

USING LAND-USE MODELLING TO STATISTICALLY DOWNSCALE POPULATION PROJECTIONS TO SMALL AREAS

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ABSTRACT: This paper demonstrates a novel approach to small-area population projection that combines cohort-component projections, at the district level, with grid-based land use projections at a fine (four-hectare) geographical scale. Residential population is directly estimated in the land use model, while a separate statistical model is used to link non-residential population to non-residential land use (by type). The model projects future small-area populations using projections of future land use from the land use model. Four data and model specifications for the statistical modelling are compared. Overall, this model is useful because it generates greater stakeholder ‘buy-in’ than black-box or naïve approaches.

KEY WORDS: Population projections; small-area projections; forecasting; land use.

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1. INTRODUCTION

Local government planners, property developers, real estate agents, large businesses and other stakeholders need good projections or forecasts of the future spatial distribution of population for planning purposes (Foss, 2002). Indeed, Myers (2001, p.384) notes that “planning analysts regard population statistics as integral to virtually all aspects of planning”. This includes planning for future land developments, schools, hospitals, child care centres, care services for elderly people, traffic flows, electorate boundaries, and so on. In the case of local government, this need for good data is often reinforced by legislation that increasingly calls for fiscal sustainability. For instance, the recently amended *Local Government Act 2002* in New Zealand, requires territorial and local authorities to engage in asset management planning with a fifty-year time horizon. In order to develop detailed asset management plans, local governments therefore need a good understanding of future population growth, not only in total but for particular localities within their districts or regions.

The risks to planners of planning on the basis of an inaccurate forecast of the future population distribution can be large. An overestimate of future population growth for a particular area will induce over-investment in infrastructure (such as roads, water and other utilities) with resultant costs on the local authority. These costs may be able to be passed onto private sector developers but, if not, they will be borne by local ratepayers. On the other hand, an underestimate of future population growth will lead to infrastructure being insufficient to meet the needs of the population, with costs (in terms of congestion or shortages of services) borne by the local populations. While accuracy is only one of several criteria on which small-area population forecasts might be judged (Tayman and Swanson, 1996; Tayman, 2011), from the perspective of local authority planners the need for accurate and timely population forecasts is clear.

A range of government and non-government organisations (typically academics or consultants) produce population projections. The projection assumptions that will lead to the most accurate forecast of future population are unknown (and some might argue, unknowable). This means that all forecasts of future population will be subject to error. The magnitude of forecast error tends to be substantially larger for areas with small populations, in comparison with more populous areas (Cameron and Poot, 2011), which poses a particular problem for those interested in the distribution of population over small areas. Moreover, the methods for projecting population at small-area level are under-developed relative to projection methods for larger areas, although research in this area has

increased recently (Chi, 2009; Chi *et al.*, 2011). In particular, it is unclear whether modellers should adopt a top-down approach to population projections (projecting large areas such as the national population first, followed by sequentially smaller component areas) or a bottom-up approach (projecting small areas first; then deriving projections for larger areas by summing the projections of their component small areas).

In this paper, a novel approach is adopted that uses a top-down cohort component population projection to define a district-level population, and then allocates the population spatially to small areas using statistical downscaling based on a model of land use. Statistical downscaling refers to using statistical methods to interpolate regional-scale variables to smaller geographical scales, and is widely used in the climate change literature (e.g. see Kim *et al.* (1984) for an early application). Four different model specifications based on land use are developed, and then compared with two naïve projections. The remainder of the paper proceeds as follows. First, the range of approaches that have been applied to the projection of population for small areas are described, and the strengths and weaknesses of each approach are outlined. Second, the study area and the projection model are described, as well as the method for evaluating the in-sample and out-of-sample forecasting performance of the model. Third, the results of the evaluation are presented. Finally, the implications of the results for the use of similar models in local authority planning are discussed.

2. SMALL-AREA POPULATION PROJECTIONS

A variety of methods have been applied by demographers and population modellers to develop small-area population projections to satisfy planning needs. These methods can be generally categorised into four types: (1) naïve models, e.g. extrapolation, or growth share models; (2) the ‘traditional’ demographic cohort component model; (3) statistical methods, using data such as building consents; and (4) urban growth modelling approaches. While there may be some overlap between these methods, and it is possible (and sometimes desirable) to combine approaches, the following paragraphs discuss the relative strengths and weaknesses for local authority planning of each of these methods separately.

