19.d summarize the same effects for TP and TN. Similar to TSS, there is a nonlinear interaction between climate and LULC for TP and TN, especially in fall months. In general, LULC change is the main driver, while climate change affects TP moderately. Combined change intensifies the TP loading in most of the months. In the case of TN, LULC is relatively important in winter and summer, but in spring and fall, climate change becomes the main factor affecting the TN loadings. Since the effects of climate and LULC change are in opposite directions, the combined change has an offsetting effect in TN.

SUMMARY AND DISCUSSION

LULC and climate change are the two main factors affecting hydrologic regimes and in turn influencing water quality. In this study, SWAT model was utilized to analyze the responses of hydrological processes and water quality to LULC and climate change effects in Wolf Bay watershed, southern Alabama. Four downscaled GCMs outputs under three green house gas emission scenarios were used to reflect the uncertainty of future climate; three LULC scenarios based on different population increasing rates represented the future LULC scenarios. Their effects were explored both separately and jointly. Results revealed the following conclusions:

1. Under climate change scenarios, Wolf Bay watershed will more likely experience increasing precipitation in future, especially in fall, and temperature is expected to rise, especially in summer and fall. Rainfall amount for large events are expected to increase, while rainfall amounts for small events tend to decrease.
2. The Wolf Bay watershed is expected to experience dramatic urbanization. The percentage of urban areas is projected to double by 2030. The increase in urban areas will be compensated by reductions in forest, pasture, cropland and wetland.
3. A redistribution of streamflow is projected when only climate change effect is considered: high flows are predicted to increase, while low flows are expected to decrease. No clear trend is detected for medium and extreme large flows. This redistribution trend is same for LULC change effect, but extreme large flows are projected to increase substantially under the LULC change scenarios. Combined change effect results in more noticeable uneven distribution of streamflow, which generates steeper flow duration curves.
4. Daily flows show seasonality under climate change. In general, large flows are projected to increase for all seasons under the wet and normal conditions, especially for fall and winter. Even under dry conditions, fall shows increasing trend in large flows. Small flows

are expected to decrease for all seasons under dry and normal conditions. Compared with climate change effect, steeper FDCs are projected for all four seasons under the combined change effect.

5. When considering climate change effect, monthly average streamflow and surface runoff are projected to increase in spring, fall and winter, especially in fall, while no clear trend was observed in summer, under normal future climate situations. Although the LULC change does not have significant effect on monthly average streamflow, increasing trends are still detected in high flow months, such as July and September. The partitioning of streamflow to baseflow and surface runoff is significantly affected. Surface runoff is predicted to increase every month, while for baseflow, an evident decreasing trend was detected. When climate change is combined with LULC change, it leads to more dramatic increasing trend in monthly average streamflow than when the climate or LULC change alone is considered. Further, more visible increasing trend in surface runoff and more dramatic decreasing trend in baseflow were detected for combined effect.
6. When only climate change effect is considered, monthly TSS and nutrient loadings follow the flow pattern. No evident difference in annual average N:P ratio is detected. LULC change increases TSS loadings but decreases TN loadings for each month. This is due to reduction of cropland in future, which reduces areas applying min-N fertilization, and in turn affects TN loadings. TP loading, which is decided by both Min-P and Org-P, is projected to decrease in summer, but increase in other months. The projected variation of Min-P follows the pattern of Min-N expect in fall. Min-P is projected to increase accompanying urbanization. Org-P is predicted to increase in spring and fall due to surface runoff increasing, but decrease in summer mainly due to the diminishing of crop

land which contains abundant organic matters, and transformation to min-P. N:P ratio is projected to decrease significantly under all LULC change scenarios. When LULC change is combined with climate change, future predicted TSS loadings are expected to increase for each month, which is similar to the responses of direct runoff. Monthly distribution and projected variation of nutrient reflect characteristics from both climate change and LULC change effects. In general TN loadings are projected to increase slightly in spring and fall, which indicates that the reduction in TN due to shrinking of crop lands is offset by increase in flow. TN and TP loadings are projected to decrease in summer, which means LULC change effect (cropland diminishing) becomes the dominant factor when flows are higher in those months. TP loadings are expected to have a more dramatic increasing trend in spring and summer, which indicates climate change effect is aggregated by management practices (tillage and harvesting). N:P ratio is projected to further decrease under the combined change scenarios.

7. Both climate and LULC change affect monthly distribution of flow and water quality. However, their effects are not additive. There is a nonlinear interaction between LULC and climate change when considering their joint effects. This is more evident in water quality than streamflow. Under the combined change effect scenario, climate change is the dominant factor influencing streamflow and TSS. In the case of TP, LULC change becomes relatively more important. For TN, while LULC has more influence in winter and summer, climate change is more influential during spring and fall.

Based on the simulation results from this research, a complex situation in flow and water quality is projected. Change in distribution of streamflow will likely lead to more flooding and drought in the future. This is supported by the fact that less baseflow and more surface runoff is projected. The increases runoff is also linked to the projected increase in soil erosion. Nitrogen and phosphorus loadings will also be affected and a decreased N:P ratio is projected, which could potentially contribute to an alteration in species dominance in the phytoplankton population.

Lessons learned from this study could be quite valuable for stakeholders and decision makers in the Wolf Bay area. Carrying out some best management practices (BMPs) in crop land and storm control measures (SCMs) in urban areas are necessary to protect the health and integration of the Wolf Bay watershed.

REFERENCES

Ahl RS, Woods SW, Zuuring HR. 2008. Hydrologic Calibration and Validation of SWAT in a Snow-Dominated Rocky Mountain Watershed, Montana, USA. *Journal of the American Water Resources Association (JAWRA)* **44(6)**:1411-1430

Arnold, JG, Srinivasan R, Muttiah RS, Williams JR. 1998. Large Area Hydrologic Modeling and Assessment - Part 1:Model Development. *Journal of the American Water Resources Association (JAWRA)* **34(1)**:73-89.

Asselman EM, Middelkoop H, Paul M. 2003. The impact of changes in climate and land use on soil erosion, transport and deposition of suspended sediment in the River Rhine. *Hydrologic Process* **17(16)**: 3225-3244

Bakri D, Rahman S, Bowling L. 2008. Sources and management of urban stormwater pollution in rural catchment, Australia. *Journal of Hydrology* **356(3-4)**:299-311

Brown LC, Barnwell TO. 1987. The enhanced water quality models QUAL2E and QUAL2E-UNCAS documentation and user manual. EPA document EPA/600/3-87/007. USEPA, Athens, GA.

Collins WD, Bitz CM, Blackmon ML, Bonan GB, Bretherton CS, Carton JA, Chang P, Doney SC, Hack JJ, Henderson TB, Kiehl JT, Large WG, McKenna DS, Santer BD, and Smith RD. 2006. The Community Climate System Model Version 3 (CCSM3). *Journal of Climate* **19(11)**: 2122–2143.

Cruise JF, Limaye AS, Al-Abed N. 1999. Assessment of impacts of climate change on water quality in the southeastern United States. *Journal of the American water resources Association* **35(6)**:1539-1550

Cuo L, Lettenmaier DP, Alberti M, Richey JE. 2009. Effects of a century of land cover and climate change on the hydrology of the Puget Sound basin. *Hydrological Processes* **23(6)**: 907-933

Dam JC. 1999. Impacts of climate change and climate variability on hydrological regimes. Cambridge University Press, Cambridge, UK, 1-20.

Delworth TL, Broccoli AJ, Rosati A, Stouffer RJ, Balaji V, Beesley JA, Cooke WF, Dixon KW, Dunne J, Dunne KA, Durachta JW, Findell KL, Ginoux P, Gnanadesikan A, Gordon CT, Griffies SM, Gudgel R, Harrison MJ, Held IM, Hemler RS, Horowitz LW, Klein SA, Knutson TR, Kushner PJ, Langenhorst AR, Lee HC, Lin SJ, Lu J, Malyshev SL, Milly PCD, Ramaswamy V, Russell J, Schwarzkopf MD, Shevliakova E, Sirutis JJ, Spelman MJ, Stern WF, Winton M, Wittenberg AT, Wyman B, Zeng F, Zhang R. 2006. GFDL's CM2 global coupled climate models - Part 1: Formulation and simulation characteristics. *Journal of Climate* **19(5)**: 643–674.

Driver NE and Tasker GD. 1988. Techniques for estimation of storm-runoff loads, volumes and selected constituent concentrations in urban watersheds in the United States. U.S. Dept. of the Interior, *U.S. Geological Survey: Books and Open-File Reports* Section 88-191.

D'Agostino DR, Trisorio LG, Lamaddalina N, Ragab R. 2010. Assessing the results of scenarios of climate and land use changes on the hydrology of an Italian catchment: modeling study. *Hydrologic Process* **24(19)**: 2693-2704

Ficklin DL, Luo Y, Luedeling E, Zhang M. 2009. Climated change sensitibity assessment of a highly agricultural watershed using SWAT. *Journal of Hydrology* **374(1-2)**: 16-29.

Githui F, Mutua F, Bauwens W. 2009. Estimating the impacts of land-cover change on runoff using the soil and water assessment tool (SWAT): case study of Nzoia catchment, Kenya. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques*. **54 (5)**: 899-908.

Gordon C, Cooper C, Senior CA, Banks H, Gregory JM, Johns TC, Mitchell JFB, Wood RA. 2000. The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments. *Climate Dynamics* **16(2-3)**:147-168.

Gul GO, Rosbjerg D. 2010. Modelling of hydrologic processes and potential response to climate change through the use of a multisite SWAT. *Water and Environment Journal* **24(1)**: 21-31

Guo H, Hu Q, Jiang T. 2008. Annual and seasonal streamflow responses to climate and land-cover changes in the Poyang Lake basin, China. *Journal of Hydrology* **335(1-4)**: 106-122

Heuvelmans G, Muys B, Feyen J. 2004. Analysis of the spatial variation in the parameters of the SWAT model with application in Flanders, Northern Belgium. *Hydrology and Earth System Sciences* **8(5)**: 931-939. http://www.hydrol-earth-syst-sci.net/8/931/2004/hess-8-931-2004.pdf, Last access on 12/12/2009.

Huang HJ, Cheng SJ, Wen JC, Lee JH. 2008.Effect of growing watershed imperviousness on hydrograph parameters and peak discharge. *Hydrological processes* **22(13)**: 2075-2085

Kalin L, Hantush M. 2006. Hydrologic Modeling of an Eastern Pennsylnania Watershed with NEXRAD and Rain Gauge Data. *Journal of Hydrologic Engineering* **11(6)**: 555-569

Konikow LF, Kendy E. 2005. Groundwater Depletion: A Global Problem. *Hydrogeology* **13(1)**: 317-320.

Kim Y, Engel BA, Lim KJ, Larson V, Duncan B. 2002. Runoff impacts of Land-Use Change in Indian River Lagoon Watershed. *Journal of Hydrologic Engineering* **7(3)**: 245-251

Lam QD, Schmalz B, Fohrer N. 2010. Modelling point and diffuse source pollution of nitrate in a rural lowland catchment using the SWAT model. *Agricultural Water Management* **97(2)**: 317-325.

Li Z, Liu W, Zhang X, Zheng F. 2009. Impacts of land use change and climate variability on hydrology in an agricultural catchment on the Loess Plateau of China. *Journal of Hydrology* **377(1-2)**: 35-42

Liu D, Chen X, Lian Y, Lou Z. 2010. Impacts of climate change and human activities on surface runoff in the Dongjiang River basin of China. *Hydrologic process* **24(11)**: 1489-1495.

Ma X, Xu J, Luo Y, Aggarwal SP, Li J. 2009. Response of hydrological processes to land-cover and climate changes in Kejie watershed, south-west China. *Hydrological Processes*. **23(8)**: 1179-1191.

Mango LM, Melesse AM, McClain ME, Gann D, Setegn SG. 2010. A modeling approach to determine the impacts of land use and climate change scenarios on the water flux of the upper Mara River. *Hydrology and Earth System Sciences Discussion* **7(4)**: 5851–5893.

