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Does soil data resolution matter? State Soil Geographic database versus Soil Survey Geographic database in rainfall-runoff modeling across Wisconsin

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Abstract: Whether or not the use of generalized, State Soil Geographic (STATSGO) data in place of higher resolution Soil Survey Geographic (SSURGO) data reduces the accuracy of hydrologic and nonpoint source pollution models has thus far been an open question. Comparative studies have yet to reveal a systematic bias in STATSGO–based model outputs on account of their small sample sizes and differences in the models employed. In an effort to determine whether a bias exists, direct runoff was modeled for a hypothetical 24-hour rainfall event, using STATSGO and SSURGO as alternative inputs to a series of standard rainfall-runoff models in nearly 300 contiguous watersheds, spanning most of the state of Wisconsin. The Long-Term Hydrologic Impact Assessment (L-THIA) modeling tool was used for this analysis. Results indicate that there is a negative bias in STATSGO–based runoff over the large majority of the study area and that the degree of underprediction is highest for spatially disaggregated (distributed parameter) models. Runoff was also modeled for daily precipitation in six gauged watersheds and was compared to observed runoff, with SSURGO–based, distributed models typically producing the most accurate outputs. In addition, a series of regression analyses was conducted to determine whether, and in what direction, the STATSGO bias is affected by the percent coverage of land uses that discourage infiltration. The results of these analyses suggest that STATSGO–based, lumped, and partially distributed models, on average, underpredict the relative impact of increasing land-use intensity. These findings indicate that two of the most common approaches to improving the computational efficiency of watershed modeling systems: the use of lower resolution soils data and the lumping of model parameters to larger spatial units of analysis, combine to reduce the accuracy of modeled runoff under current conditions, while simultaneously underestimating the impact of potential future land-use change.

Key words: hydrologic group—land use—rainfall-runoff modeling—Soil Survey Geographic (SSURGO) database—State Soil Geographic (STATSGO) database—Wisconsin

Developers and users of watershed modeling systems face a tradeoff between increased spatial detail and the amount of time and computing resources needed to build, calibrate, and run models. A number of systems have been developed that can estimate or predict surface water runoff and nonpoint source (NPS) pollution at different scales, under variable soil, land use, climate, and topographic conditions. With advances in data processing and network storage capacity, public data on these variables are increasingly available at higher resolutions. Spatially disaggregated Soil Survey Geographic (SSURGO) data are now available for the vast majority of US counties (for the current status of available SSURGO data across the United States see http://soildatamart.nrcs.usda.gov/statusmap.aspx), in addition to generalized State Soil Geographic (STATSGO) data. Early versions of the desktop Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998) relied exclusively on STATSGO for soil input variables. More recent versions accept SSURGO data as well (Di Luzio et al. 2004), although the additional time needed to build and run SSURGO–based SWAT models can be considerable (Geza and McCray 2008). Similarly, Internet-based systems such as the Long-Term Hydrologic Impact Assessment (L-THIA) tool (Engel et al. 2003) have, until recently, relied solely on STATSGO. At present, the Web-based L-THIA system utilizes SSURGO data in 2 of the 48 contiguous United States: Indiana and Wisconsin, with plans to expand to other states for which SSURGO data are available in all counties.

The STATSGO and SSURGO soil databases are structured according to widely different levels of spatial aggregation. The SSURGO map units are digitized from county-level soil surveys at spatial scales ranging from 1:12,000 and 1:63,360, and are typically comprised of a single component soil (i.e., soil series phase) or otherwise up to three components grouped together according to shared physical properties (USDA NRCS 1995). The STATSGO units are mapped at a scale of 1:250,000 by generalizing soil survey maps where they exist and otherwise interpolating map units based on broad physiographic characteristics. A single STATSGO map unit can contain up to twenty-one different component soils (USDA NRCS 1994). The STATSGO map units, therefore, lack discrete location information for most soil physical properties.

Whether or not using higher resolution SSURGO data improves the accuracy of hydrologic or NPS pollution models has, thus far, been an open question (for example, see Di Luzio et al. 2004; Gowda and Mulla 2005; Anderson et al. 2006; Peschel et al. 2006; Geza and McCray 2008). Mednick et al. (2008) reviewed eighteen comparative studies and found that while SSURGO–based predictions of various stream flow and water quality parameters were more often closer to observed conditions, results vary considerably across—and in some cases within—the different studies, with STATSGO–based models proving more accurate in a number of cases. More recently, Heathman et al. (2009) reported that uncalibrated, SSURGO–based SWAT

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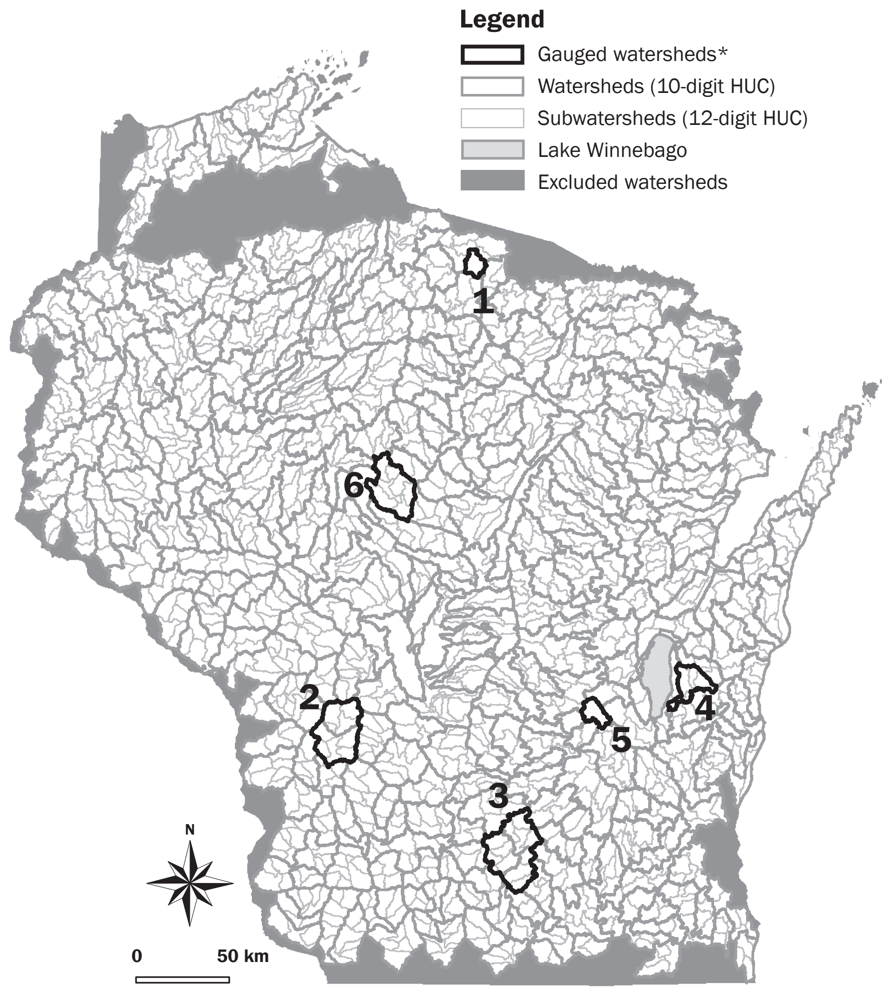
Figure 1

