GEODA CENTER
FOR GEOSPATIAL ANALYSIS
AND COMPUTATION

ARIZONA STATE UNIVERSITY

Working Paper 2009-03

An Ensemble Approach to
Space-Time Interpolation

Elizabeth A. Wentz, Donna J. Peuquet,
and Sharolyn Anderson

An ensemble approach to space-time interpolation

Elizabeth A. Wentz[1*]
Donna J. Peuquet[2]
Sharolyn Anderson[3]

[1] School of Geographical Sciences
Arizona State University
Tempe AZ 85287-5302
wentz@asu.edu

[2] Department of Geography
The Pennsylvania State University
University Park, PA 16802
peuquet@geog.psu.edu

[3] Department of Geography
University of Denver
Denver CO 80208
sander24@du.edu

* corresponding author

An ensemble approach to space-time interpolation

Abstract

There has been much excitement and activity in recent years related to the relatively sudden availability of earth-related data and the computational capabilities to visualize and analyze these data. Despite the increased ability to collect and store large volumes of data, few individual data sets exist that provide both the requisite spatial and temporal observational frequency for many urban and/or regional-scale applications. The motivating view of this paper, however, is that the relative temporal richness of one data set can be leveraged with the relative spatial richness of another to fill in the gaps. We also note that any single interpolation technique has advantages and disadvantages. Particularly when focusing on the spatial or on the temporal dimension, this means that different techniques are more appropriate than others for specific types of data. We therefore propose a space-time interpolation approach whereby two interpolation methods – one for the temporal and one for the spatial dimension – are used in tandem in order to maximize the quality of the result.

We call our ensemble approach the Space-Time Interpolation Environment (STIE). The primary steps within this environment include a spatial interpolator, a time-step processor, and a calibration step that enforces phenomenon-related behavioral constraints. The specific interpolation techniques used within the STIE can be chosen on the basis of suitability for the data and application at hand. In the current paper, we describe STIE conceptually including the structure of the data inputs and output, details of the primary steps (the STIE processors), and the mechanism for coordinating the data and the

processors. We then describe a case study focusing on urban land cover in Phoenix Arizona. Our empirical results show that STIE was effective as a space-time interpolator for urban land cover with an accuracy of 85.2% and furthermore that it was more effective than a single technique.

 Key words: space-time interpolation, urban growth, Phoenix, Arizona

1. Introduction

Better understanding of complex, earth-related processes is being viewed by scientists and governments with an increasing level of urgency to address problems such as the new global economy, the drivers and consequences of urban growth, and the effects of global climate change. Such processes are characterized by the interaction of many factors with multiple interconnections and feedbacks that vary over multiple spatial and temporal scales. Coincident with this, recent advancements in data availability and computing capacity is enabling a new era in the analysis of environmental and social phenomena. We can now begin to examine phenomena in *both* space and time at the appropriate level of detail, essential for meeting the challenge of understanding complex systems.

There has been much activity over the past 10 to 20 years in space-time representation for computer analysis (Langran and Chrisman 1988; Peuquet 2002; Yuan et al. 2005; Spaccapietra et al. 2006), the extensions of traditional techniques (SenGupta and Ugwuowo 2006; Lee and Wentz 2008), and in development of new analytical techniques (Laube and Purves 2006). Nevertheless, such techniques usually require data with continuous and consistent resolution in space-time. Despite the growth in data acquisition infrastructure, including high-resolution satellite systems, telemetry and radar, as well as

the accumulation of archival map data in digital form, few individual data sets are available that provide both the needed and/or desired spatial as well as temporal resolution. This is particularly true with respect to historical data, which poses a major obstacle for the utilization of new space-time analysis capabilities.

Interpolation is a key technique used to supplement, smooth, and standardize observational data. The interpolation process typically involves three primary steps which are often used iteratively: exploration, estimation, and validation of observational and calculated values. For data exploration, analysts typically utilize multiple techniques in tandem to explore data trends and interactions. Multiple statistical and graphical techniques are also used for model validation to determine how well the interpolated values approximate observed data. An analyst will use the multifaceted results of data exploration and validation to decide upon a single statistical or mathematical interpolation technique for estimation (e.g., exponential kriging). We view this as simplistic relative to the complex multidimensional interrelationships inherent in space-time data.

We reason that first, any single interpolation technique has its advantages and limitations in terms of the specific patterns of variation that may be present in the data. Second, results can be greatly improved by using an ensemble of interpolation techniques and utilizing ancillary data to take maximum advantage of space-time interactions. Such an approach was impractical until recently because of limitations in both data availability and computing capacity.

One of the opportunities in space-time interpolation is that data available to investigators will frequently be of two distinct types; one type with a much greater observational density in the temporal dimension than in the spatial dimension, and another

with the reverse. An example of the former is air quality data, which may be collected hourly but there may be only a few monitoring stations (i.e., observation locations) throughout an urban area. An example of the latter is Landsat data, which provide complete spatial coverage (at 30m resolution) but these 'snapshots' are repeated only once every sixteen days. These two types of data represent different sampling approaches and require different types of interpolation, but in theory they can be used in tandem to derive interpolated space-time data better than can be derived with either type alone.

