Small-Area Population Forecasting:
A Spatio-Temporal Regression Approach

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Abstract Demographic forecasting techniques generally do not work well for small areas. In this study we propose a nascent spatio-temporal approach by taking a theory-based approach, rather than a data-driven one for small-area population forecasting. In particular, a regression model incorporating spatio-temporal population effects and other neighbor characteristics is applied to examine population change at the Minor Civil Division (MCD) level in Wisconsin since 1960. For each MCD, the population growth rate for 1980-1990 is regressed on (1) its growth rate for 1970-1980, (2) its various characteristics in 1980, (3) neighborhood growth rates for 1970-1980, and (4) neighborhood characteristics in 1980. The estimated regression coefficients and spatial parameters are then used for projecting population in 2000. The accuracy and precision are measured, and a comparison is made against the state's official MCD projections for 2000. The results indicate that our spatio-temporal regression approach significantly improves the estimation of the model, but does not provide substantial advantages over the traditional population forecasting approach – primarily extrapolation modeling. This study helps meet policy demands for better small-area population forecast techniques.

Introduction

Demographic forecasting techniques generally do not work well for small areas[1]. We posit three reasons for this. First, most demographic forecasting models (e.g., the traditional cohort component model) have been developed and refined for relatively large geographic areas (counties and larger areas) where the components of population change can be dealt with separately in an age-specific context. Second, for small sub-county areas (especially in sparsely settled rural landscapes), non-demographic factors, generally ignored in traditional forecasting methodologies, assume a level of importance greater than whatever demographic forces appear to be at work. Third, nearly all population forecasting methods ignore the "neighborhood" context[2] in which local demographic trends are played out.

Keeping these reasons in mind, we revisit the regression approach for population forecasting. The use of familiar multiple regression models in the production of population forecasts for subcounty geographic entities is an empirically tested idea that has been around for more than 50 years (Schmitt 1953, 1954). Stanbery (1952) did not mention regression-based forecasts in his early "guide book" for population forecasting for small areas and communities. However, nearly a quarter century later, Pittinger (1976:68-77), in his comprehensive review of population projection[3] models, devoted considerable attention to the matter. Smith, Tayman and Swanson (2000) devote two chapters to structural modeling in their recent and well-received comprehensive overview on the topic. Of particular relevance to us in this book is Chapter 9 dealing with economic-demographic structural models. Yet it is our view that most applied demographers making population forecasts for small areas (including the second author of this paper) have largely ignored regression forecasting approaches. One justifiable reason for this appears to be that, thus far, multiple regression models do not outperform much simpler extrapolation techniques.

We argue that multiple regression approaches for small-area population forecasts can be improved in two ways: (1) by examining holistically rather than partially the relationships between population change and relevant factors, and (2) by explicitly incorporating spatial diffusion effects and other neighbor characteristics into the model. In this study, relevant data from several disciplines will be brought together using GIS and related software tools. A spatio-temporal regression model will be applied to estimate the relevance of various covariates for predicting population change. These covariates will then be used in a spatio-temporal regression specification for the population forecasts. The central research question is whether this approach is superior to existing small-area population forecasting models. Several additional questions are addressed along the way: when reasonably good data are at hand, what particular variables appear to be stronger predictors of population change? Does spatial autocorrelation in the variables or in the modeled residuals affect the statistical analysis? If so, will the incorporation of the spatial effects into the multiple regression improve the population forecasting model?

We begin with the assumption that the regression approach will outperform fundamental population forecasting techniques for subcounty units of analysis. We also assume that population change is a process operating in geographic space, and therefore that spatial dependence will affect the statistical analysis. Thus, we further assume that multiple regression methodologies incorporating spatial effects will improve the existing capability in small-area population forecasting.

To test these assumptions, we use data related to population change at the Minor Civil Division (MCD) level in Wisconsin since 1960. We propose a comprehensive approach for examining the relationships between population change and factors that extend beyond those variables available from standard census sources. For each MCD, the population growth rate for 1980-1990 (the dependent variable) is regressed on several variables covering the 1970-1980 period and stock measures from the 1980 Census. Additional variables include those from environmental, local infrastructure and policy data bases. Variables are selected based both on theoretical and empirical significance. Moreover, we introduce and formally test a revised regression specification that brings into the regression forecast approach explicit “neighborhood” influences through spatial regression (spatial econometric) techniques. Ultimately, this model is expanded to include neighborhood characteristics in 1980, and neighborhood growth rates for 1970-1980. The standard regression coefficients and spatial regression parameters are estimated using this model, and the estimation is used to forecast the population growth rate in 1990-2000. Finally, the population forecasts for 2000, thus derived, are compared to actual population counts from the 2000 census to calculate several measures of error. Similar error measures are also calculated for the 2000 population projections earlier made by demographers in the Wisconsin state demographic agency, the Demographic Services Center (DSC) of the Wisconsin Department of Administration (WIDOA).

In the following sections, we first examine theoretical foundations of the proposed spatio-temporal approach for small-area population forecasting. Subsections explore some of the possible reasons for declining interest in regression forecast models. We then investigate the theoretical foundations of population-relevant factors and spatial effects in explaining population change. We also examine some of the existing regression alternatives for small-area population forecasting. Second, we introduce the context of the study and the data which relate to population change at the MCD level in Wisconsin since 1960, and address in particular the issue of MCD boundary changes. Following this is the analytical approach section. Sub-sections first introduce four population forecasting approaches – extrapolation projection, multiple regression, multiple regression with spatial population effects, and multiple regression with both spatial population effects and other neighbor characteristics. We then discuss some necessary adjustment procedures for the population projection, and evaluate the four approaches. We conclude the paper with our principal findings followed by a discussion and summary.

Theoretical Foundations of the Spatio-Temporal Approach

In this section, we first introduce the existing multiple regression approach for population forecasting, and explore some of the possible reasons for declining interest in regression forecast models. We then propose and discuss two ways to improve the regression approach: the holistic, rather than partial, examination of the relationships between population change and relevant factors, and the incorporation of spatial effects into the regression models. Finally we comment on our exclusion of some types of regression models from this study.

Existing regression forecasting models

To begin, we define what we mean by a regression forecasting model. Using matrix notation, the standard multiple regression model is expressed as:

$$y = X\beta + \varepsilon \qquad [1]$$

where: $\boldsymbol{y}$, the dependent variable, is a (n x 1) vector of realizations of a random variable,
$\boldsymbol{X}$ is a (n x k) matrix of fixed observations on independent variables,
$\boldsymbol{\beta}$ is a (k x 1) vector of parameters to be estimated, and
$\boldsymbol{\varepsilon}$ is a (n x 1) vector of error terms.

A multiple regression forecasting model proceeds in two steps. In Step One, it takes some function f($\boldsymbol{y}$) of population change, and establishes a relationship between f($\boldsymbol{y}$) and the variables in the design matrix $\boldsymbol{X}$, which are carefully chosen covariates of f($\boldsymbol{y}$), such that unbiased and efficient estimates of the vector of parameters can be achieved using the least squares estimator:

$$\hat{\beta} = \left(X'X\right)^{-1} X'y \qquad [2]$$

By "carefully chosen" we mean that the independent variables are not highly intercorrelated, that they each are approximately linearly related to the dependent variable and that all variables are reasonably bell-shaped. The model must meet several other rather strict assumptions in order that the least squares estimates are unbiased and efficient. These are clearly spelled out in the standard regression and econometrics literature (see, for example, Draper & Smith 1998, Fox 1997, and Greene 2000). Our independent variables are fixed observations at time t, or observations over the interval (t-10, t), and the dependent variable is an observation for the period (t, t+10). In other words, our regression model establishes a set of relationships between growth over a decade (the dependent variable) with the growth over the preceding decade and several initial conditions at time t.