Study Area: 298 contiguous watersheds, Wisconsin, United States. Study area watersheds are mapped at the 10-digit hydrologic unit code (HUC) level, subdivided into 1,524 subwatersheds (12-digit HUC) and 44,821 nested stream catchments, spanning a total area of approximately 125,000 km². Numbers on map indicate six gauged watersheds that were additionally selected from within the study area for the purpose of comparing modeled runoff to observed runoff.



* Subsample: Watershed units (12-digit HUC and larger) that were continuously gauged by the US Geological Survey from 1999 through 2003. These were selected for the purpose of comparing modeled runoff to observed runoff.

models produced more accurate predictions of monthly streamflow than did otherwise identical STATSGO–based models in the Cedar Creek watershed of northeastern Indiana. Similarly, Romanowicz et al. (2005) found that uncalibrated SWAT models of the Thyle River watershed in Belgium were more accurate using spatially detailed soils data (1:25,000) in place of highly generalized data (1:500,000).

Due to the limited number of watersheds modeled in these studies (rarely more than one) and the underlying differences in the models employed, a systematic bias has yet to be revealed. Nor can any association be drawn between the relative accuracy of model outputs (using STATSGO versus SSURGO) with any of the commonly reported characteristics of the watersheds modeled (i.e., size, region, climate) or of the models themselves (Mednick et al. 2008).

Three nonmodeling studies found differences between soil physical properties reported in the two databases, which suggest the possibility of a systematic bias. Analyzing selected STATSGO map units in Colorado, Murray (2002) and Murray and McCray (n.d.) found that aerially weighted soil component values for available water capacity and hydraulic conductivity (reported in the soils databases as permeability) were higher, on average, than the corresponding, aerially weighted values in SSURGO. In a grid-based analysis across Kansas, Juracek and Wolock (2002) similarly found that STATSGO values for permeability were higher, on average, than the corresponding values in SSURGO. Furthermore, they found that the level of variability in the measured difference between the two databases increased with the spatial resolution of the averaging area (grid cell) and the proximity to streams.

In an effort to determine whether or not a systematic bias exists in STATSGO–based runoff predictions, direct runoff was estimated in nearly 300 contiguous watersheds across Wisconsin, using STATSGO and SSURGO soils, alternatively, as inputs to a series of standard rainfall-runoff models. The desktop version of the L-THIA modeling tool was used for this analysis. The first objective was to determine whether a systematic bias exists, and if so, the extent to which it is affected by the spatial "lumping" of model parameters into successively larger units of analysis: stream catchments, subwatersheds, and full watersheds. The second objective was to determine whether, and in what direction, any such bias is related to the proportion of a watershed's surface area covered by land uses that discourage infiltration. Such a relationship has implications for the use of STATSGO–based models within a land-use planning context.

Materials and Methods

Study Area. The study area (figure 1) includes 298 contiguous watersheds, mapped at the 10-digit hydrologic unit code (HUC) level. The HUC is the hierarchical referencing scheme of the national Watershed Boundary Database—a consistent and standardized system of watershed delineation spanning the United States at multiple and increasingly finer scales (Berelson et al. 2004). Hydrologic units range from regions and subregions (2 and 4 digits), basins and subbasins (6 and 8 digits), watersheds and subwatersheds (10 and 12 digits), and catchments and subcatchments (14 and 16 digits). Figure 1 also shows 1,524 subwatersheds (12-digit HUC) and 44,821 stream catchments nested therein, spanning approximately 125,000 km^2 (48,300 mi^2), or 88% of the state of Wisconsin. Watersheds falling partly outside of the state were excluded, as were watersheds for which significant portions of their nonwater surface area are missing data on soil hydrologic group in either of the two databases. These included the four watersheds containing central Milwaukee, for which no soil survey data exist, plus nine watersheds in the northwestern portion of the state, which contain parts of an extensive area classified by STATSGO as rock outcrop. Six gauged watersheds were additionally selected from within the study area for the purpose of comparing modeled runoff to observed runoff (figure 1). This subsample constitutes six of the seven 12-digit HUC or larger watershed units in Wisconsin that are gauged in their entirety by the US Geological Survey and for which continuous daily data are available for both streamflow and precipitation for the years 1999 through 2003.

The five-year period between 1999 and 2003 was selected to minimize the potential effect of land-use change on observed runoff. The National Land Cover Database reflects land use as of 2001. A gauged watershed located in the southwestern portion of the state was removed from this subsample on account of a visually apparent discrepancy in SSURGO–reported soil hydrologic group across two adjacent counties. Contiguous map units on opposite sides of the county boundary were assigned to different hydrologic groups. While this discrepancy has a minimal effect on the state-wide analysis of ungauged watersheds across Wisconsin, it has the potential to skew the comparison of modeled runoff with observations made at the local stream gauge.

