

HIERARCHICAL BAYESIAN SCALING OF SOIL PROPERTIES ACROSS URBAN, AGRICULTURAL, AND DESERT ECOSYSTEMS

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Abstract. Ecologists increasingly use plot-scale data to inform research and policy related to regional and global environmental change. For soil chemistry research, scaling from the plot to the region is especially difficult due to high spatial variability at all scales. We used a hierarchical Bayesian model of plot-scale soil nutrient pools to predict storage of soil organic carbon (oC), inorganic carbon (iC), total nitrogen (N), and available phosphorus (avP) in a 7962-km² area including the Phoenix, Arizona, USA, metropolitan area and its desert and agricultural surroundings. The Bayesian approach was compared to a traditional approach that multiplied mean values for urban mesic residential, urban xeric residential, nonresidential urban, agricultural, and desert areas by the aerial coverage of each land-use type. Both approaches suggest that oC, N, and avP are correlated with each other and are higher (in g/m²) in mesic residential and agricultural areas than in deserts or xeric residential areas. In addition to traditional biophysical variables, cultural variables related to impervious surface cover, tree cover, and turfgrass cover were significant in regression models predicting the regional distribution of soil properties. We estimate that 1140 Gg of oC have accumulated in human-dominated soils of this region, but a significant portion of this new C has a very short mean residence time in mesic yards and agricultural soils. For N, we estimate that 130 Gg have accumulated in soils, which explains a significant portion of “missing N” observed in the regional N budget. Predictions for iC differed between the approaches because the Bayesian approach predicted iC as a function of elevation while the traditional approach employed only land use. We suggest that Bayesian scaling enables models that are flexible enough to accommodate the diverse factors controlling soil chemistry in desert, urban, and agricultural ecosystems and, thus, may represent an important tool for ecological scaling that spans land-use types. Urban planners and city managers attempting to reduce C emissions and N pollution should consider ways that landscape choices and impervious surface cover affect city-wide soil C, N, and P storage.

Key words: CAP LTER; hierarchical Bayes; Phoenix, Arizona; scaling; soil inorganic carbon; soil nitrogen; soil organic carbon; soil phosphorus; urban ecology.

INTRODUCTION

Over the past several decades, scaling has been an illuminating area for development of ecological theory and application. Theoretical advances explored cross-scale linkages in which patterns observed at one scale develop from processes operating at other scales (Levin 1992), and, paradoxically, “scaling rules” that describe how some ecological phenomena vary predictably across multiple scales (Brown et al. 2004). These theoretical advances are applied to a wide variety of environmental problems. In ecosystem ecology, one of the most

common applications has been to link short-term and small-plot measurements to problems of regional or global environmental change (Davidson and LeFebvre 1993, Jenerette et al. 2006). In this paper, we advance the theory and application of scaling in ecology by using a hierarchical Bayesian framework to scale small-plot measurements of soil carbon, nitrogen, and phosphorus to predict their distribution across a mixed land-use region of central Arizona, USA.

Ecosystems research is particularly amenable to scaling across land-use types because pools and fluxes of energy and nutrients can be expressed in the same units (mass of C, N, P, and so on) in all ecosystems. Scaling up from plots is important for a variety of reasons. For C, soils are the largest terrestrial pool, and regional changes in this large pool have been linked to

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changes in global atmospheric chemistry (Pacala et al. 2001). Carbon scaling will become increasingly important in urbanized regions as municipalities initiate city-scale versions of the Kyoto Protocol (Ellison 2006, Reppert 2006). For N, humans have doubled the amount of reactive N in the biosphere, and soils are an important sink for this new reactive N with implications for biotic communities and water and air quality (Aber et al. 1998). For P, regional distributions link pedology and atmospheric dust transport to plant productivity (Okin et al. 2004). Ptacnik et al. (2005) hypothesize that humans may decouple C, N, and P cycling in urban regions because the stoichiometry (C:N:P ratio) of human mediated atmospheric transport diverges greatly from the ambient stoichiometry of element inputs to ecosystems.

Ecosystem scientists have used a variety of models to scale soil carbon and nutrient pools from the plot to the region (Burke 2000). Many are based on the use of soil surveys that couple a limited number of chemical analyses (sometimes one profile per soil series) with aerial photos and networks of field soil pits and cores to produce maps of soil types at regional scales. To calculate regional soil chemical storage from these data, the rare estimates of soil chemistry are multiplied by the area of land mapped into a specific soil type (Schlesinger 1982, Davidson and LeFebvre 1993, Zhao et al. 2006). Soil chemical analyses can also be grouped by vegetation type (Post et al. 1985) and scaled with a vegetation map, or correlated with independent variables that have well-known regional distributions (Burke et al. 1989).

There are several limitations to scaling with soil survey data. In urbanized regions, soil surveys are less useful because urban soils are not mapped. Agricultural lands are surveyed, but often the same soil type will occur on both unmanaged and agricultural land-use types without having separate chemistry values. It is known that, for a given soil type, human management can double or halve soil C storage (Kaye et al. 2005, Lewis et al. 2006). Furthermore, because the number of mapped soil types varies with map scale (coarse scale maps usually lump classes from finer scales), several authors (Davidson and LeFebvre 1993, Zhao et al. 2006) have shown that higher resolution maps increase estimates of regional soil C storage. A final shortcoming to simple scaling from soil survey data is that spatial autocorrelation can not be included in the analysis. Several studies have shown that soils display autocorrelation (e.g., Robertson et al. 1997), which defines the scale at which values for a soil property are correlated with the values from adjacent points in space. Because soil chemistry is sparsely quantified in soil surveys, spatial autocorrelation can not be calculated.

Simulation models can also be used to predict regional distributions of soil carbon and nutrient storage (Burke 2000). They have the advantage of being mechanistically based, increasing the likelihood that predictions will be accurate when the model is extrapolated to new

conditions. The problem in applying simulation models to urban ecosystems is that the mechanisms that might be used to simulate urban biogeochemistry have not been established. Kaye et al. (2006) argue that human actions, including landscape design and waste engineering need to be incorporated into urban biogeochemical models. To date, human actions are not dynamic in ecosystem simulation models; actions are defined in prescribed "management" files that are fixed. To simulate human actions, we must first discover the broad patterns that accompany human effects on urban soils and the mechanisms that underlie these patterns.

In this paper, we present a new approach to modeling the regional distribution of soil organic C (oC), inorganic C (iC), total N, and plant-available P (avP) from plot data. Our approach is based on hierarchical Bayesian regression, which is an empirical (rather than simulation) modeling technique, intended to identify broad patterns in the distribution of soil nutrients across a region of complex land use. Hierarchical Bayes offers several advantages over traditional regression when working on spatially complex ecological problems (Clark 2005). First, hierarchical Bayes enables diverse data sources to be used for predicting dependent and independent variables in cases when these data are lacking. This flexibility is especially important in describing urban ecological phenomena that may depend on diverse biophysical and socioeconomic drivers, some of which may only be described at a limited number of sampling points. Second, Bayesian models allow multiple regression to be combined with spatial dependence so that variance associated with spatial autocorrelation (which is known to be important for soil properties) can be used in conjunction with variance associated with regression parameters. Finally, hierarchical modeling allows us to couple predictions of soil element pools, allowing a more realistic representation of, for example, the coupled cycles of organic carbon and soil nitrogen.