In Step Two, we use the relationships established in Step 1 and expressed in the estimates of the $\boldsymbol{\beta}$ vector, to update the independent variables for the decade (t, t+10), and other initial conditions at time t+10 to forecast population change over the decade (t+10, t+20). The critical assumption is that the relationships between the independent variables and dependent variable, established in the base period, remain relatively constant over time and can thus be used to forecast change in a decade ten years beyond the base period where the relationships (the estimated $\boldsymbol{\beta}$ vector) were established.

While the regression approach for population forecasting has been implements by a number of demographers, the interest in regression forecasting models appears to be on the decline for three reasons. First, the assumption that the parameters estimated from the regression model based on historic data remain constant into the future is of dubious validity, and surely will hold better for some time periods than others. Second, cohort component methods have long been preferred by demographers for population forecasting, especially for larger units of geography. Third, the most important reason is that regression forecasting models practically do not perform well. We argue, however, that another look at multiple regression approaches for small-area population forecasts is warranted and that such models can be improved in two ways by (1) including in the model a wider range of explanatory variables than has been done to date, and (2) incorporating spatial diffusion effects and other neighbor characteristics.

Population change

Existing regression forecast models build on theoretical foundations between population and relevant factors. However, these theories are taken inconclusively rather than conclusively. A major shortcoming of existing regression forecasts is that they generally ignore non-demographic factors that are part of the contextual region for which the population forecasts are made. Population growth or decline has causes and consequences closely tied to levels of economic development as well as to the nature of the surrounding natural environmental. These factors can and should be incorporated into multivariate regression models for population forecasting. In this study, we take regression model forecasting in new directions by including in our design matrix, $\boldsymbol{X}$, a number of nontraditional variables.

Theories in several disciplines have addressed population growth, and each of them has strengths and limitations in explaining population change. These disciplines include human ecology, population geography, regional economics, environmental sociology, and neo-Marxism. We argue that a systematic rather than incomplete examination of these theories can help researchers better understand population change.

In the field of human ecology, most models apply holistic-oriented approaches to study the relationship between population and the environment. However, familiar models such as the POET (Population, Organization, Environment, and Technology) model (Duncan 1964) and the IPAT (Impact, Population, Affluence, and Technology) model (Commoner 1972, 1992; Ehrlich & Ehrlich 1990; Ehrlich & Holdren 1971, 1972; Holdren & Ehrlich 1974) have been criticized for incorporating few variables. The recently developed ecological footprint method cannot be applied to small areas where data are not readily available (Chi & Stone 2005; Wackernagel & Rees 1996). Other complex models are rather descriptive and qualitative (Dietz & Rosa 1994).

Population geography seeks and explains population patterns caused by spatial processes (Clarke 1965; Jones 1990). Although population geography adopts GIS and multivariate regression models to study the spatial characteristics of population as well as the spatial processes involved, it often discards the socioeconomic considerations and environmental factors, and ignores the temporal dimension of population.

Regional economics is strong in explaining and modeling the change of land use patterns, which almost always associates with population change. For example, the new economic geography (Krugman 1991) specifically attempts to predict future land development patterns. On one hand, the fact that demographers focus on "population" and regional economists are interested in "employees" provides an opportunity for borrowing regional economic theories and models to improve population forecasts. On the other hand, the fact that population forecasts are based on census districts and regional economic studies are based on economic districts imposes difficulty on matching units of analysis.

Environmental sociology attempts to critique relevant theories and theorize population-environment issues within a political economy context (e.g., Barkin 1991; Dunlap & Catton 1978; O'Connor 1988, 1989; Schnaiberg 1980; Schnaiberg & Gould 1994). While environmental sociology considers variables that often cannot be easily represented and modeled, these variables should be applied to population forecasting models once the data are available. The neo-Marxist theory states that development patterns and related population change are the result of capital in pursuit of profit (Hall 1988). The strength of neo-Marxist theories in forecasting population lies in its theoretical interpretation solely, not modeling.

Although current regression approaches for population forecasting generally do consider numerous factors in explaining population change, these factors tend to be chosen by an unnecessarily narrow demographic perspective rather than a perspective informed by other theories and potential data sets. We argue that regression forecasting models should incorporate demographic characteristics, socio-economic characteristics, physical infrastructure, environmental characteristics, cultural resources, and potential legal constraints.

The most important demographic characteristics that affect small-area population growth are population density (Greenberg, Krueckeberg & Michaelson 1978; Herendeen 1973; Humphrey 1980; Humphrey & Sell 1975; Humphrey et al. 1977; Lutz 1994), age structure (Humphrey 1980; Humphrey & Sell 1975; Humphrey et al. 1977; Johnson 2001; Lutz 1994), race and ethnic composition (Friedman & Lichter 1998; Greenberg, Krueckeberg & Michaelson 1978; Johnson 2001; Stanbery 1952), and military, prison and college populations (Humphrey et al. 1977; Humphrey & Sell 1975; Smith, Tayman & Swanson 2000).

Second, socio-economic characteristics known to have important impacts on population change include levels of education (Stanbery 1952), income (Fuguitt, Brown & Beale 1989; Johnson 2001; Johnson & Beale 1994; Lyson & Gillespie 1995; Smith, Tayman & Swanson 2000), and employment (Fuguitt, Brown & Beale 1989; Herendeen 1973; Johnson 2001; Johnson 1982; Johnson & Beale 1994; Lyson & Gillespie 1995; Smith, Tayman & 2000), local efforts to expand services (Humphrey & Sell 1975; Johnson & Beale 1994), retail sales (Herendeen 1973; Johnson 1982), market conditions, and real estate values (Herendeen 1973).

Third, local levels of physical infrastructure development are hypothesized to influence population growth. Relevant factors include limited access highways (Chi, Voss & Deller 2004; Herendeen 1973; Humphrey 1980; Smith, Tayman & Swanson 2000), and sources of water and sewer (Stanbery 1952). Highways are believed to be an important variable (Voss & Chi 2004a). Traffic volume (Herendeen 1973; Hobbs & Campbell 1967), distance to access of highways (Herendeen 1973; Humphrey 1980; Smith, Tayman & Swanson 2000), time and transportation types (Greenberg, Krueckeberg & Michaelson 1978), and other infrastructure characteristics affect population growth differently in rural areas, urban areas and along the rural/urban fringe.

Fourth, environmental and natural resource characteristics are known to influence population growth. Elements include landfills and other noxious sites, and the nature of the geophysical environment. In recent decades, natural resource characteristics such as hydrography, topography, soils, and ground cover have been viewed as influences on population change mainly through the role of natural amenities. In recent decades especially the role of natural amenities is seen as the principal contributor of non-metropolitan population growth (Fuguitt 1977; Fuguitt & Brown 1990; Fuguitt & Beale 1976; Fuguitt, Brown & Beale 1989; Humphrey 1980; Johnson 1982, 1989, 2001; Johnson & Beale 1994; Johnson & Purdy 1980; Voss & Chi 2004b; Voss & Fuguitt 1979). Equilibrium theory argues that the main determinants of migration come from differences in amenities rather than differences in economic opportunities (Graves 1983, 1979; Graves & Linneman 1979; Smith, Tayman & Swanson 2000). The life-cycle literature suggests that amenity factors become more important as people become older (Clark & Hunter 1992; Smith, Tayman & Swanson 2000).

Finally, cultural and aesthetical resources affect development patterns and related population change when legal protections limit land development within such areas or encourage land development on the boundary of these areas via tourism. Moreover, land use planning legislation (such as comprehensive plans, smart growth laws, and zoning ordinances) have direct effect on land use as well as associated population change. However, the cultural and legal data are rarely available digitally or are not always easy to manipulate in regression analysis because of boundary incompatibilities.

