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Multiscale Effects on Spatial Variability Metrics in Global Water Resources Data

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Abstract Spatial scales and methods for dealing with scale have been widely discussed in the water resources literature. Different spatial processes operate at different scales so interpretations based on data from one scale may not apply to another. Understanding the behavior of phenomena at multiple-scales of data aggregation is thus imperative to accurate integrations of data and models at different geographic resolutions. This study tests theoretical concepts of scale by presenting empirical results of multiscale GIS and statistical analyses on gridded water-availability, water use and population data for the Danube Basin in Europe, with results corroborated by similar tests in the Ganges (South Asia) and Missouri (North America) Basins. Fine-resolution datasets were aggregated to coarser grid sizes and standard statistical measures of spatial variability were computed. Statistical analysis of spatial variability demonstrated two distinctly different cases for unscaled and scaled variables. Results show that variance (and standard deviation) in unscaled variables like freshwater supply, use and population increases at coarser scales—contrary to the common assumption of decreasing variability as grid-cell size increases. On the other hand, a decreasing trend in variability with scale is noted for variables scaled to area or population (like population density, water availability per capita etc.). Moreover, relationships between variability and scale show strong non-linear trends. No mention of these relationships has been found in the water resources or socio-economic literature for scale and variability. Regression analyses suggest that power functions are the most appropriate model to fit trends in increasing variability at multiple

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scales. These results can be applied to interpretations of water-stress and water scarcity data and their locations relative to water sources or topographic barriers.

Keywords Spatial variation · Multiscale analysis · Water availability · Scarcity · Grid data

1 Introduction

Water resources are renewable but finite (Postel 1992). Given humanity's dependence on water, accurate assessments of the capacity of global freshwater systems are crucial to planning and management (Raskin et al. 1997; WWC 2000; Cosgrove and Rijsberman 2000; Shiklomanov and Rodda 2003; Gleick 2004; Liu et al. 2009). The outcome of water resources assessments depends greatly on the spatial scale and structure of the data used, although little is known of the nature of this dependency.

1.1 Data Structures for Water Resources

Studies of global water resources may use any one of three data structures: national boundaries, river basin boundaries, or gridded data. Historically, most data for global-scale water resources research has been defined by national borders, especially for demographic, economic, and other social variables. To compare or merge national data with data that are structured by river basins or grids, such as hydrologic or climatologic data, the national data must be resampled or regenerated in a grid format (Fig. 1). For example, the Center for International Earth Science Information Network (CIESIN 2002) has developed downscaled gridded datasets for population projection and GDP using the IPCC Emissions Scenario in efforts to produce socioeconomic data at fine scales that are consistent with current global climate-modeling scenarios. For studies involving multiple data structures, data rescaling or resampling is necessary for comparisons or multivariate analyses. Unfortunately, little is known about the errors or distortions that are generated by such manipulations.

In countries with wide variations in population density, economic profiles, topography, and climate, a comparison of nationally averaged water withdrawals and availability between countries may not be meaningful due to averaging of local extremes. Country level data may also obscure water availability along international rivers, where supplies to a downstream country greatly depend on inflows from upstream (Alcamo et al. 2003). While country-scale assessments are often essential, for many purposes, analyses of water resources should be conducted at the watershed level based on watershed divides (Alcamo and Henrichs 2002). Freshwater is usually generated, transported and stored within river basins, so watersheds are often the appropriate spatial unit for effective research, assessment and management (Montgomery et al. 1995). Integrated river basin or watershed management is now recognized as an important strategy for managing water use and dealing with water scarcity (Wolf et al. 1998; Revenga et al. 1998, 2000; USEPA 1996). Also, from a hydrological perspective, performing certain functions at the basin level makes sense (Molle and Wester 2007).

Several problems however limit the use of river basins as the definitive data structure for water resources studies. Existing global river-basin data bases are relatively

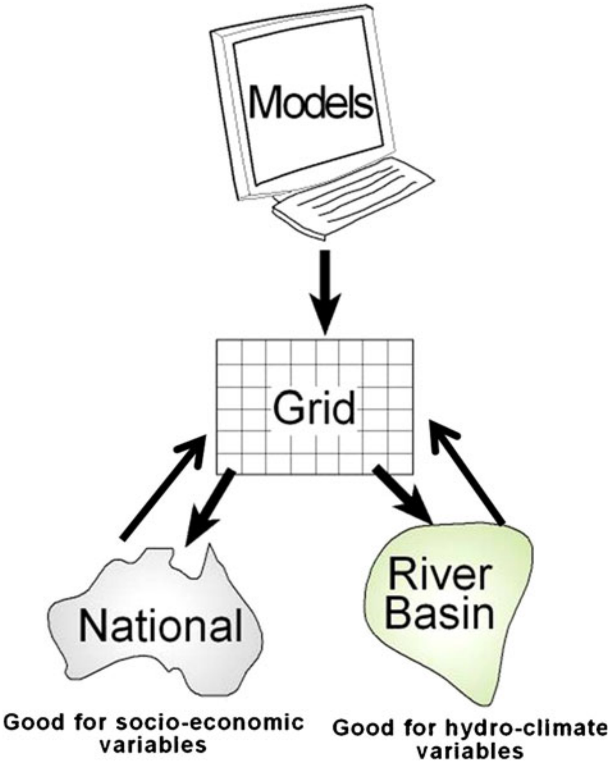

Fig. 1 Data structures for water resources

coarse grained; i.e., they consist primarily of large basins, so considerable spatial averaging of data (lumping) occurs. Further, reconciliation of water resources issues across a watershed is beleaguered by difficulties such as non-conformities between political and drainage basin boundaries, interbasin water transfers, and inequities between the political and economic influence of urban and rural service areas that extend beyond the watershed. Moreover, scientists recommending use of the watershed framework do not agree about the scale upon which studies should be undertaken (Montgomery et al. 1995). Omernick and Bailey (1997) suggest that, although the purpose of watersheds for tracking water supply is clear, use of the framework in a social science context is problematic. The physical and economic conditions relative to watershed functions have little correlation with patterns of consumption or with the distribution of most geographic phenomena that affect or reflect spatial processes (Ciriacy-Wantrup 1959).

