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Full Length Research Paper

Evaluating spatial variability and scale effects on hydrologic processes in a midsize river basin

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The impact of spatial variability and scale on the dynamics of hydrologic processes in the Monongahela river basin of USA was investigated using a physically based spatially distributed hydrologic model developed by Yildiz (2001). The hydrologic model simulations were performed at 1 and 5 km spatial scales for a 5 month period from April through August of 1993. Effects of spatial variability in topography, vegetation and hydrogeology and of spatial scale were evaluated through comparisons of the simulated and observed streamflows for the prescribed resolutions at different locations across the river basin. The evaluation of observed and simulated streamflows using the statistical measures of mean, standard deviation, coefficient of variation, root mean square error and bias showed that model statistics of streamflow followed closely the spatial patterns of those of existing observations, that is, the model captured the space-time features of the 1993 flood across the basin. The changes in the nature of the rainfall-runoff response due to changes in the spatial resolution of the model indicated that there was also a change in governing physical processes at different resolutions. Here, this change was expressed in terms of the relative contributions of surface and subsurface flows.

Key words: Spatial variability; spatial scale; hydrologic model; streamflow, digital elevation model, stream network.

INTRODUCTION

The influence of spatial variability and scale on the hydrologic response of watersheds and their importance in hydrologic modeling have been widely studied by various investigators (e.g., Amorocho 1961; Eagleson, 1970; Dunne and Leopold, 1978; Wood et al., 1988; Entekhabi and Eagleson, 1989; Wood et al., 1990; Seyfried and Wilcox, 1995). In watersheds, spatial variability often results from interactions between ecosystem characterristics such as topography, vegetation, and geology (Seyfried and Wilcox, 1995). As the spatial scale of a watershed increases, the watershed tends to attenuate the complex, local patterns of runoff generation and water fluxes, that is, it functions as a low-pass filter. As pointed out by Amorocho (1961) the runoff generation at large scales becomes somewhat insensitive to rainfall intensity changes recorded at individual gauges and the catchment-scale rainfall-runoff appears to be governed by macroscale catchment characteristics. Therefore, the transition representing hydrological processes in models using microscale to macroscale parameterization is a highly nonlinear process.

As spatial scale increases spatial variability may significantly affect hydrological processes in watersheds. investigating effects of scale on the hydrologic response of a catchment Wood et al. (1988) proposed the so-called representative elementary area (REA) concept which is considered to be the smallest or critical representation of area at which implicit continuum assumptions can be applied for the spatially variable controls and parameters in physical models and therefore, spatial patterns are no longer needed to be considered explicitly. According to the authors, a REA can be defined in large-scale hydrologic modeling beyond which spatial heterogeneities in vegetation, topography, and soil can be incorporated into hydrologic models without considering the detailed spatial pattern of such heterogeneity within each grid cell.

Conventional lumped rainfall-runoff models generally

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have not utilized spatially variable data such as topography, soil and vegetation types. Using basin-averaged parameters spatial heterogeneities in the hydrologic response of watersheds cannot be reproduced by these models. On the contrary, incorporating detailed information on climate, soil, vegetation and digital elevation physically based spatially distributed hydrologic models have the greatest potential to forecast the effects of spatial variability by utilizing parameters which have physical significance at the spatial scales of interest (Beven and O'Connell, 1982; Abbott et al., 1986a; Bathurst, 1986; Beven, 1989; and El-Kadi, 1989).

The objective of this study is to investigate the impact of spatial variability and scale on the dynamics of hydrologic processes in a midsize watershed. A physically based spatially distributed hydrologic model was therefore applied in the Monongahela river basin of USA for the simulation of 1993 extreme hydrologic regime (a wet year). With an areal extent of 13,875 km^2 the basin is characterized by strong spatial variability in the soil-terrain-hydrogeology system.

The hydrologic model simulations were performed at 1 and 5 km spatial scales for a 5 month period from April through August. Effects of spatial variability and scale were investigated through streamflow comparisons for the prescribed scales at different locations across the river basin. The ability of the hydrologic model to reproduce the streamflow hydrographs was assessed using statistical measures of mean, standard deviation, coefficient of variation, root mean square error (RMSE) and bias.