Spatial effects

In addition to systematically examining the relationships between population change and known relevant factors, we incorporate spatial effects into the regression forecast model. Nearly all existing forecasting models for small areas, even though widely disparate in their individual methodologies, share a single common shortcoming. They treat each unit of geography (e.g., a census tract, a MCD, a small city) as an independent, stand alone entity rather than as an entity surrounded by other geographic areas with which they interact (e.g., through commuting patterns, shopping patterns, etc.). In fact, population growth in one unit of geography (the "focal" unit) can be shown to be correlated (autocorrelated) with its neighboring units. This observed pattern is supported by at least three schools of theories. Tobler (1970)'s First Law of Geography states that everything is related to everything else, but nearer ones do more so. The spatial diffusion theory of population geography argues that population growth will spread to surrounding areas (Boyce 1966; Morrill 1968; Thrall et al. 2001). It implies that population growth is spatially autocorrelated. Regional economic theories such as growth pole theory apply spread and backwash notions to explain the mutual geographic dependence of economic growth and development, which in turn causes population change (Hartshorn & Walcott 2000; Richardson 1976).

Since its inception a few decades ago, spatial statistics has been applied in numerous fields (Anselin 1988). However, it has drawn demographers' attention only recently, and existing applications of spatial statistics in demographic studies have been limited primarily to studies of violent crime (e.g., Tolnay, Deane & Beck 1996). These techniques have not yet found their way into population forecasting models to include "neighborhood effects" in regression models such that the forecast for a focal unit explicitly recognizes the forecasts (and possibly other covariates) for neighboring units. Because most existing spatial regression models incorporate the same-period spatial effects (same period as the dependent variable), they cannot be used to project future population. In this study, we propose a temporally lagged spatial regression model to overcome this challenge (see Model 3 and Model 4 in the section of Analytical Approaches).

Exclusions of alternative regression models from this study

It is important to point out that we deliberately are excluding from our specification of regression forecasting models those methods based on trend modeling (linear or quadratic regressions fit on a historical time series) as well as those methods based on adaptive smoothing, Box-Jenkins ARIMA modeling and the many related time-series approaches (see, for example, Box & Jenkins 1976, McCleary & Hay 1980, Swanson 2004, and Thomopoulos 1980). These approaches have been proposed and effectively used for population forecasting (Alho & Spencer 1997; Pflaumer 1992; Saboia 1974; Smith, Tayman & 2000), although the lack of systematic regularity in population time-series generally yields little beyond a trend forecast (and confidence intervals of dubious practical value).

Also excluded from further consideration in this paper are the post-censal population estimation models (e.g., the ratio-correlation method) that rely on contemporaneous systematic indicators for the regression-based estimate. We are consciously not including these models, as they are properly estimation models. The literature covering this regression approach to post-censal estimation is large (e.g., Feeney, Hibbs & Gillaspy 1995).

Data

Various data are used for each of the four population forecasting approaches discussed in the following section. Overall, the data include population data from decennial censuses 1960-2000, highway expansion data from 1970-90 at five-year intervals provided by the Wisconsin Department of Transportation, natural amenity characteristics provided by the Wisconsin Department of Natural Resources, and many socio-demographic and economic factors derived from the census data. The units of analysis are MCDs in Wisconsin.

The boundaries, and even the names, of MCDs in Wisconsin are not stable over time. Boundaries change, new MCDs emerge, old MCDs disappear, names change, and status in the geographic hierarchy shifts, e.g., towns become villages, villages become cities. In order to adjust the data for these changes, new MCDs must be merged into the original MCDs from which they emerge. Disappearing MCD problems can be solved by dissolving the original MCDs into their current "home" MCDs, and several distinct MCDs must be dissolved into one super-MCD in order to establish a consistent data set over time. In the end, 1,837 MCD-like units (cities, villages, and towns) constitute our analytical dataset (see Figure 1).

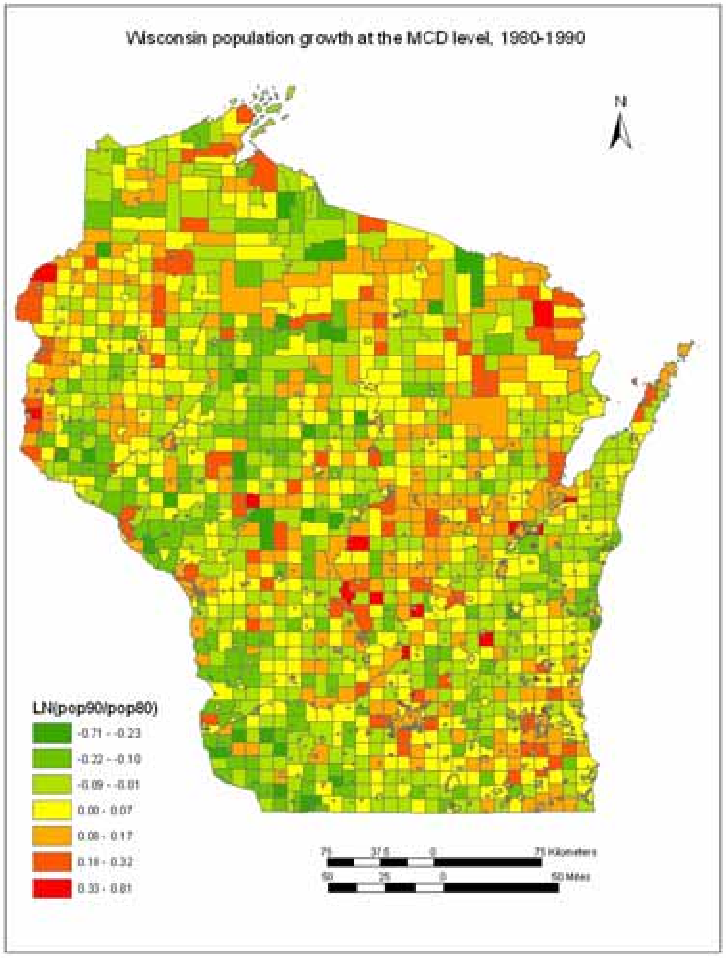


Figure 1. Population Change from 1980-90 in Wisconsin at the MCD level

Analytical Approaches

Four population forecast approaches are examined and compared in this analysis. They are: the extrapolation projections prepared by the DSC of the WIDOA, a standard (multivariate linear) regression approach, a regression approach incorporating spatial population effects, and a regression approach incorporating spatial population effects and other neighbor characteristics.

First, these four population forecast approaches are used to project the 2000 population for all MCDs in Wisconsin. Second, the MCD projected populations are proportionally adjusted so as to sum to their corresponding independently derived county population projections. Finally, the adjusted population projections are evaluated by comparing them to the actual 2000 population.

Four population forecast approaches

Model 1:Extrapolation population projection (EPP)

Population projections based on some form of extrapolation of the past into the future is an established and fundamental population forecast technique used for small geographic areas in many states for many years. For example, in 1993 the DSC of the WIDOA projected the

Wisconsin 2000 population at the MCD level using census population data from 1960, 1970, 1980, and 1990.

The first step of the EPP suggested by Voss and Kale (1985) is to calculate a weighted average annual population change rate (see Eq. 3):

$$G = \left[\frac{P_{90} - P_{80}}{10} + \frac{P_{90} - P_{70}}{20} + \frac{P_{90} - P_{60}}{30} \right] \Big/ 3 \qquad [3]$$

where G is the weighted average annual numerical population change, and P_{60}, P_{70}, P_{80}, and P_{90} are population counts from the corresponding census years. Because the formula calculates the average annual population change rate over three time periods, all ending in 1990, the more recent data have greater influence in the projection process.