Clearly, no single scale or data structure is appropriate for all objectives, so the ability to aggregate and disaggregate data to various scales and to move across data structures is desirable. Driven by vast data-generation and information-processing capabilities, the ability to generate high-resolution spatial data and transform data across structures has grown (Fig. 1). The need to go between local and regional scales to link water resources with climate and hydrologic models has encouraged the development of gridded data sets, which are also an important intermediate data form in transformations to or from national to watershed structures. Early grid-based macro-scale hydrologic models with a spatial resolution of 0.5° were produced in the 1990s (Vörösmarty et al. 1996, 1998; Arnell 1999; Yates 1997; Klepper and Van Drecht 1998). The gridded macro-scale hydrologic models have been developed to estimate the spatial variability in resources over large areas at spatial resolutions finer than can be provided by observed data alone.

1.2 Scale and Uncertainty

Recognition of the importance of *scale* in environmental assessments has grown considerably over the past decade (Gibson et al. 1998; Wilbanks 2003), but research on the effects of scale on water resources variables is conspicuously lacking. It is now known that the scale at which an environmental assessment is undertaken substantially influences the problem definition, assessment of results, and the solutions selected (MEA 2005). Conversely, if results depend on the scale of analysis, uncertainty arises from the possibility of different results at another scale. As scale changes, so do associated spatial patterns of phenomena (Goodchild and Quattrochi 1997; Hay et al. 2001). As the scale becomes coarser (e.g. larger grid-cell sizes), spatial heterogeneity often decreases due to averaging, which introduces uncertainty (Goodchild 1998). In fact, one of the largest sources of uncertainty in spatial databases is the process of cartographic generalization (Hunter and Goodchild 1996). Uncertainty also increases with spatial variability because modeling or forecasting relationships across an area is more difficult when phenomena are highly variable. Several studies have indicated changes in variability with changing geographic scales (Meentemeyer 1989; Wu et al. 2000); although relatively few scientific multiscale tests have been conducted (MEA 2005).

Empirical studies suggest that the identification of scale-dependent heterogeneity and irregularity should help define a suitable range of scales for a given process or observation (Atkinson and Tate 2000). Multiscale analysis is necessary to recognize the scales at which various processes take place, account for feedbacks between scales, ensure that perspectives at one scale are reflected in interpretations at other scales, and evaluate scale dependencies of various actions and policies (Biggs et al. 2004). Despite many appeals for multiscalar research (Miller 1978; Stone 1968; Kirkby 1985), however, it is seldom performed. Nor are empirical experiments applied to test hypothetical relationships. Wu et al. (2000) provide some insight as to why the spatial characteristics of natural processes have not been well studied: Firstly, it was not until the 1980s that the interaction among pattern, process and scale began to occupy a central place, especially in ecological studies (Wu and Levin 1994). The second reason concerns the lack of effective statistical and modeling methods for studying spatial phenomena. Only in recent years, have new methods in spatial statistics begun to be introduced and realized to alleviate this problem (e.g., Legendre and Fortin 1989; Rossi et al. 1992).

Recently developed macro-scale hydrologic models estimate the spatial variability in resources over large areas—at a spatial resolution finer than can be provided by observed data alone. This has led to focus on scale issues and concern with the nature of spatial variability in remote sensing, landscape ecology, geomorphology, hydrology, etc. Much research now reflects the view that the scale of assessment substantially influences the problem definition and assessment results, as well as the solutions and responses selected (MEA 2005). New geospatial analytical methods presented here now facilitate the simulation of data sets at multiple scales to observe and examine scaling trends in water resources and socio-economic data with scale. The availability of high-resolution geospatial datasets provides an empirical basis for study. Together, the need for such work, the availability of new analytical methods, and the availability of data should ultimately allow a new theoretical understanding to be achieved. Recent availability of tools like GIS has also facilitated better multi-variable and multi-scale analysis and integration of spatial datasets (Atkinson and Tate 2000) to explore interrelations between and across scales (Bunnell and Coe 2001). Depending on the application and spatial heterogeneity of the geographic phenomenon, it has often been argued that there should be an "appropriate" scale that will generalize the spatial pattern of a specific feature to be discovered, yet retain the important spatial variations (Levin 1992).

1.3 Effects of Scale Change on Statistics

One of the most obvious effects of scale change is to the level of detail that is present. Moving to a coarser scale (e.g. larger grid-cell sizes) involves moving away from the basic processes (Meentemeyer and Box 1987). The number of variables that are reliably depicted generally becomes smaller at coarser scales. At the scale of the entire USA for instance, climate appears to explain the broad general patterns of soil pH, soil base saturation and general soil type while masking substantial local variations. Essentially, scale often determines the results, yet spatial scale is a last consideration in many studies. The need to predict and control the scale and aggregation effects on statistical results and modeling continue to be recognized (Marceau 1999). Variability in statistics resulting from the use of different scales or aggregation levels was demonstrated first by Gehlke and Biehl (1934). Yule and Kendall (1950) demonstrated that correlation coefficients varied greatly according to the number and size of areal units used. They concluded that correlation coefficients only measure relationships between variates for the specified study units and have no validity independent of those units. Robinson (1950) introduced the term *ecological fallacy* to describe the error resulting from making statistical inferences about individual relationships from aggregate relationships. Later, McCarthy et al. (1956), Blalock (1964), Clark and Avery (1976), and others confirmed that conclusions derived at one scale are specific to that scale and should not be expected to be valid at another scale, although the full significance of the problem has not always been realized (Openshaw 1977).

1.4 Multiscale Assessments and Scaling in Water Resources

Multiscale analyses evaluate spatial phenomenon at a variety of spatial scales. Some researchers maintain that a geographic analysis is not complete without a multiple-scale approach which is essential to integrated environmental assessments (Stone 1972). Multiscale studies are motivated by several factors. They can identify scaling laws that link patterns and processes at different scales. Many environmental problems, such as global warming, continental deforestation, and regional water management, should not be studied at a single scale of observation. When investigating these complex phenomena, a primary goal is to understand how processes operate at various spatial scales and how they can be linked across scales. This necessitates understanding scale and aggregation effects on statistical results and modeling, and requires appropriate solutions to cope with these effects. In fact, one of the most important and universal characteristics of spatial heterogeneity is scale multiplicity in space (e.g., Miller 1978; Wu and Loucks 1995). The implications of scale multiplicity to landscape ecology, for instance, are essential to understanding the structure, function and dynamics of variables that are spatially related (Wu et al. 2000). Landscape variables may be hierarchically structured and exhibit distinctive spatial patterns at different scales caused by different processes. Understandably thus, extrapolating or translating information from one scale to another is a fundamental challenge in both theory and practice across all earth sciences (Wu et al. 2000), and understanding relationships between macroscale and microscale phenomena is one of the "grand queries" of the sciences (Kates et al. 2003).