Marshall E, Randhir T. 2008. Effect of climate change on watershed system: a regional analysis. *Climatic Change* **89(3-4)**: 263-280.

Maurer EP, Brekke L, Pruitt T, Duffy PB. 2007. 'Fine-resolution climate projections enhance regional climate change impact studies. *Transactions American Geogphysical Union* **88(47)**: 504.

Merz R, Bloschl G. 2004. Regionalisation of catchment model parameters. *Journal of Hydrology* **287(1-4)**: 95-123.

Montenegro A, Ragab R. 2010. Hydrological response of a Brazilian semi-arid catchment to different land use and climate change scenarios: a modeling study. *Hydrologic Process* **24(19)**: 2705-2723.

Neitsch SL, Arnold JG, Kiniry JR, Williams JR. 2005. Soil and Water Assessment Tool: Theoretical Documentation, version 2005. http://www.brc.tamus.edu/swat/downloads/doc.html. Last accessed on 12/12/2009.

Neitsch SL, Arnold JG, Kiniry JR, Srivivasan K., Williams JR. 2005. Soil and Water Assessment Tool: Inpuut/output file documentation, version 2005

Olivera F, DeFee BB. 2007. Urbanization and its effect on runoff in the Whiteoak Bayou watershed, Texas. *Journal of the American Water Resources Association (JAWRA)* **43(1)**: 170-182.

Oki T, Kanae S. 2006. Global Hydrological Cycles and World Water Resources. *Science* **313(5790**): 1068-1072.

Oudin L, Andreassian V, Perrin C, Michel C, Moine NL. 2008. Spatial proximity, physical similarity, regression and ungaged catchments: A comparison of regionalization approaches based on 913 French catchments. *Water Resources Research* **44**: W03413.

Ouyang T, Zhu Z, Kuang Y. 2006. Assessing impact of Urbanization on river water quality in the Pearl River Delta economic zone, China. *Environmental Monitoring and Assessment* **120(1-3)**: 313–325.

Ouyang W, Skidmore AK, Hao F, Wang T. 2010. Soil erosion dynamics response to landscape pattern. *Science to the Total Environment* **408(6)**: 1358-1366.

Pisinaras V, Petalas C, Gikas GD, Gemitzi A, Tsihrintzis VA. 2010. Hydrological and water quality modeling in a medium-sized basin using the Soil and Water Assessment Tool (SWAT). *Desalination* **250(1)**: 274-286.

Praskievicz S, Chang H. 2009. A review of hydrological modeling of basin-scale climate change and urban development impacts. *Progress in Physical Geography* **33(5)**: 650-671.

Qi S, Sun G, Wang Y, McNulty SG, Myers JAM. 2009. Streamflow response to climate and landuse changes in a coastal watershed in North Carolina. *Transactions of the ASABE* **52(3)**: 739-749.

Reichl JPC, Western AW, McIntyre NR, Chiew FHS. 2009. Optimization of a similarity measure for estimating ungauged streamflow. *Water Resources Research* **45**: W10423.

Rose S, Peters NE. 2001. Effects of urbanization on streamflow in the Atlanta area (Georgia, USA): a comparative hydrological approach. *Hydrological Processes* **15(8)**: 1441–1457

Russell GL, Miller JR, Rind D, Ruedy RA, Schmidt GA, Sheth S. 2000. Comparison of model and observed regional temperature changes during the past 40 years. *Journal of Geophysical Research* **105(11)**:14891-14898

Sharpley AN, Williams JR. 1990. EPIC-Erosion Productivity Impact Calculator, 1. Model documentation. U.S. Department of Agriculture, Agricultural Research Service. Tech. Bull. 1768.

Susana JD, Juan P, Pablo C, Jorge C, Bernal G. 2008. Water quality and zooplankton composition in a receiving pond of the stormwater runoff from an urban catchment. *Journal of Environmental Biology* **29(5)**: 693-700

Tu J. 2009. Combined impact of climate and land use changes on streamflow and water quality in eastern Massachusetts, USA. *Journal of Hydrology* **379(3-4)**: 268-283

Tung CP, Lee T, Yang YC. 2006. Modeling climate-change impacts on stream temperature of Formosan landlocked salmon habitat. *Hydrological Processes* **20(7)**: 1629-1649.

Wang R and Kalin L. 2010. Modeling Effects of Land Use/Cover Changes under Limited Data. *Ecohydrology* (accepted)

Wilby RL, Whitehead PG, Wade AJ, Butterfield D, Davis RJ, Watts G. 2006. Integrated modeling of climate change impacts on water resources and quality in a lowland catchment: River Kennet, UK. *Journal of Hydrology* **330(1-2)**: 204-220

Williams JR. 1975. Sediment-yield prediction with universal equation using runoff energy factor. P. 244-252. In present and prospective technology for predicting sediment yield and sources: Proceedings of the sediment yield workshop, USDA sedimentation Lab., Oxford, MS, November 28-30, 1972. ARS-S-40.

Wu K, Xu Y. 2006. Evaluation of the applicability of the SWAT model for coastal watersheds in southeastern Louisiana. *Journal of the American Water Resources Association (JAWRA)* **42(5)**: 1247-1260.

Zhang YK, Schilling KE. 2006. Increasing streamflow and baseflow in Mississippi River since the 1940s: Effect of land use change. *Journal of Hydrology* **324(1-4)**: 412-422

Table 1 Land use/cover in Wolf Bay watershed for baseline (2005) and 3 future scenarios (2030)

	2005	2030		
		LPR	MPR	HPR
Water	1.2%	0.2%	0.1%	0.1%
Urban	26.4%	50.2%	57.4%	64.2%
Forest	20.9%	15.7%	14.0%	12.4%
Pasture	9.7%	1.9%	1.5%	1.2%
Cropland	29.9%	24.1%	19.6%	15.3%
Wetland	11.9%	8.0%	7.4%	6.8%

LPR: low population increasing rate
MPR: medium population increasing rate
HPR: high population increasing rate

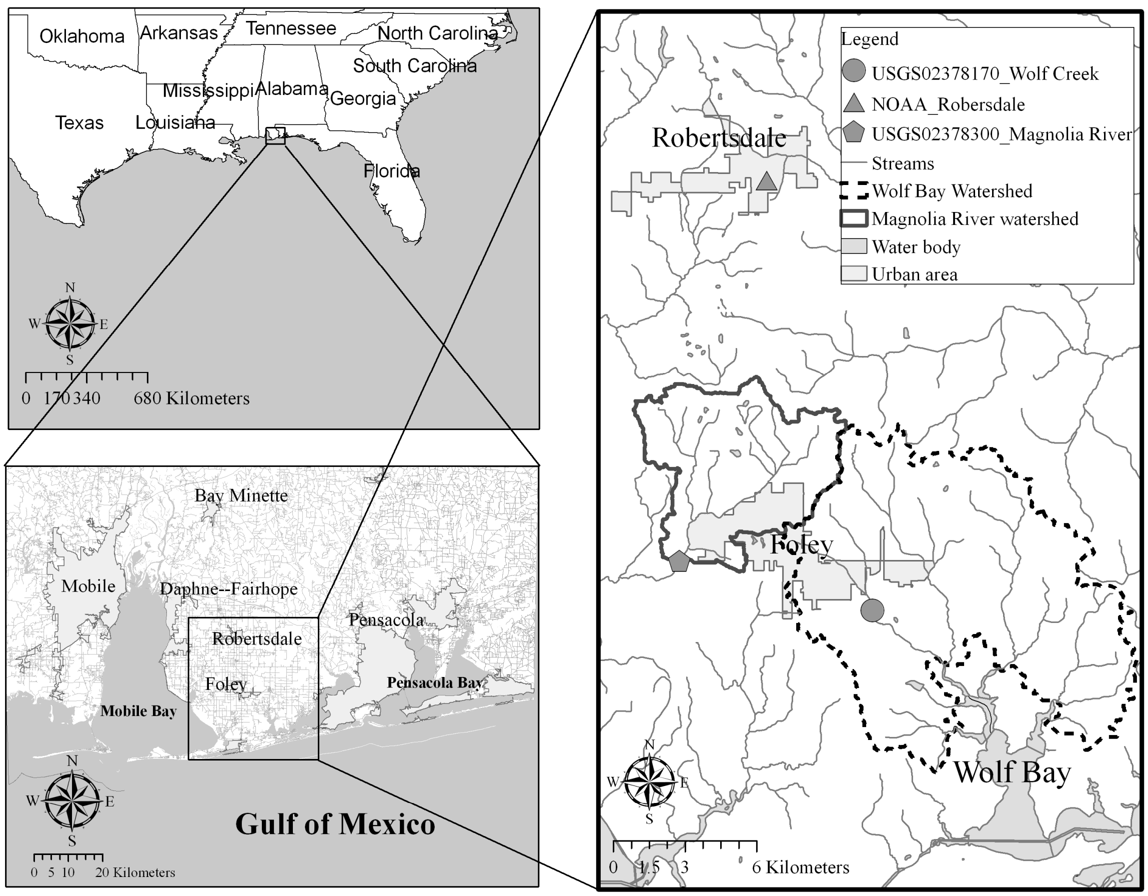

Fig.1 Geographical location of Wolf Bay and Magnolia River Watersheds

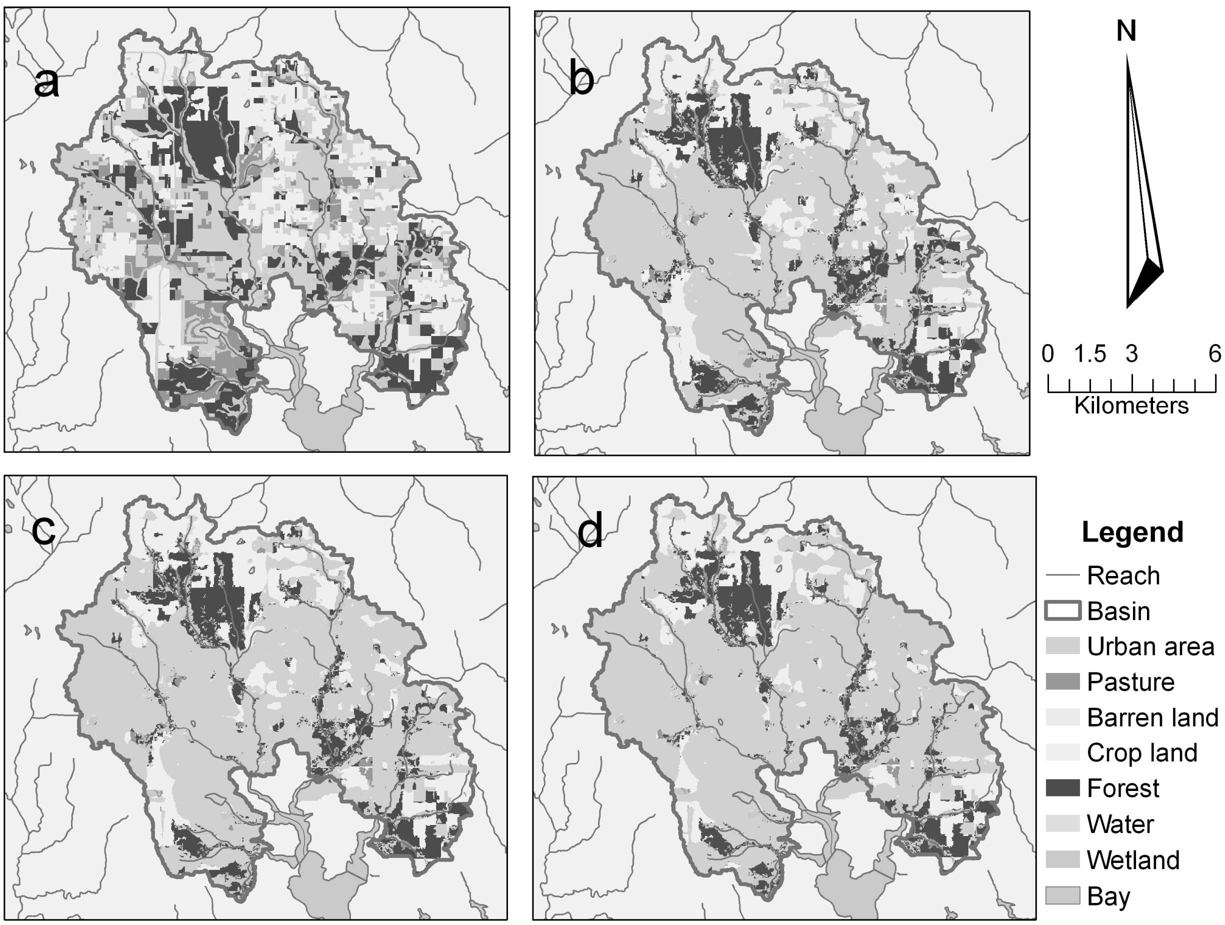

Fig. 2 Land use maps for Wolf Bay watershed: (a) Baseline: year 2005, (b) Projected future scenario based on LPR, year 2030, (c) Projected future scenario based on MPR, year 2030, (d) projected future scenario based on HPR, year 2030