Wisconsin is characterized by a wide range of soil types and land uses. Soils vary with the study area's underlying glacial and nonglacial geology. Of note are several large areas in the central and far northern regions of the state characterized by well drained, sandy soils interspersed with large areas of poorly drained, clay and loamy soils. Cultivated crops and pasture are the dominant land uses in the southern and eastern regions, while forest cover dominates the northern region. A mix of agricultural and forest land dominates the central and west-central regions. High concentrations of urban land uses occur along the Lake Michigan coast in the southeastern region, around Lake Winnebago and Green Bay in the east-central region, and around the city of Madison in the south-central region, along with several smaller cities throughout the state.

In order to create a fully nested set of watershed units, stream catchment polygons derived from 30 m (98.4 ft) digital elevation data were used as building blocks. These were obtained from the Horizon Systems Corporation's (2006) National Hydrography Dataset-Plus (NHD-Plus) and aggregated into subwatersheds and watersheds, respectively, according to which 1:24,000 12- and 10-digit HUC reference polygons contained the majority of their land area. The 12- and 10-digit HUC polygons are part the national Watershed Boundary Database, developed through a combination of manual and semiautomated watershed delineation procedures (Berelson et al. 2004). These boundaries were obtained from the USDA NRCS (2008a) Geospatial Data Gateway. With very few exceptions, the aggregated watershed and subwatershed boundaries varied minimally from the reference 12- and 10-digit HUC boundaries. Discrepancies that would have changed the shape and size of two of the six gauged watersheds were corrected by splitting NHD-Plus catchment polygons where they crossed reference watershed boundaries.

Overview of Rainfall-Runoff Models. In order to test the sensitivity of predicted runoff to alternative soil data inputs, the L-THIA extension to ArcView geographic information system software (Engel 2005) was used to model direct runoff (total runoff minus baseflow) in response to an average two-year, 24-hour rainfall event that was applied uniformly across all watersheds in the study area. The L-THIA extension was developed to provide planners and decision makers with a readily available tool for predicting the impact of proposed or potential land-use change on average annual runoff and NPS pollution (Harbor 1994; Bhaduri et al. 2000; Engel et al. 2003). It can also be used to model runoff and NPS pollution from individual rainfall events. The underlying modeling framework is a spatially distributed automation of the Soil Conservation Service curve number (CN) method (USDA SCS 1986), coupled with a series of empirically derived event mean concentration coefficients for different NPS pollutants.

The CN method predicts direct runoff depth (Q) as a function of 24-hour rainfall depth (P) and an area's estimated runoff potential (equation 1):

$$Q = \frac{(P - Ia)^2}{(P - Ia) + S}, \tag{1}$$

where Ia is the initial abstraction (the amount of rainfall intercepted, absorbed, or impounded before runoff begins) and S is the surface rainfall retention parameter (the maximum amount of water that will be absorbed after runoff begins). These parameters can be estimated according to the combination of an area's soil hydrologic group and its land use/land cover condition, as represented by one of a series of empirically derived curve numbers published in the USDA SCS (1986), which range from 30 (forest cover on well drained soils) to 98 (impervious surfaces). Modified or alternative curve numbers can also be used.

While it has been the subject of significant critiques (for example, see Garen and Moore 2005), the CN method has been characterized as simple, predictable, and stable (Ponce and Hawkins 1996) and serves as the core component of numerous hydrologic and NPS pollution modeling systems. L-THIA's automation of the CN method enabled rainfall-runoff to be modeled across the entire study area for a hypothetical rainfall event, using highly disaggregated spatial units of analysis (i.e., unique combinations of soil hydrologic group and National Land Cover Database [NLCD] land use). The STATSGO and SSURGO–reported soil hydrologic groups were used, respectively, for the alternative model runs. In this way, the effect of using one database versus the other in a spatially distributed model could be compared within each of the study area's 298 watersheds, in order to determine whether and to what extent there is a systematic bias.

In addition to the spatially distributed CN models, curve numbers were spatially averaged (lumped) across three successively larger units of analysis: stream catchments, subwatersheds, and watersheds, and L-THIA was rerun for a total of eight study area–wide models. This enabled the comparison of STATSGO versus SSURGO–based predictions under distributed, partially distributed, and lumped parameter models. Lastly, a series of STATSGO and SSURGO–based distributed, partially distributed (units of analysis = stream catchments), and lumped parameter (units of analysis = subwatersheds) models were run for observed daily precipitation in six watershed units that were continuously gauged for stream flow at their discharge

Table 1
Soil hydrologic groups.

Group	Assigned numeric code	Infiltration rates*
A	1	>0.76 cm h^{-1}
B	2	0.38 to 0.76 cm h^{-1}
C	3	0.13 to 0.38 cm h^{-1}
D	4	0.00 to 0.13 cm h^{-1}

* Rates reported in USDA SCS (1986).

Table 2
Curve numbers assigned by land use and soil hydrologic group.

National Land Cover Database land use	Curve number by soil hydrologic group A	B	C	D
Developed, high intensity	89	92	94	95
Barren land	77	86	91	94
Developed, medium intensity	77	85	90	92
Cultivated crops	64	75	82	85
Developed, low intensity	54	70	80	85
Developed, open space	49	69	79	84
Emergent herbaceous wetlands	44*	65*	77*	82*
Pasture/hay	39	61	74	80
Woody wetlands	35*	61*	74*	80*
Shrub/scrub	35	56	70	77
Grassland/herbaceous	30	58	71	78
Deciduous forest	30	55	70	77
Evergreen forest	30	55	70	77
Mixed forest	30	55	70	77

Note: Unless otherwise noted, curve numbers are based on USDA SCS (1986).
* Curve numbers recommended by Arnold and Friedel (2000).

points by the US Geological Survey between 1999 and 2003 (figure 1).