Hydrologic model description

Physically based spatially distributed hydrologic models have become an important tool to simulate effects of spatial heterogeneities in watersheds by utilizing physical parameters that have physical significance and represent spatial variability (Beven and O'Connell, 1982; Abbott et al., 1986a; Bathurst, 1986). They can easily incorporate detailed information on topography, soil, vegetation, and climate from digital and remotely sensed data resources for various hydrologic applications in watersheds (Beven and Kirkby, 1979; Abbott et al., 1986a,b; Grayson et al., 1992; Paniconi and Wood, 1993; Wigmosta et al., 1994; Yu et al. 1999; Johnson and Miller, 1997; Kite, 1995; Biftu and Gan, 2001; Yildiz and Barros, 2005, 2007, among others). Historically, conventional lumped models generally have not incorporated spatially variable data includeing topography, soil and vegetation. Further, their physical parameterizations are valid in small-scale homogeneous media and thus they only can be an approximate representation of the hydrologic processes of a real landscape. Consequently, such models can not reproduce spatial heterogeneities in hydrologic system responses by using basin-averaged parameters (Abbott et al., 1986a; Beven, 1989; El-Kadi, 1989).

Incorporating detailed information on climate, soil, vegetation, and digital elevation a physically based spatially distributed hydrologic model developed by Yildiz (2001) was used in the model experiments. With a simple, yet physically realistic representation of surface-subsurface flow interactions, the model couples an existing land surface model (Devonec, 1999) with a surface flow routing model and a lateral subsurface flow routing model (Figure 1). At the land-atmosphere interface water and energy fluxes in the vertical direction are calculated by the land surface model through the use of simplified conceptual descriptions of the physics, the so-called parameterization schemes. A vertical soil column is discretized into a number of layers with a thin superficial layer at the top to function as the interface between the ground and the atmosphere and other deeper layers to store water and energy. The surface of the soil is subdivided into vegetation and bare soil areas.

Excess rainfall on the land surface is routed by the surface flow routing model, which relies on an algorithm using a single down-slope flow direction to facilitate the simulation of surface flow. Assuming a linear flow surface across grid cells a one-dimensional kinematic wave approach is employed in overland routing to simulate the inflow and outflow discharges for each grid cell. A modified Muskingum-Cunge method of variable parameters developed by Ponce and Yevjevich (1978) is applied to route the water through the channel network to the basin outlet. Finite difference approximations were used in numerical solutions of routing equations and the time-step is adoptive changing with hydraulic conditions on the hill slopes and in structures.

Subsurface flow, that is, interflow and baseflow is routed in the lateral directions by the subsurface flow routing model. A multi-cell approach proposed by Bear (1979) for aquifer systems was adopted for subsurface flow routing. Therefore, water balance equations are written for every grid cells and the system of equations is solved simultaneously for the entire aquifer system by finite difference approximations. Given the river stage in the channel, the flux between the channel and the ground water system is determined at the end of each time step. In the model, groundwater divides are assumed to correspond with the DEM-derived basin boundaries, and thus there is no interaction between the local and regionnal groundwater system. Also, the water table is assumed to follow the topographic surface slope.

The stream network of the watershed is constructed from DEM using a threshold value of flow contributing area and is optimized through the visual comparison with the actual stream network. Specifically, a pixel with a flow contributing value lower than the threshold value is treated as a plane pixel, otherwise it is treated as a channel pixel.

Vegetation can be dynamically introduced to the model simulations through adaptive assimilation of remotely sensed or digital data.

