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THE KENTUCKY NUTRIENT WATERSHED MODEL

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Computational models for analyzing the hydrologic and water quality response of a watershed have been used for decades, beginning in the early 1960's with the development of the Stanford Watershed Model (SWM). The 1970s produced several other continuous simulation models for analyzing water quality loads from stormwater runoff and combined sewer overflow (CSO) discharges such as SWMM and STORM. With an increased emphasis on TMDLs in the 1990's, EPA sponsored the development of BASINS, a comprehensive modeling system for use by the engineering and regulatory communities that integrated existing federal databases of hydrologic and water quality data into a G IS-based modeling environment. More recently, in 2005, T etra Tech formally introduced the Loading Simulation Program in C++ (LSPC) for use in support of the simulation of watershed processes which include both point and nonpoint pollution.

While the increasing sophistication of these models has provided scientists and engineers with better tools to analyze increasingly complex phenomena, they have also created some basic limitations with regard to their use by regulators and policy makers as well as the ability for various stakeholders including the general public to either understand or accept their results. This has been especially true for models now being used as a basis for making significant policy decisions that can have profound economic implications for various stakeholders (e.g. Chesapeake Bay).

This paper will summarize the development of a macro-level nutrient simulation model (the Kentucky Nutrient Model) and describe its application to the Floyds Fork Watershed near Louisville Kentucky. The model has been constructed in an Excel spreadsheet format, and uses a daily time step for calculating the daily nutrient loads (i.e. total nitrogen and total phosphorus) for a twelve month period. The model is able to simulate both point and non-point source loads.

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MODEL PARAMETER UNCERTAINTY ANALYSIS FOR AN ANNUAL FIELD-SCALE P LOSS MODEL

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Introduction: Agriculture can be a significant source of phosphorus (P) loading to surface waters which can lead to water quality deterioration of P-sensitive water bodies. To mitigate the effects of agricultural activities on water quality, models are often used to assess the effectiveness of various conservation practices for reducing P loss. While model predictions of P fate and transport in the environment can provide useful information, an inherent amount of uncertainty exists with all model predictions, regardless of how complex or "physically-based" they may be. Sources of uncertainty include errors that are introduced when approximating complex physical phenomena with simplified mathematical models, the inherent amount of randomness within natural systems, measurement errors in the model input variables, and errors associated with the model parameters. The magnitude of the errors introduced from these different sources will depend on the validity of the model assumptions, the complexity of the model, the quality of the input data, and on how well the various model parameters have been estimated. This study presents results from an analysis investigating the effects of model input and parameter error on prediction uncertainties of P loss using the Annual P Loss Estimator (APLE) model, an empirically-based spreadsheet model developed to describe annual, field-scale P loss when surface runoff is the dominant P loss pathway. The specific objectives of this study were: 1) to estimate the model parameter uncertainty associated with five internal regression equations used in APLE, 2) to estimate uncertainties associated with model input variables based on uncertainties reported in the literature, and 3) to evaluate how the model input and parameter uncertainties affect uncertainties associated with field-scale predictions of P loss.

Methods: Using unweighted and weighted least-squares regression, parameter uncertainties were calculated for five regression equations used to estimate total soil P from measurements of soil clay content, organic matter, and labile P; the P enrichment ratio calculated from erosion rates; concentration of P in runoff calculated from labile soil P; and the partitioning of P between runoff and infiltration for applied manures and fertilizers based on runoff ratio. Our analysis included calculating both 95% confidence and prediction intervals. Uncertainties in predictions of P loss using the APLE model were calculated by including uncertainties in both model parameters and model inputs and the relative magnitude of these two sources of uncertainty to the overall uncertainty associated with predictions of P loss were compared.

Results: Statistically significant fits were observed for all five of the regression equations tested (p < 0.001) with Nash-Sutcliffe efficiency (NSE) values exceeding 0.65 for all equations except one, indicating good overall fits to the observed data. A large amount of scatter, however, was also observed indicating that a substantial portion of the variability in the observed data was not captured by these equations with median absolute percent errors ranging from 11% to 35%. Estimates of the parameter standard errors for the

regression equations ranged from 6% to 26% of the best-fit parameter estimates. The uncertainty associated with the mean response of the five regression equations due to uncertainties in the best-fit model parameters varied considerably with 95% confidence intervals (CIs) ranging from \pm 15 to 57% of the model-predicted values. The calculated 95% prediction intervals (PIs) were much wider than the CIs for each equation with values ranging from \pm 15 – 3400%. The 95% PIs are much wider than the CIs because they account for variation in the dependent variable not accounted for by uncertainties in the best-fit model parameters and thus reflect the large amount of variability in the observed data not captured by these equations. This resulted in 95% PIs including physically unrealistic values for some of the equations.

The uncertainties associated with APLE predictions of P loss were then calculated using the 95% CIs calculated for the five regression equations and estimating uncertainties associated with model inputs based on previously published work. The resulting 95% CIs for APLE predictions of P loss ranged from 6 to 20% of the modelpredicted values for model input errors of \pm 5% and 14 to 24% for model input errors of \pm 15%. The relative magnitude of the two sources of error (model parameter and model input) on t he uncertainties in model-predicted P loss varied depending on l and management practices. For instance, model parameter uncertainty was generally larger than the uncertainty resulting from \pm 5% error in the model inputs for fields with no P application, P applied as manure to fields without erosion, and P applied both as fertilizer and manure to fields with erosion. For these fields, including uncertainty with the model input variables did not noticeably increase model prediction uncertainties. Conversely, when both fertilizer and manure were applied to fields with no significant erosion, model input uncertainty contributed the majority of the uncertainty in the model predictions. When P was applied as fertilizer or manure to fields with erosion, the relative magnitude of the uncertainties from model parameters and model inputs varied between studies. When uncertainty in model inputs was increased to $\pm 15\%$, the contribution of model input uncertainty to model-prediction uncertainty became more significant. In general, uncertainties in both sources contributed to the overall model prediction uncertainty indicating the need to include both sources of error when calculating model prediction uncertainties with the APLE model.

