Modeled Watershed Runoff Associated with Variations in Precipitation Data, with Implications for Contaminant Fluxes: Initial Results

Heather E. Golden, Christopher D. Knightes, Ellen J. Cooter, Robin L. Dennis

Abstract

Precipitation is one of the primary forcing functions of hydrologic and watershed fate and transport models; however, in light of advances in precipitation estimates across watersheds, data remain highly uncertain. A wide variety of simulated and observed precipitation data are available for use in regional air quality models and watershed fate and transport models. Although these single media models can potentially link together to estimate contaminant loadings issuing from watersheds, questions remain concerning how precipitation data from diverse sources used within each model affect water and contaminant mass balances. We assess how two sets of spatially distributed precipitation data, simulated at 12-km grid and 36-km grid resolutions, affect runoff simulated from a spatially distributed grid-based mercury watershed model that has been calibrated using observed precipitation data. We focus on two headwater catchments in the Cape Fear River Basin, NC. Our initial results suggest that precipitation data simulated at a coarse resolution (e.g., 36k-m grid) decreases the efficiency and goodness-of-fit of modeled runoff, but this is watershed specific. Variations in the response to coarse resolution precipitation potentially results from differences in the size and within stream structural modifications of each watershed. These initial results are assessed within the context of a broader project that will also evaluate the effects of radar and empirically-estimated precipitation data sets on modeled runoff and variations in watershed contaminant loading resulting from these diverse precipitation inputs.

Keywords: precipitation, rainfall-runoff modeling, fate and transport modeling, runoff efficiency

Introduction

Watershed-scale fate and transport models are important tools for estimating the sources, transformation, and transport of contaminants to surface water systems. Precipitation is one of the primary inputs to watershed biogeochemical models, influencing changes in the water budget of the surface, shallow subsurface, and deep groundwater zones, and as a result, the transport of contaminants to surface water systems. Estimates of precipitation across watersheds are notably imperfect, partially stemming from the sparse coverage of monitoring networks, the coarse resolution of simulated data, and the dynamic temporal and spatial nature of precipitation events. Further, most watershed fate and transport modeling studies are limited by precipitation data representing only a few sites within or near the watersheds. Although improvements to rainfall estimates across watersheds have been made in recent years (e.g., NEXRAD, satellite imagery, modification in rainfall

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gage density), few advancements to these precipitation estimates are made within the context of rainfall-runoff and watershed contaminant flux modeling (see Andréassian et al. 2001). Questions remain concerning the response of modeled runoff generation and consequent contaminant fluxes in watersheds to these new sources of precipitation data.

Atmospheric deposition (of nutrients and metals) is also an important input to watershed models estimating non-point source loads from the landscape, particularly in portions of watersheds where atmospheric sources are a significant component of mass balance calculations (e.g., deposition of reactive nitrogen in forested areas; Boyer et al. 2002). Although estimates of atmospheric deposition for watershed fate and transport modeling are typically derived from individual point monitoring locations, these data are sparse and require multiple interpolation techniques for broad spatial coverage. Acquiring atmospheric deposition estimates from spatially-resolved (i.e., grid-cell) process-based regional air quality models (e.g., Community Multiscale Air Quality (CMAQ) for wet deposition) potentially resolves these issues, particularly for mesoscale and large watershed modeling efforts. However, precipitation rates used in these models to estimate deposition from atmospheric concentrations often derive from different sources and estimation techniques than those applied in watershed fate and transport modeling. For example, CMAQ uses regionally-simulated rainfall data while watershed fate and transport models often use observed data from monitoring stations. This leads to a potential decoupling between the rainfall component estimating atmospheric deposition from concentrations in air quality models, for example, and precipitation data (e.g, observed, radar, or other simulations) applied to estimate runoff and contaminant loads to surface waters. As a result, estimates of nutrient and metal loadings are over or underestimated because of the potential differences in the simulated water and chemical mass balance budget.