Soil and Land-Use Data. Wisconsin STATSGO map units and soil attribute tables were downloaded from the USDA NRCS (2008b) Soil Data Mart. Hydrologic group values contained in the database's Map-Unit Aggregated Attribute table were assigned to map-unit polygons via the unique Map Unit Key identifier. The SSURGO data were similarly downloaded and processed for each of Wisconsin's 72 counties and were combined into a single, state-wide layer. The STATSGO and SSURGO map units were converted from polygons to zones of 30 m (98.4 ft) grid cells, with single-digit numeric codes corresponding to their hydrologic group (table 1).

Land-use data, based on the spectral classification of 30 m (98.4 ft) Landsat 7 satellite imagery, were obtained from the 2001 NLCD (Homer et al. 2004; MLRC 2008). Each of the fourteen different NLCD classes within the study area were assigned a unique four-digit numeric identifier (e.g., "Developed, High Intensity" = 2400). The resulting grid values were then added to the single-digit STATSGO and SSURGO hydrologic group values for all 30 m grid cells, outputting two new grid layers, each containing 56 unique combinations of soil hydrologic group and NLCD land use. Finally, cells were assigned curve numbers according to lookup tables published by the USDA SCS (1986), plus CN values recommended by Arnold and Friedel (2000) for forested and emergent wetlands (table 2). Cells comprising open water were assigned a null value, as were other cells not assigned to a soil hydrologic group within SSURGO, such as open mines.

Model Execution. Using the STATSGO and SSURGO–based CN grids, respectively, L-THIA was run across the study area for a uniform 7 cm (2.75 in) rainfall event (the average two-year, 24-hour storm event over two-thirds of the area), assuming an initial abstraction *(Ia)* of 0.2 × *S* (see equation 1) and average antecedent soil moisture conditions. Raw outputs consisted of predicted runoff depth (in centimeters) per 30 m (98.4 ft) grid cell, which was then averaged across each catchment, subwatershed, and watershed. To test whether the lumping of model parameters affects the STATSGO–SSURGO differential in predicted runoff, L-THIA was rerun with CN values spatially averaged across stream catchments (i.e., partially distributed CN models), as well as subwatersheds, and watersheds, respectively (i.e., lumped CN models).

Comparison of Model Predictions to Observed Runoff. In addition to predicting runoff in response to a single, hypothetical rainfall event, a series of alternative STATSGO and SSURGO–based models were run to estimate runoff associated with historic rainfall in each of six gauged watersheds (figure 1). Data on daily rainfall and corresponding runoff were obtained for May through September, 1999, through 2003. Comparisons to observed daily runoff were limited to Wisconsin's growing season, since L-THIA models do not account for snowmelt, snow cover, or frozen soil. The midpoint of the analyzed period corresponds approximately with the 2001 NLCD land-use data. Rainfall totals, measured at cooperative weather stations within or near the gauged watersheds, were downloaded from the National Climatic Data Center (USDOC NOAA 2008). Daily runoff was derived from US Geological Survey stream gauge data using the local minimum baseflow separation method within the Web-based Hydrologic Analysis Tool (Lim et al. 2005; Purdue University 2008). In order to account for variable antecedent soil moisture conditions, CN values were adjusted over time to reflect assumed antecedent soil moisture conditions I, II, and III, according to the preceding five days of precipitation (Mishra and Singh 2003).

Within each of the gauged watersheds, daily predicted runoff was totaled per month for each model and tested for agreement with observed monthly runoff, using the Nash-Sutcliffe Efficiency (E_{NS}) coefficient (Nash and Sutcliffe 1970). Although calibration procedures exist for L-THIA (Lim et al. 2006b), models were left uncalibrated in order to avoid masking the effect of alternative soil data inputs. As a result, initial model runs significantly underpredicted runoff in all six of the watersheds. Lim et al. (2006a) achieved significant improvements in L-THIA efficiency by lowering the initial abstraction ratio, *Ia/S* (see equation 1) from the commonly used 20% to the 5% recommended by Hawkins et al. (2002). Incorporating this procedure within a second round of L-THIA runs resulted in increased sensitivity to smaller rainfall events, thereby reducing the magnitude by which the uncalibrated models under-predicted runoff, while maintaining the signal of variable soil data resolution.

Estimating the Effect of Land Use. Incremental changes in land use can have significant hydrologic impacts over time (Defries and Eshleman 2004). In particular, the replacement of natural or seminatural land cover (e.g., forest, brush, grasslands) with impervious and semi-impervious surfaces (e.g., rooftops, driveways, lawn) reduces the amount of rainfall infiltrating the soil, thereby increasing the amount of surface runoff (Arnold and Gibbons 1996). The accuracy with which different models estimate runoff under current conditions is not necessarily indicative of their ability to predict changes in runoff under alternative land-use scenarios. For example, a model that accurately predicts runoff in a rural watershed might subsequently underpredict runoff associated with urban development, if the underlying data resolution or spatial units of analysis are too coarse to detect small-scale changes to imperviousness and land-cover quality. Such errors could have significant consequences within a land-use planning context.

The limited availability of long-term streamflow data, coupled with changes in land-use classification methods from one time period to the next (e.g., Vogelmann et al. 2001; Homer et al. 2004), make it difficult to conduct longitudinal analyses (Defries and Eshleman 2004). While some of these limitations have been overcome in watershed-specific investigations (e.g., Bhaduri et al. 2000), the state-wide scope of the present study made conducting a valid pretest/posttest experiment impracticable.

As an alternative, a series of cross-sectional ordinary least squares (OLS) regression analyses were conducted in order to determine whether, and to what extent, there is an independent relationship between the intensity of land use within a watershed unit (i.e., the extent of land uses that discourage infiltration) and the difference between STATSGO and SSURGO–based model predictions. In order to minimize the potential for spatial autocorrelation among OLS residuals (Anselin 1988), these analyses were conducted on a spatially random sample of 200 subwatersheds, selected from the full sampling domain (N = 1,524) according to randomly generated geographic coordinates.