Our aim is to utilize these different but complimentary data in an ensemble approach to space-time interpolation, to create a fully populated space-time cube for one or more variables. Our proposed ensemble method consists of a multi-step and iterative process within a coordinated environment, using ancillary data to provide additional information for refining primary data in both the spatial and temporal dimensions. We name this ensemble method the Space-Time Interpolation Environment (STIE). Multiple models are combined to utilize spatial characteristics from one data set to inform the temporal dimension of the other, and vice versa. STIE consists of two primary components. The core consists of a set of interpolation processors each focusing on interpolation in a specific dimension or cross-checking between dimensions. This core is incorporated within a management structure that handles the flow of data and estimated values between processors.

The paper begins with a synthesis of recent research in space-time interpolation. We then present STIE, starting with a description of the individual processors, followed by how they work together within an overall management structure. We demonstrate the effectiveness of STIE using the example of interpolating land cover annually in Phoenix,

Arizona. Our conclusions highlight the opportunities and challenges associated with this approach.

2. Recent research

Research in space-time interpolation has generally involved refinement of a single technique. While it has been acknowledged that many spatial interpolation techniques, including inverse distance weighting, splining, kriging and spatial regression can be extended to the temporal dimension (Goldstein et al. 2004), efforts have been focused on interpolation in either the spatial or the temporal dimension but not both simultaneously, even for space-time data. To examine urban growth, for example, Goldstein et al. (2004) used Delaunay triangulation to fill-in missing urban/non-urban values for parcel records for each year between 1929 and 2001 in Santa Barbara County, California. Values for spatial neighbors were used to estimate the value of a given missing parcel value within a given time slice.

One problem with this general approach to space-time interpolation is that it ignores possible temporal correlations that could aid in the estimation process. Perhaps the primary exception is kriging. Researchers refining and extending space-time kriging have recognized the need to correlate the temporal dimension. While many applications of space-time kriging can view the spatial and temporal dimensions as equivalent, most who are dealing with the geospatial context realize that there are some fundamental and essential differences between the spatial and temporal domains (Rouhani and Myers 1990; Christakos and Vyas 1998; Kyriakidis and Journel 2001). Of primary importance with respect to space-time interpolation, values for a given variable at a specific location may be

influenced by values in any spatial direction, whereas values in time can only be influenced by values at a preceding time. Because kriging incorporates global as well as local influences for estimating values, the increased dimensionality of time as well as space, and the resultant increase in the number of observations causes a dramatic increase in the computational requirement. Kerwin and Prince (1999) proposed a recursive solution to the data dimensionality problem, coupling kriging with a stochastic state equation.

A clear improvement to ordinary spatio-temporal kriging includes the use of ancillary data to aid in the estimation process, referred to as external drift (Wackernagel 1998; Chiles and Delfiner 1999). Snepvangers et al. (2003) demonstrated the improvements possible in estimating soil water content by using net precipitation as ancillary data. They found that spatio-temporal kriging with external drift produced more realistic results than spatio-temporal kriging alone. The use of ancillary data has also proven effective in other space-time interpolation approaches. Goldstein et al. (2004) were able to better the results of the Delaunay triangulation of urban extents by utilizing cellular automata along with ancillary data, which included slope and road networks.

We recognize that any individual interpolation method has advantages and disadvantages. Integrating multiple methods has been shown to provide a flexible and coherent structure to solve problems with increased complexity (Drecourt et al. 2006; Roy 2008; Wang and Armstrong 2009). Drecourt et al. (2006) constructed an ensemble framework to set up a filter to estimate the parameters of a covariance matrix in a groundwater model finding that the framework provided information on uncertainty in the model. The approach that we propose below integrates multiple techniques with ancillary data to improve overall results for space-time interpolation of earth-related data.

6

3. Ensemble framework for space-time interpolation

The STIE uses three processors within an overall management structure that handles data flow among these. The three processors are a Spatial Interpolator, a Time-Step Processor, and a Calibration Processor. The Spatial Interpolator (SI) uses multiple temporal observations at given point locations and interpolates estimated values to all gridded locations in the study area. The Time-Step Processor (TSP) takes gridded values at a single time slice and estimates gridded values for the subsequent time slice. The Calibration Processor (CP) integrates the output from the SI to refine and constrain the output from the TSP. The specifics of each of the processors are described below.

Input to the SI is a set of observational data in ordered time sequences for specific x, y points in geographic space:

$$\{P \mid p \in (x,y)_t\} \tag{1}$$

For each x, y location there is a chronological time-series, t, where $t = (t_0, t_1, t_2, \ldots t_n)$ While the points, p, are spatially disjoint and irregularly distributed, the temporal interval between observations is constant for all points. We note, however, that the starting and ending times of the temporal sequence do not need to be the same for each $p \in P$. Meteorological stations that record hourly temperature, precipitation, and air pressure are examples of this type of temporally rich data. Data collection from two different meteorological stations may have started at different times resulting in a different number of observations in each time sequence.

Inputs to the Time-Step Processor consist of observational values ordered within a set, S, of two-dimensional regular grids, Q, each representing a complete coverage of some portion of the earth with a regular grid size (*dim*) at a single, known time (*t*):

$$\{S \mid s \in Q_{\dim,t}\} \tag{2}$$

The size and shape of the grids are regular and the spatial extent is constant among all grids. The time intervals between successive grids (i.e., successive temporal snapshots), however, do not need to be regular. Land cover and surface temperature derived from satellite remote sensing are examples of such spatially rich data.