Naïve models are essentially simple extrapolations of past populations. The simplest of these models involve an assumption of no population change (i.e. constant population), linear population growth based on past growth trends, and exponential growth (i.e. constant population growth rates) based on past growth trends. Slightly more sophisticated are growth

share models, which are top-down models where the population is initially projected at a higher geographical level, and then that projected growth is shared between the different small areas. For example, the total population for a state or county may be projected first, and then the growth share model used to allocate the state- or county-level population to the census tract level.

Naïve models tend to perform reasonably well, in terms of forecast accuracy, when compared with more sophisticated models (van der Gaag *et al.*, 2003). Wilson (2015a) tests a wide array of these naïve models for small areas in Australia, England/Wales, and New Zealand. He finds that, in terms of individual models, a constant share of population (CSP) model works best (smallest error) for England/Wales, and a variation on a constant share of growth (CSG+) model works best for Australia and New Zealand. Following White (1954), the CSG+ model assumes a constant share of growth for those areas that experienced positive population growth in the base period (i.e. just before the start of the projection), and no growth for areas that declined in population in the base period. Within the class of naïve models, more sophisticated models are not necessarily always better. For instance, Rayer and Smith (2010) have found linear extrapolation to be more accurate than growth share models for sub-county areas in Florida. However, naïve models have practical limitations. First and foremost, they lack a strong theoretical basis. The purely mechanistic and deterministic application of past time trends into the future may be appropriate for small areas that have stable and predictable growth paths, but most small areas are subject to unexpected changes in population. By ignoring the demographic or urban/land use drivers of population change (that the more sophisticated models outlined below feature), these models will fail to adequately account for changes in these drivers. On a related note, because local contextual factors are not incorporated into the model, naïve models of population change are difficult to justify to planners or, importantly, to elected officials. This is because there are no mechanisms for local policy to affect the future population distribution. This can lead to a lack of ‘buy-in’ from important end-users of the projections.

The traditional workhorse of demographic projections is the cohort component model (CCM). In the CCM the population is projected by first projecting the three components of population change: (1) births, typically projected by means of age-specific fertility rates applied to women of childbearing ages; (2) deaths, typically projected by means of age-sex-specific mortality (or its complement, survivorship) rates applied to the population of each age and sex; and (3) migration, which may be projected in a number of different ways (van der Gaag *et al.*, 2003).

The advantage of the CCM is that all of the demographic drivers of population change are explicitly included in the model, because the CCM formula is an identity. Depending on the process used for modelling each component, other known drivers of population change can be explicitly included through their influences on fertility, mortality, and/or migration. Because the drivers are included, the CCM is typically intuitively understandable for local authority planners and elected officials.

However, at small-area levels, the CCM faces significant challenges. First, the data necessary for deriving assumptions about future fertility, mortality and migration may not be available at small geographical scales (Wilson, 2015b). Where these data are available, data quality or precision may be so low that it may be difficult to derive robust age-specific rates for each component (fertility, mortality, inward and outward migration) at local levels (Wilson, 2015b; Tayman *et al.*, 1998). For instance, age-sex-specific data are typically required to estimate fertility and mortality rates. At the small-area level, the counts of births and deaths that occur each year (particularly when you consider age-specific counts) are small and highly variable, such that the estimation of fertility and mortality rates becomes extremely challenging.

Second, despite the promise that incorporating drivers of each component (fertility, mortality, migration) holds, most CCM models fail to adequately take account of a myriad of socio-economic, infrastructural, physical land use and other contextual factors that exert substantial influence over the spatial allocation of population and households at smaller geographical levels. Typically, these factors are excluded due to data unavailability and the inability to reliably forecast them. Contextual factors matter much more at the local level, such as the availability of suitable land, services and amenities, and the plans of public and private land developers (Murdock *et al.*, 1991). In particular, land use and availability constraints, planning constraints, and the availability of infrastructure are all variables that local authority planners would expect to impact on the future population distribution at the small-area level.