When using the 95% PIs prediction intervals to calculate uncertainties in the regression equations, the uncertainties in APLE predictions of P loss ranged from 35 to 270% of the model-predicted values. In comparison, the magnitude of the model input uncertainties was negligible. Using the 95% PIs to calculate model prediction uncertainties resulted in such wide error bars as to make model predictions of individual observations of P loss of limited value.

Summary: Results from this study highlight the importance of including reasonable estimates of model parameter uncertainties when using models to predict P loss. Our results also highlight the need to reduce model parameter uncertainties. To reduce these uncertainties will require developing equations that better describe the observed variability in our measurements. This will require the identification of additional soil properties that improve the predictive capability of these equations; properties which may not currently be measured in routine soil analyses.

FLOOD MODELING UISNG A VIRTUAL 3D ENVIRONMENT TO HELP STUDENT LEARNING

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Introduction

Floods can cause huge damages to properties in vulnerable river systems during severe storms. Flood plain management and mitigation require a proper understanding of watershed hydrology and river flow hydraulics. In this research, a virtual 3D lab module was created for the Little Calumet River System in the Lake Michigan Watershed. Its use in student learning was explored by integrating lab classes and regular lectures at the inter-university level.

The Little Calumet River System and its Hart Ditch tributary were considered during this work. This river system drains 300 square miles to Lake Michigan. Covering both urban and rural areas, this system was very severely flooded during storm Ike in 2008. Huge property damages were reported due to flooding. The US Army Corps of Engineers constructed a levee system for more than 20 miles in Indiana to mitigate floods.

Model development

For the considered system, unsteady flood flow simulation was done using HEC RAS software (Hydrologic Engineering Center River Analysis System). Fourteen cross sections across Hart Ditch, 5 cross sections across the Little Calumet River East and 12 cross sections across the Little Calumet River West were surveyed and used in the HEC RAS modeling. This task was accomplished by two senior design groups and a graduate student as part of thesis work. Watershed rainfall and runoff were modeled for different storms using HEC HMS software (Hydrologic Engineering Center Hydrologic Modeling System) and using USGS flow observations, flow was calibrated. Flow hydrographs from different reaches were extracted from HEC HMS model and used in HEC RAS simulation.

After successful unsteady simulation, the results (stage levels and flow hydrographs) were captured from the HEC RAS model and entered in a virtual 3D model created using the Unity 3D game engine platform. The 3D model was created using a digital elevation

model, the national hydrology dataset and local statistics. When students complete the HEC RAS model simulation, they can prepare a text file in a specified format and enter it into the 3D model. Using this text file, the 3D model creates the 3D flow simulation and inundation mapping at different time steps.

Students can enter the system and fly to different cross sections in a virtual environment to compare: 1) the flooding at different nodes, 2) the depth and area of inundation, and 3) impacts to the system with and without levees. Students can measure these details and document them using tools in the 3D environment. At four universities (Purdue University Calumet, Florida Atlantic University, the University of Kentucky and the University of the District of Columbia) these models were used in the class rooms or labs and student feedback was collected. The results are being analyzed by an Education specialist in this study.

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UPDATING THE FRESH-SALINE WATER INTERFACE MAP IN EASTERN KENTUCKY

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Since 2011, approximately 60 horizontal wells associated with the Devonian Berea Sandstone oil play have been drilled and completed in eastern Kentucky. Drilling and hydraulic fracturing occur at relatively shallow depths of 900 t o 1,800 feet from the surface. The shallow completion depth raises concerns about groundwater quality. Surface casing is intended to protect groundwater in oil and gas drilling. The depth of surface casing is often based on estimates of the base of the potable groundwater level. Hopkins (1966), mapped the elevation of the fresh-saline water interface in Kentucky, where he defined fresh water as having less than 1,000 ppm total dissolved solids. Though an often used reference for surface casing depth, the Hopkins map is often based on sparse data. Moreover, the base of fresh water is based on the total depth of the deepest potable water well in a given area. Thus, the map likely underestimates the true depth to the base of fresh water in many areas.

The scarcity of data and surge in horizontal well drilling and hydraulic fracturing prompted an effort to update the fresh-saline water interface map in Lawrence, Greenup, Boyd, Elliott, and Carter Counties. Data from the Kentucky Groundwater Data Repository (KGDR) and observations of fresh and salt water in oil and gas wells were used to update Hopkins' map. Data for groundwater wells less than 1,000 ft deep with chloride concentrations less than 500 mg/L were added as new data points for mapping. Recognizing that the revised map may still underestimate the depth to the base of fresh water, we term the new map, "deepest observed freshwater." The new map includes 120 wells in the five county study area, whereas the Hopkins map was based on 28 w ells. Elevation above sea level for the deepest observed freshwater ranges from approximately 450 ft. in Boyd County to 1050 ft. in Carter County. In most areas, the deepest observed freshwater occurs in Pennsylvanian sandstone.

The confining interval thickness between the top of the Berea Sandstone oil reservoir and the deepest observed freshwater also plays an important role in protecting potable groundwater. Our mapping shows that the confining interval thickness ranges from more than 1500 ft in Lawrence County to approximately 350 ft in Greenup County. The thinner confining interval along with shallow drilling depth thus necessitates diligence when conducting oil and gas operations in Greenup County.

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