2 Research Objectives

The goal of this study is to better understand how spatial variability in water resources data varies with scale in order to improve the resolution and reliability of estimates of water availability, use and the risk of water shortages. It provides empirical multiscale assessments of global water resources data to measure changes in the spatial variability of water resources variables associated with changes in scale. By measuring the effects of changing grid-cell size on spatial variation, it investigates fundamental questions of how spatial patterns of water availability, water use, and population change are related to the scale of the data. Changes in variability are measured across different data scales, and scaling models are developed for the observed trends. Two hypotheses can be stated that result in conflicting predictions about whether multi-cell variability will increase or decrease as grid-cell size increases:

(H1) Variability increases as grid-cell size increases due to increasing magnitudes of individual cell values, and;
(H2) Variability decreases as grid-cell size increases due to spatial averaging within each cell.

In the first case (H1), variance and standard deviation increase when geographic areas (e.g., grid-cell sizes) get bigger, because larger areas result in larger values which have greater deviations around the mean (Walsh et al. 1997). For example, large cells will have larger water availability or population than small cells. In the second case (H2), upscaling to coarser data resolutions may generate decreases in spatial variability due to spatial lumping of information; that is, heterogeneity is damped out by averaging across the grid cell. Controlled tests of these two hypotheses are applied in the Danube Basin (Europe) and confirmed with similar tests in the Missouri (North America) and Ganges Basins (South Asia). These basins were selected to represent diverse developed and developing nations in different demographic and climate regimes.

Calculations of water stress and scarcity at a broad scale may not represent the true risk of water shortages at a more local scale. With high spatial variability, measures of mean water stress are lumped and may obscure local areas with conditions of extreme shortage. In order to estimate the effects of averaging and the likelihood of extreme outliers, variance or standard deviation is used as a statistical metric of spatial variability, and empirical testing is performed to see how this metric changes with scale. These tests are designed to see if measures of water scarcity may be more artifacts of scale than underlying changes in the variables. Furthermore, if spatial heterogeneity increases with changes in scale, this translates into increasing uncertainty. Insensitivity to these relationships may result in underestimates of the magnitudes and likelihood of water shortages in isolated areas.

3 Datasets and Methodology

Empirical tests are applied in three river basins—Danube (Europe), Missouri (North America) and Ganges (South Asia)—which represent diverse economic, demographic and climatic regimes (Table 1). The Missouri Basin in North America is the largest of the three basins with an area of 1,333,748 km^2 but has the lowest population density of 8.7 people km^{-2}. The Ganges Basin, on the other hand, has slightly less areal extent (1,029,261 km^2) but the population density is the highest among the three basins under study with approximately 360 people km^{-2}. The Danube Basin occupies the smallest area of the three basins under study (806,360 km^2), although the population density is intermediate between the two basins at 107 people km^{-2}. The three basins differ in climate, rainfall, seasonality, physiographic conditions, and trends in water availability, and demand.

This study uses recent high-resolution gridded model outputs of global water availability, water use, and population to perform multiscale assessments. Water availability, water use, and population data were selected as test variables because they form the basis for traditional water-stress and water scarcity calculations. Two of the most widely used metric for calculating water resources vulnerability at the country level are—Falkenmark Index (Falkenmark and Widstrand 1992) and Criticality Ratio (Raskin et al. 1997). While the former is defined as per capita water available per year, the latter is computed as the ratio of water use to availability.

Water availability and use data were obtained from the *Water-Global Assessment and Prognosis* (WaterGAP 2.1) model (Döll et al. 1999; Alcamo et al. 2003). The model was designed to simulate the macro-scale behavior of the terrestrial water cycle, the impact of demographic, socio-economic, and technological changes on water use, and the impact of climate change and variability on water availability and use. These data are in 0.5° × 0.5° vector grids (shapefiles); that is, a series of square polygons with numeric attributes referred to henceforth as grid cells. This small grid-cell size is considered relatively high-resolution data for global water-resources. The WaterGAP model has been calibrated and tested against observed values.

Table 1 The three case study basins and their physiographic characteristics

Case study basins	Area (km^2)	Population	Pop. density (km^{-2})	Climate variability	Lat-long extent
Danube (Europe)	806,360	86,279,052	107	3% arid	8–30° E 42–50° N
Missouri (NA)	1,333,748	11,666,418	8.7	64% arid	90–115° W 36–50° N
Ganges (S. Asia)	1,029,261	369,594,036	360	26% arid	70–88° E 22–31° N

Though macro-scale hydrologic models are not an ideal substitute for site-specific observations, they provide estimates in regions where little or no direct data are available. These data are particularly well-suited for evaluations of global-scale trends and have been used successfully to evaluate first-order basins in Europe (Alcamo et al. 2001), although it is suggested that detailed conclusions about individual annual values, mean monthly values, or small watersheds should be made with caution (Alcamo et al. 1997; Lehner and Kaspar 2001).

Another high-resolution raster population dataset (30″ × 30″) for population was acquired from Oak Ridge National Laboratory, Tennessee (ORNL LandScan 2005). The accuracy of this data set was improved with the help of GIS, remotely sensed slopes, land cover, road proximity, and night-time lights to refine population cell values (Dobson et al. 2000).

To examine the effects of changing grid-cell data resolutions, two methods of data aggregation were followed using the geo-processing tools in GIS—“fishnets” for water availability and use vector-grid data and “aggregate” tool for raster population data. Before the aggregation procedure, however, the gridded data layer for water and population were clipped using the vector layer for basin divides. Figure 2 compares the two different data structures for the Danube basin. The water availability and use data were aggregated with ArcGIS 9.2 (ESRI) software using