The projected 2000 population equals the 1990 population plus 10 times G (see Eq. 4). These projections, based on the 1960-1990 data, were available to us. However, the way in which the boundaries of MCDs are adjusted by the DSC is not quite the same as our method. Therefore, in order to make the MCDs consistent for the four approaches, we modified the 2000 population projections by the DSC based on our adjusted boundaries.

$$P_{2000} = P_{90} + 10 \times G \qquad [4]$$

Model 2: Multivariate regression

For the following three population forecast approaches, we begin with a standard regression approach to model population change and then, in the latter two approaches, we modify the regression specification to include explicit spatial spillover effects using the tools of spatial econometrics (Anselin 1988). Model 2, as well as Model 3 (regression with spatial population effects) and Model 4 (regression with spatial population effects and other neighbor characteristics) in the following sub-sections, share similar procedures for projecting population. They differ only in the variables taken into account in the models. For all three regression models, we assume that the factors affecting population change have constant effects on population change over time. Therefore, we can first use historical data to estimate these effects, and then apply these effects (via the estimated parameters) to project future population. The detailed steps are illustrated in the following paragraphs.

The first step is to use a multivariate linear regression model to build relationships between population change and relevant covariates. As mentioned in the section of theoretical foundations of population change, many variables relate to population change, and many of them often are not adequately controlled in multivariate analyses (Lichter & Fuguitt 1980). A wide range of results is possible by omitting relevant variables from the model (Dalenberg & Partridge 1997; Mikelbank 1996). In the regression model, we attempt to incorporate all relevant variables derived from theories and empirical studies as long as the data availability allows. The dependent variable is a population growth rate, which is expressed as the natural log of the later census population over the earlier census population (i.e., 1990 population over 1980 population as shown in Figure 1) to achieve the desired bell-shaped distribution and better linearity with the independent variables. The independent variables include population growth rate 1970-1980, and 31 variables[4] from the 1980 Census, from data made available by the Wisconsin Department of Natural Resources, the Wisconsin Department of Transportation, and from other sources. Some of these independent variables are transformed in order to achieve maximum conformance to OLS assumptions. The estimation model (Model 2 Estimation) in matrix form is:

$$Ln\left(\frac{P_{90}}{P_{80}}\right) = \left[Ln\left(\frac{P_{80}}{P_{70}}\right) + X_{80}\right] \times \beta + \varepsilon \qquad [5]$$

X_{80}'s are the independent variables in 1980, and the β's are the corresponding coefficients expressing marginal relationships with the dependent variable. The intercept is excluded from the regression model. An intercept (the constant term) represents the overall growth rate, which is identical for all MCDs. However, the overall growth rate does change from decade to decade. Therefore, we should not incorporate the intercept in the regression model for population projection, instead we can force the overall growth rate into the coefficients of independent variables.

In the second step, insignificant independent variables, or those showing lower levels of significance, are discarded from the regression model, and this process continues until four or five variables are left in the model (population growth rate from the early decade is always kept due to its theoretical importance). There are two reasons for this step. One is that too many independent variables often raise the problem of serious and unnecessary multicollinearity which affects the efficiency of the multivariate regression model, and the other is that the too many variables influence the accuracy of forecasting and are not easily handled in forecasting (Armstrong 2001).

In the third step, we employ the variables derived from the second step to build a projection model (Model 2 Projection, Eq. 6), and the variables are represented using data for the period ten years later.

$$\widehat{\ln\left(\frac{P_{00}}{P_{90}}\right)} = \left[Ln\left(\frac{P_{90}}{P_{80}}\right) + X_{90}\right] \times \hat{\beta} \qquad [6]$$

X_{90}'s are the independent variables in 1990, and the $\hat{\beta}$'s are the estimated parameters from the second step. From the left-land term in Eq. 6, we can calculate the projected 2000 population.

Model 3: Regression with spatial population effects

Model 3 adopts the same approach as Model 2, except that the former includes a term representing neighbor population effects. To Model 2 we add a weighted neighbor population growth rate to the right side of the model.

In order to test for the neighborhood effect, spatial lag and spatial error models can be specified and estimated (see Voss & Chi 2004a). However, these Simultaneous Autoregressive Regression (SAR) models (Eq. 7) account for same-period spatial effects rather than temporally lagged spatial effects. For example, in the traditional SAR model, the weighted neighbor population growth rate in 1980-90 would be used as an independent variable to explain population growth rate in 1980-90. This imposes difficulty for population forecasting, because our goal is to project the future population rather than the same-period population. Thus, for all variables, we add their corresponding time-lagged variables to the right side of the model to make a full version of the spatio-temporal econometric model (Eq. 8)(Elhorst 2001). Since we cannot use the same-period (the projection year) data, we use the time-lagged variables. Deleting the same-period independent variables, we obtain a spatio-temporal econometric forecasting model (Eq. 9).

$$Y_t = X_t\beta + \rho WY_t - \rho WX_t\beta + \varepsilon \qquad [7]$$

$$Y_t = X_t\beta + \rho WY_t - \rho WX_t\beta + \tau_1 Y_{t-1} + X_{t-1}\tau_2 + \tau_3 WY_{t-1} + WX_{t-1}\tau_4 + \varepsilon \qquad [8]$$

$$Y_t = \tau_1 Y_{t-1} + X_{t-1}\tau_2 + \tau_3 WY_{t-1} + WX_{t-1}\tau_4 + \varepsilon \qquad [9]$$

For Model 3, we only add the weighted neighbor population growth rate one decade earlier to explain population growth rate. The estimation model then (Model 3 Estimation, Eq. 10) is:

$$Ln\left(\frac{P_{90}}{P_{80}}\right) = \left[Ln\left(\frac{P_{80}}{P_{70}}\right) + X_{80}\right] \times \beta + \lambda \times W \times Ln\left(\frac{P_{80}}{P_{70}}\right)_{neighbor} + \varepsilon \qquad [10]$$

Here we need pay attention to the weights (W). A spatial weights matrix is necessary for lattice data analysis, but there is scant theory by which to choose an optimal one for the neighborhood structure. The weights matrix is defined exogenously, and it behooves the analyst to compare several weights matrices in order to select a defensible one (Anselin 2002). Practically, we can create and compare several weights matrices, and select the optimal one based on the levels of the coefficient of spatial autocorrelation achieved, and on the levels of statistical significance attained (Voss and Chi 2004a). In an early study, the 7-nearest neighbor weights matrix was found to provide the highest spatial correlation of population growth out of 40 different types of weights matrices tested. We continue to use this weights matrix for this study. In fact, the k-nearest neighbor structures are often superior to distance and continuity weights in lattice data analysis (Anselin 2002).

Following Model 2, we assign the parameters estimated from the Model 3 Estimation into the corresponding projection model (Model 3 Projection, Eq. 11):

$$\widehat{Ln\left(\frac{P_{00}}{P_{90}}\right)} = \left[Ln\left(\frac{P_{90}}{P_{80}}\right) + X_{90}\right] \times \hat{\beta} + \hat{\lambda} \times W \times Ln\left(\frac{P_{90}}{P_{80}}\right)_{neighbor} \qquad [11]$$

Model 4: Regression with spatial population effects and other neighbor characteristics

Model 4 shares the approach adopted for Model 3, the only difference being that Model 4 takes into account one additional neighbor characteristic. This additional neighbor characteristic is selected by following the Model 2 procedures for choosing the best independent variables. In stepwise fashion, all the four independent variables representing neighbor characteristics are added to Model 3, and the four are iteratively tested and eliminated until one strong neighborhood effect remains. The Model 4 Estimation (Eq. 12) is specified as:

$$Ln\left(\frac{P_{90}}{P_{80}}\right) = \left[Ln\left(\frac{P_{80}}{P_{70}}\right) + X_{80}\right] \times \beta + \lambda_1 \times W \times Ln\left(\frac{P_{80}}{P_{70}}\right)_{neighbor} + \lambda_2 \times W \times (X_{80})_{neighbor} + \varepsilon \qquad [12]$$

Correspondingly the Model 4 Projection (Eq. 13) is specified as:

$$\widehat{Ln\left(\frac{P_{00}}{P_{90}}\right)} = \left[Ln\left(\frac{P_{90}}{P_{80}}\right) + X_{90} \right] \times \hat{\beta} + \hat{\lambda}_1 \times W \times Ln\left(\frac{P_{90}}{P_{80}}\right)_{neighbor} + \hat{\lambda}_2 \times W \times (X_{90})_{neighbor} \qquad [13]$$

Population projection adjustments

There are many steps to adjust populations projected from the four population forecast approaches, and the two major ones are modification of abnormal change rates, and adjustment to county projections (Wisconsin Department of Administration 2004; Voss & Kale 1986).