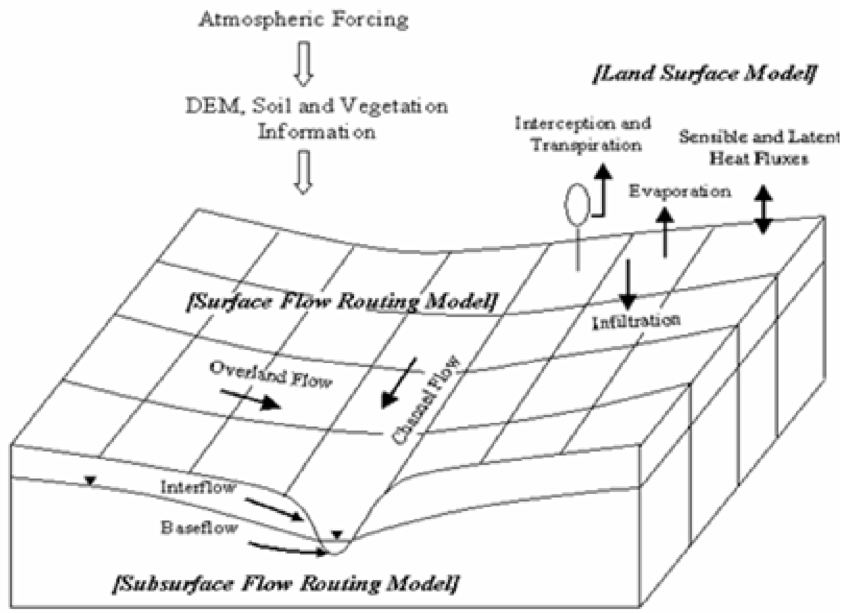

Figure 1. Structure of the hydrologic model.

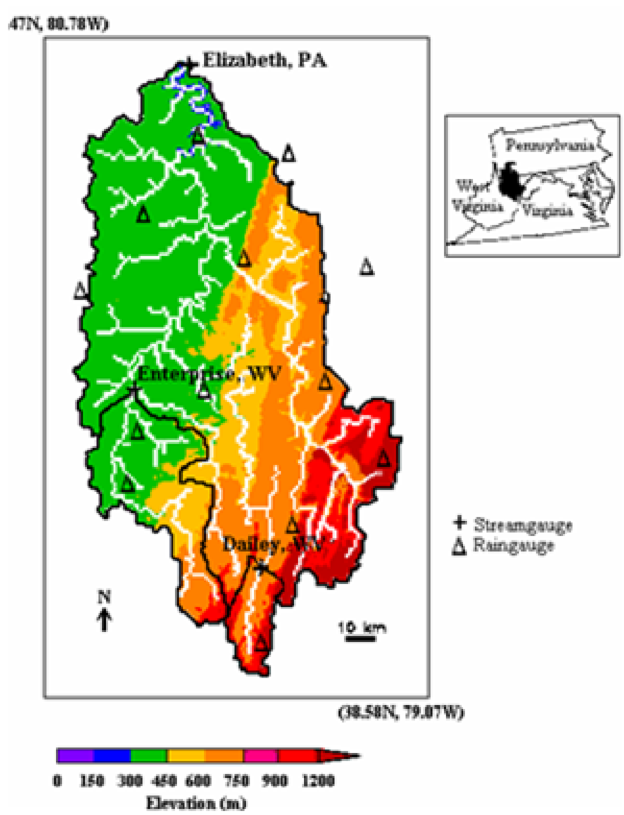

Figure 2. Digital elevation model (DEM) of the Monongahela river basin including streamgauge and rain gauge locations, stream network and delineated subbasins with stream gauges at the outlets.

Study area

The Monongahela river basin is located on the western slopes of the Appalachian mountains (38.56 - 40.47N, 79.07 - 80.76W) with portions in Pennsylvania and west Virginia (Figure 2). The basin is a tributary of the Ohio river basin and has a drainage area of approximately 13,875 km^2 with outlet at Elizabeth, PA. The delineated subbasins of Enterprise and Dailey have areal extents of about 1695 and 496 km^2, respectively. The actual stream network includes the West Fork, Tygart valley, Cheat and Monongahela rivers and their tributaries.

As part of the appalachian Plateau, the basin is characterized by strong spatial variability in the soil-terrain-hydrogeology system. Elevations in the basin range from about 400 to 1200 m being greatest in the southern mountainous areas and lowest in the northern areas. At elevations above 400 - 500 m, the bedrock is highly dissected and consists of sandstone with almost flat-lying layers of shale, clay, stone and dense limestone. The soil layers above the bedrock are very thin and thus most of the rainfall runs off the slope. The little amounts of water that infiltrate move vertically through fractures and then move horizontally through sandstone or coal layers over large distances until they find another region of fractures or an unconfined flow region such as colluvium and alluvium deposits. Accordingly, the base flow and inter-flow is very small during non-rainy periods in the warm season. At low elevations, productive unconsolidated alluvial aquifers ensure a significant and sustained base-flow and interflow contributions during summer months (Trapp and Horn, 1997).