In a previous paper, we outlined the mathematical derivation of a hierarchical Bayesian regression model and its ability to capture variance in soil data from the Phoenix, Arizona, USA metropolitan region (Majumdar et al. 2008). Our goals here are to (1) compare traditional and hierarchical Bayesian approaches to scaling soil nutrients from small plots to the region, (2) use the scaled data to determine the role of humans in changing the distribution of soil carbon and nutrients in the region, and (3) evaluate the significance of the Bayesian model in advancing ecological theory and applications in regions of mixed land use.

METHODS

Study site

The research was conducted within and around the Phoenix Metropolitan area of 3.5 million people (U.S. Census Bureau 2000). Natural vegetation is Sonoran desert, but Native American irrigation agriculture was



PLATE 1. The 204 sampling sites used in our research were selected randomly from throughout the study region. This approach allowed us to capture the diversity of urban soils but also presented some challenges for field sampling. The sampling site in this image included the highway and the adjacent roadside. When sampling points fell on impervious surfaces, such as the highway, the nearest pervious surface was sampled. Photo credit: Tim Trumble, courtesy of CAP LTER/ASU.

prevalent up to the 1400s and Anglo-American agriculture and urbanization have occupied large portions of the region since the 1950s (Fig. 1). Agricultural land is mainly flood irrigated and urban land includes both xeric (desert-like) and mesic landscaping with various modes of irrigation. Annual daily (1948–2003) maximum and minimum temperatures are 30°C and 15°C, respectively, and annual average rainfall is 193 mm. The study region was a roughly rectangular area of 7962 km² that includes the city and surrounding agricultural lands and desert (Fig. 1a).

We use probability-based sampling to acquire a spatially dispersed, unbiased group of sample points from the region (Stevens 1997, Peterson et al. 1999; see Plate 1). A randomized, tessellation-stratified design was achieved by superimposing a 4 × 4 km grid on the study area, giving 462 potential sampling units. We expected high landscape heterogeneity in the urban core (Luck and Wu 2002), so a random sample point was assigned within every square inside the urban core and in every third square outside that area, giving a total sample size of 206 (Fig. 1). No a priori stratification according to land cover, land-use type, or other characteristics was used. A 30 × 30 m plot was centered on each sample point, regardless of land cover or ownership. Access was granted to all but eight sites, six of these were relocated to the nearest (within 100 m) similar site, but for two sites access was denied and no suitable surrogate could be found, giving a total of 204 sample sites. These 204 sample sites are permanent plots monitored every five years by the Central Arizona Phoenix Long-Term Ecological Research Program to assess long term change

in a suite of social and biophysical variables. We are reporting on the first soil sample collection (spring of 2000) in this project, and further details on these plots and their plant and soil properties can be found in Hope et al. (2003, 2005), Zhu et al. (2006), and Oleson et al. (2006).

Soil samples

Soil cores were taken using a hand-impacting corer (2.5 cm diameter to a depth of 30 cm) at four points in each plot (10 m from the randomly selected plot center in all cardinal directions). In cases when these random sampling points fell on an impervious surface, the nearest pervious surface was sampled. Core samples were separated into 0–10 cm (top) and 10–30 cm (bottom) depth intervals. Soils from the four cores for each depth were composited and refrigerated. At a small number of survey plots where the entire surface was covered by impervious urban surface, soil samples were collected from the nearest accessible site within 100 meters of the plot boundary. The composite samples were sieved (2 mm) at field moisture, air dried, and homogenized by hand. To determine available P (avP) pool sizes, a 10-g subsample of composited soil was extracted with NaHCO₃, and ortho-phosphate concentrations were determined colorimetrically (Clesceri et al. 1998). A second subsample of composited soil was ground to a fine powder and analyzed for total nitrogen (N) and total carbon by dry combustion elemental analysis and for inorganic C (iC) by pressure calcimeter (Sherrod et al. 2002). Organic carbon (oC) was calculated by subtracting iC from total carbon.

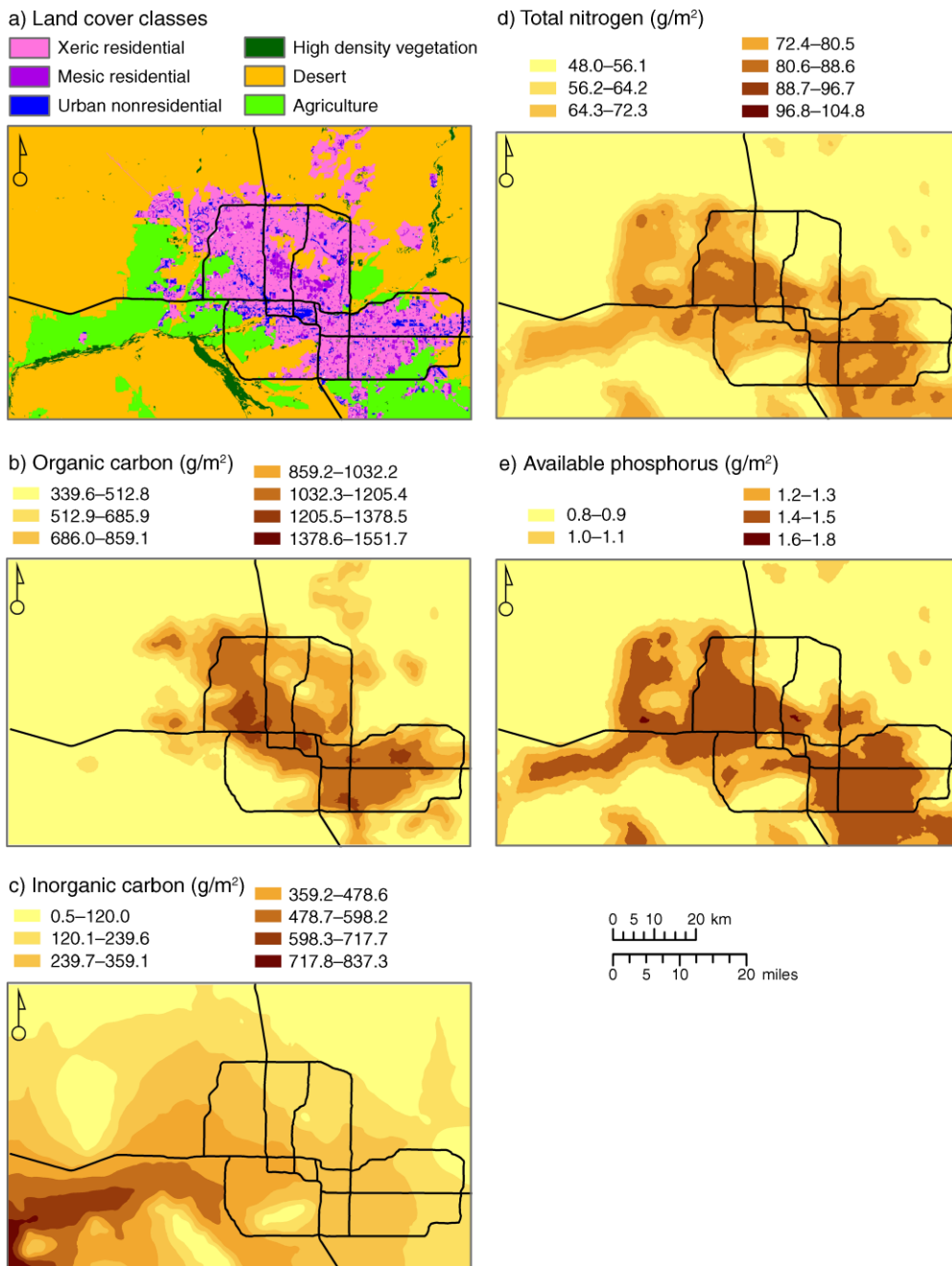


FIG. 1. Maps of (a) land use, and (b–e) soil carbon or nutrient pools in the study region within and around the metropolitan area of Phoenix, Arizona, USA. In all maps, black lines are major roads. Soil maps were generated by interpolating between 5000 points where carbon and nutrient content were estimated using the Bayesian regression model.