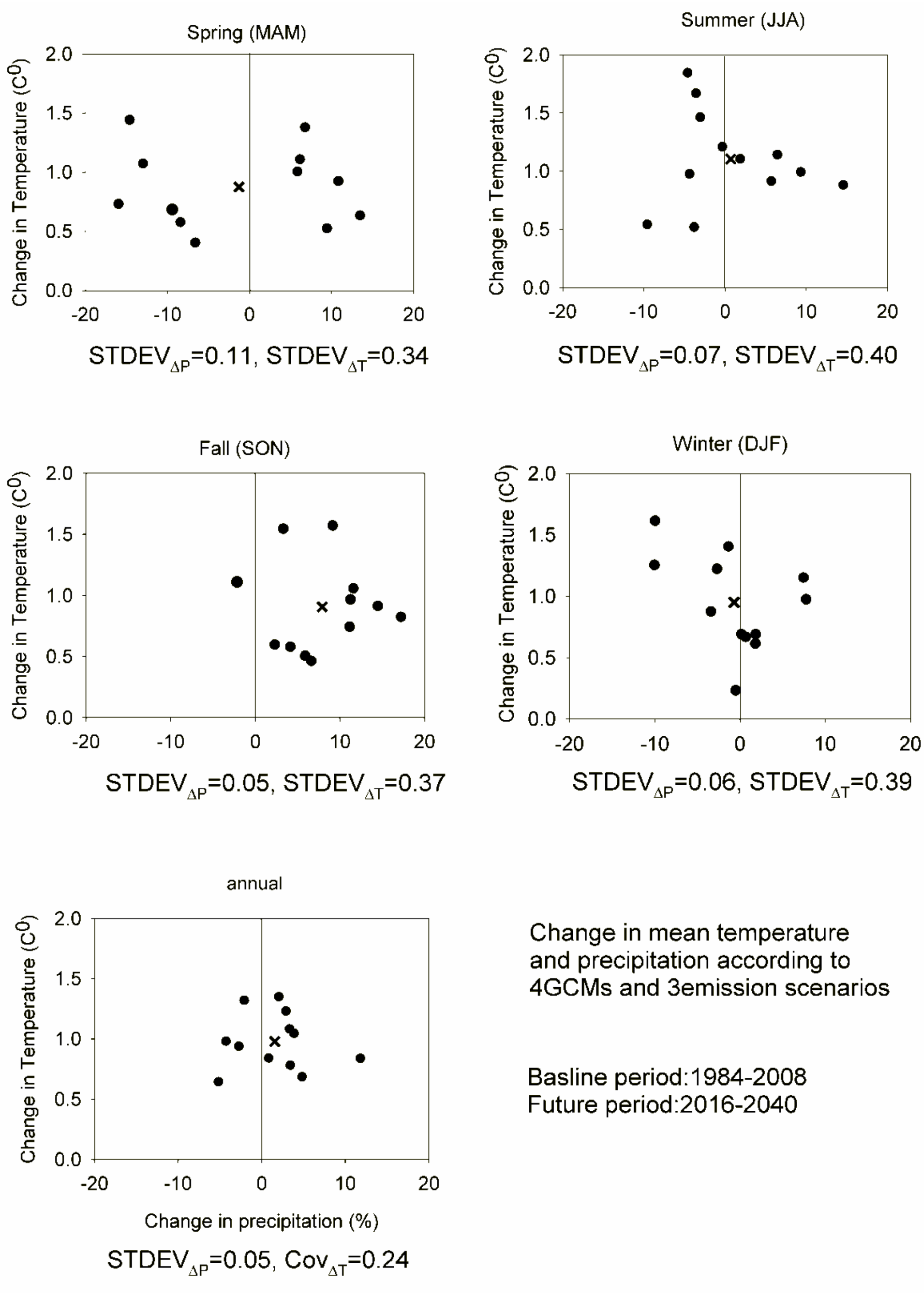

Fig. 3 Seasonal mean temperature and precipitation variation from baseline (1984-2008) period according to 4 GCMs under 3 emission scenarios in wolf Bay watershed

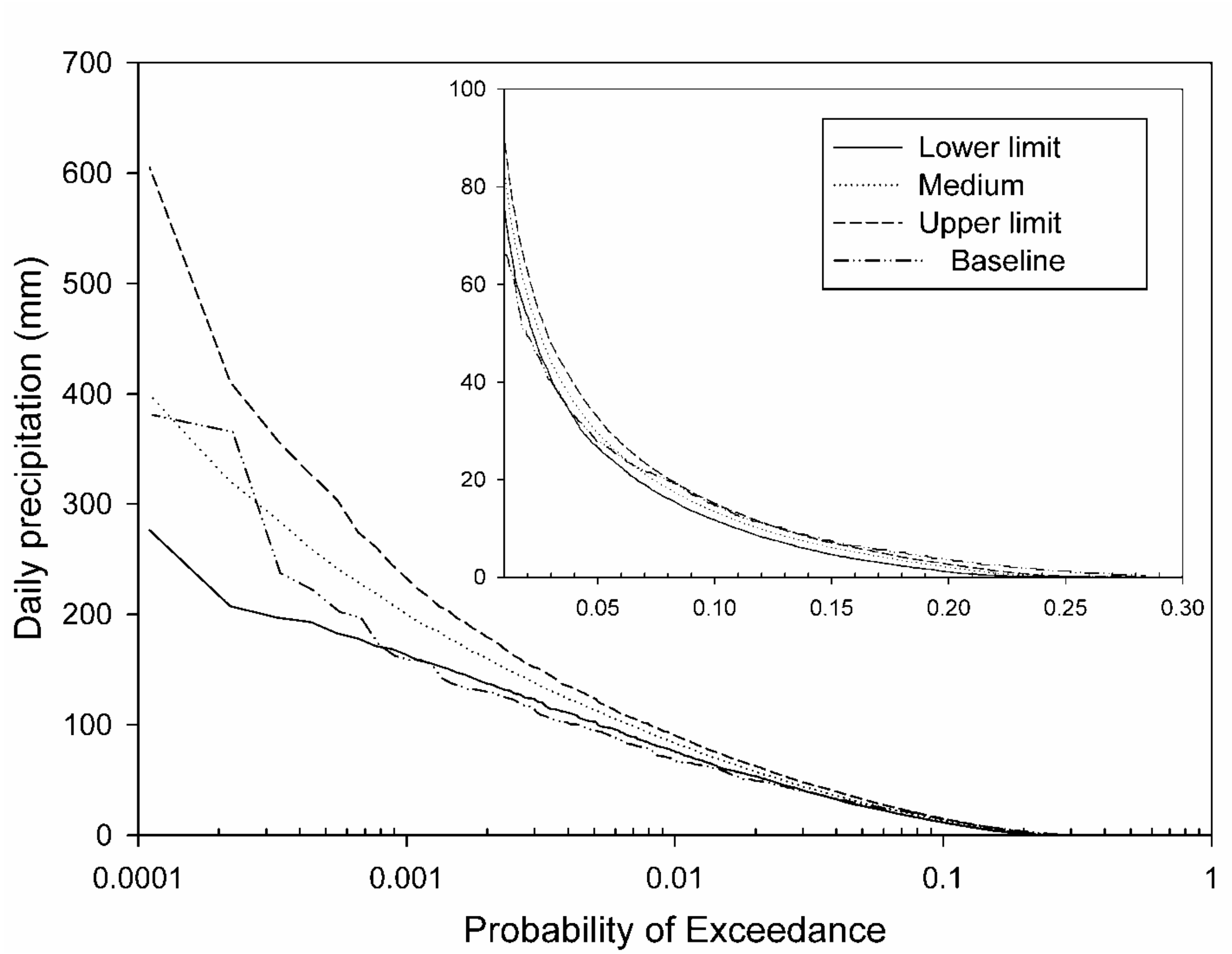

Fig. 4 Exceedance probabilities of daily precipitation in Wolf Bay watershed

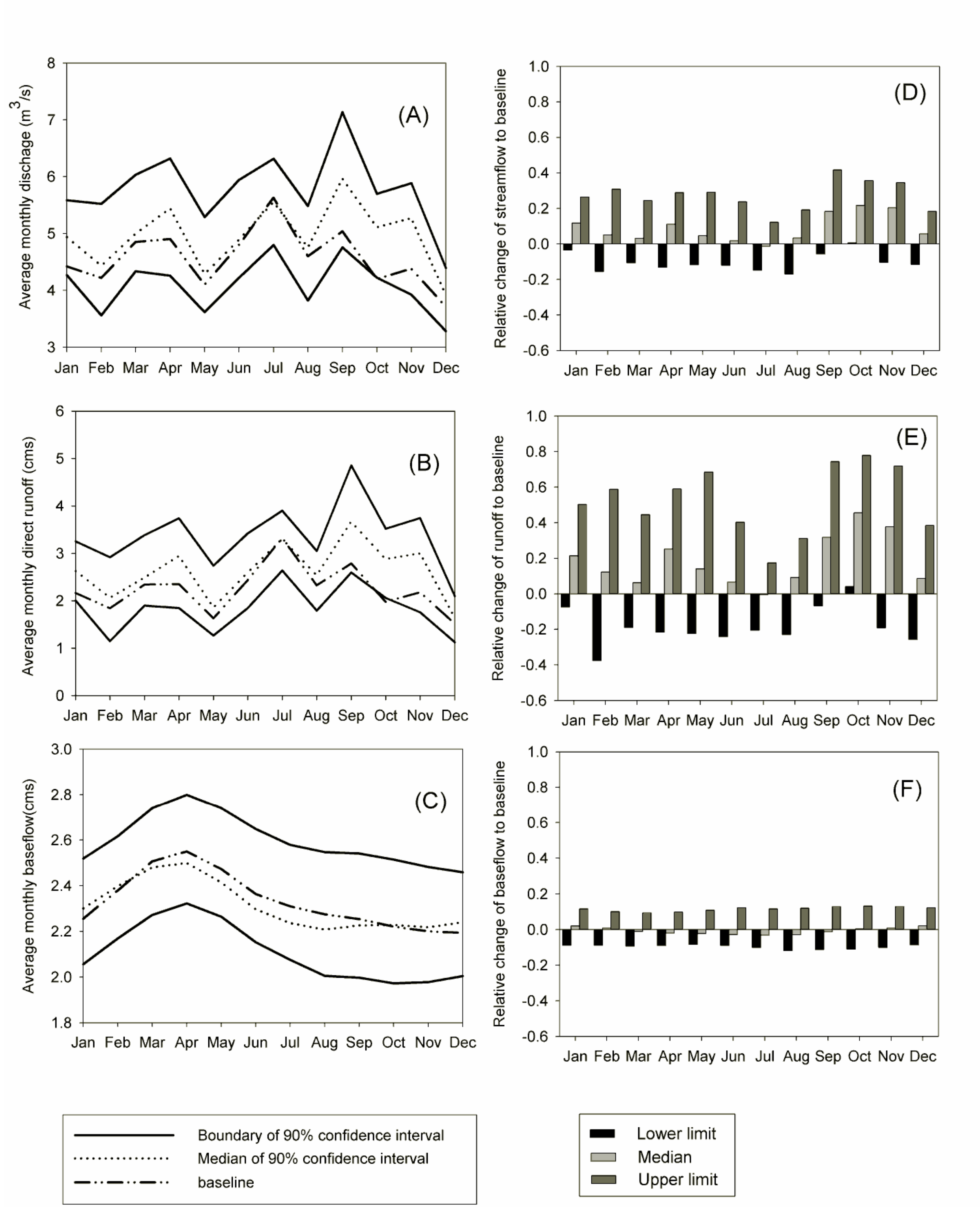

Fig. 5 Monthly responses of flow and respective relative changes from the baseline (only climate change effect)