Of course, the quantitative test of the CCM is whether it outperforms other models in evaluations of small-area projections. Unfortunately, past studies have shown that CCMs do not outperform simpler methods in projecting small area populations (Smith, 1997; Smith and Tayman, 2003). Statistical models offer one way to include the important contextual variables that are absent from the naïve models, and often missing from CCM models. For instance, regression models have become increasingly common in small-area projections (Alho and Spencer, 2005), including

more recently spatial regression models (Chi *et al.*, 2011). Spatial regression models may be preferred over aspatial models because the effects of the characteristics and contexts of neighbouring areas may also be important drivers of population change in each small area (Chi *et al.*, 2011), and traditional regression models are unable to account for all of the spatial interactions (Lesage and Pace, 2009). For example, Chi *et al.* (2011) used spatial lag models to derive population projections for census tracts in Milwaukee, Wisconsin.

However, as with the limitation for including more detailed population drivers within CCM models, data availability may be a serious issue, and all data that is used within the statistical model must also be projected. Statistical models also suffer from a range of well-recognised issues, including temporal instability of coefficients and over-fitting (Tayman and Schafer, 1985). Finally, like CCM models, statistical models have not been demonstrated to outperform even simple models of small-area populations in terms of forecast accuracy, even when the statistical model includes spatial interactions. For instance, Chi *et al.*, (2011) found that their spatial lag model for Milwaukee did not unambiguously outperform projections derived from simple extrapolation methods.

The final category of small-area projection models is models based on urban growth modelling approaches, including: (1) Cellular Automata (CA) modelling; (2) Artificial neural networks; (3) Fractal modelling; (4) Agent-based modelling; and (5) Decision-trees modelling. CA modelling involves separating each area into a grid of cells, each of which has a number of characteristics (which may include population size). In each time step of the model, each cell may change its characteristics in response to shifts in the characteristics of neighbouring cells and changes in the nature of the system as a whole (see also the description of the land use model in the following section). These urban growth modelling methods are described and reviewed in detail by Triantakonstantis and Mountrakis (2012). The advantages of urban growth modelling approaches include a much stronger theoretical base than statistical modelling, and that these models are able to more explicitly account for the local socio-economic conditions and physical and planning constraints at the small-area level. However, the limitations of urban growth modelling approaches are similar to those for statistical models, including high data requirements.

An alternative to applying one of the four approaches above is to combine two or more approaches in order to leverage their particular strengths, and attempt to address their limitations. One increasingly common combined approach involves using demographic projections such as CCM models to derive estimates of the future population at a relatively

broad geographical scale, then using one of the other approaches to systematically downscale or apportion the population to the small-area level. Combining two approaches can take account of both the underlying demographic processes that drive population change, and the local-level conditions that primarily determine the spatial allocation of households and people (Wilson, 2015b). Moreover, by combining two methods the demographic model is not overextended to a point where the data necessary to derive population projection assumptions (fertility, mortality, and migration) are not readily available.

In the combined approach the method of allocating population between small areas becomes the most important determinant of forecast accuracy at the small-area level. Land use based models have been used to downscale or allocate population to small areas for at least the last two decades. Tayman (1996) reports results of a forecast based on a spatial interaction land use model for San Diego County. The land use model uses place-of-work employment to allocate population, such that the population tends to locate closer to their place-of-work, while constraining population based on each zone's capacity to accommodate additional residential development. Tayman and Swanson (1996) used similar models for San Diego and Dallas-Fort Worth.

3. DATA AND METHODS

Data

The Waikato Region of New Zealand had a 2013 total population of approximately 425 000 (about 10 per cent of the total New Zealand population). It has a central main city (Hamilton City) with a 2013 population of approximately 150 000, two districts that are peri-urban (Waikato District and Waipa District), and a number of other Territorial Authority (TA) areas (the second tier of local government administration in New Zealand) in whole or in part (refer to Table 1). The region is not a simple aggregation of the TAs because the region is largely based on a water catchment area, whereas the TA boundaries reflect administrative divisions that are historical and somewhat arbitrary.

Table 1. Territorial Authority Populations for the Waikato Region, 2013.