In order to isolate the effect of land use, a control variable was created to account for the extent to which STATSGO misclassifies soil hydrologic group. First, state-wide STATSGO and SSURGO grids were combined and reclassified as either "match" (i.e., infiltration reported in STATSGO is equal to that reported in SSURGO) or one of 12 possible types *(T)* of hydrologic group misclassification (table 3). Next, the percent of each subwatershed covered by each misclassification type ($PctMC_T$) was calculated. The STATSGO – SSURGO differential in modeled runoff *(SSDiff)* was then regressed on this control variable, as well as a land-use intensity variable, measured as the combined aerial coverage of the five NLCD land uses with the highest CN values *(PctLU)*. These included "Cultivated Crops," "Barren Land," and all three levels of "Developed" (table 2).

Table 3

State Soil Geographic (STATSGO) database misclassification of soil hydrologic group across the study area.

Type*	STATSGO hydrologic group	SSURGO hydrologic group	Area (km^2)†	Percent of total area†
STATSGO overestimates infiltration				
A (D)	A	D	2,942	2%
A (C)	A	C	678	1%
A (B)	A	B	4,116	3%
B (D)	B	D	11,369	9%
B (C)	B	C	8,245	7%
C (D)	C	D	5,534	4%
			32,884	**26%**
STATSGO underestimates infiltration				
D (A)	D	A	1,385	1%
D (B)	D	B	2,191	2%
D (C)	D	C	1,363	1%
C (A)	C	A	679	1%
C (B)	C	B	4,657	4%
B (A)	B	A	4,848	4%
			15,123	**13%**
No misclassification			75,679	61%
Total			**123,686**	**100%**

SSURGO = Soil Survey Geographic database.

* Type of misclassification (*T*) in equation 2.

† Area and total area do not include open water or SSURGO map units not assigned to a soil hydrologic group; e.g., open mines.

For each subwatershed, i, the basic regression formula (equation 2) was

$$SSDiff_i = \alpha + (\beta_1 \times PctLU_i) + (\beta_T \times PctMC_{Ti}) + \varepsilon_i, \quad (2)$$

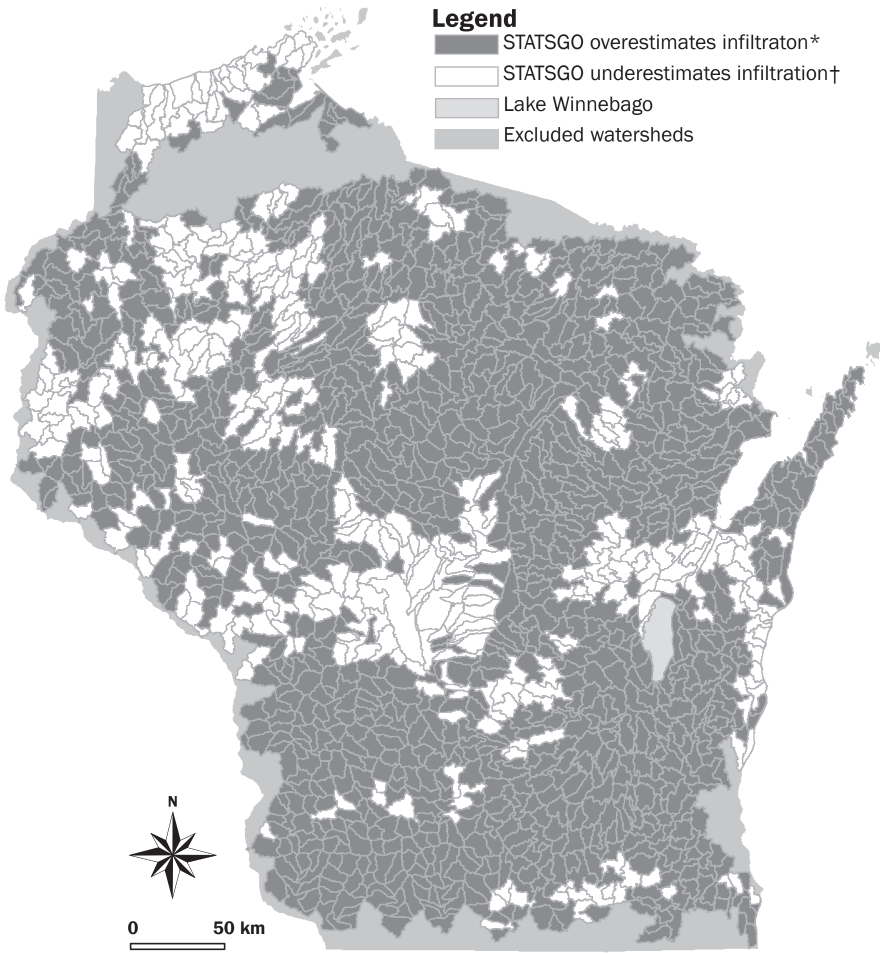
where α is a constant, β_1 is the partial regression slope coefficient for the land-use intensity variable, β_T is the slope coefficient for hydrologic group misclassification type T, and ε is the error term. Separate analyses were conducted for *SSDiff* associated with the distributed, partially distributed, and lumped CN models. Pearson's correlation matrices and variance inflation factors were used to confirm the absence of multicollinearity between the thirteen explanatory variables (Kutner et al. 2004).

Results and Discussion

STATSGO Bias in Estimated Runoff Potential. As summarized in table 3, STATSGO misclassifies soil hydrologic group in a manner that overestimates infiltration relative to SSURGO across approximately 36,000 km^2 (13,900 mi^2) or 26% of the study area. By comparison, STATSGO underestimates infiltration relative to SSURGO across 12% of the study area. These results generally agree with the findings of Jurasek and Wolock (2002), Murray (2002), and Murray and McCray (n.d.), and indicate a systematic bias in estimated runoff potential as reported by STATSGO. Subtracting SSURGO–based minimum infiltration rates from STATSGO–based minimum infiltration rates (table 1) for each 30 m (98.4 ft) grid cell outputs a continuous surface of variable over and underestimation. Spatially averaging these values across nested watershed units pro-

Figure 2

State Soil Geographic (STATSGO) database bias in estimated runoff potential, relative to Soil Survey Geographic (SSURGO) database.