Several studies have assessed the effect of using multiple precipitation data sets on modeled runoff; however, the approach is either focused on broad, global data sets of precipitation (e.g., Fekete et al. 2004), variations in the density of observed rainfall stations (Andréassian et al. 2001), or comprehensive uncertainty analyses of radar rainfall estimation and modeled runoff (Carpenter and Georgakakos 2004, Hossain et al. 2004). Few studies have focused on the effects of using several different types of precipitation data sets, which vary both spatially and in how estimates are derived (i.e., observed vs. simulated, radar, and empirically-estimated), on watershed loading estimates.
The goal of this paper is to present results from our study assessing how precipitation data derived from multiple sources (currently, observed and regionally-simulated) and at different spatial scales affect the rainfall-runoff component of a watershed fate and transport model. This paper is the initial phase of a larger project investigating how decoupled precipitation data used within regional atmospheric and watershed fate and transport models affect both water flux and contaminant loading from watersheds to surface waters. We pose the questions:

1. How does the spatial resolution of simulated precipitation affect modeled runoff generated from a semi-distributed watershed fate and transport model that is calibrated using observed precipitation data?
2. As data sets of precipitation at multiple spatial scales become increasingly available for use in mesoscale to large scale water quality modeling, what precipitation data generates runoff most accurately?

The findings presented here are initial assessments and begin to advance current understanding of the relationships between the spatial variability and sources of precipitation estimates and accuracy of simulated runoff, particularly related to linking air quality and watershed fate and transport models. The next phase of our project will analyze the effects of additional precipitation data sets (including the National Multi-sensor Precipitation Analysis (NPA)) on watershed runoff and contaminant loading esimates.

Study Area

The study was conducted in two watersheds located within the headwaters of the Cape Fear River Basin, NC (Figure 1). The two watersheds include the Deep River Watershed (area above stream gage = 906 km^2) and Haw River Watershed (area above stream gage = 3,296 km^2) located in the Piedmont region of North Carolina and draining to the Coastal Plain system. Both watersheds have similar landcover characteristics (41–45 percent forested, 25–28 percent pasture, 18–27 percent developed) and topographic variations. Our goal was to assess watersheds within the same climatic

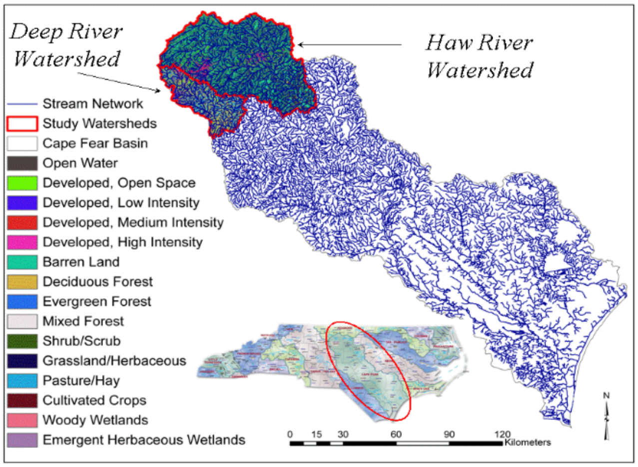

Figure 1. The Deep and Haw River Watersheds within the Cape Fear River Basin, including landcover (MRLC 2001).

regime and with relatively similar landcover and elevation characteristics, though some physical variations (e.g., size and flow alterations such as lock and dam systems and channelization in developed areas) do exist.

Methods

Precipitation data

As part of the initial phase of the project, we utilized three precipitation data sets with varying spatial resolutions for comparision: (1) observed monitoring data from National Oceanic and Atmospheric Administration National Climatic Data Center (NCDC) COOP stations (National Climatic Data Center 2008) at two sites within or bordering the Deep River Watershed and five sites within or bordering the Haw River Watershed; (2) 36-km grid cell simulated data from the Pennsylvania State University/National Center for Atmospheric Research mesoscale model (MM5); and (3) 12-km grid cell simulated MM5 data (Figure 2). We used data from 2001–2003, which are representative of wet, dry, and normal years across the southeastern United States (National Oceanic and Atmospheric Administration 2008) The MM5 model is a regional (mesoscale) modeling system that simulates and predicts regional atmospheric circulation (Grell et al. 1995). Both 12-km and 36-km MM5 precipitation data sets are used in computations of depositional fluxes of nitrogen, sulfur, and mercury species within the CMAQ regional air quality model (Bullock and Brehme 2002, Byun and Schere 2006),which will be implemented in subsequent phases of the project.

Daily precipitation data from each source were applied to a grid-based mercury model (GBMM; see below) to assess how variations in precipitation affect modeled runoff in the Deep River and Haw River subwatersheds of the Cape Fear River Basin, NC.