A separate soil core (5 cm diameter by 15 cm deep) was collected at the center of each plot. Particle size distribution in each of these soil cores was determined by the hydrometer method (Gee and Bauder 1986). Rock-free bulk density was determined by weighing soil that passed through a 2-mm sieve and dividing by the core volume. The mean density of the <2 mm fraction ranged from 0.95 g/cm³ in deserts to 1.14 g/cm³ in agricultural

sites, but did not differ among land-use types (Zhu et al. 2006). Nutrient concentrations from the composite samples from both depths (0–10 cm; 10–30 cm) were converted to areal density (g/m²) using the <2-mm soil density from this central core (0–15 cm). Ideally, the bulk density and nutrient concentration data would have been collected from the same depth, but this was not possible because the large diameter core (which is

superior for bulk density determination) could not be consistently used at depths below 15 cm. To assess errors arising from this, Zhu et al. (2006) calculated bulk density from a subset of small diameter cores from the 0–10 cm and 10–30 cm depths and found that the ratio (10–30 cm density):(0–10 cm density) was 1.05.

Land use and cover sampling

Many other key biotic, abiotic, and human variables were collected during the field survey. The cover of all ground surfaces (e.g., turf, bare soil, and impervious surfaces such as concrete, asphalt, tile, gravel, permanent structures) were mapped using a combination of high-resolution (1 m) air photos and a field GPS unit (Trimble Pro XL Mapping Grade; Trimble Navigation Limited, Sunnyvale, California, USA). Surface cover types were mapped without overlap, so total aerial coverage was 100%. For the analysis in this paper, we summed the percentage of all impervious surfaces in each plot to calculate our percent impervious surface variable. From the pervious surface area, we calculated the percentage of area covered by lawns (ranging from 0% to 100%) and the percentage of area covered by tree canopies (ranging from 0% to 108%). Tree canopy area was estimated by measuring the width of the canopy twice (two measurements perpendicular to each other) and calculating the area of a circle with diameter equal to the average of the two field measurements. When canopies extended beyond the plot or originated from stems outside the plot, only the area of the canopy inside the plot was included in the aerial coverage estimate. The irrigated area and type of irrigation on each plot was also recorded. Slope, aspect and elevation were measured. Land use at each of the 204 surveyed sites was classified according to the Maricopa Association of Governments (1997) land-use definitions and then modified for compatibility with land-use maps. The main land-use/land-cover categories used in our analysis were (1) urban residential with xeric vegetation ($n = 22$ plots), (2) urban residential with mesic vegetation ($n = 23$ plots), (3) urban residential with a mixture of xeric and mesic vegetation ($n = 8$ plots), (4) urban nonresidential (includes industrial, commercial, transportation, parks, and golf courses; $n = 41$ plots), (5) water and riparian vegetation ($n = 4$ plots), (6) desert ($n = 73$ plots), (7) agriculture ($n = 23$ plots), and (8) a mixture of multiple land-use types ($n = 11$ plots).

Scaling approaches

The first challenge in scaling the data described above to the regional scale was the lack of information from soils beneath urban impervious surfaces. We calculated total urban soil pools (pervious plus impervious) using the weighted average of pervious and impervious areas in three ways. First, we assumed that soil pool sizes (g/m^2 of oC, iC, N, and avP) beneath impervious areas were equal to the pool sizes in the pervious areas we sampled. Second, we assumed that soil pools beneath

impervious areas were equal to the desert mean. Third, we assumed that soil pools beneath impervious surfaces were equal to the desert mean for sites with no agricultural history and equal to the agricultural mean for sites that had been cultivated in the past. Using these three data sets, we took two approaches to scaling the 204 data points to the region. The first approach was the “traditional” one of taking the mean value for soil pool sizes (g/m^2) for a given land-use type and multiplying that by the area covered by the land-use type. We compared means ($\alpha = 0.10$) with a one-way ANOVA (land use as the main effect) on the natural logarithm (the data were normally distributed following this transformation) of the soils data (iC, oC, N, avP).

The area covered by each land-use type was derived from the land-use/land-cover classification of Landsat ETM+ images acquired in the spring of 2000. The classification was created using the National Land Cover Data scheme and the object-oriented hierarchical approach implemented in the eCognition software (Baatz et al. 2003; data scheme and data set *available online*).^{9,10} We aggregated several of the land cover categories in this map to six classes (with aerial coverage in parentheses): (1) urban residential land with xeric landscaping (1607 km^2), (2) urban residential land with mesic landscaping (175 km^2), (3) urban industrial, commercial, and transportation (176 km^2), (4) water and high-density riparian vegetation (169 km^2), (5) Sonoran desert (4697 km^2), and (6) agricultural land (1130 km^2); with 9 km^2 remaining unclassified. This classification scheme matched the Maricopa Association of Governments scheme that we used during our field surveys of the 204 points except that the remotely sensed land-use map does not include “mixed” land-use categories.

The second approach was hierarchical Bayesian scaling that included two steps: (1) develop a regression model that explained variance in soil properties in terms of a limited set of independent variables, and (2) to combine the regression model with spatially explicit data sets for our independent variables to predict soil properties for the entire region. Because hierarchical Bayes is relatively new to ecology and computationally complex, we describe step 1 in detail in Majumdar et al. (2008) and only briefly here. In addition, because of the computational complexity, the Bayesian scaling (step 2) was only carried out on the top soil layer.

Developing the regression model

All statistical analyses were conducted on the natural logarithm of soil carbon and nutrient concentrations because the raw data were not normally distributed (transformed data were). Model development began by selecting 13 independent variables that included likely

⁹ <http://www.epa.gov/mrlc/definitions.html>

¹⁰ <http://caplter.asu.edu/home/products/showDataset.jsp?keyword=remote%20sensing&id=372>

geomorphic, ecological, and socioeconomic drivers of soil properties: (1) whether the plot was ever used in agriculture or not (δ , a 0–1, categorical variable called “ever-in-agriculture” hereafter), (2) elevation (E), (3) slope (S), (4) percent pervious surface area covered by lawn (L), (5) percentage of pervious surface area covered by tree canopies (T), (6) percentage of total plot area covered by impervious surfaces (P), (7) land-use type (LU, a categorical variable with the eight categories described in *Methods: Land use and cover sampling*), (9) population density, (10) income per capita, (11) irrigation type (a categorical variable with three categories: flood, none, other), (12) aspect, and (13) soil texture (percent clay on a soil mass basis). We screened these data using Bayesian information criteria in a simple multiple regression analysis, and seven were significant in explaining the natural logarithm of soil oC, iC, N, and avP content in the surface and deeper soil layers (Table 1).

This diverse array of explanatory variables, while realistic, presented a challenge for scaling results from our plots to the region. We did not have spatially explicit regional values for impervious surface (P) and lawn cover (L), so we used Bayesian interpolation (including stochasticity and spatial autocorrelation), to predict values for these independent variables across the region. The double natural logarithm was used to transform P and L (e.g., $\ln[\ln(P)]$) to meet the assumption of normal distributions. From our 204 sample points, we found land-use type and its interaction with elevation and agricultural history to be strong predictors of impervious surface and lawn cover (Majumdar et al. 2008).