The interpolated values are output in the form of a space-time cube:

$$\{ST \mid st \in Q_{\dim,t}\} \tag{3}$$

Where *ST* is a set of grids with a spatial extent and support (*dim*) defined by the input set S and *t* is the regular, chronological time-series consistent with the set P.

Given these definitions, the overall process of STIE can be interpreted as refining or filling-in the missing values for specific space-time locations within the cube. This conceptual cube can be extended into four or more dimensions to accommodate two or more variables. Using the inputs from Equations 1 and 2, the SI and the TSP are run in parallel to produce estimated values for a single time slice as shown in Figure 1. The CP is then used to refine all values in the estimated time slice for that iteration by imposing known constraints specific to the local context for the given attribute. The completed estimated time slice is then used as input for estimation of the next time slice in the next iteration. This process is repeated until the complete space-time cube is constructed.

Selection of specific estimation techniques for each of these three processors depends on specifics of the data and the application at hand. This means that before any

actual estimates are made, the source data must be examined to determine the appropriate combination of interpolation and modeling techniques for the given application. This typically includes exploratory techniques such as visualizing raw data and calculating descriptive statistics for dependent and independent variables. This type of data exploration is an essential preliminary step. For example, to select the best geostatistical kriging model (if, indeed, kriging was earlier determined to be the best interpolation technique), analysts will explore the input data by calculating first and second order statistical moments, creating graphical views of autocorrelation of the dependent variables (e.g., histograms, variograms), and manipulating and mapping data subsets. Important components of this step are to remove trends and to determine data stationarity.

4. Case Study of STIE

We demonstrate STIE using a case study on urban growth for the Phoenix Metropolitan Area, a region that includes the City of Phoenix and 14 other incorporated areas covering approximately 7,650 km^2 of central Arizona (Figure 2). An explosion in population growth is resulting in unprecedented conversion of natural semiarid desert vegetation and historic agricultural land to urban land cover. Questions arise regarding the drivers of this type of growth and the environmental and social consequences.

Recent research investigating urban growth in the Phoenix metropolitan area has shown most land transformations are from agricultural to single family residential, and that the spatial pattern of development is movement outward from the urban core (Keys et al. 2007). This study, however, was very basic in its conclusions because the land use data used were decadal. Additional land use values at a finer temporal resolution, such as annual data, would enhance this study by being able to better understand trajectories of land use

change in greater detail as well as macro-scale growth patterns. Extracting this type of historical observational data, however, is nearly impossible because of time constraints on data development and simply the lack of historical aerial photographs (Wentz et al. 2006). Since multiple time periods of detailed historic land use and/or land cover data are needed by scientists, urban planners, and other decision-makers in order to understand the impact of human activities on the environment (Lopez et al. 2001), the goal for the case study was to demonstrate how it is possible to estimate realistic annual land cover values in for the years 1985-2005 using ancillary data in an implementation of STIE.

Our selection of the variables and processors for this implementation of STIE is based on a known relationship between surface temperature and land cover type, as documented most frequently in the literature on the urban heat island effect (Jenerette et al. 2007). There are higher surface temperatures associated with impervious surfaces compared with undeveloped and vegetated land covers. We use the surface temperature-land cover relationship to better assign the conversion of land cover from undeveloped to developed classes. What this means is that instead of using strictly a spatial process (e.g., that a neighboring cell has changed), we incorporate a temporal change of temperature (e.g., identifying when the land cover change may have occurred).

4.1 Data

To generate land cover estimates over a twenty year period (1985- 2005), three variables were used. They were average air temperature from 36 meteorological stations as well as land cover and surface temperature derived from remotely sensed imagery.

Air temperature data were collected from 36 meteorological stations (Selover 2001), (Figure 2). The meteorological stations were not evenly distributed across the study area but rather were concentrated in the urban core on four different land cover types. Average air temperature at 10:30 AM (to correspond to the Landsat capture time for Phoenix) was calculated by selecting four days in May for all years (1985-2005). The selection criteria were four days without recorded precipitation at the Cooperative Observer Stations and as close to the middle of the month as possible. Different days were used for different years to meet these criteria. These data represent our temporally rich data, set *P* (Eqn. 1)

Land cover and surface temperature data were derived from Landsat TM images for the following dates: May 14, 1985, May 12, 1988, May 18, 1990, May 24, 1998, May 21, 2000, and March 8, 2005. The middle to late May dates were selected to maintain annual consistency in terms of minimal weather extremes, minimal cloud cover, and maximum vegetation leafout. For 2005, the only data available to us were for March, which is not a significant problem since these data were not used to calibrate the model for subsequent years.

For the land cover, the images were classified into nine categories using the Stefanov (2001) knowledge-based classification model. The resulting classes are: ACTVEG (irrigated non-residential vegetation), NATVEG (native vegetation), CANAL (fluvial and man-made cannels), MESIC (residential with irrigated landscaping), XERIC (residential with low-water landscaping), COMM (commercial and industrial), ASPH (asphalt including roads and parking lots), UNDEV (undeveloped), and WATER (lakes, rivers, and reservoirs). Surface temperature for each image was calculated using the

Thermal Band (band 6). Land cover and surface temperature are our two spatially rich data, set S (Eqn. 2).