* Subwatersheds over which the average difference between STATSGO and STATSGO-reported minimum infiltration rates (table 1) is positive.

† Subwatersheds over which the average difference is negative.

vides an indication of whether, and to what degree, model-based runoff predictions are likely to be biased in one direction or the other for a given stream catchment, subwatershed, or watershed. Positive values indicate watershed units for which STATSGO overestimates infiltration, on average relative to SSURGO, and, therefore, underestimates runoff potential. Across the study area, this outcome occurs in 66% of stream catchments, 75% of subwatersheds (figure 2), and 81% of watersheds.

STATSGO Bias in Model-Predicted Runoff. The negative bias revealed in STATSGO–based runoff potential across the study area, relative to SSURGO, is reflected in the outputs of the STATSGO versus SSURGO–based rainfall-runoff models. Table 4 lists descriptive statistics for the STATSGO – SSURGO differential in predicted runoff for the uniform 7 cm (2.75 in) rainfall event. These results indicate that STATSGO–based model predictions are lower, on average, than SSURGO–based predictions and that the degree of underprediction is highest for the distributed CN (i.e., spatially disaggregated) models. Moreover, the degree of dissimilarity between the STATSGO and SSURGO–based predictions increases as watershed units become successively smaller: from watershed, to subwatershed, to stream catchment. The latter results are similar to comparative statistics on soil permeability reported by Juracek and Wolock (2002).

Relative Accuracy. As shown in table 5, the various STATSGO and SSURGO–based models for three of the six gauged watersheds (1, 2, and 3) had positive E_{NS} values, indicating that they were more accurate than using the mean of observed monthly runoff as the predictor. Only Watershed 1 had E_{NS} values that could be considered "good" to "very good" (Moriasi et al. 2007). The remaining watersheds fell into the "unsatisfactory" range (i.e., $E_{NS} < 0.5$), with Watershed 6 producing highly negative coefficients reflecting extreme fluctuations in observed streamflow (table 5).

It is important to note that these models are not calibrated and that the principal focus here is on the relative, as opposed to absolute, efficiency of the STATSGO versus SSURGO–based models. In five of the six watersheds, the model with the highest E_{NS} value was the SSURGO–based, distributed CN model. This particular model predicted the highest runoff values for each watershed, whereas the STATSGO–based, lumped CN model predicted the lowest values. In Watershed 5, all of the models overestimated runoff, such that the negative bias in STATSGO models resulted in improved efficiency (table 5).

Land-Use Effect. Results of the OLS regression models (see equation 2) indicate the presence of an independent relationship between the extent to which a watershed unit is covered by impervious surfaces—or otherwise lower quality vegetative cover—and the degree to which STATSGO–based models underpredict runoff relative to SSURGO. Table 6 reports the partial regression slope coefficients for the land-use variable *PctLU* and the control variable $PctMC_T$. Nearly all of the variation in the dependent variable *SSDiff* (STATSGO minus SSURGO–based runoff predictions) can be explained by the combined variation in *PctLU* and $PctMC_T$. Adjusted r^2 values are 0.997, 0.962, and 0.921, respectively, for the distributed, partially distributed, and lumped CN models.

As shown in table 6, *SSDiff* for the distributed CN models increases with *PctLU*, when controlling for $PctMC_T$. The slope coefficient is small (0.001) but statistically significant, indicating that an additional 10% of a subwatershed's area covered by urbanized, cultivated, and/or barren land will, on average, correspond with a 0.01 cm increase in STATSGO–based runoff predictions, relative to SSURGO, controlling for the extent of soil hydrologic group misclassification. This finding suggests that STATSGO–based,

Table 4
State Soil Geographic (STATSGO) database – Soil Survey Geographic (SSURGO) database differential (*SSDiff*) in modeled runoff for a 7 cm rainfall event.

		Difference (cm), STATSGO – SSURGO				
Watershed unit	**Model type**	**Mean**	**Median**	**Minimum**	**Maximum**	**Standard deviation**
Catchment	Distributed CN	−0.23	−0.18	−3.23	3.23	0.60
(*N* = 44,821)	Lumped CN	−0.13	−0.10	−3.41	3.26	0.63
Subwatershed	Distributed CN	−0.24	−0.22	−1.43	1.22	0.33
(*N* = 1,524)	Partially distributed*	−0.13	−0.12	−1.27	1.51	0.34
	Lumped CN	−0.15	−0.14	−1.44	1.58	0.34
Watershed	Distributed CN	−0.23	−0.21	−1.00	0.87	0.26
(*N* = 298)	Partially distributed*	−0.13	−0.14	−0.93	1.05	0.26
	Partially distributed†	−0.15	−0.14	−0.92	1.03	0.27
	Lumped CN	−0.17	−0.15	−0.98	1.01	0.27

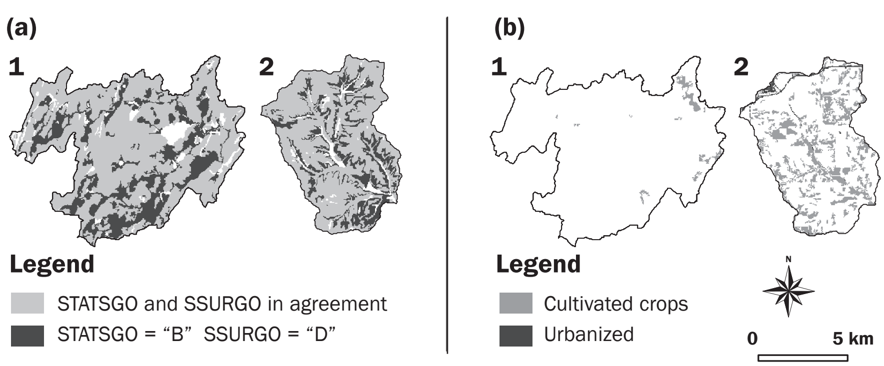
Note: CN = curve number.
* Unit of analysis = stream catchment.
† Unit of analysis = subwatershed.