The final model included eight dependent variables (oC, iC, N, and avP at two soil depths; Table 2). To incorporate their association in the model, we used eight levels of hierarchy, incorporating one extra independent variable at each step. There were also two dependent variables that needed prediction (P and L) and these variables were associated among themselves, so we modeled their interdependence through another model with two levels of hierarchy (one for each independent variable being predicted). With 10 stochastic processes in the model (see Table 1 for model variable descriptions) the joint distribution form was $f(Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, L, P | S, E, \delta, LU, T)$, which we factor as follows:

$$\begin{aligned} & f(P|S, E, \delta, LU, T) f(L|P, S, E, \delta, LU, T) \\ & \times f(Y_1|L, P, S, E, \delta, LU, T) \cdots \\ & \times f(Y_8|L, Y_7, Y_6, Y_5, Y_4, Y_3, Y_2, Y_1, L, P, S, E, \delta, LU, T). \end{aligned} \quad (1)$$

To model the distributions we denote the dependent variables as Y_{ij} , for the i th variable ($i = 1$ to 8) at the j th location ($j = 1$ to 204). The spatially random effects, specified by a joint covariance matrix (Majumdar et al. 2008) are denoted W_{ij} for the i th dependent variable at the j th location or W_{kj} , for the k th independent variable

TABLE 1. Variables used in the model, their definitions, and units.

Variable	Definition
Y_1	total nitrogen in the soil at 0–10 cm depth (g/m ² ; ln-transformed)
Y_2	organic carbon in the soil at 0–10 cm depth (g/m ² ; ln-transformed)
Y_3	inorganic carbon in the soil at 0–10 cm depth (g/m ² ; ln-transformed)
Y_4	available phosphorus in the soil at 0–10 cm depth (g/m ² ; ln-transformed)
Y_5	total nitrogen in the soil at 10–30 cm depth (g/m ² ; ln-transformed)
Y_6	organic carbon in the soil at 10–30 cm depth (g/m ² ; ln-transformed)
Y_7	inorganic carbon in the soil at 10–30 cm depth (g/m ² ; ln-transformed)
Y_8	available phosphorus in the soil at 10–30 cm depth (g/m ² ; ln-transformed)
S	slope (degrees)
E	elevation (m)
δ	agricultural index: 0 if never in agriculture; 1 if ever used for agriculture
P	surface area covered by impervious surfaces (%)
L	pervious area covered by turfgrass lawn (%)
LU	land-use category
T	pervious area covered by tree canopies (%)
W	spatially random effects
j	unique spatial location
β	regression coefficients
σ^2	random error variance

at the j th location. Solving for the first distribution, the percentage of surface area covered by impervious surfaces, we assume that the $\ln[\ln(P_j)]$ are conditionally jointly Gaussian given the S_j , E_j , δ_j , LU_j with the spatially random effect, W_{Pj} , so that P_j are conditionally independent and identically distributed given S , E , δ , LU , and W_P , giving

$$\begin{aligned} & \ln[\ln(P_j)] | S, E, \delta, W_P \\ & \sim \mathcal{N}(\beta_{P0} + \beta_{P|S}S_j + \beta_{P|E}E_j + \beta_{P|\delta}\delta_j \\ & \quad + \beta_{P|LU}LU_j + W_{Pj}, \sigma_P^2). \end{aligned}$$

The second distribution, percentage of pervious area covered by turfgrass lawn, uses similar assumptions:

$$\begin{aligned} & \ln[\ln(L_j)] | P, S, E, \delta, LU, W_P \\ & \sim \mathcal{N}(\beta_{L0} + \beta_{L|P}P_j + \beta_{L|S}S_j + \beta_{L|E}E_j + \beta_{L|\delta}\delta_j \\ & \quad + \beta_{L|LU}LU_j + W_{Lj}, \sigma_L^2). \end{aligned}$$

The last eight distributions, the dependent variables, use similar assumptions and the spatial component is independent Gaussian over i and j , giving

$$\begin{aligned} & Y_{ij} | Y_1, \dots, Y_{i-1}, L, P, S, E, \delta, LU, T, W_1, \dots, W_i \\ & \sim \mathcal{N}(\beta_{i0} + \beta_{i1}Y_{1j} + \cdots + \beta_{i,i-1}Y_{i-1j} + \beta_{i|P}P_j + \beta_{i|S}S_j \\ & \quad + \beta_{i|E}E_j + \beta_{i|\delta}\delta_j + \beta_{i|LU}LU_j + \beta_{i|T}T_j + W_{ij}, \sigma_i) \\ & i = 1, 2, 3, 4, 5, 6, 7, 8. \end{aligned} \quad (2)$$

After fitting the full Bayesian model, the 95% credible

TABLE 2. Results of the Bayesian regression analysis of factors correlating with soil pools.

Soil pools	Significant regression coefficients	Correlation between modeled and measured values (<i>r</i>)	Fraction of unexplained variance attributed to spatial autocorrelation
Surface layer (0–10 cm)			
oC	surface layer N, surface area covered by impervious surfaces (%)	0.94	0.48
iC	elevation	0.87	0.42
N	ever in agriculture, pervious area covered by turfgrass lawn (%)	0.94	0.35
avP	surface layer N	0.89	0.55
Deeper layer (10–30 cm)			
oC	deeper layer N, surface layer oC	0.88	0.41
iC	surface layer iC, latitude, elevation	0.95	0.45
N	surface layer iC, surface layer N, pervious area covered by turfgrass lawn (%), pervious area covered by trees (%)	0.91	0.46
avP	surface layer oC, deeper layer oC, surface layer avP, latitude	0.85	0.34

Notes: Abbreviations are oC, organic carbon; iC, inorganic carbon; N, total nitrogen; avP, available phosphorus. “Ever in agriculture” is a categorical variable recording whether the plot was ever used in agriculture.

interval of the coefficient for “slope” contained zero, so this independent variable does not appear in Table 2. Further details regarding the development of the model are in Majumdar et al. (2008). The model was fit to the three soil pool data sets (corresponding to the three assumptions regarding pools beneath impervious surfaces) using simulation-based methods, i.e., Gibbs sampling (Gelfand and Smith 1990) and Markov chain Monte Carlo methods.

Hierarchical Bayesian scaling

We could have interpolated between our 204 sample points to scale to the region, but the sample plots covered a small fraction of the 7962-km² study region and we felt this sampling intensity was too sparse to justify simple interpolation. Instead, we randomly selected an additional 5000 points from the study area, collected data for four independent variables at those points (slope, elevation, ever-in-agriculture, and current land use), and used the regression model to predict our two remaining independent variables (percentage of the area in impervious surfaces and percentage of pervious surface covered by lawn) and all dependent variables at each of the 5000 points. Elevation and slope at each of the 5000 points were derived from the 10-m National Elevation Dataset (NED) assembled by the U.S. Geological Survey (data set *available online*).¹¹ The ever-in-agriculture value (0 or 1) for each site was determined by sampling the time-series of historic land-use maps for 1912, 1934, 1955, 1975, and 1995 prepared by the Central Arizona–Phoenix LTER (Knowles-Yáñez et al. 1999). Current land use at each site was derived from the same land-cover/land-use map described in *Methods: Scaling approaches* (see footnote

10). Once values for the 5000 points were calculated, we used the new points to derive the median and 95% confidence intervals for each major land-use class. By calculating 5000 points instead of 200, we simulate a more complete sampling of our study region and thus, the median values we calculate should better reflect the true median. The medians were back-transformed (i.e., from ln(median) to median, measured in grams per square meter) and multiplied by the area occupied by each land-use type.