Modification of abnormal change rates

This step is to soften the occasional high population change rates that emerge when making small-area projections. It is anticipated that these adjustments will improve the overall performance of population forecast techniques (Voss & Kale 1985). If the population change rate in a MCD is unusually high relative to neighboring MCDs, the projected rate is softened under the assumption that a rapid population change may not be sustained for long. In order to identify unusually high population change rates (in absolute terms), an average annual population change rate for each MCD is determined by considering all MCDs in the county, and a mean and standard deviation (SD) of local change is obtained. If an MCD falls out of the range:

(Mean - 1.5*SD, Mean + 1.5*SD),

it will be adjusted to the nearer of either

Mean + 1.5*SD or Mean - 1.5*SD.

In addition, using these four basic models it is possible for a projected MCD population to be negative. In such instances, we adjust the MCDs' projected population to be zero at exactly 80 years later, which is the year of 2070. It prevents the population from becoming zero within the time frame of our projection horizon.

The modification of abnormal change rates was originally designed for the extrapolation projection, and is not well-appropriate for the regression approaches[5]. Nevertheless, in this study we apply this adjustment for all the four approaches for the purpose of comparing their performance.

Adjustment to county projections

The MCD projections are then further adjusted by comparing the sum of the MCD population projections with their parent county population projections. Empirically, county-level projections are more accurate than sub-county-level projections, and common practice is to control the sum of the MCD projections to a projection for the parent county.

In addition to the above steps, theoretically we need to consider yet further adjustments. First, if the projected population in any MCD seems unreasonable, it should be checked and/or adjusted again using uniform and sound procedures. Second, if a restriction to population growth is known, the projected population should be adjusted to conform to the restriction. Such restrictions are zoning restrictions, land use plans, or geophysical conditions that absolutely restrict or limit growth. These adjustments are not conducted in this analysis due to time constraints and the unavailability of data we are seeking to acquire.

Projection evaluations

There are a number of measures for evaluating the accuracy of population forecasts (Smith, Tayman & Swanson 2000), and two of the most commonly used measures are the Mean Percent Error (MPE) and the Mean Absolute Percent Error (MAPE). The MPE is a measure where the positive and negative values can offset each other, so it is used mainly as a measure of bias (Keilman 1999; Smith 1987; Tayman and Swanson 1996). A positive MPE indicates an over-projected population, and a negative MPE indicates an under-projected population (Eq. 14). In contrast, the MAPE is a measure where positive and negative values do not offset each other (Eq. 15). It indicates the average percent difference between the forecasted population and the actual population, regardless of over- or under-projection. The MAPE is used widely as a measure of forecast precision in evaluating population projections (Ahlburg 1982; Isserman 1977; Long 1995; Smith & Sincich 1992; Tayman & Swanson 1996). Both the MPE and the MAPE are calculated for all approaches, and are then compared.

$$MPE = \left(\frac{1}{n}\right) \times \sum \frac{\text{Forecasted population - Actual population}}{\text{Actual population}} \qquad [14]$$

$$MAPE = \left(\frac{1}{n}\right) \times \sum \left| \frac{\text{Forecasted population - Actual population}}{\text{Actual population}} \right| \qquad [15]$$

Findings

In Model 2, five independent variables are finally chosen for model estimation (Table 1), and they are: the log of 1980 population over 1970 population (lnpop7080), the log of population density in 1980 (lndns80), the square root of the proportion of young population aged 12-18 in 1980 (srpyng80), the square root of the median house value in 1980 (srhuv80), and the proportion of housing units 40 years and plus in 1980 (phu40yrs80). Model 3 has another independent variable, the weighted neighbor population growth rate from 1970 to 1980 (lnpop7080nhb). Model 4 has one more independent variable, the weighted neighbor's square root of the proportion of young population in 1980 (srpyng80nhb).

Table 1 summarizes the estimates of multivariate regression model, regression with spatial population effects, and regression with spatial population effects and other neighbor characteristics. All independent variables are significant in explaining population growth in all three models. The adjusted R-square, the likelihood statistic, and the Akaike Information Criterion (AIC) statistic indicate that Models 3 and 4 are better than Model 2 at the goodness-of-fit, and Model 4 outperforms Model 3. These measures of goodness-of-fit point out that the incorporation of spatial population effects and other neighbor characteristics does improve the estimation of the regression model.

All the three models have significant low Moran's I values for residuals, which do not signal any strong spatial autocorrelation. However, the robust Lagrange Multiplier (error and lag) tests indicate that there is spatial lag effect in Model 2, and spatial error effect in Model 3. Neither of them remains in Model 4. This again proves that Model 4 outperforms Models 2 and 3 in estimation.

The four approaches are then conducted for population projection. The results are evaluated and compared on the basis of whether adjustments are used or not. For the population projected in 2000, all three regression approaches slightly under-perform the traditional approach in terms of both MPE and MAPE (see Table 2). The projection's accuracy decreases as the complexity of the model increases, as indicated by their corresponding MPE and MAPE.

Table 1. Estimations of multivariate regression model, regression with spatial population effects, and regression with spatial population effects and other neighbor characteristics

	Model 2: multivariate regression		Model 3: regression with spatial population effects		Model 4: regression with spatial population effects and other neighbor characteristics	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
lnpop7080	0.135	0.000	0.105	0.000	0.092	0.000
lndns80	0.006	0.000	0.007	0.000	0.004	0.015
srpyng80	-0.356	0.000	-0.392	0.000	-0.705	0.000
srhuv80	0.001	0.000	0.001	0.000	0.000	0.000
phu40yrs80	-0.067	0.000	-0.039	0.022	-0.060	0.001
lnpop7080nhb	/	/	0.201	0.000	0.194	0.000
srpyng80nhb	/	/	/	/	0.415	0.000
Diagnostics						
Goodness-of-fit						
R-square adjusted	0.1791		0.2029		0.2200	
Likelihood	1446.26		1474.28		1485.77	
AIC	-2882.53		-2936.56		-2957.55	
Remaining spatial dependence						
Moran's I for residuals	0.079	0.00	0.073	0.00	0.079	0.00
Robust LM (error)	1.533	0.22	11.107	0.00	0.069	0.79
Robust LM (lag)	17.766	0.00	2.151	0.14	2.696	0.10

Table 2. Population projection into 2000 without adjustments

Without adjustments	Model 1: extrapolation projection	Model 2: multivariate regression	Model 3: regression with spatial population effects	Model 4: regression with spatial population effects and other neighbor characteristics
≤ -10%	34.35%	35.87%	42.79%	43.82%
-10% < ≤ -5%	19.11%	17.91%	19.76%	19.81%
-5% < < 0%	17.15%	19.27%	17.42%	17.15%
0% < < 5%	13.55%	12.96%	9.69%	9.20%
5% ≤ <10%	7.68%	5.66%	4.19%	4.25%
≥10%	8.17%	8.33%	6.15%	5.77%
MPE	-5.80%	-6.13%	-8.28%	-8.55%
MAPE	10.99%	10.97%	11.86%	12.03%

After conducting the adjustment procedures, all three regression approaches generate very similar MPE and MAPE (see Table 3). The regression approaches produce lower MPE (in an absolute term) and higher MAPE than the extrapolation approach. It indicates that regression approaches are less biased but also less precise than the extrapolation approach. In addition, the increasing complexity of the models results in more exactly projected population (error = 0%).