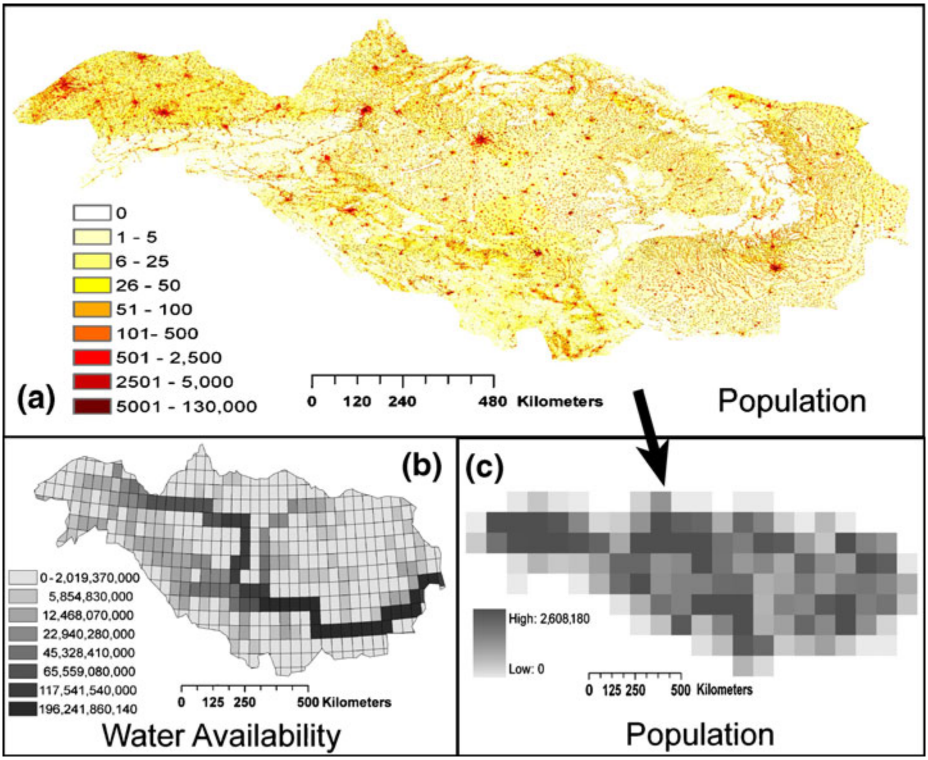

Fig. 2 Comparison of data structures for Danube Basin. **a** Raster 30-s population data (ORNL 2005). **b** Vector-grid 0.5° water availability data (Döll et al. 1999). **c** Raster 1° population data aggregated from the 30-s raster data (ORNL 2005)

two-dimensional “fishnets” as lattice grids placed over the study area. Fourteen grids were generated from 0.5° grid data for water availability by aggregating to 1°, 1.5°, 2°, 2.5°, ... up to 7° × 7° grid-cell sizes. Partial cells along watershed boundaries were partitioned using area-weighted cell values to avoid over-estimation of watershed total values (Schlossberg 2003). For the raster population dataset, 27 data grids were generated from the high resolution (30″ × 30″) pixels by aggregating multiple grid cells to coarser resolutions using the aggregate function in ArcToolbox. The large number of population data resolutions generated in this manner allowed examination of changes in variability at finer scales. For both data structures, each new dataset at a larger grid-cell size was generated by directly aggregating the original data set, instead of using a cumulative procedure that could amplify errors. Aggregation involved simple sums of multiples of cells to avoid sub-cell resampling that could complicate interpretations.

Values of each grid cell at a given scale were used to compute statistical variability at that scale. Statistical variability (variance and standard deviation) was computed and analyzed on SPSS 16.0 and SAS 9.1 statistical packages for both water and population in each of the three river basins. For all the datasets, statistical regression analysis using ordinary least squares (OLS) was conducted to find the best-fit model expressing changes in variability across multiple scales. Several univariate models were examined and evaluated on the basis of the strength of model fit as measured by the coefficient of determination (r^2), the visual fit of the models, and unrealistic predictions of extrapolated values such as negative values at small grid-cell sizes.

4 Results

Statistical analysis of spatial variability demonstrated two distinctly different cases: for unscaled and scaled dependent variables. Unscaled variables such as population, water availability and water use increase with the area of the sample (i.e. grid-cell size). Scaled variables (that are ratios of an area-sensitive factor) such as water availability per capita and population density do not increase with increasing grid-cell sizes.

4.1 Unscaled Variables

Statistical mean cell values and variability consistently increased for water use, water availability, and population when data for the three basins were aggregated from fine to coarser scales. Figures 3, 4 and 5 demonstrate these increasing trends in the Danube Basin, which conform to the first hypothesis (H1). Changes in variability differ between these three basins in detail, but the overall increase is unequivocal. This simple relation is not necessarily intuitive because it goes contrary to the commonly held notion that spatial averaging caused by cell aggregation at coarser resolutions should damp out variability (H2). In these unscaled data, however, data aggregated at coarser scales have substantially larger grid-cell values and larger deviations around the mean than data in fine grid cells.

The increase in variance in water availability with grid-cell size (degrees) could be approximated by a simple linear model ($r^2 = 0.895$; Fig. 6a), although the relationship is not truly linear. The dimensions of geographic grids and lattices are commonly given as degrees or multiples of degrees (e.g., 0.5° × 0.5°) which is a linear unit. They