Territorial Authority	Population	Count of Area Units (AUs)	Mean AU Population	Median AU Population	Minimum AU Population	Maximum AU Population
Thames-Coromandel District	27 040	10	2 704	2 845	730	4 490
Hauraki District	18 740	8	2 343	1 945	500	4 790
Waikato District	64 890	31	2 093	1 860	0	5 550
Matamata-Piako District	32 200	13	2 477	2 510	300	4 520
Hamilton City	150 250	46	3 266	3 305	160	7 750
Waipa District	46 380	29	1 599	1 300	200	3 770
Otorohanga District	9 330	5	1 866	1 750	350	4 180
South Waikato District	22 530	16	1 408	1 060	160	3 690
Waitomo District (part)	9 330	7	1 333	1 000	210	4 670
Taupo District (part)	34 120	28	1 219	625	10	4 410
Rotorua District (part)	3 640	4	910	870	160	1 740
Waikato Region (Total)	418 450	197	2 124	1 840	0	7 750

Source: Authors' calculations

In this paper, projections are developed at the Area Unit (AU) level. Area Units are the next smaller geographical area below TAs in the geographical hierarchy used by Statistics New Zealand. They serve no particular administrative purpose – however, each AU is a distinct geographical entity, and in urban areas they generally coincide with suburbs and have a population of 3 000-5 000. As shown in Table 1, in the Waikato Region there are 197 non-marine non-island AUs, with a mean population size in 2013 of 2 124 (median 1 840), and a range from a minimum of zero to a maximum of 7 750.

Statistical Downscaling Method

In this paper, statistical downscaling was combined with projections of future land use to allocate projected TA-level populations to each AU. The three-step approach is similar to that employed by Tayman and Swanson (1996) and Tayman *et al.* (1998), but uses a combined statistical and urban growth modelling approach to allocate population to the AUs.

First, the population was projected at the TA level for the region (including for each part-TA) by the National Institute of Demographic and Economic Analysis, using a cohort component model (Cameron and Cochrane, 2014). The ‘Baseline Medium’ TA-level projected populations were used as an input in the following stages, including a backcast projection from 2013 (the base year of the TA-level projections) to 2006. Second, land use was projected using the Waikato Integrated Scenario Explorer (WISE) model. The WISE model is a systems-based integrated model that incorporates economic, demographic, and environmental components across the entire Waikato Region (Rutledge *et al.*, 2008; 2010). The WISE model begins with a base land use map in 2006, incorporating 24 different land uses, of which there are three residential land use classes (medium-high density, low density, and lifestyle blocks) (Rutledge *et al.*, 2010). At each annual time step, the economic and demographic sub-models generate demands for economic and residential land use, which are inputs into a dynamic, spatially explicit land use change model (Huser *et al.*, 2009). The demographic inputs into the WISE model are the TA-level population projections for the Waikato region developed in the first step.

The land use change model is a CA model specified at the level of four-hectare grid cells (200m x 200m). The CA model apportions land to different uses at each annual time step based on a combination of four factors: (1) zoning (which constrains the land uses that are available in each area); (2) suitability (the biophysical suitability of land for different uses);

(3) accessibility (assesses the attractiveness of a location for different land uses based on proximity to desirable or undesirable features); and (4) local influence (assesses the attractiveness of a location for a land use based on the composition of land use in the surrounding neighbourhood). The CA land use model attempts to meet the external demands for land (from the economic and demographic models) by assigning cells with the highest transition potentials (determined by their zoning, suitability, accessibility and local influence) to new land uses. Transitions are made at each annual time step.

The demand for residential land of each type is determined by first assigning a given proportion of population in each territorial authority to each residential land use type, and the residual proportion is spread across all non-residential land uses. The proportions are generally stable but vary over time for some TAs. Next, the number of residential land use cells of each type required is determined by combining the population in each residential land use calculated in the first step with population density values for each residential land use type. These population densities also vary over time, between pre-determined maximum and minimum values. The area of each land use type (in hectares) and the residential population densities (by residential land use type) were exported from the WISE model for 2006 and 2013 for use in the next step.