Table 3. Population projection into 2000 with adjustments

With adjustments	Model 1: extrapolation projection	Model 2: multivariate regression	Model 3: regression with spatial population effects	Model 4: regression with spatial population effects and other neighbor characteristics
≤ -10%	27%	29.01%	29.18%	28.85%
-10% < ≤ -5%	17.53%	16.06%	16.60%	16.71%
-5% < < 0%	20.63%	19.11%	17.58%	17.80%
0%	0%	0.33%	0.38%	0.49%
0% < < 5%	15.41%	13.72%	14.26%	14.70%
5% ≤ <10%	10.13%	9.04%	9.09%	8.76%
≥10%	9.31%	12.74%	12.90%	12.68%
MPE	-3.65%	-3.38%	-3.39%	-3.34%
MAPE	9.63%	10.79%	10.78%	10.78%

Figure 2 illustrates the geographic patterns of population projection errors. Each of the four approaches tends to over- and under-project population in the same geographic manners. While our spatio-temporal model eliminates spatial autocorrelations in the estimation model, it does not in the projection model.

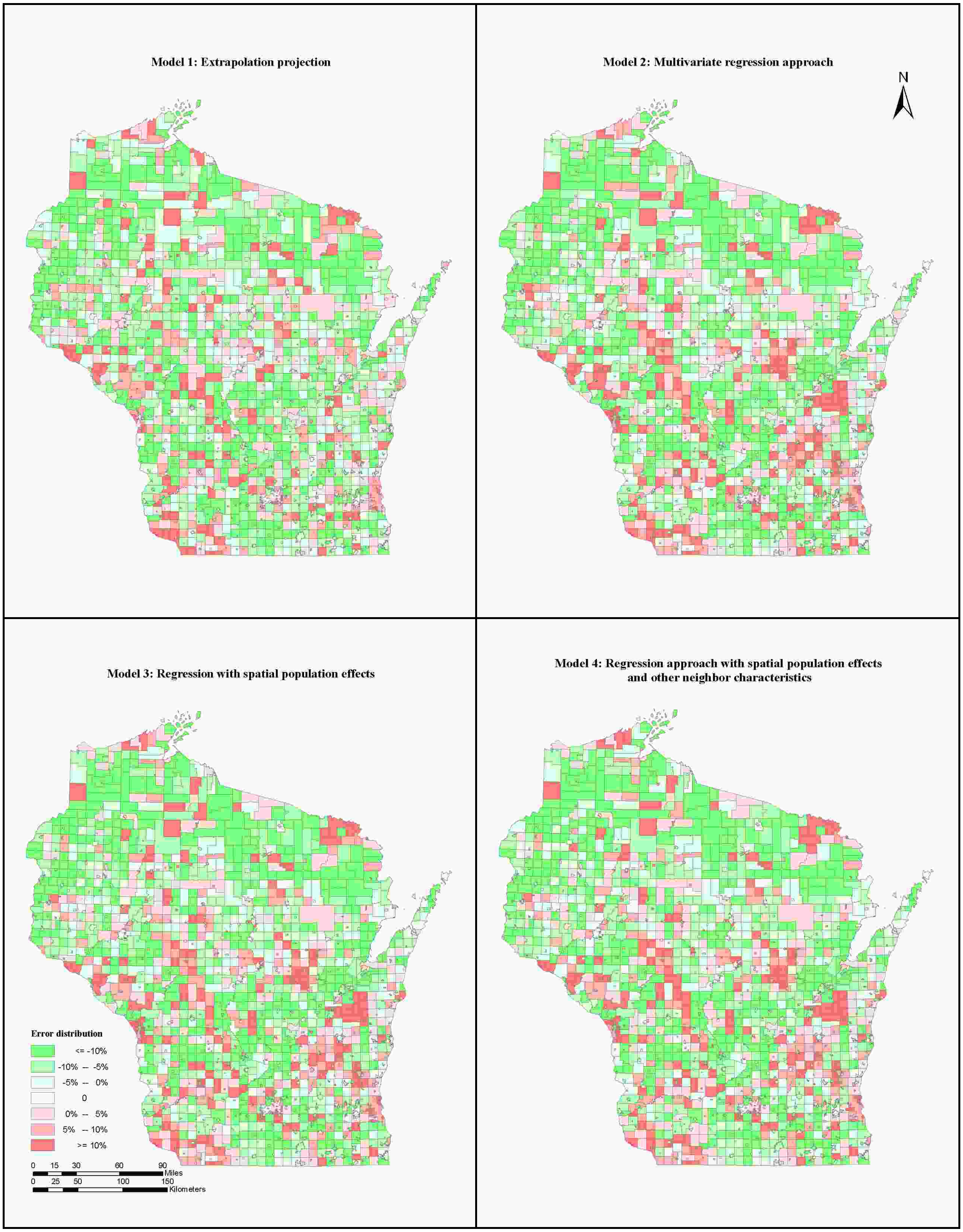
Summary

Overall, the regression approaches do not provide significant advantages over the traditional population forecasting approach. Without projection adjustments, the regression models that incorporate spatial effects under-perform the extrapolation projection in terms of bias and precision. However, after adjusting the projections, regression with spatial population effects and other neighbor characteristics does slightly improve population projection. Therefore, then, the projection evaluations do not suggest unambiguously a clear preference for regression approaches over the extrapolation projection.

This bothers us since sound theoretical foundations support our spatio-temporal model. The findings disagree with our assumption that geophysical factors and spatial effects are important in predicting population at small scales. As a consequence, in further studies we want to make the unit of analysis smaller and bring more environmental and geophysical factors into the model to make this approach work, because we still believe that as the units of analysis become smaller, non-demographic factors and spatial effects become more important in projecting population. We believe that further exploration of such an approach can provide a sound alternative for small-area population projection.

This study attempts to provide a nascent spatio-temporal approach by taking a theory-based (inductive) approach, rather than a data-driven (deductive) one for population forecasting.

Figure 2. Error distributions of population forecasts



Our synthetic examination of population-related theories suggests strong correlations between population and socio-economic and environmental factors, as well as spatial effects. This study 1) offers potential improvements to population forecasting techniques, 2) revises conventional spatial econometric models to a spatio-temporal one for forecasting purposes, and 3) attempts to meet policy demands on population forecast techniques.

Although the proposed spatio-temporal regression approach for small-area population forecasting does not outperform extrapolation population projection, this analysis contributes to two aspects of population forecasting techniques. First, the spatio-temporal regression approach improves the estimation of the traditional multivariate regression approach for projecting population, by incorporating spatial population effects and other neighbor characteristics. Second, this article provides a holistic theory-based approach for population forecasting. It builds on the theoretical foundations, which hypothesize strong correlations between population and environmental factors (a general term, including socio-economic factors and environmental factors). Existing multivariate regression approaches often choose only some relevant variables based on theories and empirical studies incompletely. We argue, however, such an approach is not enough for finding the best variables in population forecasting. Cohen (1995) recognizes that population forecast is a complex work and forecast accuracy is far from enough. The reason is that there are huge variables in affecting population change. Although recognizing the role of population growth in this network, unfortunately, demographers especially applied demographers have not implemented this approach to do their homework – population forecasting, because the complexity demands advanced statistical and spatial analysis tools.

On the methodological perspective, we propose to replace the same-period spatial effects with the temporally-lagged spatial effects. Such an approach is theoretically reasonable. More important, it makes population forecast conductible. On the legislation perspective, we attempt to propose an approach to meet policy demands on population forecast techniques. The recent "Smart Growth" law requires local governments involved in comprehensive planning to prepare a set of demographic forecasts (State of Wisconsin 1999). However, existing small-area population forecasting techniques have been used for several decades are not very impressive. Although the proposed approach is not superior to existing extrapolation population projection in this analysis, further exploration of spatial regression approach for population forecasting may produce attractive findings, given the strong theoretical foundations.