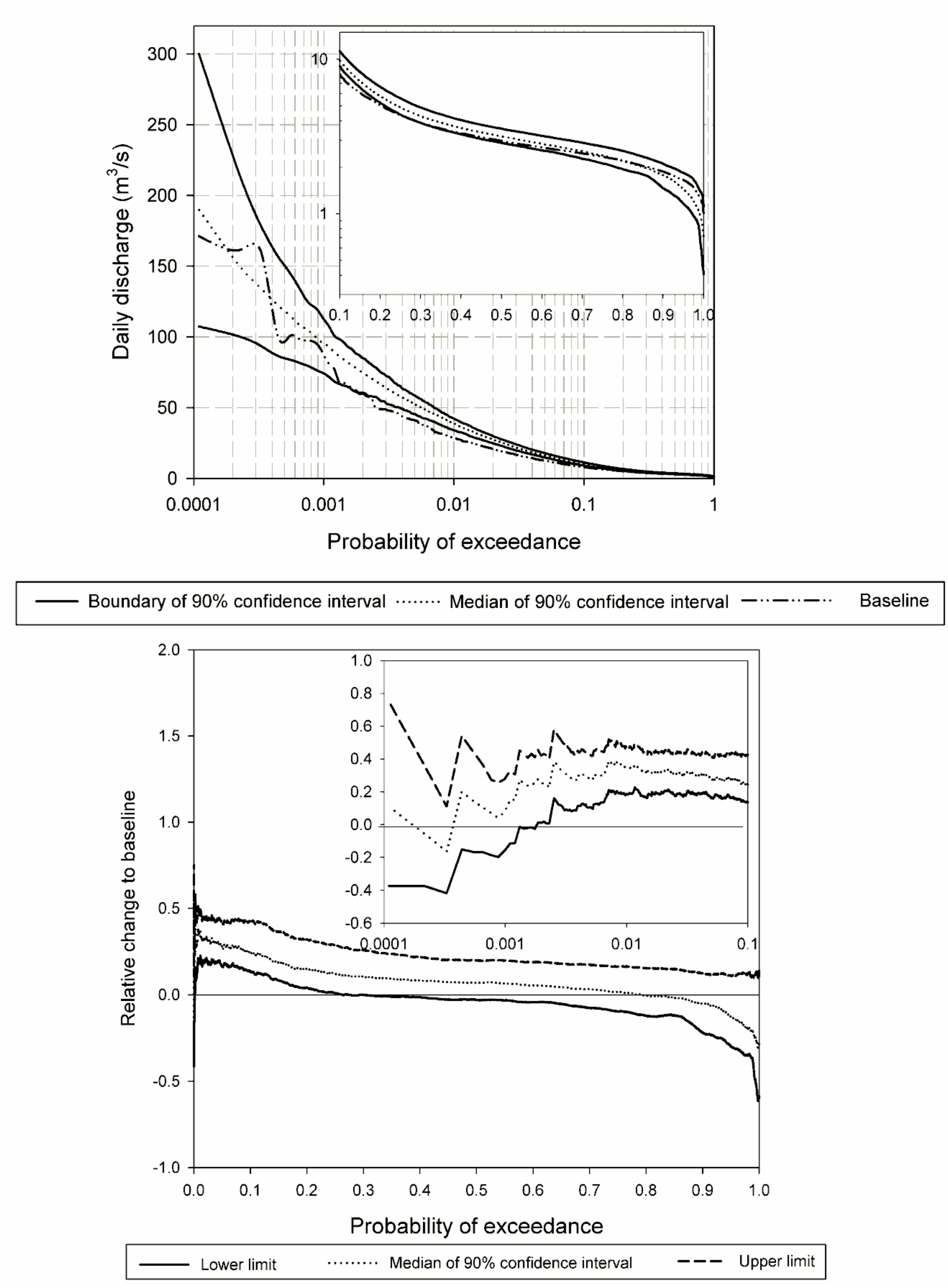

Fig. 6 a.25-years flow duration curves(FDCS) under projected future climate and current(baseline) climate, and b. Relative changes of future FDCs from the baseline (only climate change effect)

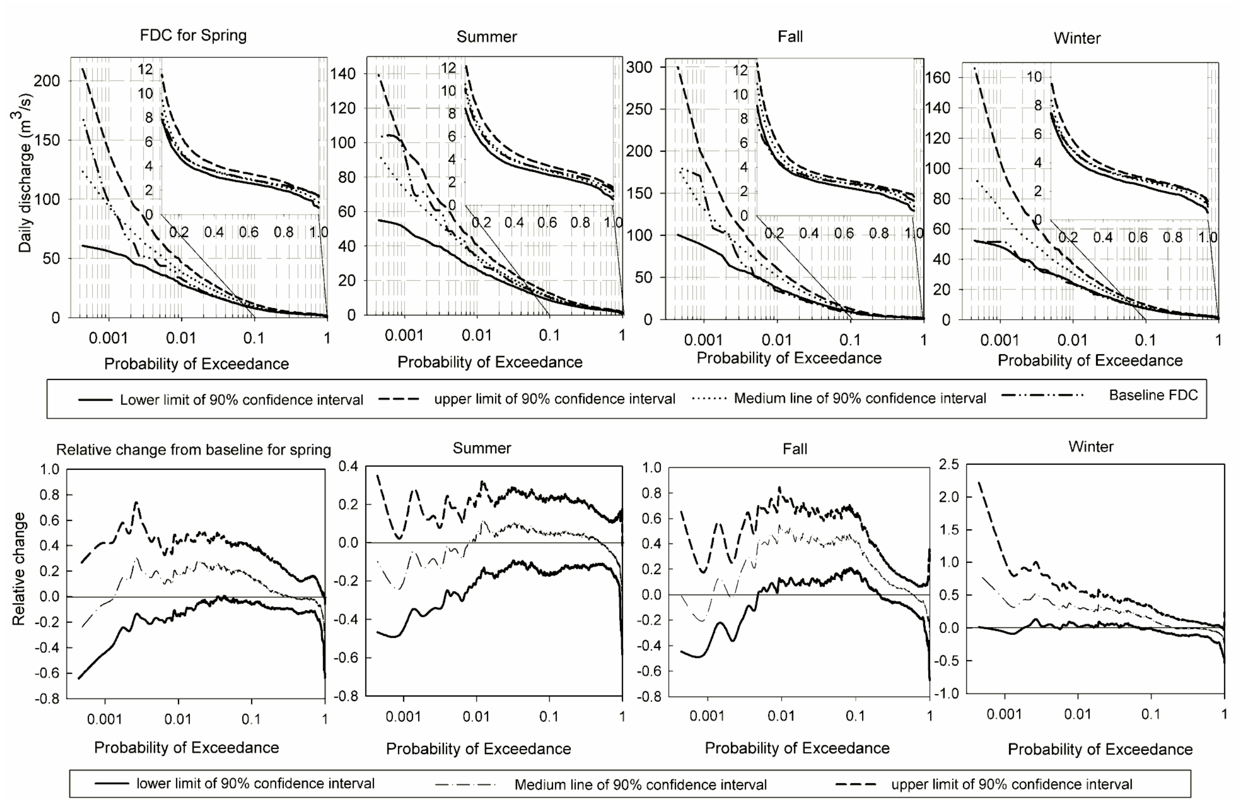

Fig. 7 Seasonal future and baseline FDCs, and seasonal relative changes of future FDCs from the baseline period (only climate change effect)

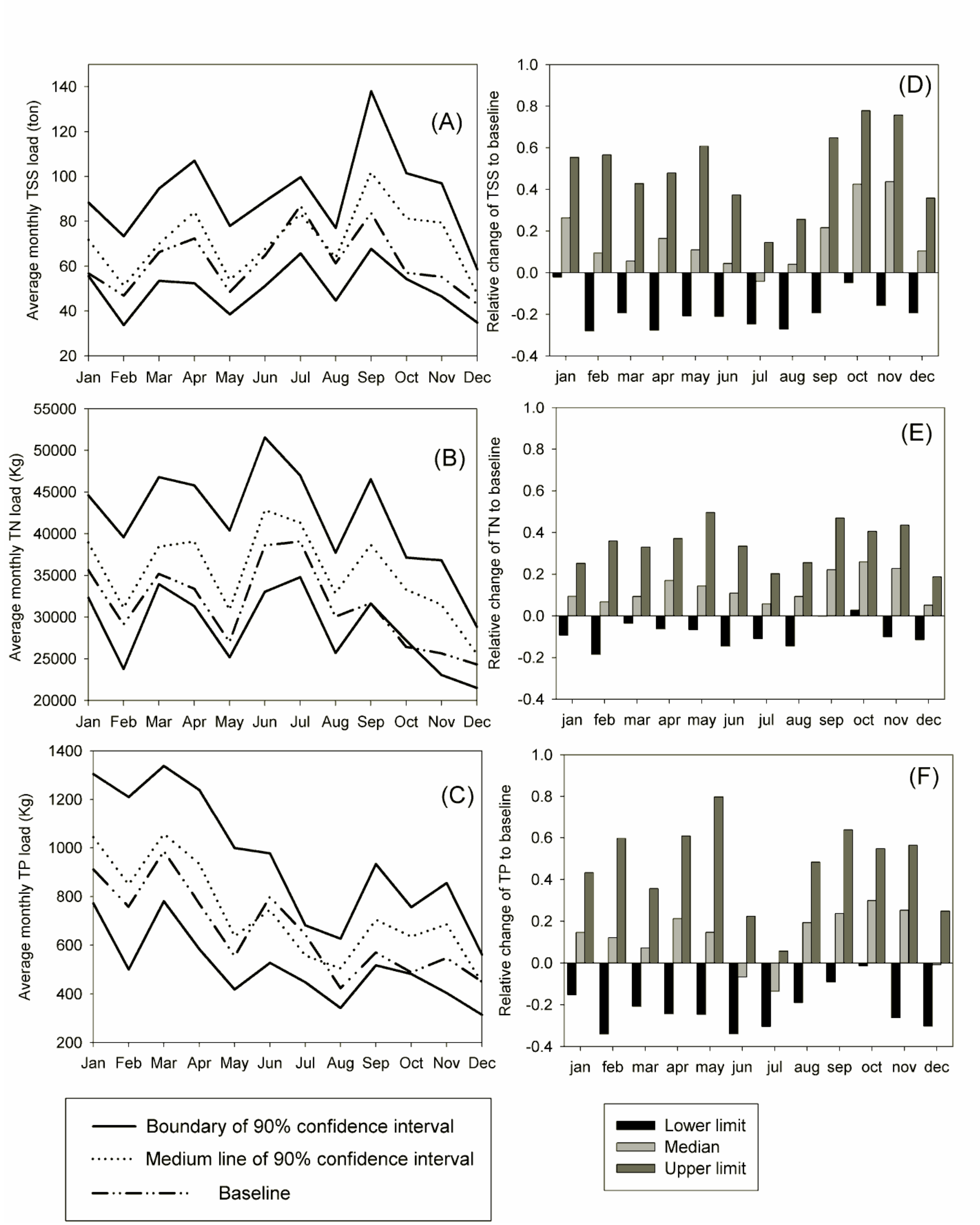

Fig. 8 Monthly responses of TSS, TN, TP and respective relative change from the baseline period (only climate change effect)