4.2 Model Processors

Figure 3 shows the management structure for the three processors and data for this implementation of STIE. The inputs to the Spatial Interpolator (SI) are land cover, digital elevation model, and air temperature. Inputs to the Time Step Processor (TSP) are land cover data. The output from these processors are estimated surface temperature and estimated land cover respectively for the next time slice. These become the inputs to the Calibration Processor (CP), which refines the estimated land cover values using known land cover and surface temperature relationships. The estimated time slice showing land cover is then used as input for the next iteration. This process is repeated until all values within the output space-time cube have been estimated (Figure 4).

The SI selected for this case study has two stages. First is the point to grid interpolation; second is the estimation of surface temperature based on air temperature. Interpolated air temperature was calculated using inverse distance weighting (IDW). While kriging would have been preferable because it provides more detailed results (e.g., variance, error estimates), the spatial concentration of observation points around the urban core made IDW more suitable in this particular case. Regression-based mapping was used to calculate surface temperature from air temperature for each land cover type. For each land cover type in the study, the dependent variable surface temperature at a specific time $(Ts(z))$ is estimated on the basis of maximum and minimum monthly air temperatures $(Ta_{max}$ and $Ta_{min})$, observed air temperature for that time (Ta_z), and elevation (EL) as

independent variables. Beta (β) denotes the coefficient for each of the independent

variables (Johnson 1986; Stoll 1990):

$$Ts(z)= a + \beta_1 \, Ta_{max} + \beta_2 \, Ta_{min} + \beta_{3 \, Taz} + \beta_4 \, EL \qquad\qquad (4)$$

One regression equation was estimated for each of the eight land cover classes, each

statistically significant at <0.0001. The ninth category (UNDEV) required two different

equations because of a large air temperature range for the UNDEV category. There are

UNDEV cells at relatively high elevation (with lower air temperature) and low elevation

UNDEV cells (with higher air temperature). The ten equations were derived from sample

values for the surface temperature (dependent variable), elevation, and interpolated air

temperature values (independent variables). We selected 100 sample locations per land

cover class (10 classes total, resulting in n=1000). The sample means were plotted against

the means from the populations to insure population representation. The R^2 values range

from 0.169 to 0.659. The independent variables explain approximately 17% to 66% of the

temperature variance for the specified land cover classes. The land cover classes with the

lowest R^2 are ACTVEG, CANAL, and the lower elevation UNDEV class.

The TSP in this study uses a cellular automata model to derive the intermediate

estimated gridded land cover values for the next time slice (t+1). Cellular automata are

dynamic models that calculate a new value for a grid cell based on the relationship of the

current target cell to its neighborhood. We defined the neighborhood with a 3 x 3 matrix of

eight cells. With a cell size of approximately 30 x 30 m ground resolution, the distance

from the center of the target cell to the edge of the neighborhood is less than 100 m. This

resolution allows local microclimate influences to be seen (Hubble 1993) and is also below

the 120 m resolution of the surface temperature data.

We initiated the cellular automata with land cover derived from the interpreted and calibrated satellite data from 1985. From there, we applied rules to govern the transition from time t to time $t+1$ for a target cell (j) relative to the set of eight cells around j, which we define as Ω_j.

As reflected in the discussion in section 4.1, we define all land cover classes in our study area that remain temporally stable over time as:

A = {MESIC, XERIC, CANAL, COMM, WATER, ASPH}

and the land cover classes that can change over time as;

B = {UNDEV, NATVEG, ACTVEG}

therefore the set of all nine land classes in our study data can be expressed as:

$C_i = A \cup B$.

We can then express the unique land cover types in the neighborhood Ω_j as

$$D = \bigcap_{i \in \Omega_j} C_i, \ \forall \ d_i \in D, d_i \neq d_{i+1}$$

Then, $K_a = \{(k, m_k) : k \in D, m_k \in M \subset \mathbb{N}: m_k \leq 8 \text{ and } m_a + m_b \ldots = 8\}$. K_a is a multiset where each pair (a) represents the land cover type (k) and the number of occurrences (m_k) of that type in the neighborhood Ω_j. For example, we could define $K_a = \{(UNDEV, 3), (CANAL, 3), (NATVEG, 2)\}$. Finally, we define the integer, $\max(m_k) := m_i > m_{i+1} \ \forall \ (k, m_k) \in K_a$, is the highest number in the set M and $\max(m_{k-1})$ is the second highest, etc. Informally, the rules for the transition for j_t to j_{t+1} are as follows:

If the target cell is a land cover type that is temporally stable, **then** the target cell remains unchanged.

Else if there the majority of land cover types is stable in the neighborhood **then** the target cell is assigned the majority neighborhood land cover type.