Notes

[1] In this study, small areas refer to any geographic units below county. Some examples are MCDs, census tracts, block groups, partial block groups, and blocks.

[2] The neighborhood context is not wholly ignored in traditional models given that controls to higher geography are usually applied. For instance, the MCD populations projected by extrapolation are often adjusted by comparing to their parent county population projections. However, this neighborhood context is different from the spatial population effects and other neighbor characteristics that we have examined in our model. See the Analytical Approaches section for detailed explanations.

[3] We use "forecast" and "projection" interchangeably in this article, and we do recognize their difference. A projection embodies one or more assumptions, and a forecast is a projection that is most likely to occur based on judgments.

[4] An extensive review of the relevant literature results in more than 31 variables that significantly affect population change theoretically or empirically. These 31 variables are chosen for this research on the basis of a combination of judgment established theoretical or empirical relationships, and the availability of data. They are: the natural log of population density, square root of the proportion of young population (Age 12-18), square root of the proportion of old population (Age 65+), square root of the proportion of black population, square root of the proportion of hispanic population, square root of the proportion of college population, the proportion of population (Age 25+) who finished high school, square root of the proportion of population (Age 25+) with Bachelor's degree, the proportion of non-movers(Age 5+), square root of the proportion of families headed by female with children under 18 years old, square root of median household income, square root of unemployment rate, square root of the proportion of workers in retail industry, square root of the proportion of workers in agricultural industry, square root of the proportion of workers using public transportation to work, square root of the proportion of workers traveling 30 minutes and over to work, square root of median house value, the proportion of housing units 40 years +, square root of the proportion of seasonal housing units, the proportion of housing units using public water, the proportion of housing units using public sewer, county seat or not, having urban buses in May 2001 or not, square root of total lengths of major roads, natural amenity more on river lengths and proportion of forest areas, natural amenity more on proportion of water areas, dummy north rural areas, MCDs within 10 miles of highway expansion finished 5 years before population change period, MCDs at a range of 10-20 miles from highway expansion finished 5 years before population change period, MCDs within 10 miles of highway expansion finished just before population change period, and MCDs at a range of 10-20 miles from highway expansion, finished just before population change period.

[5] A comparison of the three regression approaches' performance with to without the modification of abnormal change rates indicates that such a modification improves the regression models very negligibly for population forecasting.

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References

Ahlburg, D. (1982). How accurate are the US Bureau of the Census projections of total live births, *Journal of Forecasting* 1:365-374.

Alho, J. & Spencer, B. (1997). The practical specification of the expected error of population forecasts, *Journal of Official Statistics* 13:203-225.

Anselin, L. (1988). *Spatial econometrics: Methods and models*. Dordrecht, the Netherlands: Kluwer Academic Publishers.

———. (2002). Under the hood: Issues in the specification and interpretation of spatial regression models, *Agricultural Economics* 27:247-267.

Armstrong, J.S. (2001). Standards and practices for forecasting, pp. 679-732, in: J. S. Armstrong (eds.), *Principles of Forecasting: A handbook for researchers and practitioners*. Boston: Kluwer Academic Publishers.

Barkin, D. (1991). State control of the environment: Politics and degradation in Mexico, *Capitalism, Nature, Socialism* 2:86-108.

Box, G.E.P. & Jenkins, G.M. (1976). *Time series analysis: Forecasting and control*. San Francisco, CA: Holden-Day.

Boyce, B.N. (1966). The edge of the Metropolis: The Wave Theory analog approach, *British Columbia Geographical Series* 7:31-40.

Chi, G. & Stone, B. (2005). Sustainable transportation planning: Estimating the ecological footprint of vehicle travel in future years, *Journal of Urban Planning and Development* 131(3):xxx-xxx.

Chi, G., Voss, P.R. & Deller, S.C. (2004). Reviewing the causality between highway expansion and population change. Paper read at the annual meeting of the Mid-Continent Regional Science Association, June 3-5, 2004, at Madison, WI.

Clark, D. & Hunter, W. (1992). The impact of economic opportunities: Choosing the optimal distance to move, *Journal of Regional Science* 36:235-256.

Clarke, J.I. (1965). *Population geography*. Oxford: Pergamon.

Cohen, J. (1995). *How many people can the earth support?* New York, NY: W.W. Norton & Company.

Commoner, B. (1972). The environmental cost of economic growth, pp. 339-363, in: *Population, resources and the environment*. Washington, DC: Government Printing Office.

———. (1992). *Making peace with the planet*. New York: The New Press.

Dalenberg, D.R. & Partridge, M.D. (1997). Public infrastructure and wages: Public capital's role as a productive input and household amenity, *Land Economics* 73 (2):268-284.

Draper, N.R. & Smith, H. (1998). *Applied regression analysis*. New York, NY: John Wiley &Sons, Inc.

Dietz, T. & Rosa, E.A. (1994). Rethinking the environmental impacts of population, affluence and technology, *Human Ecology Review* 1 (2):277-300.

Duncan, O.D. (1964). From social system to ecosystem, *Sociological Inquiry* 31:140-149.

Dunlap, R.E. & Catton, W.R. (1978). Environmental sociology: A new paradigm, *American Sociologist* 13:41-49.

Ehrlich, P.R. & Ehrlich, A.H. (1990). *The population explosion*. New York: Simon and Schuster.

Ehrlich, P.R. & Holdren, J.P. (1971). Impact of population growth, *Science* 171 (3977):1212-1217.

———. (1972). Impact of population growth, pp. 365-377, in: *Population, resources and the environment*. Washington, DC: U.S. Government Printing Office.

Elhorst, J.P. (2001). Dynamic models in space and time, *Geographical Analysis* 33 (2):119-140.

Feeney, D., Hibbs, J. & Gillaspy, R.T. (1995). Ratio-correlation method, pp. 118-136, in: N. W. Rivers, W. J. Serow, A. S. Lee, H. F. Goldsmith and P. R. Voss (eds.), *Basic methods for preparing small-area population estimates*. Madison, WI: University of Wisconsin-Madison/Extension.

Fox, J. (1997). *Applied regression analysis, linear models, and related methods*. Thousand Oaks, CA: SAGE Publications.

Friedman, S & Lichter, D.T. (1998). Spatial inequality and poverty among American children, *Population Research and Policy Review* 17:91-109.

Fuguitt, G.V. & Brown, D. (1990). Residential preferences and population redistribution, *Demography* 27:589-600.

Fuguitt, G.V. (1977). Recent trends in nonmetropolitan net migration. Paper read at the Annual Meeting of the American Association for the Advancement of Science, February 23, 1997, at Denver, Colorado.

Fuguitt, G.V. & Beale, C.L. (1976). Popualtion change in nonmetropolitan cities and towns. Washington, D.C.: Economic Research Service, U.S. Department of Agriculture.

Fuguitt, G.V., Brown, D.L. & Beale, C.L. (1989). *Rural and small town America*. New York: Russell Sage Foundation.

Graves, P. (1979). A life-cycle empirical analysis of migration and climate by race, *Journal of Urban Economics* 6:135-147.

———. (1983). Migration with a composite amenity, *Journal of Regional Science* 23:541-546.

Graves, P. & Linneman, P. (1979). Household migration: Theoretical and empirical results, *Journal of Urban Economics* 6:383-404.

Greenberg, M.R., Krueckeberg, D.A. & Michaelson, C.O. (1978). *Local population and employment projection techniques*. New Brunswick, NJ: Center for Urban Policy Research.

Greene, W.H. (2000). *Econometric analysis*. 4th ed. Upper Saddle River, NJ: Prentice-Hall, Inc.

Hall, P. (1988). The city of theory, pp. 391-393, in: R. LeGates and F. Stout (eds.), *The city reader*. New York, NY: Routledge.