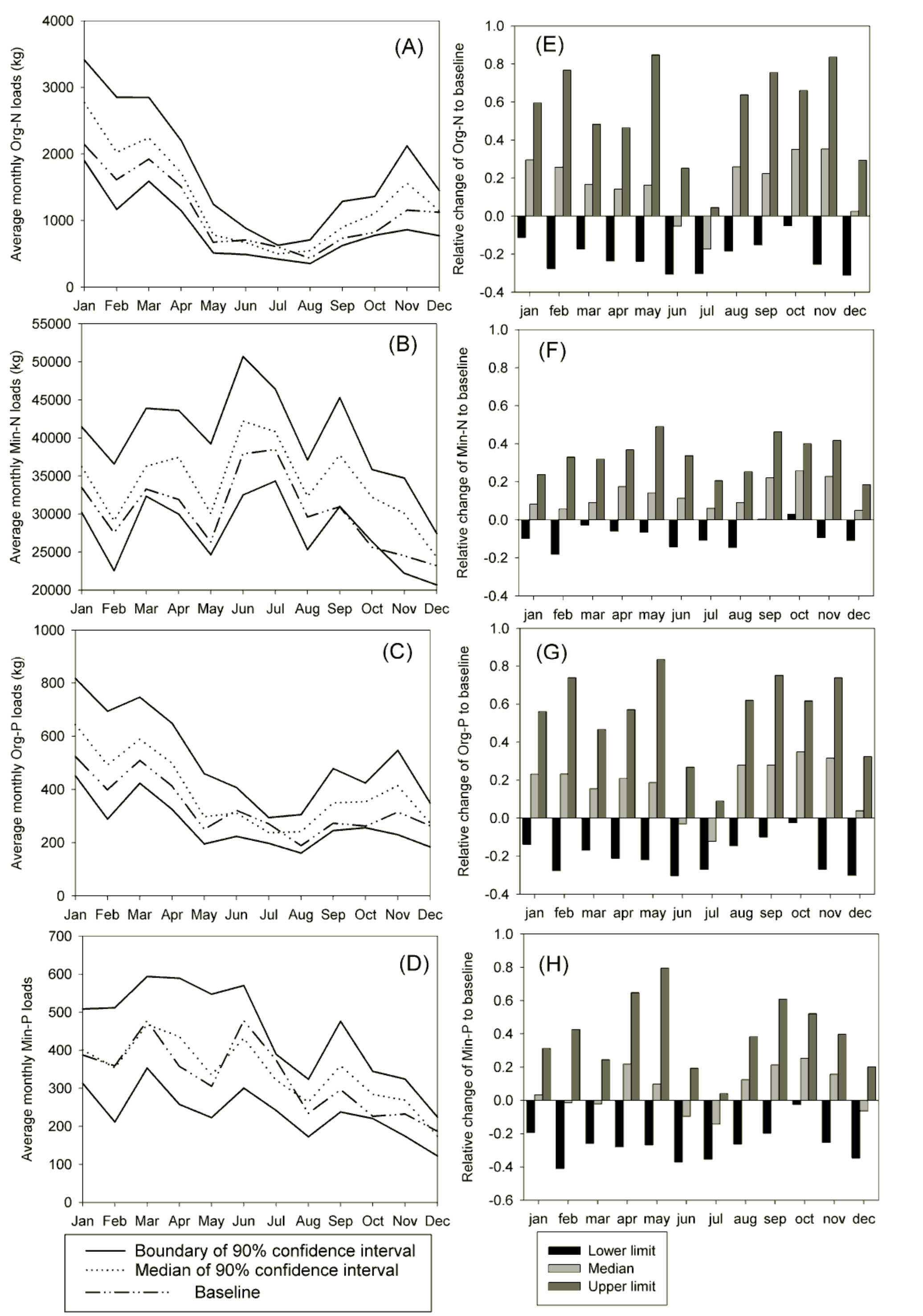

Fig. 9 Monthly responses of organic and mineral nutrient, and respective relative change from the baseline period (only climate change effect)

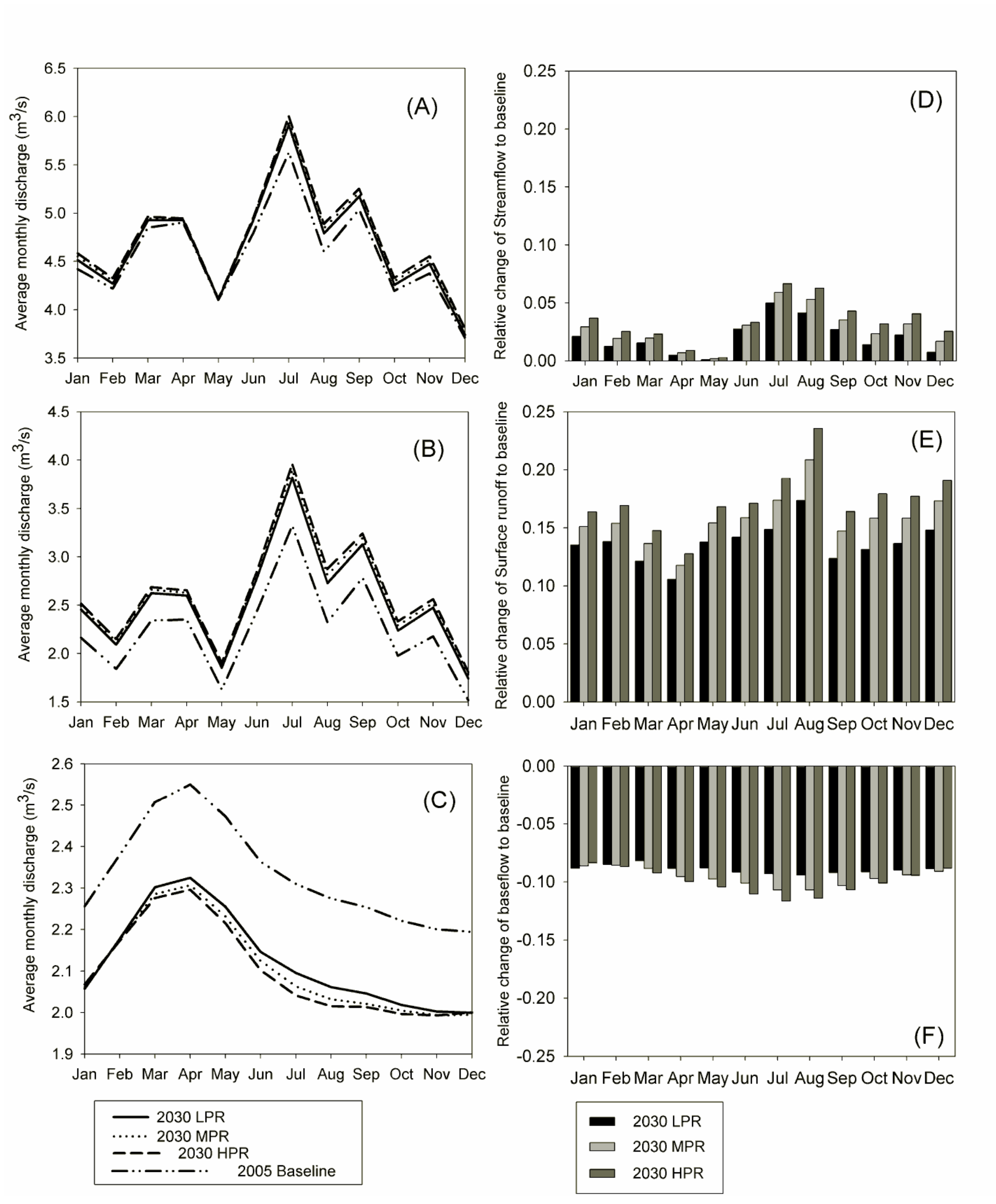

Fig. 10 Monthly responses of flow and respective relative change from the baseline LULC (only LULC change effect)

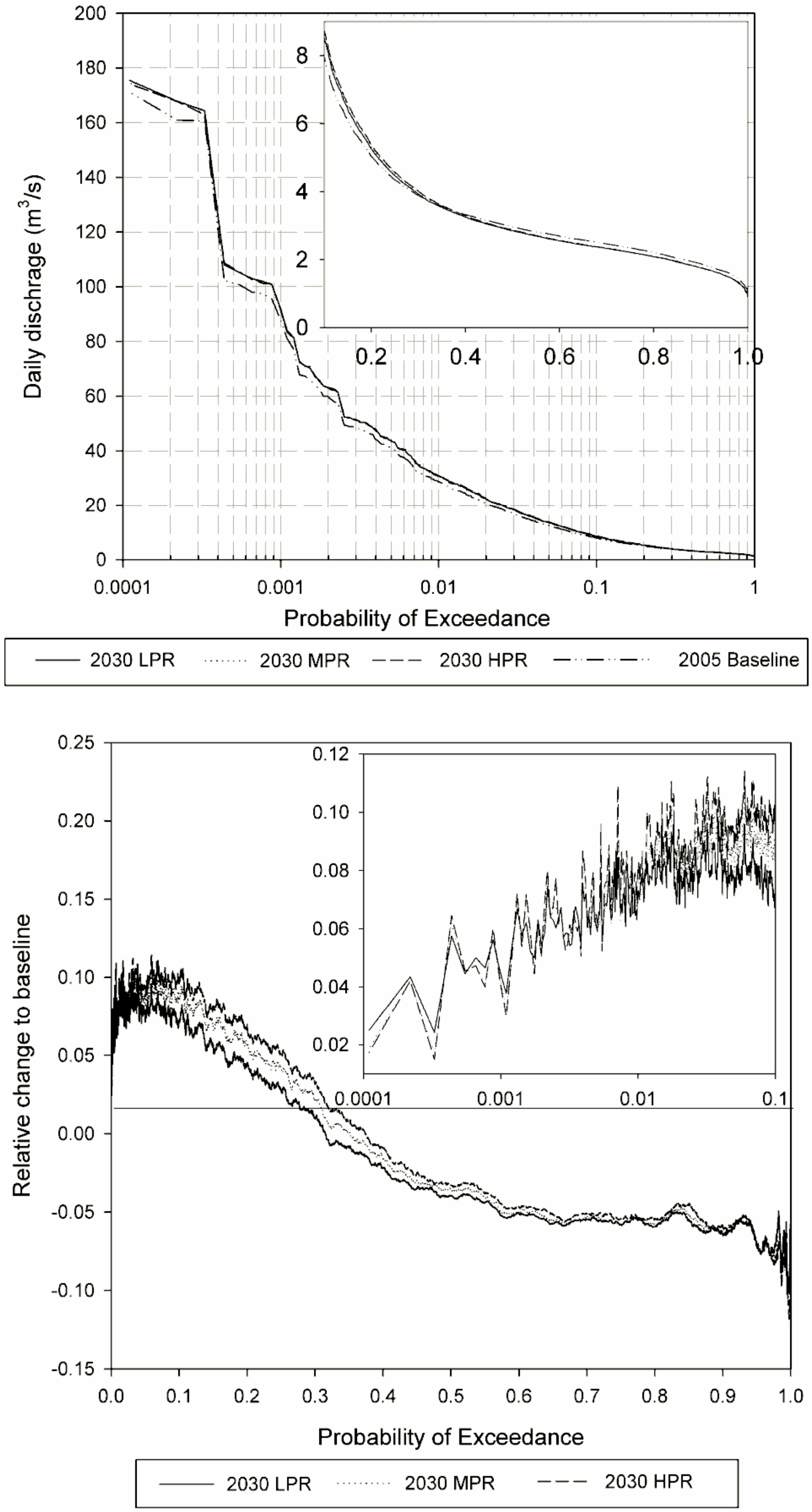

Fig. 11 a. 25-years flow duration curves (FDCs) under projected future LULC and current (baseline) LULC, and b. Relative changes of future FDCs from the baseline (only LULC change effect)