Else the target cell is assigned the next highest majority stable land cover. Note that in case of a tie in land cover frequency, the program will simply assign the land cover type that is the first in the stored sequence for land cover types in the neighborhood. Formally, the rules can be stated as follows:

If $j_t \in A \Rightarrow j_{t+1} = j_t$

If $j_t \in B$ and $|D| \geq 1$ and $m_k = max(m_k) : k \in A \Rightarrow j_{t+1} = k$

If $j_t \in B$ and $|D| \geq 1$ and $k \in B: (k, max(m_k)) \Rightarrow j_{t+1} = k: m_k = max(m_{k-1})$ and $k \in A$

These rules were developed from other published cellular automata models of land use/cover change developed in different settings (Clarke and Hoppen 1997; Meyler et al. 1998; Ward et al. 2000; Ward, et al. 2000; Jenerette and Wu 2001). We modified the rules from those prior models to reflect specific Phoenix context. In Phoenix, there is rapid urban expansion and therefore a greater likelihood that cells with values in set B will change to developed types (set A).

The CP for this study invokes a set of rules to adjust the land cover values that were estimated by the TSP. This is a refinement performed by cross-checking those values with the gridded surface temperature at the corresponding cell for the same time slice. The rules used, governing the relationship between surface temperature (Ts) and specific land cover classes (LC), are based on empirical observations and supported in the literature (Quattrochi and Ridd 1994). Some land cover classes are not included in the rules because the surface temperature ranges are not narrowly enough defined to be adjusted reliably.

The CP rules are as follows:

If LC = ACTVEG &

Ts > Tmax_ACTVEG then LC = ACTVEG

Else If Ts < Tmax_ACTVEG & IN_BOUND = TRUE then LC = MESIC

Else If LC = NATVEG &

Ts > Tmean_UNDEV & IN_BOUND = FALSE then LC = UNDEV

Else If Ts > Tmax_UNDEV & IN_BOUND = TRUE then LC = XERIC

Else If Ts > Tmean_UNDEV & IN_BOUND = TRUE then LC = MESIC

Else If LC = MESIC &

Ts < Tmin_UNDEV & LU = Agriculture & IN_BOUND = TRUE then LC = ACTVEG

Else If Ts > Tmean_UNDEV & IN_BOUND = FALSE then LC = UNDEV

Else If LC = COMM &

IN_BOUND = FALSE then LC = UNDEV

Else If Ts > Tmax_ACTIVE & LU = Residential then LC = XERIC

Else If Ts < Tmax_ACTVEG & LU = Residential then LC = MESIC

Else If LC = ASPH &

IN_BOUND = FALSE then LC = UNDEV

Else If LC = UNDEV &

Ts < Tmean_ACTVEG & LU = Agriculture then LC = ACTVEG

Else If Ts < Tmin_NATVEG then LC = NATVEG

Where Tmin, Tmax, and Tmean are the overall minimum, maximum, and mean surface temperature values, respectively, for the named land cover types; IN_BOUND is within the urban boundary; LU is observed Maricopa Association of Governments land use.

The three processors are executed 19 times to create a fully populated space-time cube of air temperature, surface temperature, and land cover that are represented by a 30 m grid over space and annually in time (Figure 4). STIE begins in 1985 with a land cover

classified satellite image (calibrated with CP) and spatially interpolated temperature data (interpolated with the SP), which are then used as input into the TSP. There are several years when observed surface temperature and land cover data are available (1988, 1990, 2000, and 2005) and were not used for validation (1998). In these years, the observed data are used in place of the estimated values.

4.3 Case Study Validation

We evaluated our results by answering two fundamental questions: (1) does the space-time interpolation procedure we developed using the three processors work effectively; and (2) does it work better than an alternative approach. In this section, we describe how these two questions were answered.

To evaluate if the approach estimated land cover corrected, we compared our estimated values to observed data from satellite imagery for the year 1998, using standard accuracy measures from the remote sensing field (Foody 2002; Congalton and Green 1999). The measures we used were overall accuracy, Kappa coefficient, and user's and producer's accuracy. Overall accuracy is a ratio of the number of pixels assigned to a particular class to the number of pixels that actually belong to the class. The Kappa coefficient examines the measure of agreement beyond chance with a ratio of the difference between the observed and expected accuracy over 1 minus the expected accuracy. The user's measure identifies errors of commission and the producer's measure identifies errors of omission, each for a particular class. A standard for an acceptable classification is least 85% (Foody 2002).

To assess whether our approach worked better than previous approaches, we estimated land cover from 1985 to 2005 with a cellular automata model without the ancillary temporal temperature data. We used the same adapted rules for Phoenix as described above. We calculated the overall accuracy, Kappa coefficient, and user's and producer's statistics as described above using the 1998 observed data and estimated values.

5. STIE evaluation

Our case study resulted in a conceptual space-time cube of 20 years with ~30 m cells containing annual estimates of land cover and surface temperature for the Phoenix metropolitan area. The dimension (e.g., size of the study area as well as the time span) and the resolution (e.g., ~30 m spatially and annual temporally) used by the STIE can be changed depending on the availability of input data.

The STIE case study above was successful at estimating land cover with an overall accuracy of 85.2%, higher than the standard of 85%. The Kappa statistic, another measure of agreement, is 82.9. Both suggest strong agreement between observed land cover from satellite imagery and output from STIE. Tables 1 and 2 show the contingency matrix reports the producer's and user's accuracies for the 1998 land cover data. The land cover classes having both a producer's and user's accuracy greater than 85% are the ACTVEG, CANAL, XERIC, COMM, ASPH, and WATER. The classes with accuracies lower than the standard 85% are the NATVEG, MESIC, and UNDEV.