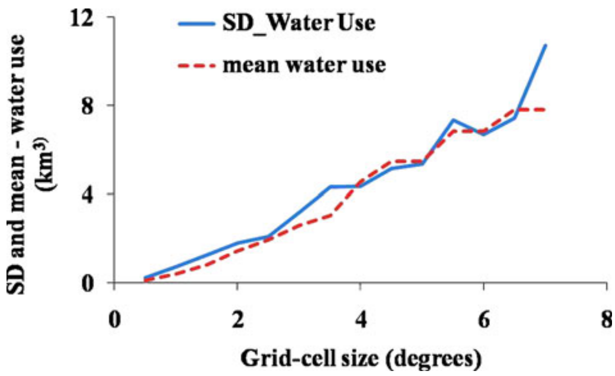

Fig. 3 Standard deviation of water use in Danube Basin against scale

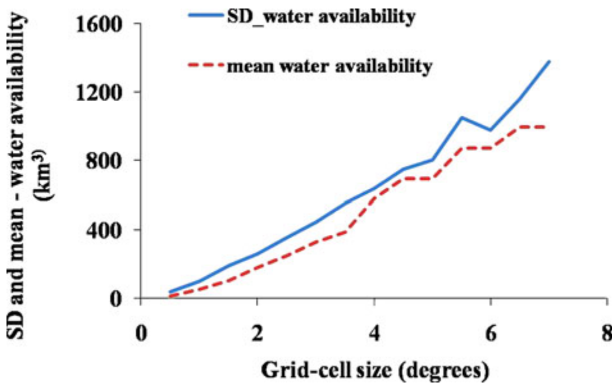

Fig. 4 Standard deviation of water availability in Danube Basin against scale

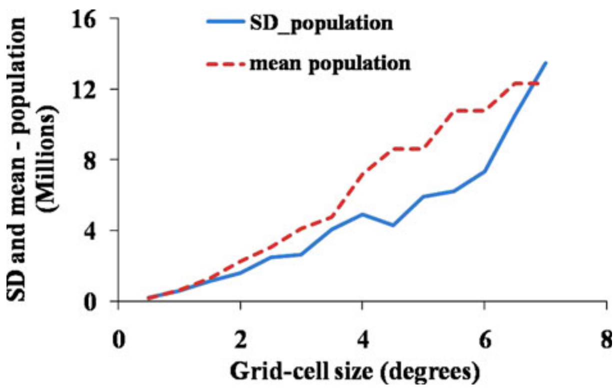

Fig. 5 Standard deviation of population in Danube Basin against scale

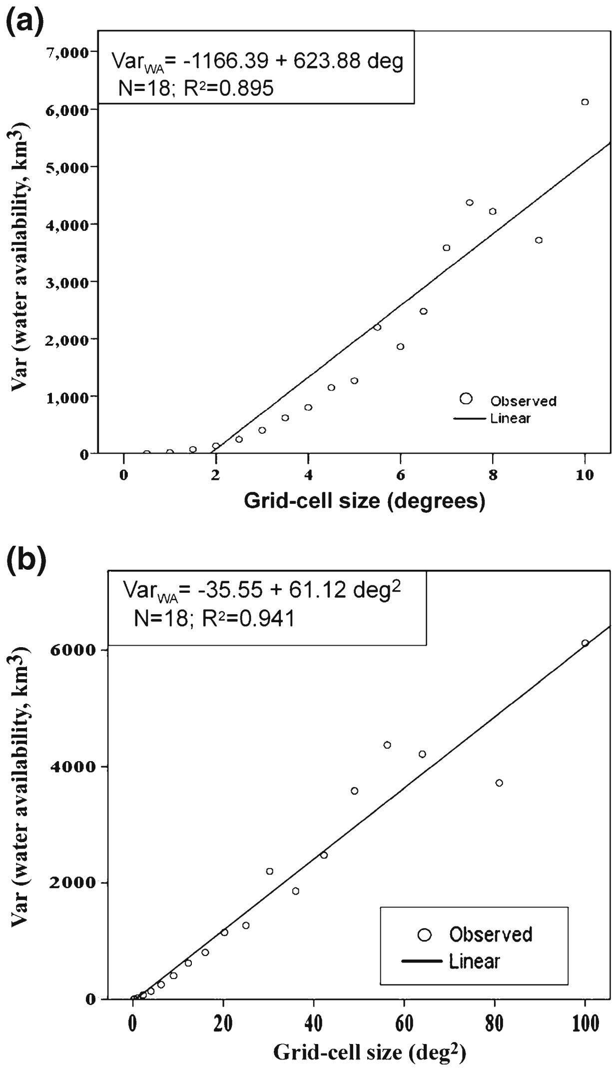

Fig. 6 **a** Variance of Danube Basin water availability against scale (degrees). **b** Variance of Danube Basin water availability against scale (degrees-squared)

are rarely referred to or analyzed in dimensions of degrees squared, but the linear correlation between variance and degrees squared within the range of observed data is stronger ($r^2 = 0.941$; Fig. 6b). As a corollary, linear regression models for standard deviation against grid-cell size in degrees give a good fit ($r^2 = 0.975$) within the range of observed data (Fig. 7). Though seemingly intuitive, no discussion of these fundamental concepts could be found in the water resources literature for scale and spatial variability. These results also go counter to the concept that cell aggregation results in spatial averaging and decreased variability (H2).

The discussion thus far implies that linear models ($Y = a + bX$) may be used to estimate changes in variability with scale if the appropriate units of scale are used. Based on the limited range of grid-cell scales obtainable for water availability ($0.5° \times 0.5°$), the linear function may appear acceptable (Fig. 7). However, as

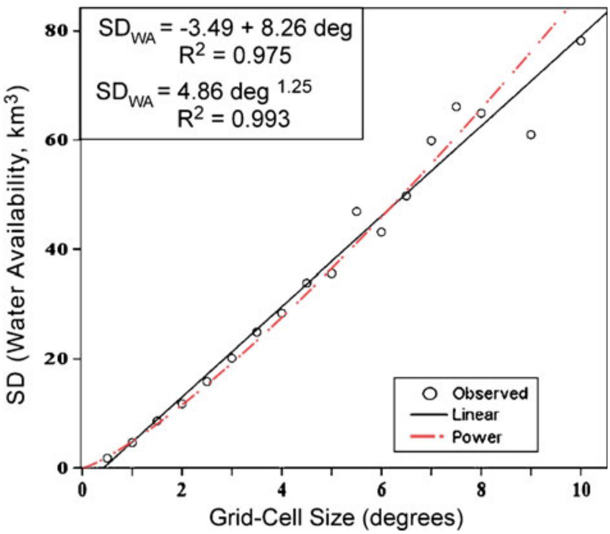

Fig. 7 Linear and power regression functions for standard deviation (SD) of water availability (km^3) against scale in Danube Basin

grid-cell sizes (scale) approach zero, linear models predict values of standard deviation and variance less than zero, which is not possible (Table 2). This discrepancy may be problematic as finer resolution data become available. The fine-resolution population dataset from ORNL (at 30″ or 0.00833° resolution) was used to develop a better model. The plot of standard deviations of population grid cells against grid-cell size in degrees clearly shows the non-linear trend in the range of cell sizes less than 0.5° and the bias in the linear model which predicts negative values in that range (Fig. 8). Several univariate models were fit to the population and water availability data including semi-log and quadratic equations. Power functions (e.g., $Y = aX^b$) consistently provided the highest correlation coefficients and the best visual fit for population and water availability data in the three river basins because they linearize logarithmic relationships (Fig. 9). Results for linear and power function models for standard deviations of water availability, water use and population data for the Danube Basin are compared in Table 2. Unrealistic negative constants resulted for all of the linear functions. Power functions, on the other hand, were also found to be robust for modeling the relationship between variability and grid-cell size as they are not as sensitive to the presence of noise introduced by large outliers at coarser resolutions.