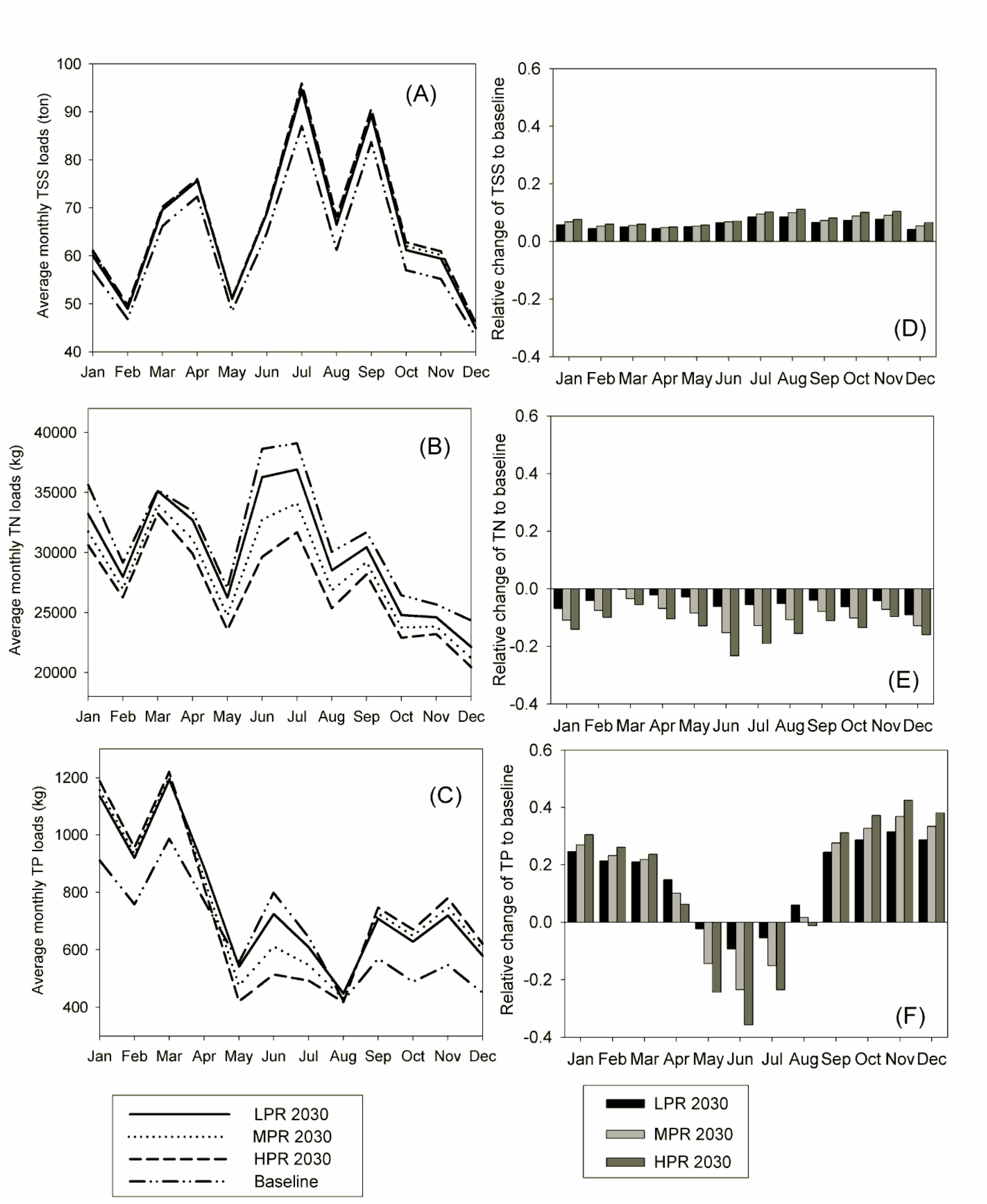

Fig. 12 Monthly responses of TSS, TN, TP and respective relative change from the baseline (only LULC change effect)

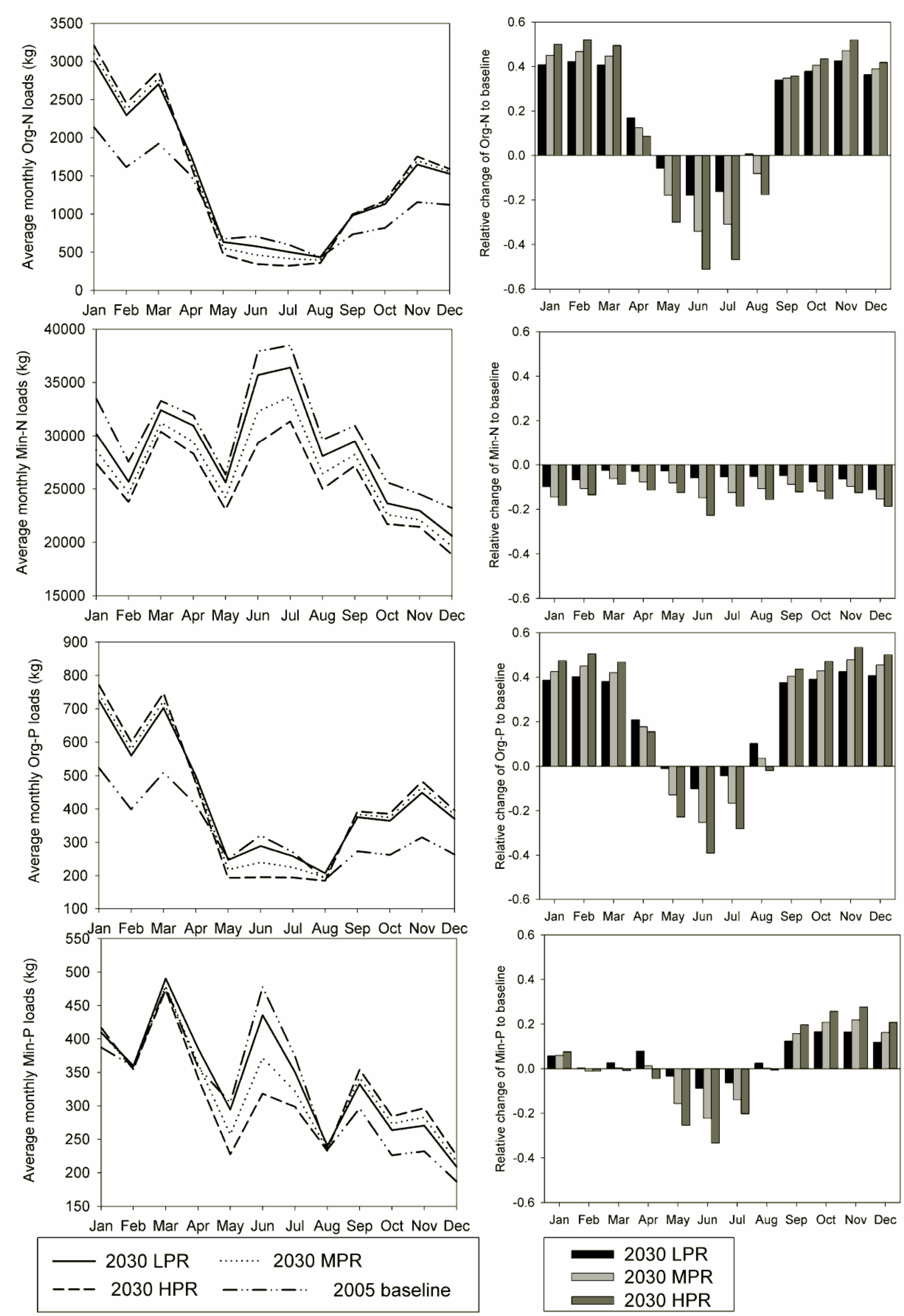

Fig. 13 Monthly responses of organic and mineral nutrient and respective relative changes from the baseline (only LULC change effect)

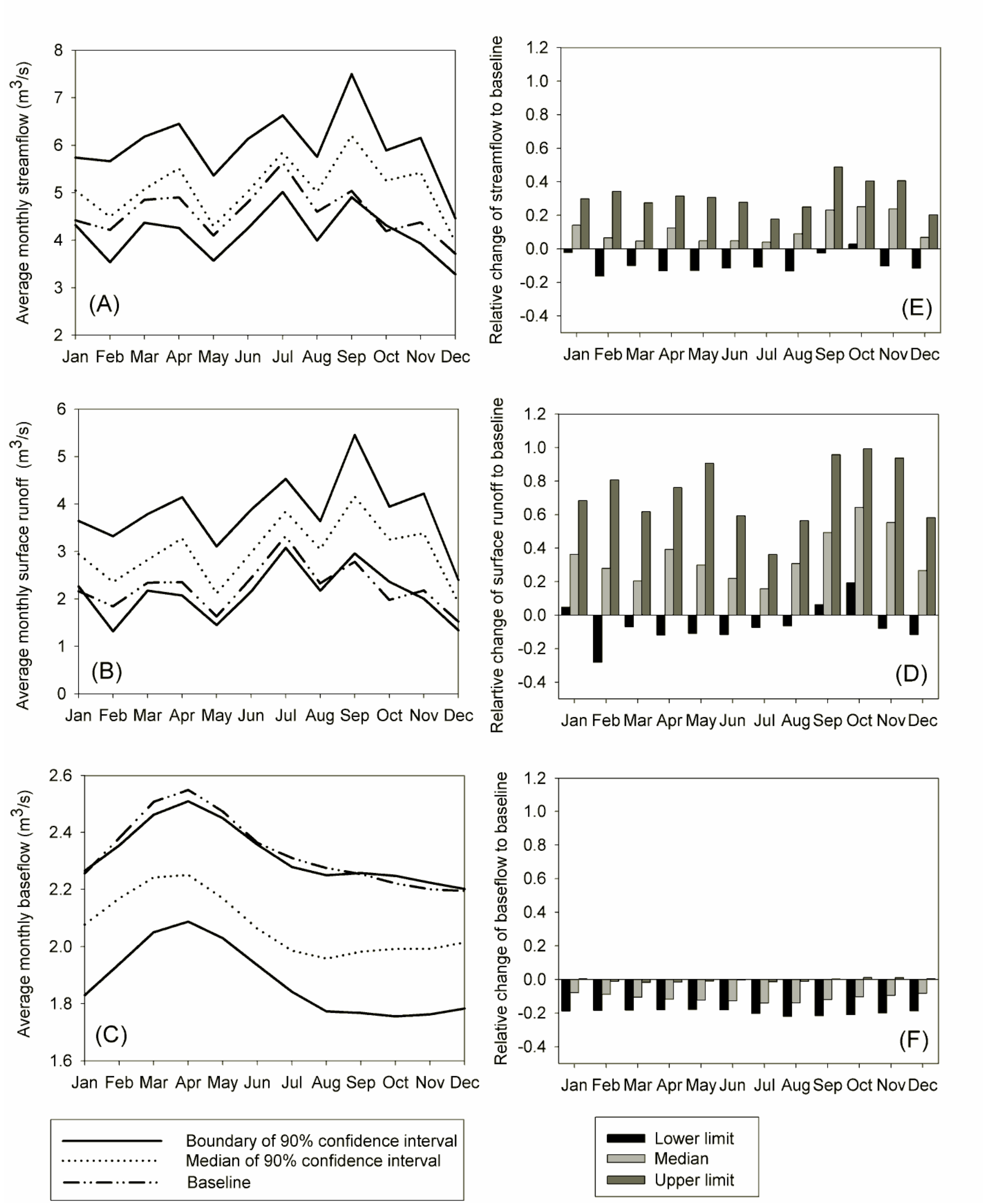

Fig. 14 Monthly responses of flow and respective relative change from the baseline (combined change effect)