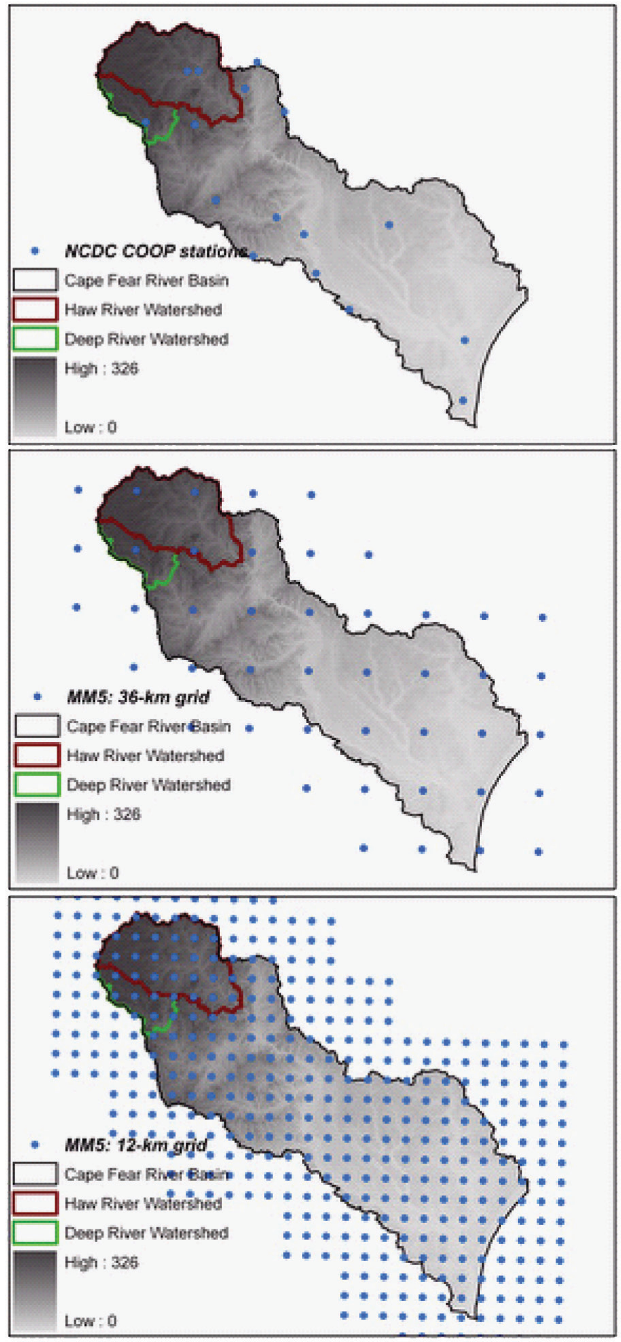

Figure 2. Comparison of the spatial resolutions of precipitation data in the Cape Fear River Basin: National Climatic Data Center observed precipitation sites (top), 36-km MM5 simulation grids (middle), and 12-km MM5 simulations grids (bottom). Each point on the MM5 grids is the centroid of the grid cell for which precipitation values are simulated.

Grid based mercury model

Rainfall-runoff evaluations are conducted using a recently developed spatially distributed grid-based watershed mercury (Hg) model (GBMM v2.0, Tetra Tech, 2006) that computes daily mass balances for hydrology, sediment, and mercury within each GIS raster grid cell and produces daily flux estimates of each to a tributary network.

GBMM implements a simple water balance to compute available soil water in the unsaturated zone (S_w; cm) using the equation:

$$S_w = S_{w_o} + P_{tot} - R_o - ET - P_c$$

Where S_{w_o} is the initial water in the unsaturated zone (cm), P_{tot} is the total available water inputs at the soil surface (cm), R_o is the surface runoff (cm), ET is actual evapotranspiration (cm), and P_c is soil percolation (cm). Runoff is computed using a modified curve number approach, similar to SWAT (Neitsch et al. 2005), and ET derives from the Hamon formula for potential evapotranspiration (Hamon 1961). Precipitation from multiple stations is weighted using the Thiessen polygon method.