Table 2 Linear and power regression model results for standard deviation (SD) against grid-cell size (degrees) for water availability, use and population in Danube Basin

Function	r^2	Constant (a)	b1
Water availability (km^3; SD against scale)			
Linear	0.983	−116.98	197.08
Power	0.997	104.87	1.30
Water use (km^3; SD against scale)			
Linear	0.948	−0.94	1.40
Power	0.990	0.67	1.36
Population (SD against scale)			
Linear	0.889	−1,783,294	1,723,634
Power	0.987	612,310.95	1.45

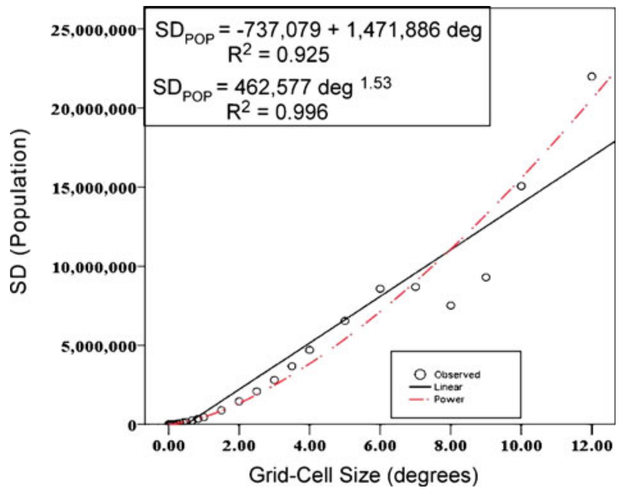

Fig. 8 Linear and power functions for standard deviation of population against scale in Danube Basin

These results from the Danube Basin were largely replicated by similar analyses of water resources and population data in the Missouri and Ganges Basins. The power function model was fit to all possible combinations of variability and scale, viz., standard deviation with degrees, standard deviation with degrees squared, variance with degrees, and variance with degrees squared for water availability, use and population in the three basins. Although specific values of the power functions varied between the datasets, the overall trends and relationships between values for a given dataset were entirely consistent providing empirical verification that the relationships are robust (Table 3). Values for the power model ($Y = aX^b$) parameters 'a' and 'b' display a consistent underlying pattern. As might be expected, values of 'b' exponents are the same for standard deviation–degrees and variance–degrees^2 combinations of variability and scale (bolded in Table 3); indicating that power function slopes do not change between these two relationships for a given dataset. The observed values of b are clearly greater than 1, corroborating the interpretation that relations between spatial variability and scale are non-linear for these data, and that rates of increase in spatial variability are greater at coarser resolutions. As might also be expected,

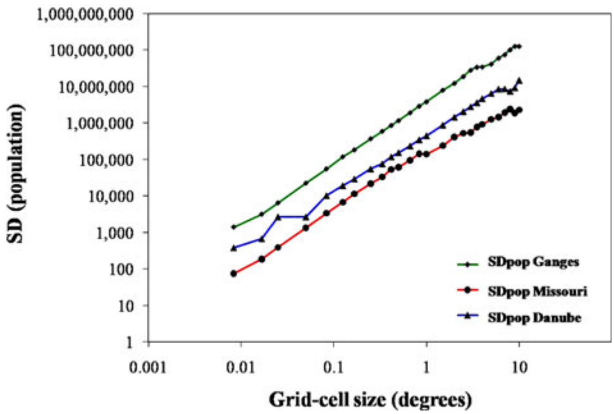

Fig. 9 Log–log transformed standard deviation of population against degrees in the Danube, Missouri and Ganges Basins

Table 3 Power function ($Y = aX^b$) constants for spatial variability in water availability, water use and population with scale for the Danube Basin

Variability-scale/constants	a	b	r^2
Danube (water availability, km^3; N = 14)			
Standard deviation against degrees	104.88	1.30	0.997
Standard deviation against degrees squared	104.88	0.65	0.997
Variance against degrees	10,999	2.61	0.997
Variance against degrees squared	10,999	1.30	0.997
Danube (water use, km^3; N = 14)			
Standard deviation against degrees	0.665	1.36	0.990
Standard deviation against degrees squared	0.665	0.68	0.990
Variance against degrees	0.442	2.73	0.990
Variance against degrees squared	0.442	1.36	0.990
Danube (population; N = 27)			
Standard deviation against degrees	462,577	1.53	0.996
Standard deviation against degrees squared	462,577	0.76	0.996
Variance against degrees	213,977,022,840	3.05	0.996
Variance against degrees squared	213,977,008,957	1.53	0.996

the scaling constant ‘a’ for variance approximates the square of the values observed for those of standard deviation for a particular parameter in a river basin. The linear and power functions for the mean and standard deviation of unscaled variables in the Danube Basin are provided in Table 4. Like variability, the mean of the unscaled variables at various scales conforms to model fitting fairly well and power functions are the best-fit model for changes in mean values with scale.

4.2 Scaled Variables

Quite a different set of trends emerged when spatial variability was correlated with scaled variables that are ratios of an area-sensitive factor so they do not increase substantially with area. For scaled variables like population density and water availability per capita, variability decreases at coarser scales (larger grid-cell sizes). Figures 10 and 11 demonstrate the decreasing trend in standard deviation with scale for population density and water availability per capita (m^3) in the Danube Basin, respectively. For the scaled variables, variability decreases at coarser scales, presumably due to spatial averaging between cells.

Table 4 Linear and power functions for unscaled variables in the Danube Basin

	Mean	Standard deviation
Water availability (km^3)		
Linear	$Y_{WA} = 168.44X - 129.35$	$Y_{WA} = 197.08X - 116.98$
Power	$Y_{WA} = 54.05X^{1.60}$	$Y_{WA} = 104.88X^{1.30}$
Water use (km^3)		
Linear	$Y_{WU} = 1.32X - 1.01$	$Y_{WU} = 1.40X - 0.94$
Power	$Y_{WU} = 0.42X^{1.60}$	$Y_{WU} = 0.67X^{1.36}$
Population		
Linear	$Y_P = 2{,}085{,}986X - 1{,}601{,}925$	$Y_P = 1{,}723{,}634X - 1{,}783{,}294$
Power	$Y_P = 669{,}357X^{1.60}$	$Y_P = 612{,}311X^{1.45}$