Table 5
Nash-Sutcliffe Efficiency coefficients (E_{NS}) for the various models.

	Lumped CN†		Partially distributed CN‡		Distributed CN	
Watershed	**STATSGO**	**SSURGO**	**STATSGO**	**SSURGO**	**STATSGO**	**SSURGO**
1	0.80	0.80	0.80	0.81	0.81	0.84*
2	0.18	0.22	0.19	0.22	0.25	0.30*
3	0.37*	0.26	0.37	0.24	0.32	0.16
4	−0.91	−0.84	−0.90	−0.82	−1.36	−0.74*
5	−1.05	−0.91	−1.03	−0.89	−0.94	−0.79*
6	−35.9	−35.4	−35.7	−35.3	−35.3	−34.9*

Note: CN = curve number. STATSGO = State Soil Geographic database. SSURGO = Soil Survey Geographic database.
* Most efficient model (highest E_{NS}) for each watershed.
† Unit of analysis = subwatershed.
‡ Unit of analysis = stream catchment.

Figure 3
Two subwatersheds (1 and 2) with similar soil hydrologic conditions but different land-use intensities. (a) Approximately 70% of each subwatershed is covered by soils for which STATSGO (State Soil Geographic database) and SSURGO (Soil Survey Geographic database) are in agreement. (b) Comparison of intensive land use in both watersheds.



distributed parameter models will tend to overpredict the impact of increasing land use intensity (e.g., the removal of farmland from conservation reserve). This makes sense intuitively, since the effect of increasing land-use intensity should be higher, all else being equal, in areas where underlying soils have higher infiltration rates. Because STATSGO–based models tend to underestimate runoff under baseline conditions, it follows that they will tend to overpredict the effect of increasing land-use intensity.

The sign of the slope coefficient for *PctLU* changes, however, when the dependent variable is *SSDiff* for the partially distributed or lumped CN models (table 6). In both cases, the coefficient is –0.001, indicating that a 10-point increase in *PctLU* will correspond, on average, with a 0.01 cm (0.004 in) decrease in STATSGO–based runoff predictions, relative to SSURGO. This suggests that STATSGO–based lumped and partially distributed models will tend to underpredict the effect of increasing land-use intensity. The reason for this reversal is the fact that urban development and cultivated cropland typically avoid areas reported in SSURGO as poorly drained but in STATSGO as well- or moderately-well drained. Often, such areas represent pockets of land that are less suitable for intensive use than their surroundings but are too small to be captured by STATSGO map units.

Figure 3 illustrates this pattern in two subwatersheds (1 and 2) with similar hydrologic group rankings but different land-use intensities. Approximately 70% of each subwatershed is covered by soils for which STATSGO and SSURGO are in agreement, while 26% of each is covered by soils rated as D (poorly drained) in SSURGO, but B (moderately well-drained) in STATSGO. Subwatershed 1, however, has little in the way of intensive land uses, with just 2% in cultivated crops, whereas one-quarter of subwatershed 2 is covered by cultivated crops (23%) and low-to-medium intensity urban development (2%). Over three-quarters of the land characterized by more intensive uses in subwatershed 2 coincide with areas where STATSGO and SSURGO are in agreement, whereas only 15% coincide with areas classified as hydrologic group D in SSURGO but B in STATSGO.

As illustrated in Figure 4, the spatial lumping of curve numbers increases the degree to which STATSGO underpredicts run-

Table 6

Partial regression slope coefficients (n = 200 subwatersheds).

	Model 1 distributed CN	Model 2 partially distributed CN	Model 3 lumped CN
Constant	−0.019	0.064	0.042‡
PctLU*	0.001	−0.001	−0.001‡
***PctMC$_T$*†**			
T = A (D)	0.026	0.026	0.018
T = A (C)	0.016	0.026	0.020
T = A (B)	0.005	0.014	0.017
T = B (D)	0.018	0.020	0.023
T = B (C)	0.011	0.012	0.011
T = C (D)	0.008‡	0.004‡	0.004§
T = D (A)	−0.025	−0.013	−0.016
T = D (B)	−0.019	−0.017	−0.017
T = D (C)	−0.007	−0.007	−0.006
T = C (A)	−0.017	−0.030	−0.035
T = C (B)	−0.011	−0.012	−0.012
T = B (A)	−0.006	−0.008	−0.009

Note: CN = curve number. Dependent variable = STATSGO – SSURGO differential in predicted runoff *(SSDiff)* in centimeters per 7 cm rainfall event. Unless otherwise noted, coefficients are statistically significant at a 95% level of confidence.

* Explanatory variable. Combined percent aerial coverage of the five land use classes with the highest curve number values, as listed in table 2.

† Control variable. Percent aerial coverage, respectively, of each of 12 types of soil hydrologic group misclassification, T, where the first letter is the soil hydrologic group reported by STATSGO and the second letter (in the parentheses) is that reported by SSURGO.

‡ Significant at a 90% level of confidence.

§ Not statistically significant.

off in more heavily developed areas. For the distributed CN models (figure 4a and 4c), the difference between STATSGO and SSURGO–based predictions *(SSDiff)* varies little, increasing by 0.006 cm (0.002 in) or 1%, between subwatershed 1 and the more intensively developed subwatershed 2. When CN values are averaged across stream catchments (figure 4b and 4d), however, *SSDiff* decreases by 0.094 cm (0.037 in), or 23%. That is, the STATSGO–based model underpredicts runoff to a greater extent in subwatershed 2, when the CN parameter is lumped. Many of the areas where STATSGO overestimates infiltration in subwatershed 2 are characterized by low intensity land uses on poorly drained soils. These areas are often surrounded by more intensive uses on better drained soils, where the STATSGO and SSURGO databases are more typically in agreement. When STATSGO–based curve numbers are spatially averaged across stream catchments, the original numbers in the less-developed pockets, which are artificially low, cancel-out the higher curve numbers in their more intensively developed surroundings.