Land cover change from 1985 to 2005 as determined by STIE is similar to other reports on urban growth in Phoenix (Jenerette and Wu 2001; Keys et al. 2007). Our efforts show a 46.9% increase in the area of urban land covers from 1985 to 2005 with changes to

individual categories shown in Figure 5a. In contrast to Figure 5a, which shows the percent change from year to year for each land use category, Figure 5b shows these same years with observed data alone. While the same trends from beginning and end are included in both figures, we are able to use the STIE interpolated values to create graphs, maps, and animations of estimated land cover at finer temporal resolutions providing a richer examination of space-time trends.

We conclude that STIE provides better results than a spatial processor alone. The estimated land cover using a cellular automata model resulted in an overall accuracy for 1998 is 55.6%. This is lower than the accuracy from the STIE (85.2%) as well as below the 85.0% accuracy standard. To deepen the comparison between the 1998 land cover estimated from STIE and the cellular automata, we calculated and compared user's and producer's accuracy scores (Table 3). All classes had higher scores with STIE approach except for one class in the producer's (CANAL) and one class in the user's (COMM). The difference between these, however, is relatively small. In the Phoenix area, commercial areas (COMM) tend to develop slowly temporally and remain spatially clustered, which is well-matched with simple cellular automata. The greatest improvement over the cellular automata is reported by the user's score for UNDEV and XERIC (Table 3). The cellular automata performed poorly for UNDEV because a large portion of the study area in 1985 is classified as UNDEV. When the cellular automata evaluates a target for the next time slice, the value of neighboring cells are examined and used to reassign the value of the target. For XERIC, the surface temperature in the calibration processor provided guidance on the type of development. With just a cellular automata, there were no rules to account for the amount or type of Phoenix's rapid urbanization (e.g., assigning several cells in a

neighborhood) or leapfrog development (new development occurring without adjacency) (Morrison 2000). Using STIE with the temporal information can aid in identifying the location of these growth trends.

As shown in Figures 5a and 5b, the overall trends in all categories remain the same. The difference, however, is that for categories with significant year-to-year variability, use of the ancillary data to adjust those values reveal significant details in that variability. In our case study, this is particularly evident in land cover categories that are sensitive to climate variables (e.g., temperature and precipitation). There is a spike in NATVEG in 1987 and 1992 (Figure 5b) not visible in the observed data (Figure 5a) but is known via the association between vegetation and climate variables. The increased precipitation in these specific years increased vegetation, which has the effect of decreasing temperature. Air temperature is our observed ancillary data used in the SI and CP to modify interpolated land cover values. ACTVEG is not as sensitive to short-term changes in precipitation (reflected in temperature) because it is generally irrigated. However, there is seemingly a lag and modified amplitude effect due to enhanced irrigation in subsequent years. MESIC shows the overall trend of urban growth, but also has some annual sensitivity to climate variables revealing possible competition with ACTVEG for irrigation in Figure 5b.

From both the overall results and the individual class results we conclude that for this case study, the ensemble approach improved space-time interpolation over a single technique. We attribute this to two distinct advantages of the STIE approach. The first advantage is that as hypothesized, STIE provides greater interpretative power. The advantage of the ensemble method is increased accuracy that results from integrating multiple interpolation methods and using the space-time autocorrelations inherent in

different elements of a phenomenon through use of ancillary data. A second advantage of the STIE approach is that it can take advantage of parallel processing environments or distributed systems for improved performance (Plumejeaud et al. 2008; Wang and Armstrong 2009). This makes our approach scalable for dealing with the immense data sets becoming available, particularly high-resolution geospatial data sets over long time periods.

A challenge of STIE is selecting the most suitable technique(s) for each processor and assuring that the data relationships have been defined appropriately. While selecting the most suitable technique for the specific characteristics of the input data is the normal circumstance for selecting any statistical or computational technique to perform a given task, the selection task is made more complex in the case of the STIE approach in that multiple interpolation techniques and the associated data must work in concert with each other. Nevertheless, a range of exploratory and validation tools have recently become available to aid the researcher in this process (Andrienko and Andrienko 2006).

6. Conclusions

Past research on space-time interpolation has relied on a single technique for estimating attribute values and often without ancillary data or including space-time interdependencies. This research project presented an ensemble style framework for space-time data interpolation to address these challenges. We demonstrated that a suite of techniques can provide interpretive power far beyond what a single method can provide. These techniques are selected to include the use of ancillary data.

Furthermore, the exercise in investigating the space-time interrelationships, specifically, to select the appropriate processors may yield unexpected insights.

The definition of STIE confirms that high resolution spatial data can be utilized to enhance temporal data and vise versa.