RESULTS

Traditional scaling

Mean surface (0–10 cm) oC was lower in desert and xeric yards (~450–500 g/m²) than in mesic yards or agroecosystems (750–1100 g/m²; Fig. 2). In deeper soils (10–30 cm) mean oC was higher in agricultural soils (1020 g/m²) than in other ecosystems (530–730 g/m²). At both soil depths, desert mean iC (180 g/m² at surface and 640 g/m² in deeper soil) was lower than all other ecosystems (450–620 g/m² at surface and 975–1040 g/m² in deeper soil). Patterns in mean N were similar to oC, with mesic yards and agroecosystems having 75–125 g/m² more N in the top 30 cm of soil than xeric yards or desert. Mean avP to 30 cm was also greater in mesic yards and agroecosystems (3.8–4.7 g/m²) than in other ecosystems (1.8–2.4 g/m²). When these mean values were multiplied by the aerial extent of the land-use types (Fig. 1a), deserts contained the largest pools of all elements in the region, followed by xeric yards and agriculture, and then mesic yards and nonresidential urban areas (Fig. 3). The values were relatively insensitive to our assumptions regarding soils beneath impervious surfaces in the urban environment (Fig. 3). If we assume that prior to human development, the entire region had mean element storage similar to the mean of our desert samples (*n* =

¹¹ <http://ned.usgs.gov/Ned/about.asp>

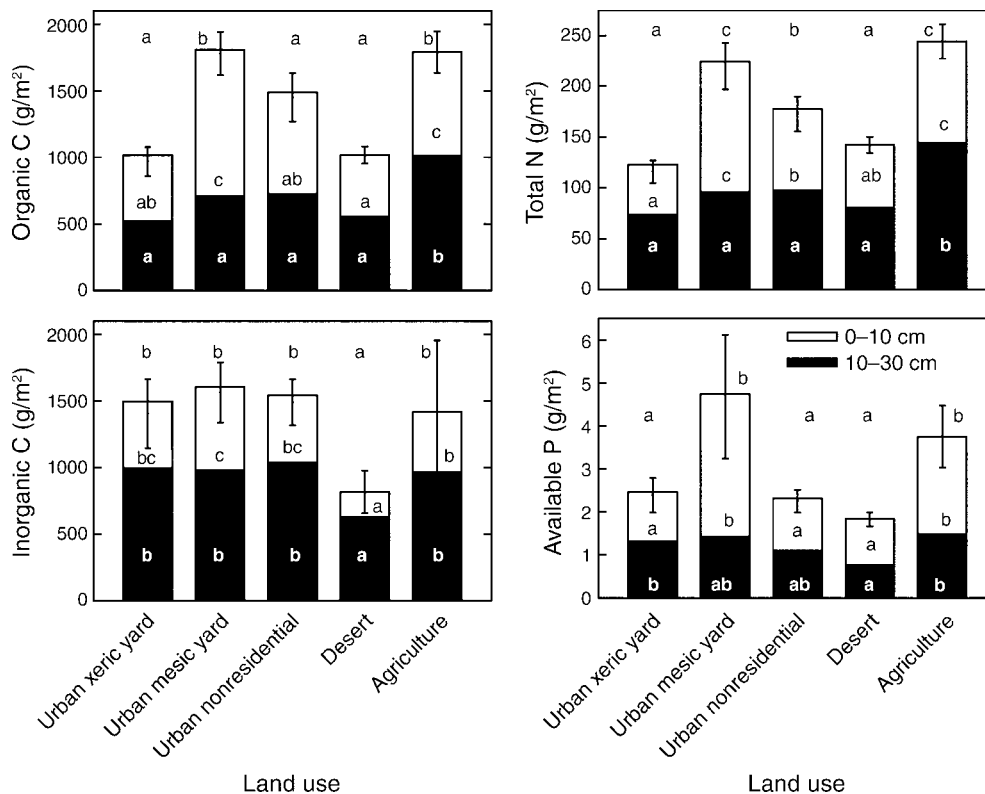


FIG. 2. Mean soil carbon and nutrient pools in common land-use types of the study region from 204 measured points. Bars are means \pm SE ($n=22-73$ plots) for the 0–30 cm depth. Different lowercase letters within a bar denote statistical differences ($P < 0.10$) among land-use types for the 0–10 or 10–30 cm depths, while lowercase letters above bars denote statistical differences for the total 0–30 cm depth.

73 samples), then the top 30 cm of soil in all the human-dominated ecosystems (all urban + agricultural) have accumulated 1140 Gg (350 g/m^2) of oC, 1280 Gg (390 g/m^2) of iC, 130 Gg (39 g/m^2) of N, and 3.6 Gg (1.1 g/m^2) of avP in the top 30 cm of soil (Table 3).

Bayesian scaling

Ecologists generally use the mean as the measure of central tendency (thus, data in the prior section are discussed in terms of means) because ANOVA analyses compare means, or more broadly because ecologists are most comfortable with Gaussian distributions, where the mean is an accurate description of central tendency. Our Bayesian analysis compared medians so we facilitate comparisons by plotting median values from the data (204 field sampling points) beside the median values from the 5000 points generated by the Bayesian regression model (Fig. 4). Bayesian estimates of median oC in the top 10 cm of soil (Fig. 4) followed roughly the same pattern as data means (Fig. 2) for mesic yards, urban nonresidential land, and deserts. However, for xeric yards, modeled estimates of median oC (824 g/m^2) were about twice as great as the data median or mean. In contrast, for agricultural ecosystems, modeled oC (450 g/m^2) was 30–40% of the data mean or median. These differences in estimated central tendency lead to

proportional differences in region-wide estimates of soil oC storage (Fig. 5 vs. Fig. 3). Estimates of region-wide oC storage in agricultural soils were lower with Bayesian scaling (540 Gg) than with traditional scaling (868 Gg). In contrast, Bayesian estimates of oC storage in xeric yards (1633 Gg) were about twice as great as the value (860 Gg) from a traditional scaling approach. The Bayesian scaling approach suggests that xeric yards that cover about 20% of the land area account for as much oC storage as deserts that cover 59% of the land area. Our assumptions regarding storage beneath urban impervious surfaces had a large impact on the estimate of regional oC storage in xeric residential areas (Fig. 5), but this assumption can not account for differences between Bayesian and traditional scaling approaches. Summing over all ecosystems that we analyzed, the Bayesian model (4460 Gg) was similar to the traditional approach (4210 Gg) in estimating soil oC in the top 10 cm (Table 3).