Hartshorn, T.A. & Walcott, S.M. (2000). The three Georgias: Emerging realignments at the dawn of the new millennium, *Southeastern Geographer* 41 (2):127-150.

Herendeen, J.H. (1973). Quantitative evaluation of the relationship between the highway system and socio-economic changes in non-urban areas. Dissertation, Department of Civil Engineering, the Pennsylvania State University.

Hobbs, D.J. & Campbell, R.R. (1967). Traffic flow and population change, *Business and Government Review* (May/June):5-11.

Holdren, J.P. & Ehrlich, A.H. (1974). Human population and the global environment, *American Scientist* 62:282-292.

Humphrey, C.R. (1980). The promotion of growth in small urban places and its impact on population change, *Social Science Quarterly* 61:581-594.

Humphrey, C.R. & Sell, R.R. (1975). The impact of controlled access highways on population growth in nonmetropolitan communities, 1940-1970. Working Paper. University Park, PA: Population Issues Research Office, the Pennsylvania State University.

Humphrey, C.R., Sell, R.R., Krout, J.A. & Gillaspy, R.T. (1977). Net migration turnaround in Pennsylvania nonmetropolitan Minor Civil Divisions, 1960-1970, *Rural Sociology* 42 (3):332-351.

Isserman, A. (1977). The accuracy of population projections for subcounty areas, *Journal of the American Planning Association* 50:208-221.

Johnson, K.M. (1982). Organization adjustment to population change in nonmetropolitan America: A longitudinal analysis of retail trade, *Social Forces* 60 (4):1123-1139.

———. (1989). Recent population redistribution trends in nonmetropolitan America, *Rural Sociology* 54 (3):301-326.

———. (2001). More coffins than cradles: the continuing high incidence of natural decrease in American counties. Paper read at the Annual Meeting of the Rural Sociological Society, at Albuquerque, NM.

Johnson, K.M. & Beale, C.L. (1994). The recent revival of widespread population growth in nonmetropolitan areas of the United States, *Rural Sociology* 59 (4):655-667.

Johnson, K.M. & Purdy, R.L. (1980). Recent nonmetropolitan population change in fifty-year perspective, *Demography* 17 (1):57-70.

Jones, H.R. (1990). *Population geography*. New York, NY: The Guilford Press.

Keilman, N. (1999). How accurate are the United Nations world population projections? pp. 15-41, in: D. Ahlburg (eds.), *Frontiers of population forecasting*. New York: The Population Council.

Krugman, P. (1991). *Center and periphery, geography and trade*. Boston, MA: MIT Press.

Lichter, D.T. & Fuguitt, G.V. (1980). Demographic response to transportation innovation: The case of the interstate highway, *Social Forces* 59 (2):492-512.

Long, J. (1995). Complexity, accuracy, and utility of official population projections, *Mathematical Population Studies* 5:203-216.

Lutz, W. (1994). Population and environment - What do we need more urgently: Better data, better models, or better questions? pp. 47-62, in: B. Zaba & J. Clarke (eds.), *Environment and population change*. Liege: Derouaux Ordina Editions.

Lyson, T.A. & Gillespie, G.W. (1995). Producing more milk on fewer farms: Neoclassical and neostructural explanations of changes in dairy farming, *Rural Sociology* 60 (3):493-504.

McCleary, R. & Hay, R.A. (1980). *Applied time series analysis for the social sciences*. Landon, England: Sage Publications.

Mikelbank, B.A. (1996). The distribution and direct employment impacts of public infrastructure investment in Ohio. Paper read at the annual meeting of the Mid-continent Regional Science Association, June 7, 1996, at Madison, WI.

Morrill, R.L. (1968). Waves of spatial diffusion, *Journal of Regional Science* 3:1-17.

O'Connor, J. (1988). Capitalism, nature, socialism: A theoretical introduction, *Capitalism, Nature, Socialism* 3:93-106.

———. (1989). Political economy of ecology of socialism and capitalism, *Capitalism, Nature, Socialism* 3:93-106.

Pflaumer, P. (1992). Forecasting U.S. population totals with the Box-Jenkins approach, *International Journal of Forecasting* 8:329-338.

Pittenger, D.B. (1976). *Projecting state and local populations*. Cambridge, MA: Ballinger Publishing Company.

Richardson, H. (1976). Growth pole spillovers: The dynamics of backwash and spread, *Regional Studies* 10:1-9.

Saboia, J. (1974). Modeling and forecasting populations by time series: The Swedish case, *Demography* 11:483-492.

Schmitt, R.C. (1953). A new method of forecasting city population, *Journal of the American Institute of Planners* 19 (1):40-42.

———. (1954). A method of projecting the population of census tracts, *Journal of the American Institute of Planners* 20 (2):102.

Schnaiberg, A. (1980). *The environment: From surplus to scarcity*. New York: Oxford University Press.

Schnaiberg, A. & Gould, K.A. (1994). *Environment and society: The enduring conflict*. New York: St. Martin's Press.

Smith, S.K. (1987). Tests of forecast accuracy and bias for county population projections, *Journal of the American Statistical Association* 82:991-1003.

Smith, S.K. & Sincich, T. (1992). Evaluating the forecast accuracy and bias of alternative population projections for States, *International Journal of Forecasting* 8:495-508.

Smith, S.K., Tayman, J. & Swanson, D.A. (2000). *State and local population projections: Methodology and analysis*. New York: Kluwer Academic/Plenum Publishers.

Stanbery, V.B. (1952). *Better population forecasting for areas and communities: A guide book for those who make or use population projections*. Washington D. C.: Superintendent of Documents, U.S. Government Printing Office.

State of Wisconsin. (1999). *1999 Wisconsin Act 9*. Retrieved 06/08/2005 (http://www.legis.state.wi.us/1999/data/acts/99Act9.pdf).

Swanson, D.A. (2004). Advancing methodological knowledge within state and local demography: A case study, *Population Research and Policy Review* 23:379-398.

Tayman, J. & Swanson, D.A. (1996). On the utility of population forecasts, *Demogrpahy* 33:523-528.

Thomopoulos, N.T. (1980). *Applied forecasting methods*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Thrall, G.I., Sidman, C.F., Thrall, S.E. & Fik, T.J. (2001). The cascade GIS diffusion model for measuring housing absorption by small area with a case study of St. Lucie County, Florida, *The Journal of Real Estate Research* 8 (3):401-420.

Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region, *Economic Geography* 46:234-240.

Tolnay, S.E., Deane, G. & Beck, E.M. (1996). Vicarious violence: Spatial effects on Southern lynchings, 1890-1919, *American Journal of Sociology* 102 (3):788-815.

Voss, P.R. & Chi, G. (2004a). On the causality between highway expansion and population change: A spatial multivariate regression analysis, *Applied Demography* 17:5-6.

--------. (2004b). Mover-stayer model within a hierarchical regression approach. Paper read at the annual meeting of the Southern Demographic Association, October 14-16, 2004, at Hilton Head Island, SC.

Voss, P.R. & Fuguitt, G.V. (1979). *Turnaround migration in the Upper Great Lakes region*. Working report. Madison, WI: University of Wisconsin-Madison.

Voss, P.R. & Kale, B.D. (1985). Refinements to small area population models: Results of a test based on 128 Wisconsin communities. Paper read at the Annual Meeting of Population Association of America, March 28-30, 1985, at Boston, MA.

———. (1986). *Wisconsin small-area baseline population projections*. Working report. Madison, WI: Applied Population Laboratory, and Demographic Services Center.

Wackernagel, M. & Rees, W. (1996). *Our ecological footprint: Reducing human impact on the earth*. Garbriola Island, Canada: New Society Publishers.

Wisconsin Department of Administration. (2004). *Methodology for developing Minor Civil Division projections*. Retrieved 06/08/2005 (http://www.doa.state.wi.us/pagesubtext_detail.asp?linksubcatid=105&linkcatid=11&linkid=7).