The vegetation cover in the watershed area also presents significant spatial variability with a predominance of deciduous trees at high altitudes and short grass and crops at low altitudes. A small fraction of the southeast-tern part is covered by coniferous trees, while a narrow band of bare ground can be found along the northeast-southwest direction.

The regional climate is humid to temperate, with topographic difference influences leading to local anomalies. The average annual temperature is about 9°C. Mean monthly temperatures range from 2 to 22°C. Average annual precipitation is 1067 mm and ranges from 940 mm in northern areas to 1524 mm in the southern mountainous areas. Precipitation during the winter is cyclonic in origin, whereas thunderstorms are responsible for most of the summer rainfall. The average annual runoff (1951 - 1980) ranges from 635 to 1016 mm in the mountainous southeastern areas and from 458 to 660 mm elsewhere. The average annual recharge is estimated to range from 200 to 378 mm. The remainder of the average annual precipitation is estimated as evapotranspiration ranging from 90 to 410 mm across the north-south direction (McAuley, 1995).

Data description

The hydrologic model was driven by atmospheric forcing data including air temperature, pressure, humidity, wind velocity, shortwave and longwave radiations obtained from regional climate forecasts. The data were produced by the National Center for Atmospheric Research (NCAR) Regional Climate Model (RegCM2) for spring and summer 1993 periods over the midwest United states. The climate model was driven at the lateral boundaries by European Center for Medium Range Forecast (ECMWF) data analyses and model outputs were produced at a temporal resolution of 6 h for the pressure and 3 h for the remaining data sets at 25 km spatial scale (Jenkins and Barron, 1997). The climate forecast data were downscaled from 25 to 1 and 5 km spatial resolutions with a bilinear interpolation scheme. The downscaled data were further linearly interpolated into 1 h temporal scale.

Although the RegCM2 precipitation exhibited a close temporal correlation with the basin averaged observed precipitation, the climate model simulated excessive precipitation during the entire simulation period. Therefore, observed precipitation of 14 point measurements within the basin and the nearby from April to August at an hourly time step were used in the model simulations. Spatially distributed precipitation over the entire river basin was obtained by interpolating techniques using a modified Thiessen polygon approach in which each Thiessen polygon is represented by a raingauge, and thus at a given time step, rainfall is uniform over a Thiessen polygon but spatially variable over the entire river basin. The standard Thiessen polygon method was modified in order to include orographic precipitation effects, especially, during the spring months.

3 arc second DEM (approximately 100 m) from the United States geological survey (USGS) were aggregated into 1 and 5 km spatial resolutions for watershed boundary delineation and stream network construction.

The physically based model parameters were derived from the ancillary data using digital and remotely sensed data resources. Specifically, soil parameters including hydraulic conductivity, porosity, field capacity and wilting point were obtained from the STATSGO data base, which was designed primarily for regional, multi-county, river basin, state, and multi-state resource planning, management, and monitoring (USDA, 1995). The dominant soil texture in the basin was found silt loam, while loam and sandy loam were found scattered across the river basin, especially in the south.

Vegetation was included dynamically into the hydrologic model utilizing time-series of remotely sensed data. Vegetation characteristics including leaf area index (LAI) and fractional vegetation coverage (F_r) were estimated by parameterizations (LAI: Choudhury et al., 1994; Spanner et al., 1990; and F_r : Carlson and Ripley, 1997) using normalized vegetation difference index (NDVI) data from advanced very high Resolution radiometer (AVHRR). Given the soil and vegetation information, other model parameters were selected from the literature (Monteith and Unsworth, 1990; Dingman, 1994; roughness length and minimum stomatal resistance, Dickinson et al., 1993; Manning's roughness coefficients, Chow, 1959).