Initial calibration of the GBMM hydrology module (using a 90-m grid resolution) focused on daily discharge at six U.S. Geological Survey (USGS) stream gages and used daily observed precipitation from 15 NCDC stations within the Cape Fear River Basin to simulate runoff. However, because the length of model runs for the entire Cape Fear River Basin (16 hrs per run for a 24,144-km^2 watershed) was too time consuming for effective calibration, we completed the calibrations at a watershed in the upper basin (Deep River Watershed), comparing modeled runoff to discharge at USGS stream gage 02100500 (Deep River at Ramseur, NC) for 2001–2003. We used two NCDC stations (Randleman, Stn: 317097, and Siler City 2 N, Stn: 317924) for precipitation estimates in model calibration runs. Monthly—compared to daily—calibration results exhibited the best fit Nash-Sutcliffe and R^2 in the Deep River Watershed (NS = 0.81, R^2 = 0.82). Validation was conducted during the same period in the Haw River Watershed using USGS stream gage 02096960 (Haw River near Bynum) and five NCDC COOP precipitation sites: Siler City 2 N (Stn: 317924), Chapel Hill 2 W (Stn: 311677), Durham (Stn: 312515), Graham 2 ENE (Stn: 313555), and Burlington Fire Station #5 (Stn: 311239). Monthly validation results for the Haw River Watershed were NS = 0.83 and R^2 = 0.86.

Parameter adjustments for model calibration were conducted using an automated parameter optimization method (OSTRICH; Matott 2005) with a global dynamically-dimensioned search (DDS) algorithm (Tolson and Shoemaker 2007) and a weighted sum of squared errors objective function. Subsequent trial-and-error parameter-fitting and calibration exercises were conducted to cross-check and complete this exercise.

Analysis

We used monthly calibration statistics to compare the modeled runoff results because (1) our model calibrated best using monthly statistics, and (2) our conceptual model of simulated rainfall data associates MM5 with a greater capacity to reflect broader temporal trends (i.e., monthly) rather than shorter, intense patterns of precipitation. Our initial analysis focuses on the effects of precipitation on runoff only; however, subsequent work will also concentrate on direct comparisons among variations in precipitation data sources and indices to correlate precipitation data directly with modeled runoff. Currently, we evaluate deviations in modeled runoff by introducing the two simulated data sets (12-km and 36-km MM5) into GBMM simulations.

We utilized the Nash-Sutcliffe efficiency index (Nash and Sutcliffe 1970) and R^2 to compare the monthly runoff statistics from the simulated runoff with observed runoff USGS stream gages 02100500–Deep River at Ramseur, NC, in the Deep River Watershed and 02096960–Haw River near Bynum, NC, in the Haw River Watershed. Further, we evaluated the effect of observed or simulated rainfall data on the timing and magnitude of peak discharge of the modeled runoff.

Preliminary Results and Discussion

The efficiency of modeled runoff resulting from the use of spatially-distributed precipitation data in GBMM decreased in both watersheds. For example, GBMM simulations using 12-km MM5 precipitation data suggest a decrease in runoff efficiency and goodness-of-fit (NS = 0.49, R^2 = 0.54) compared to GBMM simulations using observed precipitation data (NS = 0.81, R^2 = 0.82) (Figure 3A). Introduction of the coarser 36-km data into model runs results in a further