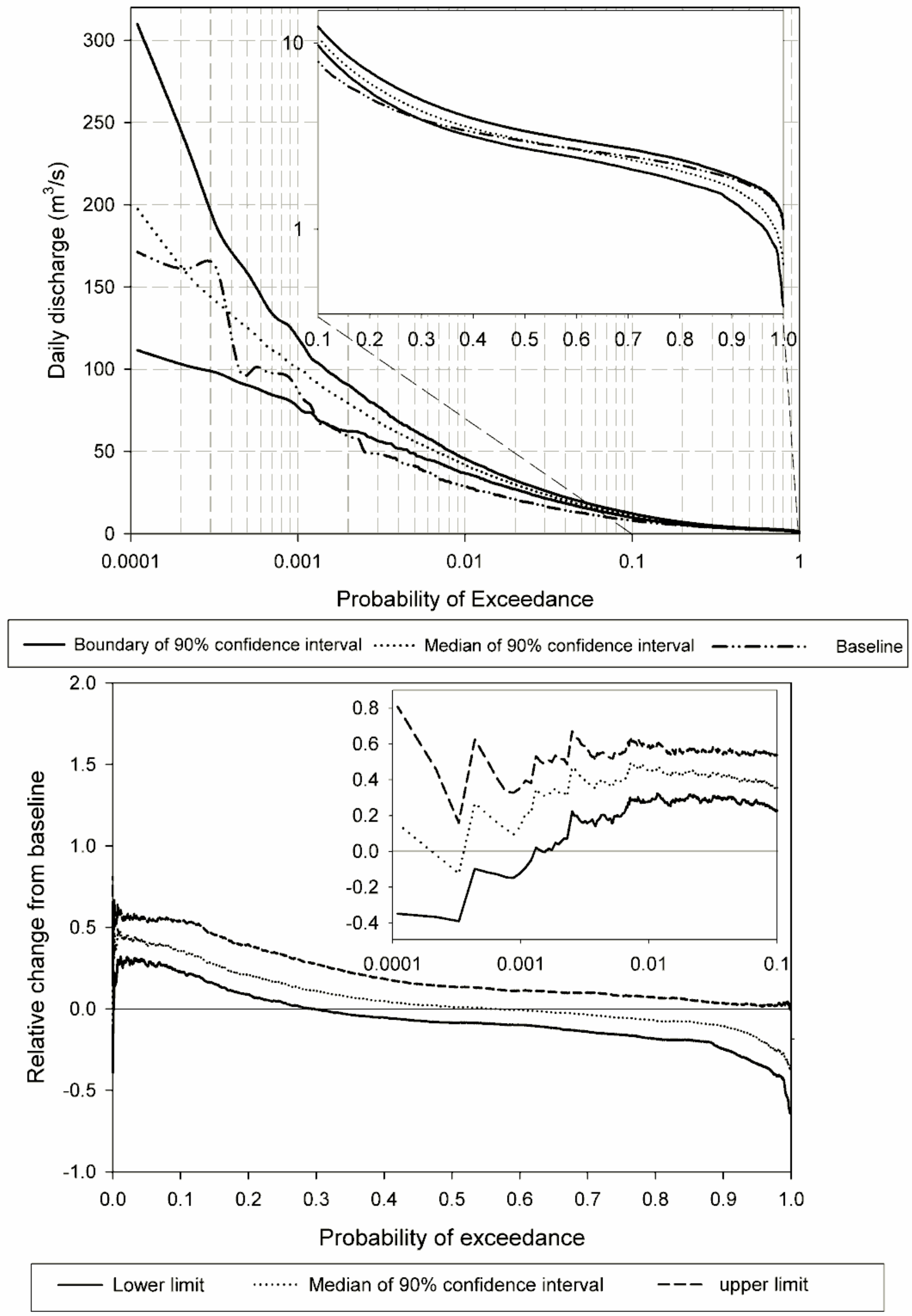

Fig. 15 a.25-years flow duration curves (FDCs) under projected future situations and current (baseline) situation, and b. Relative changes of future FDCs from the baseline (combined change effect)

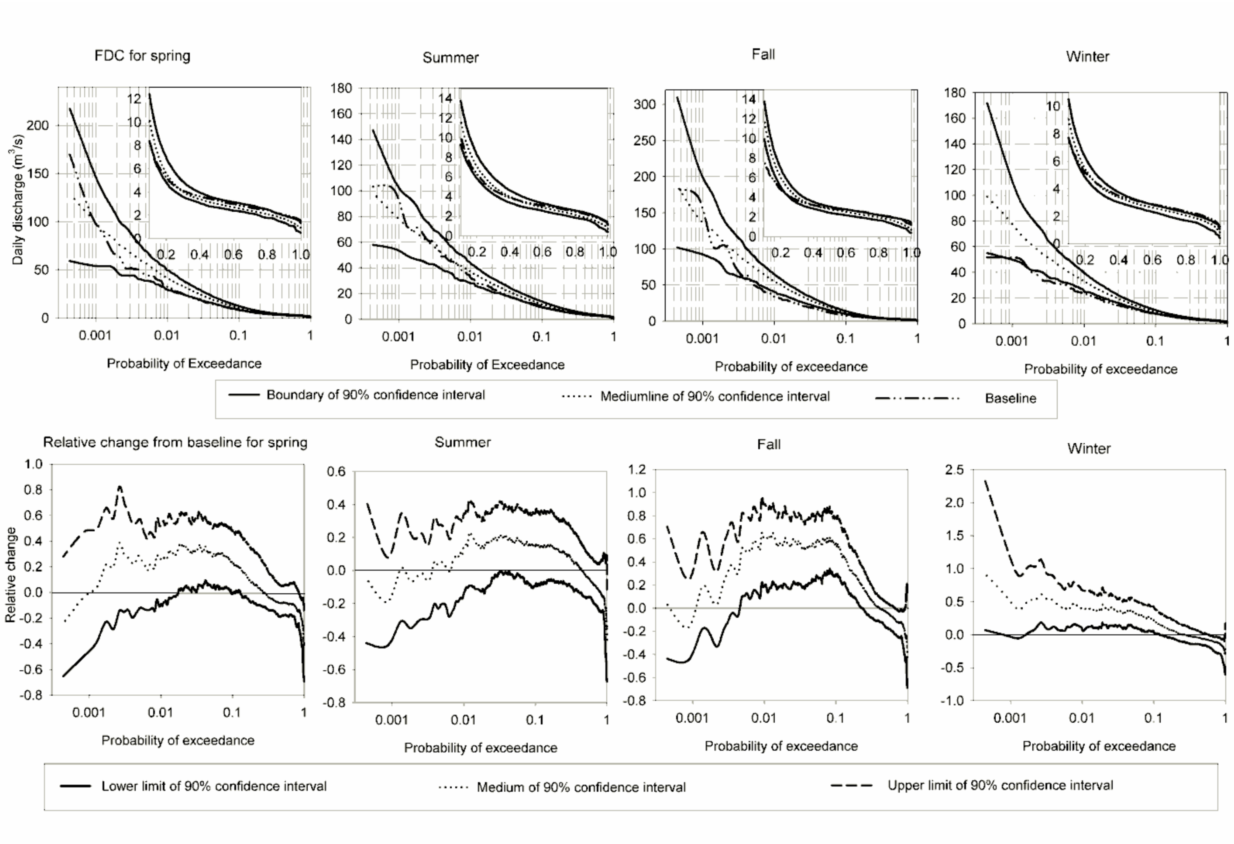

Fig. 16 Seasonal future and baseline FDCs; seasonal relative changes of future FDCs from the baseline (combined change effect)

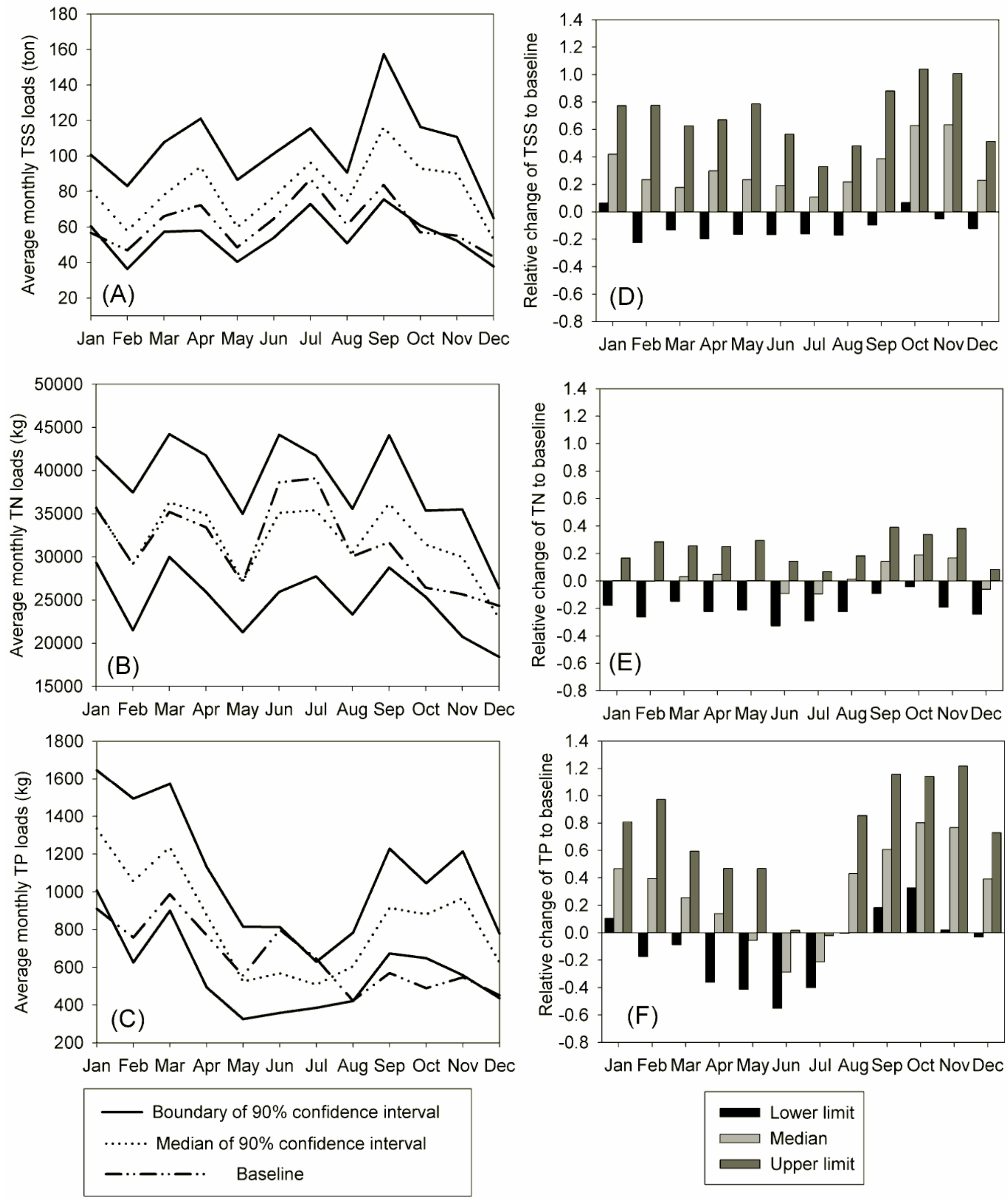

Fig. 17 Monthly responses of TSS, TN, TP and respective relative changes from the baseline (combined change effect)