The hydrologic regime of 1993

Being among the most severe occurrences of climatic extremes in the continental United states during the last decades the 1993 summer flooding in the Mississippi river basin was produced by one of the largest rainfall anomalies of the century (Kunkel et al., 1994). The occurrence of this climatic extreme has been linked to modifycations in the general circulation induced by pronounced sea surface temperature anomalies in the tropical Pacific (Mo et al., 1995; Trenberth and Guillemot, 1996). Heavy rainfall that persisted through June and July caused record high river levels in the central United states. The total rainfall over the summer period was twice as large as the normal value. During the spring of 1993, rainfall in the central United States was already above the normal and the soil moisture levels were near saturation and thus, this region was poised for potentially severe flooding prior to the onset of excessive and localized rainstorms in the beginning of June (Kunkel et al., 1994; Bell and Janowiak, 1995; Mo et al., 1995; Beljaars et al., 1996).

Hydrologic model simulations

Hydrologic model simulations of the 1993 hydrologic regime were performed at 1 and 5 km spatial resolutions with an hourly time step for a 5 month period between April and August. The hydrologic model was initialized for a period of 1 month (spin-up period) at the beginning of the simulation in order to allow the state variables to reach equilibrium conditions. The model was not calibra-

Table 1. Selected model parameters for the model sensitivity analysis.

Parameter Name	Classification
Leaf area index	Land use/Land cover
Fractional vegetation coverage	Land use/Land cover
Root depth	Vegetation
Minimum stomatal resistance	Vegetation
Albedo	Land use/Land cover
Roughness length	Land use/Land cover
Soil field capacity	Soil hydraulics
Soil wilting point	Soil hydraulics
Hydraulic conductivity	Soil hydraulics

ted, that is, the physically based model parameters extracted from the ancillary data were not submitted to optimization, because the simulation year of 1993 represented an extreme hydrologic regime. As suggested by the study of Bindlish and Barros (2000) calibration of model parameters is particularly sensitive to the underlying climate regime and thus calibration does not lead to an improved model response.

Using the fractional factorial design method (Box et al. 1978) a sensitivity testing of the hydrologic model to selected model parameters listed in Table 1 showed that the impact of vegetation is significant on the hydrology of the Monongahela river basin. The evaluation of the model sensitivity analysis results showed that fractional vegetation coverage and leaf area index have major effects on the model results. During the wet year of 1993, in addition to the above vegetation parameters, soil hydraulic conductivity seems to have significant effects on the model results due to higher soil water availability (Yildiz and Barros, 2007).

The model simulations of streamflow hydrographs were produced at daily time scales at the outlet of the basin, that is, Elizabeth and the subbasins, that is, Enterprise and Dailey. In order to evaluate the model's ability to reproduce the temporal patterns of the streamflow hydrographs, statistical measures of mean, standard deviation, coefficient of variation, root mean square error, and bias were calculated for the 1 and 5 km grid resolu-tions separately.

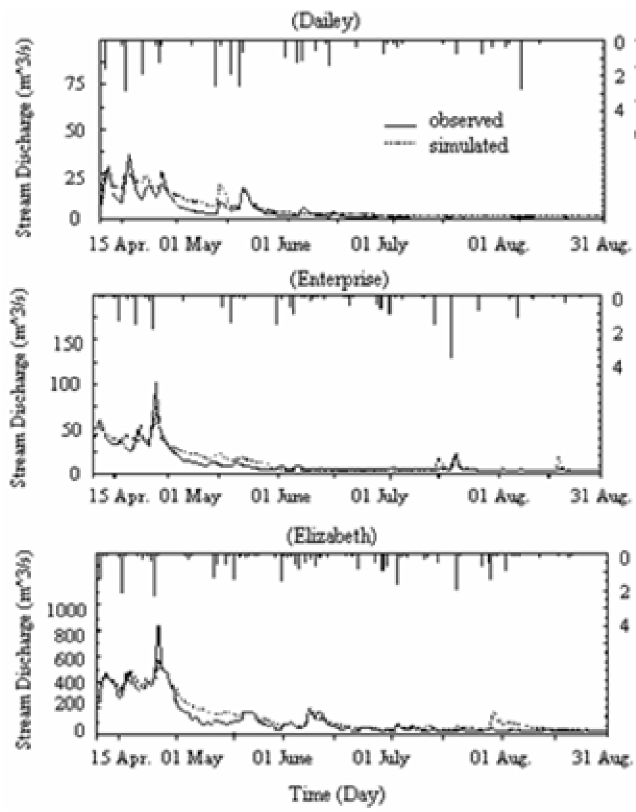

Figure 3. Observed and simulated streamflow hydrographs between 09 April and 31 August 1993 at 1 km spatial resolution.