Modeled median iC values for all urban land-use types ($230-296 \text{ g/m}^2$) were lower than data medians and means ($350-650 \text{ g/m}^2$; Figs. 2 and 4). In deserts and agricultural ecosystems, modeled median iC was higher than the data median and lower than the data mean. When scaled to the region, differences between the Bayesian and traditional approaches were most appar-

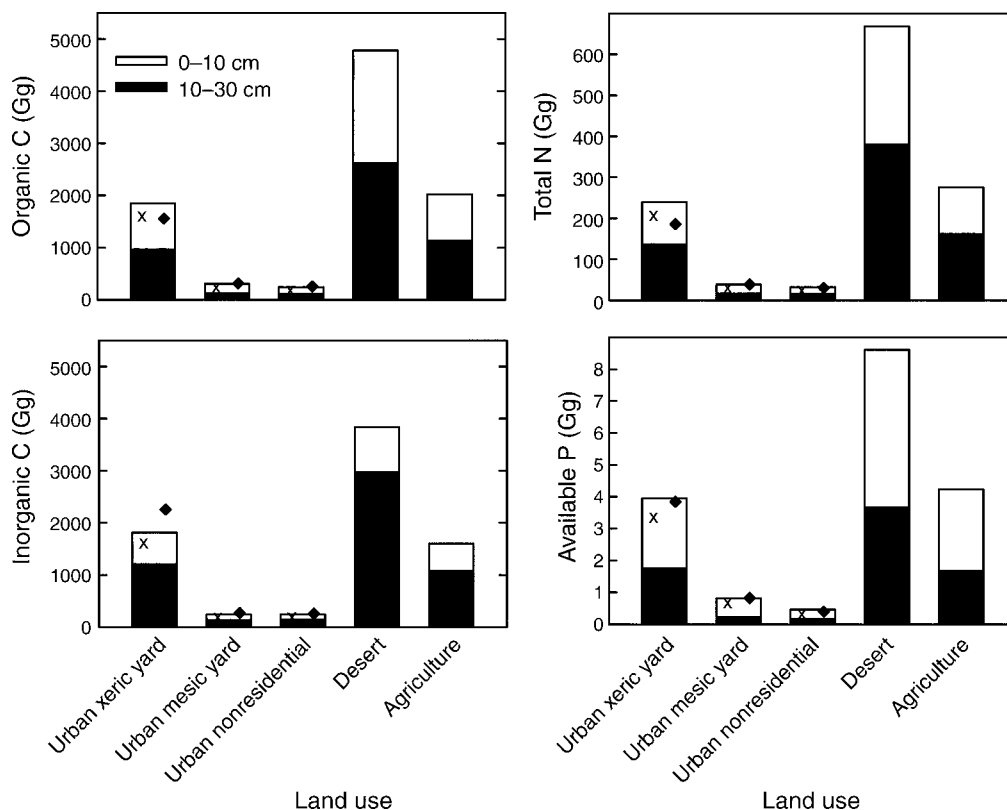


FIG. 3. Soil carbon and nutrient storage in common land-use types of the study region calculated using the means from 204 measured points (Fig. 2) and the aerial extent of land-use (i.e., traditional scaling approach). There are no error estimates for these values because we have no error estimates for the aerial extent of land use (Fig. 1a). For the urban ecosystems, bars reflect the assumption that storage beneath impervious surfaces depends on agricultural history (see *Methods*). The symbol \times is the value assuming impervious surface pools are equal to desert pools, and the diamond symbol is the value assuming that impervious pools are equal to pervious pools at the same plot.

ent in xeric yards and deserts (Fig. 5 vs. Fig. 3). Bayesian estimates of iC in xeric yards (362 Gg) and desert soils (563 Gg) are 60 and 67% of the values generated by the traditional scaling approach. Summing over all the land-use types that we analyzed, Bayesian scaling estimates 1490 Gg of region-wide iC storage in surface soils while the traditional scaling estimates 2160 Gg (Table 3).

The data and Bayesian model medians were similar for N and avP in all ecosystems (Fig. 4). Likewise, for N and avP, the Bayesian and traditional scaling approaches produced similar estimates of regional soil storage in the top 10 cm (Table 3).

Geostatistical modeling of the 5000 points used in our Bayesian scaling analysis allowed us to produce spatially continuous maps of soil carbon and nutrient storage

TABLE 3. Regional soil carbon and nutrient stocks and the potential amount (a subset of the total stock) attributable to net accumulation in urban and agricultural ecosystems (in Gg).

Soil depth	Scaling approach	oC	iC	N	avP
Total region stocks					
0–10 cm	Bayesian	4460	1490	477	8
0–10 cm	traditional	4210	2160	540	8
10–30 cm	traditional	5140	5790	730	11
0–30 cm	traditional	9360	7950	1270	18
Potential accumulation in urban and agricultural ecosystems					
0–10 cm	Bayesian	1350	470	55	0.9
0–10 cm	traditional	540	680	50	1.4
10–30 cm	traditional	600	600	80	2.1
0–30 cm	traditional	1140	1280	130	3.6

Note: Abbreviations are: oC, organic carbon; iC, inorganic carbon; N, total nitrogen; avP, available phosphorus.

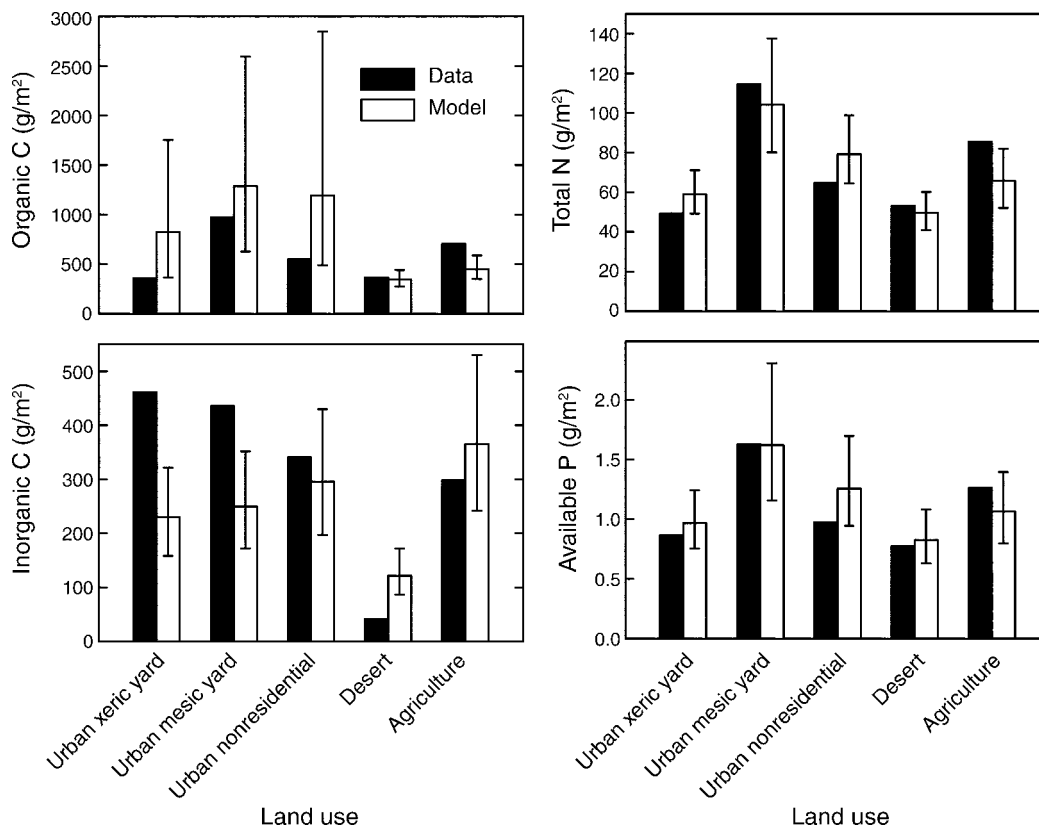


FIG. 4. Median soil carbon and nutrient pools (0–10 cm depth) in common land-use types of the study region calculated from data (from 204 measured points) or the hierarchical Bayesian model (from 5000 points predicted by the regression model). Bars are medians ($n = 22\text{--}73$ plots), and errors show the 2.5 and 97.5 percentiles.

across the region (Fig. 1b–e). We applied the ordinary co-kriging interpolator and used land-use codes as the second variable in semivariogram modeling. The maps show that oC, N, and avP share spatial patterning throughout the city; all are highest in urban and agricultural areas and lowest in the desert. In contrast, iC, which is predicted with elevation, is highest in the southwestern portion of the study area and declines abruptly as elevation increases near isolated mountains or gradually as elevation increases toward the northeastern part of the study area.