Based on the case study results, we conclude that an ensemble technique provides an improved methodology for interpolating space-time values when there are missing spatial and/or temporal data. Some might argue that the interpolated space-time values do not reliably represent true values and therefore results and conclusions drawn can be questioned. This argument, however, remains a challenge for any interpolation technique and should not be viewed as an excuse to avoid 'imperfect' data sets and the virtue of estimated values. A better strategy is to recognize that the estimated values should be used to evaluate overall macro-scale patterns and trends rather than as a means to determine specific values at a exact times and locations (Goldstein et al. 2004). There is also the advantage that interpolation methods provide a means to eliminate suspect values as a cleaning technique.

We demonstrated that an ensemble approach improves estimation over a single approach. We anticipate that ancillary data and an ensemble of appropriate techniques in other applications would yield similar improved results. We propose a generalized framework that can be adapted to numerous application contexts.

References

Andrienko, N. and G. Andrienko, 2006. *Exploratory analysis of spatial and temporal data: A systematic approach*, Springer-Verlag, Berlin.

Chiles, J. and P. Delfiner, 1999. *Geostatistics: modeling spatial uncertainty*, John Wiley & Sons, New York.

Christakos, G. and V. M. Vyas, 1998. A composite spatiotemporal study of ozone

distribution over eastern United States. *Atmospheric Environment,* 32, 2845-2857.

Clarke, K. C. and S. Hoppen, 1997. A self-modifying cellular automaton model of

historical urbanization in the San Francisco Bay area. *Environment and Planning B:*

Planning and Design, 24, 247-261.

Congalton, R. G. and K. Green, 1999. *Assessing the accuracy of remotely sensed data:*

Principles and Practices. Boca Raton, Lewis Publishers.

Drecourt, J. P., H. Madsen, and D. Rosbjerg, 2006. Bias aware Kalman filters: Comparison

and improvements. *Advances in Water Resources,* 29 (5), 707-718.

Foody, G. M., 2002. Status of land cover classification accuracy assessment. *Remote*

Sensing of Environment, 80, 185-201.

Goldstein, N. C., J. T. Candau, and K. C. Clarke, 2004. Approaches to simulating the

"March of Bricks and Mortar" *Computers, Environment and Urban Systems,* 28,

125-147.

Hubble, M., 1993. Monitoring and Assessing Surface and Near-Surface Urban Climate

with Landsat Satellite Imagery. Geography. Tempe, Arizona State University. 122.

Jenerette, G. D. and J. Wu, 2001. Analysis and simulation of landuse change in the Central

Arizona - Phoenix region. *Landscape Ecology,* 16, 611-626.

Jenerette, G. D., S. L. Harlan, A. Brazel, N. Jones, L. Larsen, and W. L. Stefanov, 2007.

Regional relationships between surface temperature, vegetation, and human

settlement in a rapidly urbanizing ecosystem. *Landscape Ecology*, 22, 353-365.

Johnson, J., 1986. *Multivariate statistical analysis in geography*. Essex, London, Longman

Group, Limited.

23

Kerwin, W. S. and J. L. Prince, 1999. The Kriging update model and recursive space-time function estimation. *IEEE Transactions on Signal Processing,* 47 (11), 2942-2952.

Keys, E., E. A. Wentz, and C. Redman, 2007. The spatial structure of land use from 1970 - 2000 in the Phoenix, Arizona Metropolitan Area. *The Professional Geographer,* 59 (1), 131-147.

Kyriakidis, P. C. and A. G. Journel, 2001. Stochastic modeling of atmospheric pollution: a spatial time-series framework. Part I: methodology. *Atmospheric Environment,* 35, 2331-2337.

Langran, G. and N. R. Chrisman, 1988. A Framework for Temporal Geographic Information. *Cartographica,* 25 (3), 1-14.

Laube, P. and R. S. Purves, 2006. An approach to evaluating motion pattern detection techniques in spatio-temporal data. *Computers, Environment and Urban Systems,* 30, 347-374.

Lee, S.-J. and E. A. Wentz, 2008. Applying Bayesian maximum entropy to extrapolating local-scale water consumption in Maricopa County, Arizona. *Water Resources Research,* 44 (1).

Lopez, E., G. Bocco, M. Mendoza, and E. Duhau, 2001. Predicting land-cover and land-use change in the urban fringe - A case in Morelia city, Mexico. *Landscape and Urban Planning,* 55, 271-285.

Meyler, A., G. Kenny, et al., 1998. Forecasting Irish inflation using ARIMA models.

Morrison, 2000. Hits and Misses: Fast growth in metropolitan Phoenix. Phoenix, Morrison Institute for Public Policy. 50.

Parent, C., S. Spaccapietra, and E. Zimányi., 2006. *Conceptual Modeling for Traditional and Spatio-Temporal Applications: The MADS Approach*, Springer-Verlag.

Peuquet, D. J., 2002. *Representations of Space and Time*. New York, Guilford.

Plumejeaud, C., J.-M. Vincent, C. Grasland, S. Bimonte, H. Mathian, S. Guelton, J. Boulier, and J. Gensel, 2008. HyperSmooth: A System for Interactive Spatial Analysis Via Potential Maps. *Web and Wireless Geographical Information,* 5373 (W2GIS), 4-16.

Quattrochi, D. A. and M. K. Ridd, 1994. Measurement and analysis of thermal energy responses from discrete urban surfaces using remote sensing data. *International Journal of Remote Sensing,* 15 (10), 1991-2022.