DISCUSSION OF RESULTS AND CONCLUSIONS

The hydrologic model simulations of streamflow hydrographs performed at the prescribed grid resolutions were compared against the observations in Figures 3 and (that is, Elizabeth) and subbasins, that is, enterprise and 4. Referring to the figures, the model generally captured the temporal patterns reasonably well both at the basin dailey scales. Overall, the model performed much better in the summer period than it did in the spring period. The timing of most spring and summer peaks were estimated reasonably well, although, not all the peaks were reproduced successfully. At both Elizabeth and Enterprise, most spring peaks were overestimated (large positive biases) while most summer peaks were simulated close to the observations (relatively lower positive biases) at the coarser resolution, that is, 5 km. At dailey, however, the streamflow response was generally overestimated, especially during the spring and early summer periods, at the same resolution. This result is consistent with the fact that orographic enhancement was imposed as a uniform constraint in creating the spatial distribution of rain-

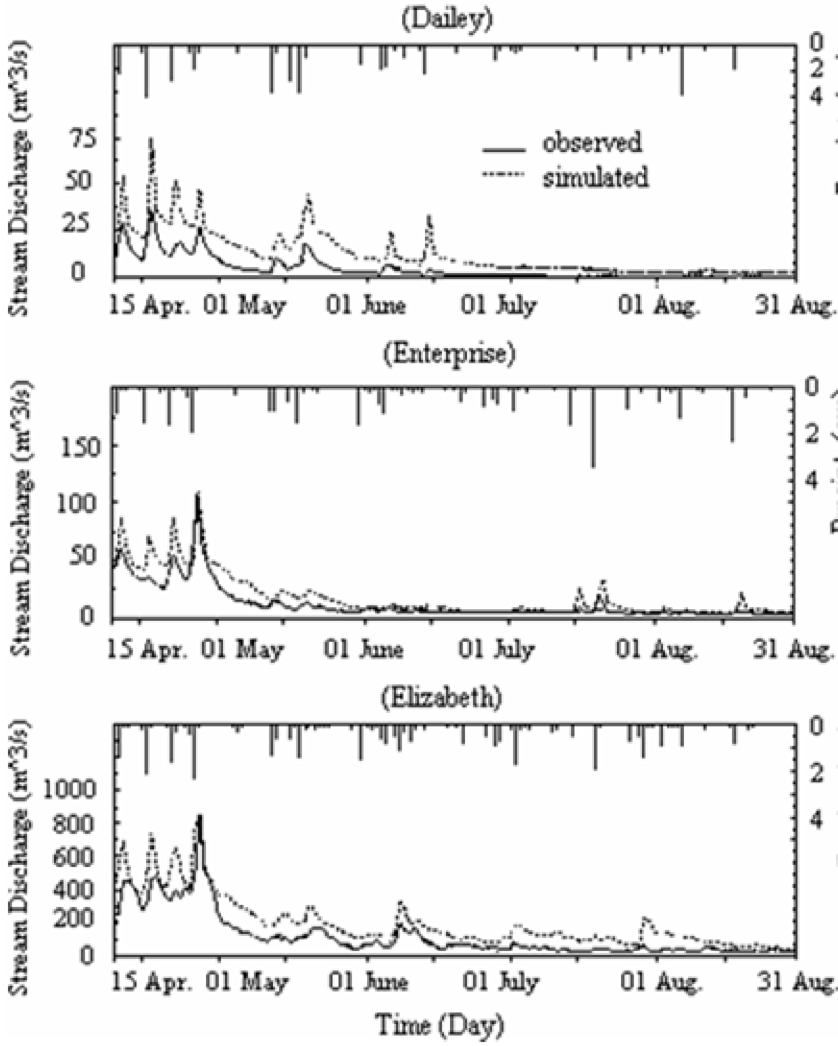

Figure 4. Observed and simulated streamflow hydrographs between 09 April and 31 August 1993 at 5-km spatial resolution.

rainfall in parts of the basin where elevations are relatively high and topographic gradients are steep (Figure 2). As compared to the 5 km results, except the maximum peak at the end of April, spring and summer peaks were better simulated at Elizabeth and enterprise at the finer resolution, that is, 1 km). Similarly, the streamflow response, at dailey, was better simulated producing relatively lower biases at this resolution.