DISCUSSION

Traditional vs. Bayesian approaches

One of our main objectives was to compare traditional and hierarchical Bayesian approaches to scaling. The Bayesian model is computationally complex; to justify the effort, the model must represent a significant improvement over the simple spreadsheet calculations required for traditional scaling. The two approaches generated similar results for soil N and avP for both the distribution among land-use types (Fig. 3 vs. Fig. 5) and the total regional stocks (Table 3). For soil C pools, the results were more complex. The Bayesian approach predicts greater oC storage in xeric yards and lower oC

storage in agricultural soils than the traditional approach leading to comparable estimates of region-wide oC storage between the two methods. The Bayesian model consistently predicted lower iC storage than data means, leading to a much lower estimate of region-wide iC storage (Table 3).

Two factors likely account for the differences between the Bayesian and traditional approaches in their predictions of oC and iC. First, it is well known that soil properties display spatial autocorrelation, that is, that the value for soil properties at one location is correlated with values from nearby locations (Robertson et al. 1997). While the variance explained by spatial autocorrelation cannot be attributed to measured independent variables, it can be taken into account when predicting soil properties at new points in the landscape. Hierarchical Bayes allowed us to compute the spatial structure of the data to increase the portion of data variance explained by the model and inform interpolation for region-wide scaling. In our data, from 34% to 55% of the unexplained variance in our regression model was due to spatial autocorrelation (Table 2). In the traditional scaling approach, this variance is not taken into account.

The second factor that accounts for differences between methods was the use of multiple regression in

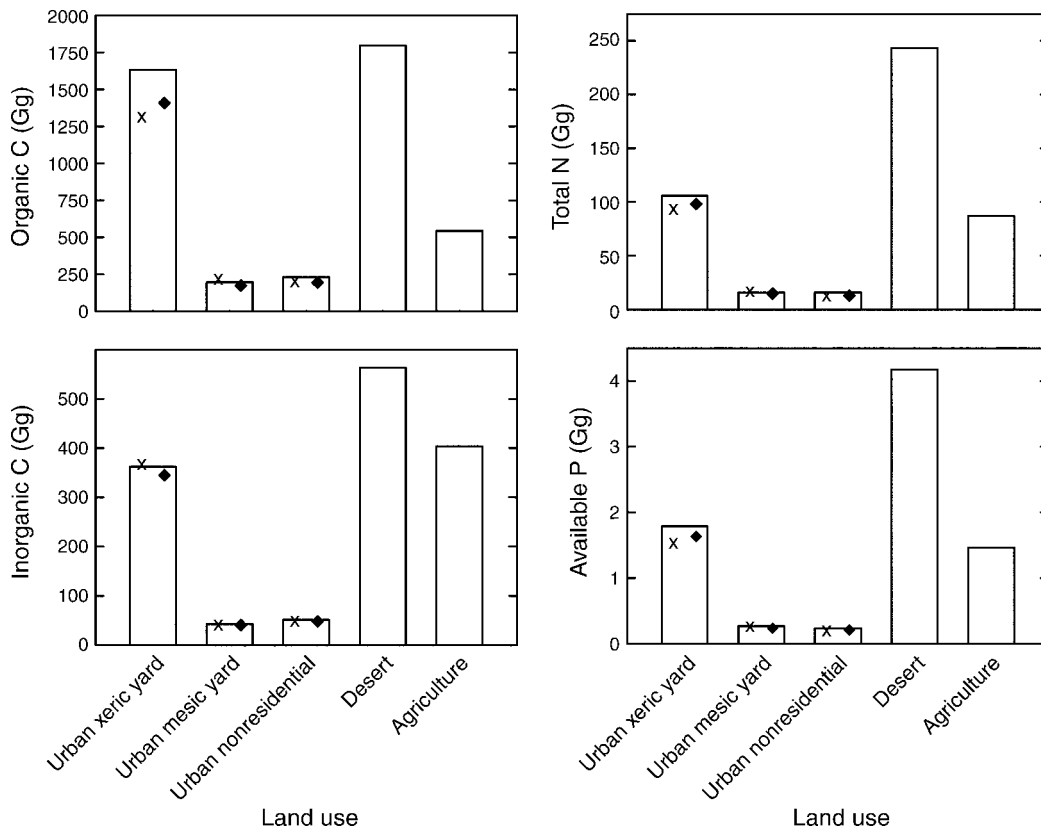


FIG. 5. Soil carbon and nutrient storage (0–10 cm depth) in common land-use types of the study region derived from 5000 estimates predicted with the Bayesian regression model (i.e., the Bayesian scaling approach). There are no error estimates for these values because we have no error estimates for land area coverage (Fig. 1a). For the urban ecosystems, bars reflect the assumption that storage beneath impervious surfaces depends on agricultural history (see *Methods*). The symbol \times is the value assuming impervious surface pools are equal to desert pools, and the diamond symbol is the value assuming that impervious pools are equal to pervious pools at the same plot.

the Bayesian approach. The traditional scaling approach assumed that (1) most of the soil variance in the region is attributable to one factor—contemporary land use—and (2) that the mean of our soil samples was representative of the mean value for a given land-use type in our region. Our Bayesian regression analysis shows that the first assumption was violated (Table 2) and allowed us to include a diverse array of biophysical and socioeconomic independent variables to predict soil properties. We also modeled the dependent variables simultaneously, so that our predictions of oC concentrations were improved by their correlation with N. With strong predictive power (Table 2), we were able to simulate soil properties at 5000 points and use these data to estimate the central tendency for each land-use type. This new estimate of central tendency should be closer to the “true” value because it accounts for the variance attributable to several factors (independent variables, spatial autocorrelation, and correlation with other dependent variables) that are not taken into account when the simple mean from our 200 data points is multiplied by land-use area.

Given these qualitative differences between the scaling methods it is not surprising that our estimates of regional nutrient storage differed between the Bayesian and traditional approaches. We believe the Bayesian estimates should be closer to the “true” values for the reasons described above. Yet, the limitations of time and computational effort are substantial. The bottom layer of soil contains a significant amount of C and we chose not to apply Bayesian scaling to these data due to the computational burden.

Distribution of soil carbon and nutrients in a human-dominated region

Despite differences among the scaling methods, there are some generalities that can be discerned regarding the regional distribution of soil C, N, and P. First, oC, N, and avP appear to be correlated (Table 2; Fig. 1). Urban mesic yards contain more oC, N, and avP per square meter than other ecosystems and all human-dominated (agricultural and urban) ecosystems contain more oC, N, and avP than deserts. Deserts still dominate the aerial coverage of the region (59% using our land-use map; Fig. 1), but account for only 38–40% of regional oC and

iC stocks and 51–52% of regional N and avP stocks in surface soils (0–10 cm) using the Bayesian scaling approach (Fig. 5). Results from the traditional scaling approach are similar (Fig. 3), with desert carbon and nutrient stocks in the 0–30 cm depth accounting for 48–53% of the regional total. While the relative importance of the desert vs. human-dominated land-use types is totally dependent on our choice of regional boundaries, it is still significant that in our relatively large (7962 km²) study region, the “slow” variables of soil C and N stocks have been altered. Because soil oC, N, and avP are tightly linked in soils through biological processing, their correlation at the regional scale with human-dominated landscapes suggest that humans are altering regional soil properties by altering biological nutrient cycling.