Rouhani, S. and D. E. Myers, 1990. Problems in space– time kriging of geohydrological data. *Mathematical Geology,* 22, 623-661.

Roy, S. S., 2008. Impact of aerosol optical depth on seasonal temperatures in India: a spatio-temporal analysis. *International Journal of Remote Sensing,* 29 (3), 727-740.

Selover, N., 2001. Data from Office of Climatology.

SenGupta, A. and F. I. Ugwuowo, 2006. Asymmetric circular-linear multivariate regression models with applications to environmental data. *Environmental and Ecological Statistics,* 13, 299-309.

Snepvangers, J. J. J. C., G. B. M. Heuvelink, J. A. Huisman, 2003. Soil water content interpolation using spatio-temporal kriging with external drift. *Geoderma,* 112, 253-271.

Stefanov, W. L., M. S. Ramsey, and P. R. Christensen, 2001. Monitoring urban land cover change: An expert system approach to land cover classification of semiarid to arid urban centers. *Remote Sensing of Environment,* 77, 173-185.

Stoll, M. J., 1990. Analysis of land use effects on surface to air temperature relationships in an urban environment. Tempe, Arizona State University.

Wackernagel, H., 1998. *Multivariate geostatistics: an introduction with applications*, Springer-Verlag.

Wang, S. and M. Armstrong, 2009. A theoretical approach to the use of cyberinfrastructure in geographical analysis. *International Journal of Geographical Information Science,* 23 (2), 169-193.

Ward, D., S. R. Phinn, and A. T. Murray, 2000. Monitoring growth in rapidly urbanizing areas using remotely sensed data. *Professional Geographer,* 52 (3), 371-386.

Ward, D. P., A. T. Murray, and S. R. Phinn, 2000. A stochastically constrained cellular model of urban growth. *Computers, Environment and Urban Systems,* 24, 539-558.

Wentz, E. A., W. L. Stefanov, C. Gries, and D. Hope, 2006. Land use and land cover mapping from diverse data sources for an arid urban environment. *Computers, Environment and Urban Systems,* 30 (3), 320-346.

Yuan, M., D. Mark, M. Egenhofer, and D. Peuquet, 2005. Extensions to Geographic Representation: A Research Agenda for Geographic Information Science. *Research Challenges in Geographic Information Science*. R. McMaster and L. Usery. Boca Raton, CRC Press. 129-156.

Tables

Table 1. Contingency matrix showing observed (Landsat) versus predicted (STIE) land cover classes for 1998

Class Name	ACTVEG	NATVEG	CANAL	MESIC	XERIC	COMM	ASPH	UNDEV	WATER	Total
ACTVEG	48	0	0	2	0	0	0	1	0	51
NATVEG	1	13	0	0	1	0	0	0	0	15
CANAL	0	1	43	0	1	0	0	0	0	45
MESIC	3	2	0	36	0	3	2	7	0	53
XERIC	0	3	1	0	59	1	2	3	0	69
COMM	1	1	0	0	1	53	0	3	0	59
ASPH	0	0	0	1	0	0	40	5	0	46
UNDEV	0	2	3	5	4	4	3	81	0	102
WATER	0	1	1	0	0	0	0	0	24	26
Total	53	23	48	44	66	61	47	100	24	466

Table 2. Producer's and user's accuracy results for observed and STIE estimated land cover in 1998 (n=466)

Land cover	Producer's	User's
ACTVEG	0.906	0.941
NATVEG	0.565	0.867
CANAL	0.896	0.956
MESIC	0.818	0.679
XERIC	0.894	0.855
COMM	0.869	0.898
ASPH	0.851	0.870
UNDEV	0.810	0.794
WATER	1.000	0.923

Table 3. Producer's and user's accuracy results for 1998 interpolated land cover from the Spatial Processor (SP) compared with the ensemble space-time interpolation environment (STIE)

	Producer's			User's		
	SP	STIE	Difference	SP	STIE	Difference
ACTVEG	0.566	0.906	0.340	0.768	0.941	0.173
NATVEG	0.292	0.565	0.273	0.600	0.867	0.267
CANAL	1.000	0.896	-0.104	0.642	0.956	0.314
MESIC	0.667	0.818	0.151	0.275	0.679	0.404
XERIC	0.619	0.894	0.275	0.265	0.855	0.590
COMM	0.403	0.869	0.466	0.899	0.898	-0.001
ASPH	0.830	0.851	0.021	0.565	0.870	0.305
UNDEV	0.100	0.810	0.710	0.080	0.794	0.714
WATER	1.000	1.000	0.000	0.489	0.923	0.434

Figure Captions

Figure 1. The three model processors of STIE showing the required and possible flow of data between them. Solid arrows show required data flow between the processors. Dashed arrows illustrate where data flow may exist depending on data relationships in a given application.

Figure 2. The spatial extent of the study area in Phoenix Arizona and the locations of the meteorological stations used for the climate data.

Figure 3. A single iteration of STIE for this case study showing the three processors and input data along with the management structure that supports data flow and the iteration of the processors

Figure 4. The sequence of multiple iterations of STIE illustrating the relationship of one time slice to the next

Figure 5a. Shows the changes of different land covers over time with observed data alone; Figure 5b represents the same land covers over time with the STIE interpolated values