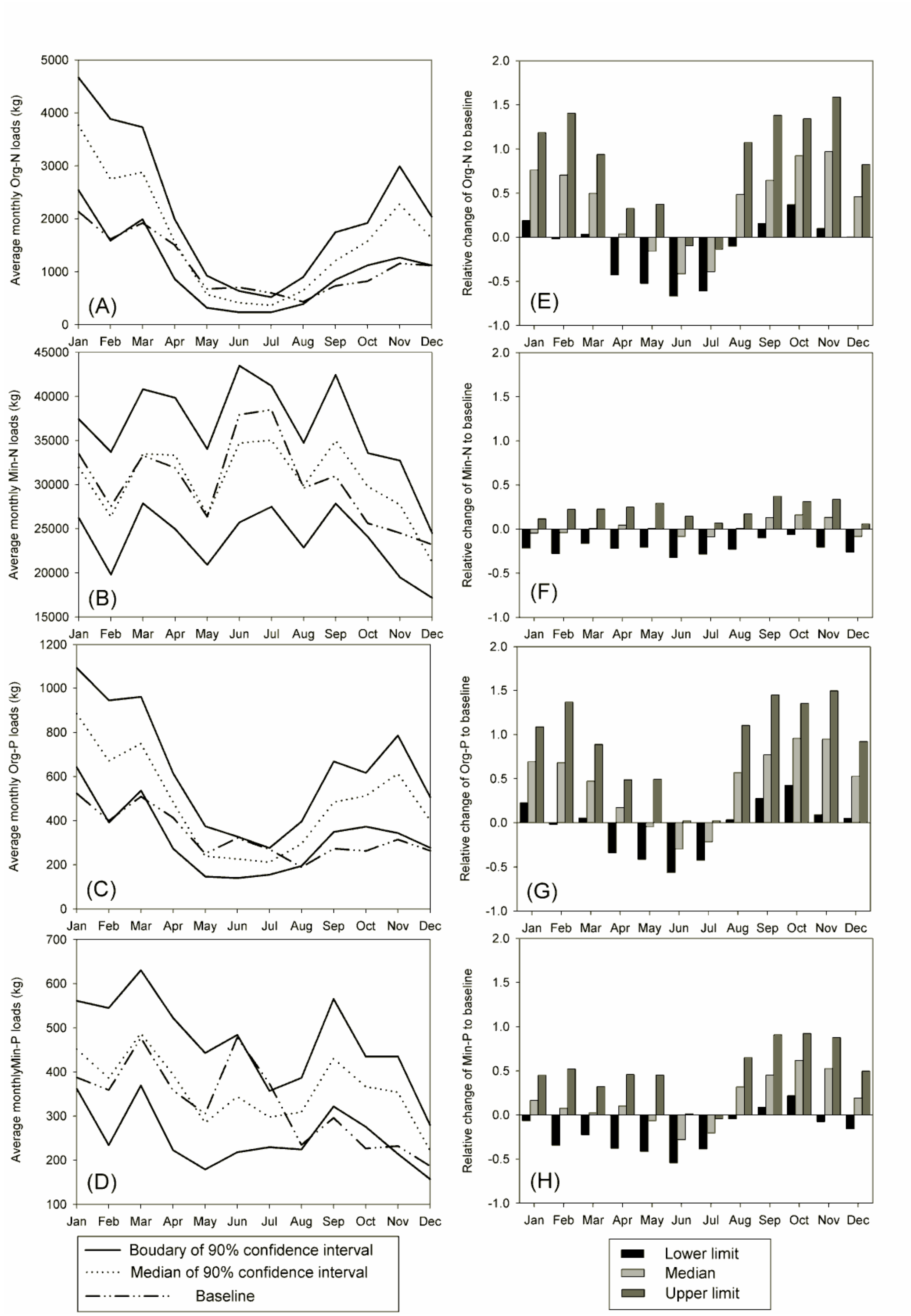

Fig. 18 Monthly responses of organic and mineral nutrient, and respective relative changes from the baseline LULC (Only LULC change effect)

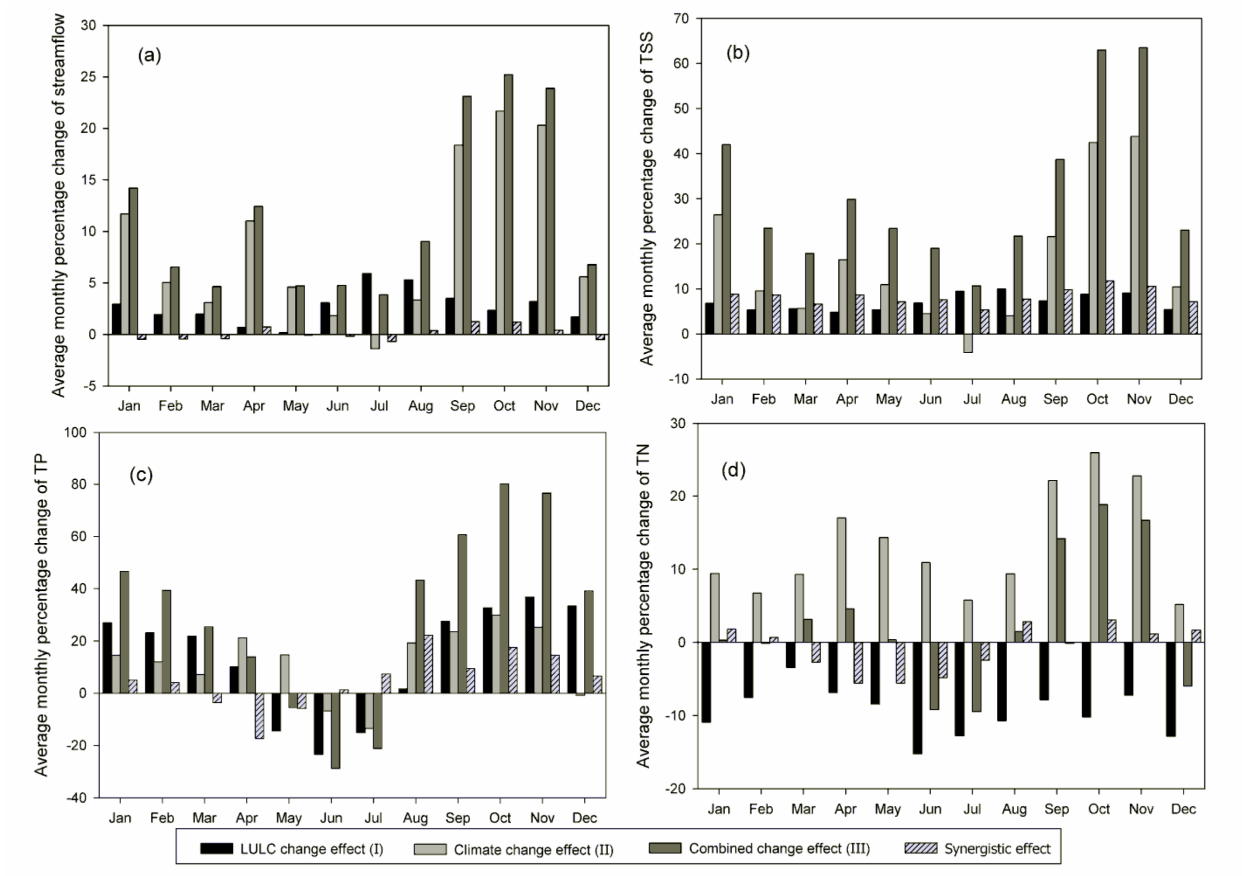

Fig. 19 LULC, climate, combined and synergic effect on average monthly percentage change of (a) streamflow, (b) TSS, (c) TP, (d) TN.

CHAPTER III

Summary and Conclusions

Environment change induced by natural variability and human activities influences both water quantity and quality at global, regional and local scales. Land use/cover (LULC) and climate change are two main factors directly affecting regional hydrology and water quality. Wolf Bay watershed, which is located in southern Alabama along the coast of Gulf of Mexico, has been experiencing heavy urbanization due to population growth and this trend is expected to continue in the near future. Combined with the projected changes in climate, such as increase/decrease in temperature and precipitation, such changes could have serious affects on the water resource and water quality of the region, which could impair the ecological services and biodiversity. In this study, the future potential impacts of LULC and climate changes on the hydrologic and water quality of the Wolf Bay watershed were explored independently and mutually by the Soil and Water Assessment Tool (SWAT).

Model calibration and validation is a standard procedure in most modeling studies to ensure model credibility. This is especially the case with empirical and semi-physically-based models such as SWAT. Due to lack of observed data to calibrate the SWAT model in the target watershed, i.e Wolf Bay watershed, SWAT was calibrated in the nearby Magnolia River watershed, and calibrated model parameters were transferred to the Wolf Bay watershed. Although inferior to direct calibration in target watershed, results indicate that transferred parameters improved model performance when compared to simulations carried out with default parameters which come from the built in SWAT database. Therefore, when observed data is limited, regionalization method based on proximity is an acceptable alternative to ensure model reliability. Next, the effects of parameter transferring on modeling LULC changes were assessed. Two LULC maps from 1992 and 2005 and three parameter sets (default, transferred and calibrated) were utilized. The relative changes in FDCs due to differing LULC showed a similar pattern with each parameter set: relative change was highest at 1-2% exceedance probability. The impact of LULC change diminished gradually as the event sizes got smaller beyond the 2% probability of exceedance. Results suggested that the choice of the parameter set only has a marginal effect on modeling the impacts of different LULC scenarios.

At the next level transferred parameter set was employed in the SWAT model to explore future climate and LULC change effects in the Wolf Bay watershed. Four GCMs under three green house gas emission scenarios were used to capture climate uncertainty, while three projected LULC maps based on different population growth rates were used to reflect LULC uncertainty. Results revealed the followings:

(1) Under the only climate change scenario, high flows were predicted to increase during all seasons under wet and normal conditions, especially during fall and winter. Even under dry conditions, flow showed increasing trend with large flows in fall. Small flows are expected to decrease in all seasons under the dry and normal conditions. No clear trend was found for extreme large flows. Monthly average streamflow and surface runoff were projected to increase in spring, fall and winter, especially during fall, while no clear trend is expected in summer. The monthly distribution of sediment and nutrients are affected by flow and management practices. Projected variations of TSS, TN and TP loadings

followed the same pattern with flow. No evident difference in annual average N:P ratio was predicted.

(2) Under the only LULC change scenario, redistribution of streamflow was similar to the climate change effect. The only difference was that extreme large flows are expected to increase accompanying urbanization. LULC change did not appear to have a significant effect on monthly average streamflows, while increasing trends were still detected in high flow months, such as July and September. However, the partitioning of streamflow to baseflow and surface runoff was considerably affected. Surface runoff was predicted to increase in every month, while an evident decreasing trend was detected for baseflow. LULC change increased TSS loadings but decreased TN loadings in each month. TP loadings were projected to decrease in summer, but increase in other months. The N:P ratio was projected to decrease significantly.

(3) Under the combined change scenarios, a more noticeable uneven distribution of streamflow was predicted, which indicated toward steeper flow duration curves for all four seasons. The combined scenario also led to a more dramatic increasing trend in monthly average streamflows than when climate or LULC change alone was considered. Further, more visible increasing trend in surface runoff and more dramatic decreasing trend in baseflow were detected. Under the combined scenario, TSS loadings are expected to increase for each month. Since LULC and climate change effect are considered simultaneously, water quality is affected by both. If future loadings are expected to increase/decrease under either climate or LULC change scenarios, combined change scenario intensifies that trend. On the other hand, if their effects are in opposite directions, then the combined change has an offsetting effect. The synergistic effect

coming from the interaction of LULC and climate change showed that there is a nonlinear interaction between them as their combined effects were not additive. This nonlinear interaction was more evident in water quality than flow.

FUTURE PROSPECTIVE

Several potential new ideas originate from this study:

1. The feasibility of model parameter transferring based on spatial proximity was confined to flow only in this study. Regionalization could be extended to a larger parameter set that includes water quality parameters, if observed sediment and nutrient data is available from nearby watersheds.
2. The quality of precipitation data is one of the most important aspects in watershed modeling. In areas like Alabama, precipitation patterns show large spatial variation, especially in summer months. Radar technology presents an opportunity to capture such variations, in spite of its known deficiencies. It is worth exploring how better representation of spatial variation in precipitation would impact some of the conclusions drawn out of this work.
3. In this study, monthly outputs of GCMs were spatially downscaled by a statistical approach and then temporally downscaled by a weather generator. The impacts of using a dynamic downscaling technique, such as a regional climate model, on some of the results obtained in this study remain to be explored.
4. The uncertainty analysis in this study was limited to climate inputs (precipitation and temperature) and LULC senarios. Uncertainties originating from model structure and model parameters were not studied. Inclusion of those uncertainties would provide a

more comprehensive and complete analysis of the impacts of climate and LULC change on water quality and quantity.