A survey of the statistical measures of observed and simulated streamflows, which were included in Tables 2 and 3 on a spatial context with increasing basin area, indicates that as the watershed area increases, mean, standard deviation, root mean square error (Equation 1) and bias (Equation 2) in the streamflow simulations also increase. Referring to the tables, the coefficient of variation is usually higher in the summer season than that in the spring and it decreases as the watershed area increases indicating reduced variability due to spatial integrating effects of streamflow propagation. In short, the data show that model statistics of streamflow follow closely the spatial patterns of those of existing observations, that is, the model captures the space-time features of the 1993 flood across the basin.

$$\text{RMSE} = \left(\frac{1}{n}\sum_{i=1}^{n}[Q_S(i) - Q_O(i)]^2\right)^{1/2} \quad (1)$$

$$\text{Bias} = \left(\frac{1}{n}\sum_{i=1}^{n} Q_S(i) - \frac{1}{n}\sum_{i=1}^{n} Q_O(i)\right) \quad (2)$$

where $Q_s(i)$ and $Q_o(i)$ are the simulated and observed streamflow rates respectively and n is the number of data. Comparison of the 1 and 5 km streamflow simulations at the outlet of the basin and the subbasins reveals that the contribution of subsurface flow to the streamflow substantially increased at 1 km grid scale, especially in the spring

Table 2. Streamflow statistics at 1 km resolution in the order of increasing watershed area.

	Watershed Name	Spring		Summer	
		Observ	Simulated	Observed	Simulated
Mean[1]	Dailey	10.3	13.5	0.7	2.0
	Enterprise	25.5	28.5	5.3	4.1
	Elizabeth	237.9	276.6	44.5	61.9
Std. Dev.[2]	Dailey	7.7	6.6	1.1	0.6
	Enterprise	20.1	14.7	2.2	3.4
	Elizabeth	169.0	140.0	32.2	33.3
CV[3]	Dailey	0.75	0.49	1.57	0.30
	Enterprise	0.79	0.52	0.42	0.83
	Elizabeth	0.71	0.51	0.72	0.54
RMSE[4]	Dailey		5.1		1.5
	Enterprise		8.6		2.9
	Elizabeth		73.9		29.5
Bias[5]	Dailey		3.3		1.2
	Enterprise		3.0		-1.2
	Elizabeth		38.7		17.4

[1]Arithmetic average; [2]Standard deviation; [3]Coefficient of variation (Std. Dev./Mean); [4]Root mean square error defined by Eq. (1); 5Bias defined by Eq. (2).

Table 3. Streamflow statistics at 5 km resolution in the order of increasing watershed area.

	Watershed Name	Spring		Summer	
		Observed	Simulated	Observed	Simulated
Mean	Dailey	10.3	24	0.7	5
	Enterprise	25.5	36.7	5.3	5.2
	Elizabeth	237.9	351	44.5	111
Std. Dev.	Dailey	7.7	12.5	1.1	4.5
	Enterprise	20.1	24.0	2.2	4.3
	Elizabeth	169.0	179	32.2	50
CV	Dailey	0.75	0.52	1.57	0.89
	Enterprise	0.79	0.61	0.42	0.55
	Elizabeth	0.71	0.51	0.72	0.44
RMSE	Dailey		16.7		5.4
	Enterprise		21		4.2
	Elizabeth		134		75
Bias	Dailey		14		4.3
	Enterprise		11		2.7
	Elizabeth		113.6		67.1

period when heavy rainstorms are more frequent. As shown in Figure 5, the model generated streamflow was comprised mostly of subsurface flow at 1 km resolution in all watersheds. Also, the difference between subsurface flow contributions at 1 and 5 km scales becomes very small in late spring and summer seasons, thus indicating that when soil water availability is high, evapotranspiration does not play the same governing role in controlling the partitioning of surface/subsurface runoff contributions to streamflow.