While the distribution of oC, N, and avP seem related to human manipulation of biogeochemistry, the pattern for iC is not so clear. Both scaling approaches suggest that iC is higher in all human-dominated ecosystems than in deserts. One interpretation for this pattern is that salt inputs from irrigation water lead to the accumulation of iC in soil (Schlesinger 1985, 1999). Irrigation water in this region can be saturated with CaCO₃ (L. Baker, *unpublished data*), which precipitates out of solution as water is removed in the root zone, concentrating salts in the high CO₂ environment of the soil. However, our Bayesian regression analysis did not find irrigation presence or type to be an important predictor of iC, in fact, no independent variables corresponding to human management were good predictors of iC, only elevation and latitude were significant (Table 2). At this point, we cannot determine whether urban and agricultural development happened to occur on soils with high iC, or whether management practices lead to iC accumulation. However, in desert soils of this region, high iC accumulation is associated with older surfaces on higher elevation terraces. Thus, if natural pedogenic processes were driving regional iC distribution we would have expected a positive correlation between iC and elevation, which is the opposite of our data pattern.

Our estimates of regional soil C and N storage can be compared to previous studies of N and C fluxes in the same study region. Baker et al. (2001) constructed a budget of N fluxes for the same region and could not account for 17–21 Gg of N per year. They assumed that this N was accumulating somewhere in the region because inputs and outputs were well constrained. Zhu et al. (2006) suggested that 46 Gg of soil inorganic N had accumulated in the region's soils (mainly in urban and agricultural soils). Here we calculate (Table 3) that 130 Gg N accumulated in the top 30 cm of soil of human-dominated ecosystems. Together, these results suggest that (1) soil N accumulation accounts for <8 yr (130 Gg/[17 Gg/yr] = 7.6 yr) of the N that was unaccounted for in the budget of Baker et al. (2001), and (2) a large fraction of the accumulating soil N is inorganic (46 Gg

inorganic N/130 Gg total N = 0.35). Additional N is likely stored in the vadose zone and in underlying groundwater (Baker et al. 2001). Urban ecosystems have very large N inputs compared to unmanaged ecosystems (Kaye et al. 2006). Our results suggest that urban soils are an important sink for urban N at regional and decadal scales. Retention of N in soils mitigates the effects of imported urban N on water and air quality and future research on the longevity and stability of urban soil N will be needed to understand variability in urban N pollution.

Koerner and Klopatek (2002) evaluated the distribution of CO₂ sources in our study region. Vehicles accounted for 80% of regional CO₂ emissions, but soil respiration (15%) was the second largest source of CO₂ emissions. They found that deserts (~180 g C·m⁻²·yr⁻¹) and xeric residential sites (~400 g C·m⁻²·yr⁻¹) had low soil respiration rates compared to agricultural land (2000–3000 g C·m⁻²·yr⁻¹) and urban mesic yards (~2500 g C·m⁻²·yr⁻¹). Coupling these soil respiration estimates with our soil oC data enables us to make preliminary calculations regarding land-cover effects on the mean residence time of oC in soils (Schlesinger 1977, McCulley et al. 2004). If between 33% and 67% of soil respiration is from heterotrophic microbial respiration, then the mean residence time of soil oC in deserts (8.5–17 yr) and xeric residential soils (3.4–7.2 yr) is much longer than in agricultural (1–3 yr) and urban mesic (1–2 yr) soils. These preliminary calculations underestimate oC residence times because they only included soil oC to 30 cm. Adding deeper soil oC (Schlesinger 1982) to the calculation could double or triple our estimates of mean residence time, but probably would not change relative differences between land-use types because deeper soil C varies less with land management than surface C (Fig. 2; Kaye et al. 2005). Raich and Schlesinger (1992) used a similar approach to calculate the mean residence time of soil C for whole biomes and the shortest mean residence times occurred in tropical grasslands (~10 yr). Thus, even after tripling the mean residence time to account for deep soil C, agricultural and urban mesic soils in our study region have very short oC residence times compared to other ecosystems. We are currently examining multi-pool estimates of soil C residence times to increase our understanding of soil-atmosphere gas exchange in Phoenix residential soils.

CONCLUSION

Using Bayesian models to advance ecology in mixed-use regions

We used a single statistical model to predict soil properties simultaneously across a wide variety of land-use types in central Arizona, USA. We achieved large scale predictability by modeling traditional ecological parameters and socioeconomic variables that reflect human actions. One of the emerging tenets of urban ecological theory is that human actions must be included in models of urban ecosystem functioning (Kaye et al.

2006) and our statistical model provides support for this idea; human choices regarding turfgrass cover, impervious surface cover, and tree cover were all significant predictors of soil element distributions. While values of regional soil element stocks are important for understanding our regional ecosystem (see below), an equally important result, in terms of advancing the ecology of mixed-use landscapes, are maps (Fig. 1b–e) that portray soil properties of the region as subtle and dramatic gradients spanning all ecosystem types. These images (and the model that produced them) better represent the connectedness of landscape components than traditional models that use discrete land-use or soil type boundaries to depict landscape soil patterns.

Hierarchical Bayes enabled this seamless cross-system analysis, and we suggest that Bayesian modeling could be a key tool for an ecology that spans ecosystems. Our model includes four advances over traditional ecological approaches. First, it enabled us to use diverse types of data to predict soil properties. This flexibility is important when both biophysical and socioeconomic factors may be driving environmental change. Second, we include spatial autocorrelation in our predictions of regional soil pools. Spatial autocorrelation explains a large fraction of variance in soil pools at small scales (Robertson et al. 1997), but has not previously been invoked to map regional patterns of soil carbon and nutrient distributions. Third, hierarchical Bayes allowed us to predict values for independent variables at points where data are lacking, and used variance in the existing data to generate confidence intervals for our predictions of soil element storage. Traditional scaling approaches are limited to interpolating only at points where values for independent variables have been quantified. Finally, we modeled the joint distributions of oC , iC , N , and avP , which is consistent with the idea of coupled biogeochemical processes in ecosystems. The model predicts spatial coupling of biologically mediated pools (oC , N , and avP) across this diverse landscape, despite the myriad human impacts on regional soils.

Our results have several implications for urban land managers. In general, our data show that soils are an important component of city-scale C , N , and P budgets and that some urban soils store more C , N , and P than adjacent deserts. Thus, as cities strive to mitigate air and water pollution, soil element accumulation may play a role. An important caveat is that our study did not fully account for the costs and longevity of soil element storage. For example, in Phoenix, high soil C , N , and avP storage occurs in mesic residential areas with high turfgrass cover. These landscapes are associated with high irrigation and fertilizer inputs, a short mean residence time for soil C , and high gaseous N losses (Zhu et al. 2004). Thus, the overall environmental benefits of soil element storage may not be significant relative to environmental costs that we did not measure.

We also found that variability in urban soil element storage is correlated with cultural variables that reflect

land development and management choices. In Phoenix, choices regarding the location of development affect urban element storage because urban plots on former agricultural fields had higher C and N storage than plots on former deserts (Tables 1 and 2; Lewis et al. 2006). Choices about the amount of impervious cover, turfgrass lawn cover, and tree cover were also correlated with soil N , P , and C storage. These are urban characteristics that are often managed by individual home owners, but they were important predictors of city-wide element storage.

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