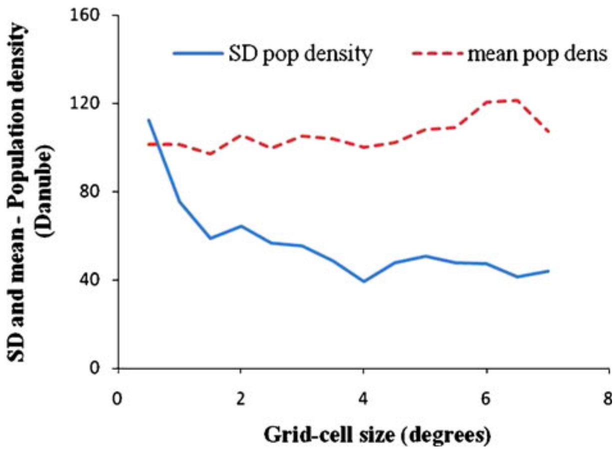

Fig. 10 Standard deviation of population density against scale (degrees) in Danube Basin

Another common metric used for water stress and scarcity calculations is *criticality ratio,* defined as the ratio of water use to availability. Given that it is a ratio of two unscaled variables (dimensionless) theoretically predicting how it would change with scale is problematic. Empirically, changes in variability with scale for criticality ratio in the Danube Basin decrease with increasing grid-cell size like a scaled variable (Fig. 12). This behavior is corroborated by similar results from the Ganges and Missouri Basins.

Unlike unscaled variables, however, no appropriate model could be found for fitting the changes in variability with scale for the scaled variables, within the range of observed values. The models appear to be curvilinear, so the assumption of linearity with scale and subsequent calculations of stress and scarcity values seem not only erroneous but invalid. Model fitting shows that for criticality ratio, standard deviations are inversely related to grid-cell size; viz., inverse functions are the most appropriate to demonstrate the nature of change in variability at multiple scales. This is similar to population density for which inverse functions seem the most appropriate. For water availability per capita, however, no one best-fit model emerged. Also, unlike the unscaled variables, the mean of the variables do not conform to any appropriate model fit or display a consistent trend with scale.

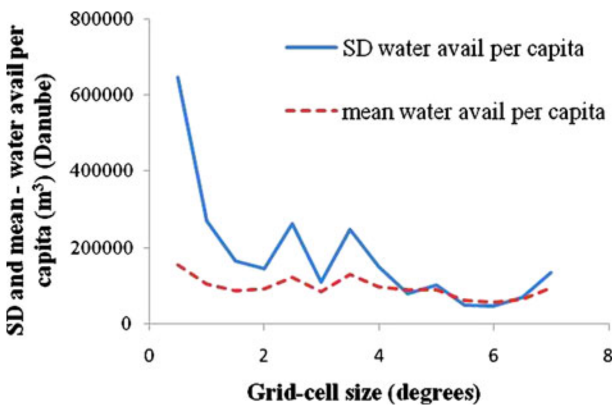

Fig. 11 Standard deviation of water availability per capita (m^3; Falkenmark indicator) against scale (degrees) in Danube Basin

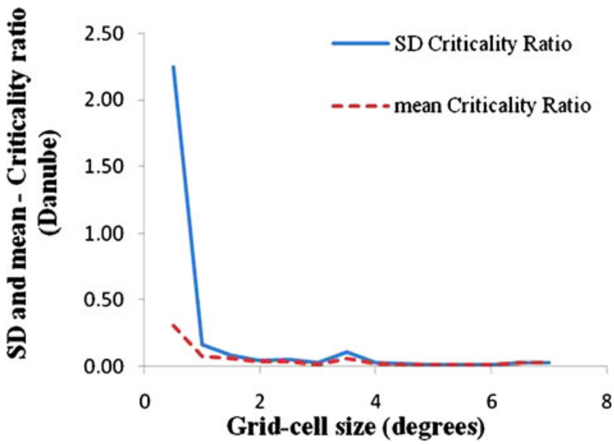

Fig. 12 Standard deviation of criticality ratio against scale (degrees) in Danube Basin

Many processes do not scale linearly (Lam et al. 2004), but researchers often fail to consider alternative non-linear models (Gould 1970). The assumption of linearity is inherently a conservative interpretation that tends to underestimate the actual strength of a relationship (Gould 1970). So far, little documentation of non-linear changes in spatial variability of water resources variables with scale has been published. Linear relationships are additive, but the effect on Y in a non-linear function is multiplicative.

5 Discussion

The results of empirical multi-scale testing show that trends in spatial variability can be predictable once the governing principals are understood. At first glance, these results may seem obvious, but the relationships vary with data scaling and scale units, and recognition of the primary distinctions is lacking in the water resources literature. Given that spatial variability translates into uncertainties in spatial models and data transformations, predictability of variability can provide a measure of uncertainty at a given scale. The results for the influence of scale on variability and model fit for unscaled variables in all three basins can be summarized by four general principles (Table 5): Power functions are best for unscaled variables, linear functions consistently underestimate variance at small grid-cell sizes (e.g., negative constants),

Table 5 Multi-scale behavior of unscaled variables

1	Power functions are robust models of changes in spatial variability with scale for unscaled variables
2	For linear equations ($Y = a + bX$), the constants ('a') were always negative, so negative values of mean or standard deviation were predicted at finer scales, which are meaningless
3	Changes in mean values of unscaled variables with increasing grid-cell size can be modeled with power functions like the variability functions (Table 4)
4	To the extent that changes with scale in the mean and standard deviation of unscaled variables (population, water availability and water use) can be expressed accurately by power function equations (Table 4), these empirical functions can be used in any basin to calculate values of the mean or variability at any scale

mean values may follow these same trends, and once the empirical functions of scale have been calibrated for a basin they can be used to estimate mean values and variances for the basin for a range of scales.

No one best-fit model could be identified for changes in variability with scale for scaled variables (water availability per capita, population density, and criticality ratio). Measures for water stress and scarcity use unscaled variables as input, hence the power functions for these can be used to calculate stress/scarcity (or the scaled variables) at any scale in a basin. For example, using the power functions for mean of water availability and population in Danube basin (Table 4), one can calculate the average values of the two at any scale (X), and calculate water stress/scarcity using Falkenmark index (calculated as water availability per capita). The power functions for standard deviation in any variable at a chosen scale (X) gives the variability around the mean at that scale.