The model production of excessive surface runoff at 5 km scale suggests that when soils are near saturation,

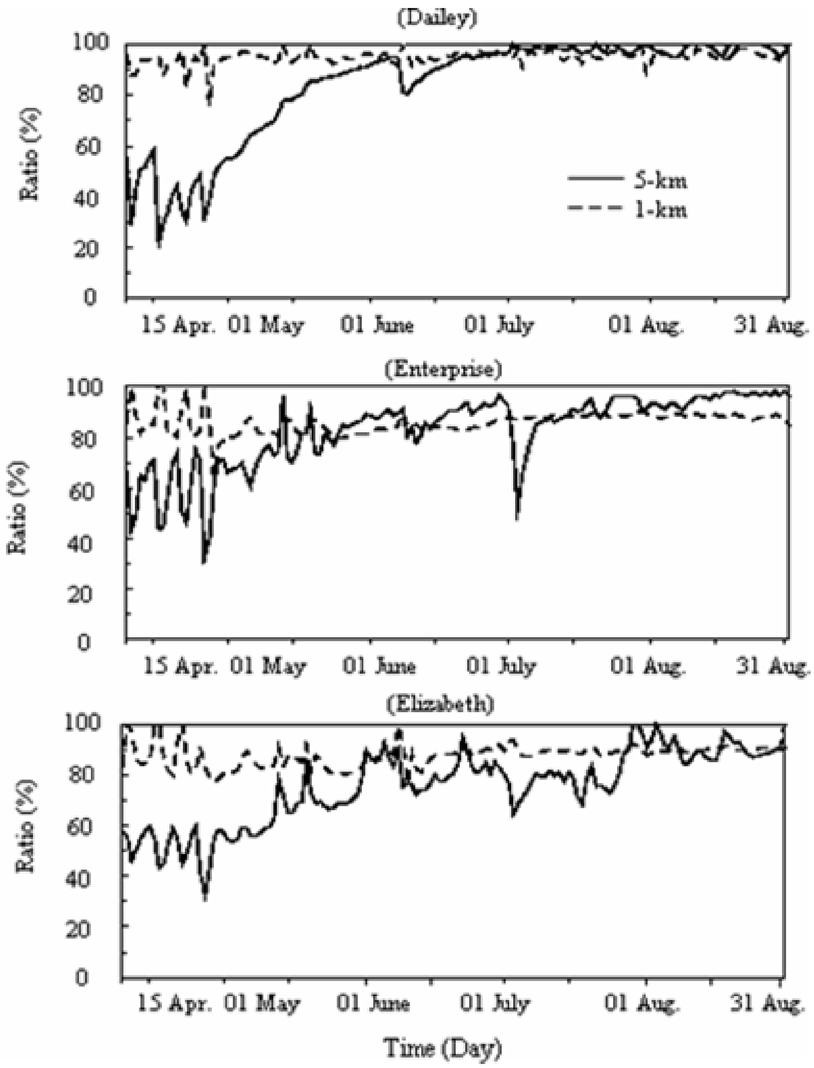

Figure 5. The ratio of subsurface flow contribution to total streamflow at 1 and 5 km resolutions.

especially during the early spring season, the subsurface flow response both in vertical and lateral directions is "slower" than that at 1 km scale. This is consistent with a larger characteristic time-scale at 5 km resolution, given that the underlying hydraulic conductivity fields are the same at both resolutions. If calibration were performed with respect to hydraulic conductivity, the result would be that hydraulic conductivity at 5 km would be larger than that at 1 km, as found by Bindlish and Barros (2000).

The changes in peak streamflow as well as spatial distribution of runoff with respect to rainfall exhibit linear, albeit complex features, where the complexity results from the spatial heterogeneity of soils, vegetation and topography. However, the changes in the nature of the rainfall-runoff response due to changes in the spatial resolution of the model indicate that there is also a change in governing physical processes at different resolutions. Here, this change was expressed in terms of the relative contributions of surface and subsurface to streamflow and can be linked to evapotranspiration and change in root zone soil moisture. One implication of this finding is that there is a dependency between model resolution and model physics, and therefore diagnostic studies using virtual laboratories, that is, models may be limited in their value for understanding complex systems.

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