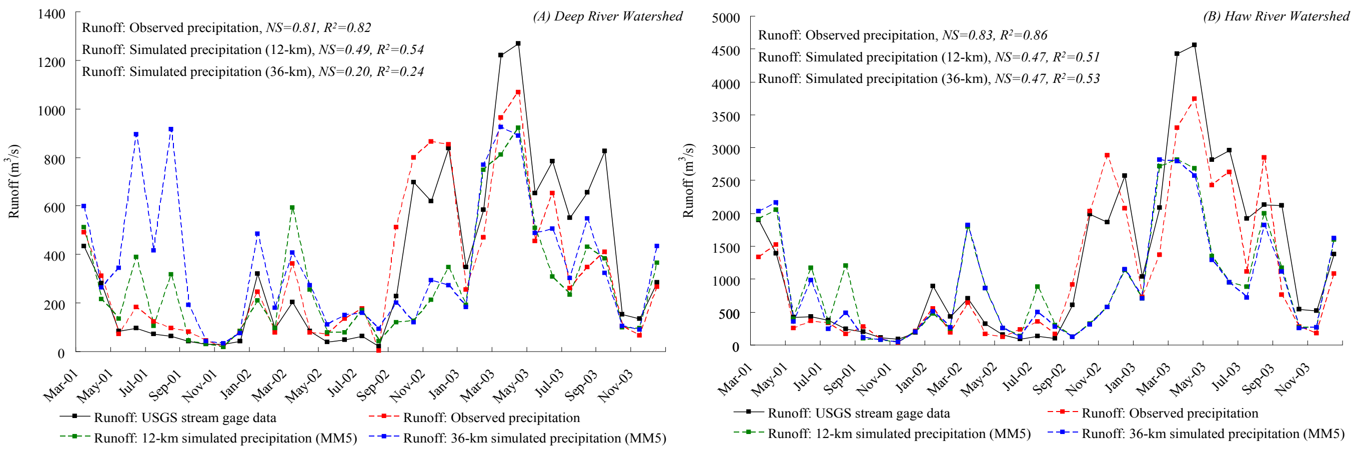

Figure 3. Comparison of modeled runoff from observed precipitation data, simulated MM5 12-km gridded precipitation data, and MM5 36-km gridded precipitation data in the Deep River Watershed (A) and the Haw River Watershed (B).

decline of both NS and R^2 (NS = 0.20, R^2 = 0.24). If only one watershed was analyzed, we might conclude that coarser resolution simulated data result in decreased runoff efficiency compared to finer resolution (12-km) data. However, the Haw River Watershed (Figure 3B) does not respond concomitantly. While both Nash-Sutcliffe and R^2 for monthly runoff decrease using both sets of simulated precipitation data, modeled runoff using the 12-km and 36-km data exhibits no difference in NS, and the coarser data has a slightly higher R^2. Thus, although both 12-km and 36-km precipitation dramatically affect modeled runoff efficiency and goodness-of-fit in both watersheds, differences in the resolution of simulated data results in a nonuniform runoff response. Response to these variations is therefore watershed specific; however, physical characteristics, such as different sizes of the watersheds and flow alterations via dams and channelization, as well as model structure potentially influence modeled runoff variability. Further investigation is required to assess why such diverse response occurs. These steps are forthcoming in the next phase of the project.

Runoff simulations using the spatially-distributed precipitation data also suggest both missed peaks in discharge and early peak predictions. Simulations in both the Haw and Deep River Watersheds using the 12-km and 36-km modeled precipitation resulted in unexplained monthly peak runoff values considerably higher than stream gage data during June and September 2001, the representative dry year in the southeastern United States (Figure 3). Further, in the Haw River Watershed, simulations using both 12-km and 36-km MM5 data predicted peaks in runoff a month earlier than that of stream gage data during the representative wet year (2003, March). While GBMM simulations using observed precipitation data underpredicted monthly peak runoff during the same period, temporal fluctuations in modeled runoff correspond to that of stream gage data. These findings correspond with our initial hypothesis that while simulated data improves the spatial density of precipitation estimates within mesoscale to large watersheds, these data do not capture the temporal variations in precipitation—and consequently, modeled runoff—as well as observed data. Although GBMM calibration was conducted using observed data, the goal of the long-term project is to assess how precipitation introduced from a variety of sources (e.g., a regional air quality model) affects water and contaminant loadings to and from watersheds. Thus, although we might expect data other than the observed precipitation to influence model behavior, our intent is to evaluate the extent to which this occurs.

The next phase of the project will incorporate additional precipitation data sets, including observation-resolved radar precipitation data from the National Multi-Sensor Precipitation Analysis (NPA; *http://wwwt.emc.ncep.noaa.gov/mmb/ylin/pcpanl*) and the Parameter-Elevations Regressions on Independent Slopes Model (PRISM) method (Daly et al. 2002). We will also include a validation year (2005) and develop indices for direct statistical comparisons among precipitation data sets and modeled runoff, similar to Andréassian et al. (2001). As part of this next phase, we will investigate how other precipitation data sets used in regional air quality models affect simulated runoff and contaminant loadings from watersheds to surface water bodies. The initial results suggest that mass hydrological imbalances will occur, thus affecting chemical loadings to and from watersheds. Further research will evaluate the extent of the mass imbalances and implications for estimating and modeling watershed contaminant loading.

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