While this case study and the broader OLS regression analyses are cross-sectional, the results are relevant to future-oriented land-use planning. Assuming that future land conversions will largely continue to occur near, but not directly in, pockets where STATSGO significantly overestimates infiltration, the use of STATSGO soils in lumped-parameter or partially distributed models has the potential to significantly underpredict the impact of such conversions on direct runoff. Across the full study area, 68% of the land characterized by more intensive uses coincide with areas where STATSGO and SSURGO are in agreement, versus only 8% that coincide with areas classified as hydrologic group D in SSURGO but A or B in STATSGO. Many of the areas misclassified by STATSGO follow stream networks (see, for example, figure 3a), providing support for the earlier findings of Juracek and Wolock (2002) with respect to soil physical properties and proximity to streams. These results have implications for the use of STATSGO soils for land-use planning purposes in general, and in particular, for their use within partially distributed watershed modeling systems, such as SWAT.

Summary and Conclusions

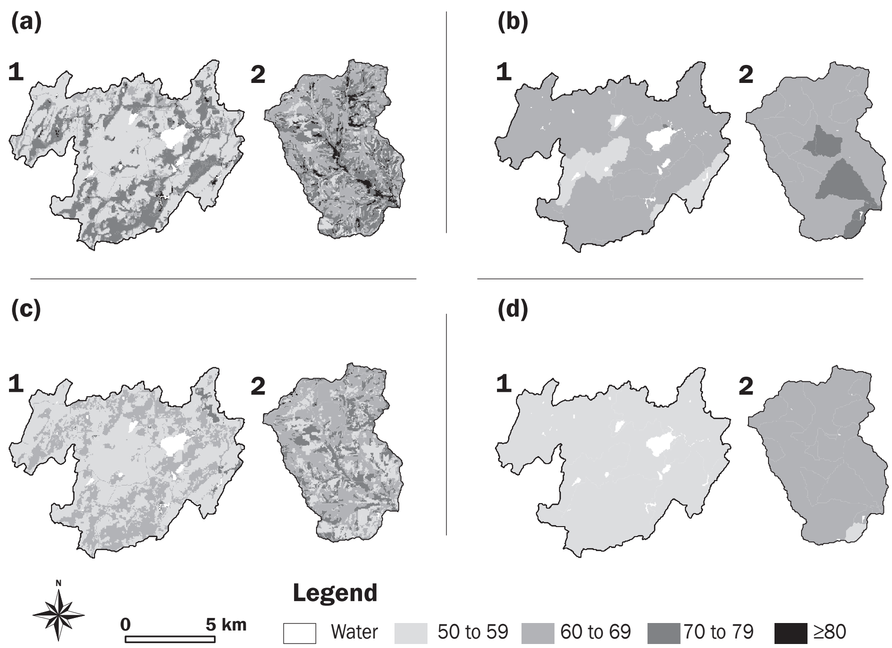
This study has revealed a systematic, negative bias in STATSGO–based runoff models across the majority of Wisconsin relative to SSURGO. This bias is the result of the spatially generalized database's widespread overestimation of infiltration rates, as reflected in soil hydrologic group rankings. Based on previous comparative studies of STATSGO versus SSURGO–reported soil physical properties in Kansas (Juracek and Wolock 2002) and Colorado (Murray 2002; Murray and McCray n.d.), it appears likely that the bias revealed in Wisconsin exists in other regions of the United States as well. These findings may also be relevant in other parts of the world, where similar pairs of alternative small and large-scale soil databases are available (e.g., Romanowicz et al. 2005). Comparisons between modeled runoff and observations for the six gauged watersheds within the study area further suggest that SSURGO–based, distributed CN models are, on average, the most accurate of the various combinations of the two databases and different levels of model aggregation—with STATSGO–based, lumped CN models typically producing the least accurate outputs.

While the different STATSGO as well as SSURGO–based uncalibrated models variably underestimated runoff under current conditions, this has limited bearing on their ability to predict relative changes associated with alternative land-use scenarios. Although it was not possible to test model accuracy in this regard through pretest/posttest experiments, the results of cross-sectional OLS regression analyses of 200 randomly selected subwatersheds suggest that STATSGO–based models will, on average, overpredict the impact of land conversions from lower intensity uses (e.g., forest and pasture) to higher intensity uses (e.g., cultivated crops and urban development). This finding, however, only holds for distributed CN models. The use of more common, partially distributed models (as well as fully lumped models) produces the opposite outcome, with STATSGO–based models predicting less, rather than more, runoff in more intensively developed subwatersheds relative to SSURGO.

Taken as a whole, the implication of these findings is that two of the most common approaches to improving the computational efficiency of hydrologic and NPS pollution models—the use of lower resolution soils data and the lumping of model parameters—combine to reduce the accuracy of modeled runoff under current conditions, while simultaneously underestimating the impact

Figure 4

Curve numbers (CNs) for distributed and partially distributed models in two subwatersheds (1 and 2) with similar soil hydrologic conditions but different land-use intensities. (a) Soil Survey Geographic (SSURGO)–based, distributed CNs.* (b) SSURGO–based, partially distributed CNs.* (c) State Soil Geographic database (STATSGO)–based, distributed CNs.† (d) STATSGO–based, partially distributed CNs.†



* Units of analysis = unique combinations of land use and soil hydrologic group.

† Units of analysis = stream catchments.

of land-use change. With this in mind, developers and users of watershed modeling systems should carefully weigh the potential for systematic biases associated with the use of STATSGO data in their models against the additional time and resources needed to incorporate higher resolution SSURGO data. Special care should be taken when making this choice within land-use planning contexts, since a bias in the predicted impacts of alternative land-use scenarios can have significant, long-term consequences. Given the now widespread availability of SSURGO and the continued advances being made in data storage and computer processing, it is hoped that the use of lower resolution STATSGO data will be phased out for models aimed at predicting the hydrologic impacts of proposed or potential land-use change.

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