5.1 Implications and Applications

This study demonstrates the need for developing appropriate scaling functions for linking and modeling data at multiple scales. To cite an example, out of the 15 sub-basins in the Danube watershed (IAD 2008), the smallest sub-basin occupies an area of only 9,330 km^2 (Delta Liman Region) whilst the largest covers 157,220 km^2 (Tisa). This range of areas spans approximately 1° to 5° grid-cell sizes for the Danube region, indicating the range of scales represented by sub-watersheds in the basin. Power function models developed for variability in population, water availability, and water use in the Danube Basin will provide a useful reference to water resources scientists to calculate water stress/scarcity at any scale. When extended to other river basins, the evaluation of trends in variability at multiple scales can help scientists and decision makers to understand spatial heterogeneities in water resources variables. Increasing availability of high-resolution gridded water resources datasets will provide detailed spatial information that will improve the ability to identify local anomalies and outliers that are critical to humane water resources management.

Scale and data aggregation have important effects on the modeling and interpretation of water resources data. As found by previous researchers in other fields (Wu et al. 2000; Meentemeyer and Box 1987; Marceau 1999, Wu 1999 etc.), this study clearly demonstrates that spatial variability in water resources data and statistics derived from them are dependent on scale. On first evaluation, these scale dependencies appear complex with non-linear increases and decreases with grid-cell size. Upon closer inspection, however, simple relationships between variability and scale emerge that can be predicted by specifying the type of dependent variable used. The identification of guiding principles that allow researchers to combine data and models at different spatial and temporal scales and to extrapolate information between scales remains a challenge (Risser 1986).

Many scientists agree that a crucial need exists for an understanding of the nature of scaling effects when spatial or temporal scale is an independent variable (Turner et al. 1989a). Scale problems may not occur in spatially homogeneous systems because process measurements can be summed directly. However, in heterogeneous landscapes or aquatic systems, process measurements obtained at fine scales often cannot be summed directly to produce regional estimates. Weighted averages do not always produce reasonable measures (King et al. 1988) because heterogeneity may influence processes in nonlinear ways. This suggests the possibility that increasing the level of spatial heterogeneity also increases the difficulty of extrapolating information across scales (Turner et al. 1989b).

5.2 Future Research

Ongoing study is examining multiscale water stress and scarcity (water resources vulnerability) in the three river basins using both the *Falkenmark index* and *criticality ratio*. While the former employs water availability per capita for calculations of water stress or scarcity, the latter defines threshold values of water stress based on the ratio of water use to water availability. Taken together, these indicators provide objective measures of the total water stress or scarcity in a region (Kulshreshtha 1993). The reasoning is that vulnerability increases as the two conditions become more critical: (1) total water resources are used up (i.e., critical ratio becomes larger), and (2) the pressure on existing resources increases (water availability per capita declines; Alcamo et al. 1997).The results from this study suggest that variability in both measures of water stress/scarcity—water availability per capita and criticality ratio—decreases as grid-cell size increases. The decrease is much faster at finer scales (Figs. 11 and 12) than at coarser scales. This non-linear decrease has important implications because linear calculations of stress and scarcity at various scales may lead to incorrect estimates of vulnerability. Research is being done on how variability in water stress and scarcity is affected by scale and how uncertainty arises in calculations of water stress measures.

The methods described here can be used to map specific locations under various degrees of water resources vulnerability, as past studies on vulnerability have been too aggregated (Kulshreshtha 1998). Preliminary results from the multiscale study for water stress and scarcity (vulnerability) in the three basins suggest that the responses of phenomena to spatial scale may each form a continuum that reveals useful information about the phenomenon only if we make observations at multiple scales. No single scale fully characterizes the variation. Kasperson (2001) suggests that a key research issue in seeking to understand vulnerability is the need to better grasp the current patterns of vulnerability using cross-scale analyses. In going from fine to coarse scales, aggregation and generalization set in. The rate of information loss is influenced by spatial pattern. Heterogenous landscapes for instance may lead to more information loss as aggregations at coarser scales are done. Clumped land cover types for instance, disappear slowly with decreasing resolution and those that are dispersed are lost rapidly (Turner et al. 1989a). However, a methodology needs to be developed in GIS to find out how much the loss of information takes place. Multiscale analysis was necessary to show that variability for different types of variable is inherently different, and that models (scaling laws) for each can be different. They demonstrate, however, a consistent pattern that can be immensely useful for hydrologic modelers and water resources managers.

6 Conclusions

This study demonstrates how grid-cell mean values and spatial variability of freshwater supply, use and population change systematically across data scales.

Competing and conflicting hypotheses were presented about expected relationships that were empirically tested. Both hypotheses are shown to be valid in different cases and logical explanations for the observed differences between responses are presented. Cell means and variability in water availability, use and population (unscaled) data increased as the size of grid-cells increased, because the magnitude of individual cell values increased with grid-cell size. Conversely, although means showed no trend with scale, the spatial variability of water stress/scarcity values measured by the Falkenmark index (per capita water availability) and criticality ratio (water use by availability) decreased as grid-cell size increased, presumably because intra-cell averaging damps out variability. These findings indicate the need for an understanding of the underlying dimensionality and scale of data used in order to accurately describe spatial variability in multiscale phenomena. Linear increase models provided reasonably good first-order approximations of cell mean and variability increases in unscaled variables at coarse resolutions (e.g., water availability data at scales greater than $0.5° \times 0.5°$). Non-linearity of the trends becomes obvious, however, at grid-cell resolutions less than 0.5°, and power functions provide a better model of changes in variability with grid-cell size in these cases. Decreasing variability with increasing grid-cell size is apparently an underlying process that may be masked by increased magnitudes in unscaled variables but emerges as a clear trend with scaled variables. Decreasing trends in spatial variation of scaled variables with grid-cell size were highly variable, however, and no single function was identified that characterizes those trends.

Theoretical and empirical research on the magnitude and pattern of spatial variation in water stress and scarcity with scale has been largely missing from water resources analyses. Past efforts were often limited by practical difficulties in obtaining adequate data and in performing spatially explicit analyses. Within the last decade, many of these obstacles have been removed by the availability of large, computerized databases, and the development of GIS, geostatistics and other tools for spatial analysis. The motivation to address questions of spatial variation in water availability and demands at multiple scales has grown in the face of increasing resource pressures. Ultimately, water resources scientists should be able to use empirically derived indicators of spatial variability to evaluate uncertainties associated with water stress calculations at a given scale and the likelihood of extreme risks in a proportion of sub-areas of the region.

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