In the third step, land use was used to statistically downscale the TA-level population projections to the AU level. This was achieved in two stages, projecting: (1) the population located in residential land uses; and (2) the population located in non-residential land uses. In the first stage, the number of hectares of each residential land use type in each AU and the residential population densities (both from the WISE model) were used to calculate the residential population of each AU (i.e. the population located in residential land uses) for each year (2006 and 2013). The difference between the sum of the residential populations across all AUs in each TA and the overall projected TA-level population provides an estimate of the total non-residential population in that TA (i.e. the population located in non-residential land uses).

To estimate the non-residential population in each AU, linear regression models were used, with the 2006 TA-level non-residential population as the dependent variable, and the 2006 baseline non-residential land use (by type) as explanatory variables. That is, regression model is estimated of the general form:

$$NRP_i = \alpha + N_{ki}\beta + \varepsilon_i \quad (1)$$

Where NRP_i is the non-residential population of area unit i , N_{ki} is a vector of land uses k in AU i , and ε_i is an idiosyncratic error term. Four alternative model and data specifications were tested for this model: (I) standard ordinary least squares (OLS) regression, based on absolute land use; (II) standard OLS, based on principal components of land use; (III) a spatial Durbin model, based on absolute land use; and (IV) a spatial Durbin model, based on principal components of land use.

The rationale for applying these four different specifications was as follows. Absolute land use (in hectares) is the most basic land use variable, and this data specification was included because the coefficients for each land use type would be easy for planners to interpret (as the number of people per hectare). In contrast, principal components analysis takes the land use dataset and converts it into a set of linearly uncorrelated components (Joliffe, 2010). This avoids any problems of multicollinearity between the land use variables. The principal component specifications also allow the model to account for different types of internal land use structures that may be reflected in different land-use-specific population densities at the AU level. Spatial Durbin models account for neighbourhood effects (i.e. where the non-residential population in AU i is affected by the size of the non-residential population in surrounding AUs) and for lag effects (where the non-residential population in AU i is affected not only by the amount of each land use type in that area unit, but also the amount of each land use type in surrounding AUs) (Lesage and Pace, 2009).

Eleven land uses were initially excluded from the models (bare surfaces; indigenous vegetation; other exotic vegetation; wetlands; fresh water; marine; aquaculture; utilities; mines and quarries; urban parks; and airports), because they were unlikely to contain much of the population. The three residential land uses were also excluded from the models, as the population in those land uses was already accounted for. That leaves ten land use variables in the model. Separate regression models were fitted for Waikato District, Hamilton City, and Waipa District, with a fourth regression model fitted for the remaining TAs (due to small individual sample sizes). The fourth model initially included TA-level fixed effects to account for unobserved differences in population density profile between each TA. Each regression model was reduced to a final preferred model by removing the least significant variable in a backward stepwise fashion until the root mean squared error (RMSE) was minimised. The resulting regression models are a reasonably good fit for the data, with adjusted coefficients of determination (R^2) between 0.17 and 0.80 (These results are available on request from the authors.).

The regression model coefficient estimates were then used, along with projected land use from the WISE model for 2013, to provide a projection of the non-residential population of each AU in 2013. When added to the residential population from the first stage of step 3, the sum provides an un-scaled population projection for each AU. However, two issues arose with these un-scaled projections: (1) the projections demonstrated significant discontinuity with the known population trend between 2001 and 2006 for a number of AUs; and (2) a number of AUs were projected to quickly fall to zero (or negative) population. To reduce the impact of the discontinuities, the in-sample residual was calculated for each AU in 2006 (being the difference between the actual 2006 population and the estimated 2006 population). This in-sample residual for each AU was added to the projected AU population. This reflects the fact that the residuals in the population projection model are likely to be correlated over time. To reduce the impact of projected de-population of (particularly rural) AUs, each un-scaled AU population projection was constrained so that population would not fall by more than 25 per cent over a ten-year period. This maximum constraint is similar to the maximum long-run population decline observed in any AU over the period 1996-2006. Moreover, this adjustment is justifiable because the spatial distribution of population is subject to a substantial degree of inertia – once houses have been constructed in a given location, some population is likely to remain in that location for a long time. That is, population decline at small spatial scales is a relatively slow process, unlike that projected in the initial unconstrained models.

Finally, the combined population of all AUs in each TA was constrained to be consistent with the projected population of the TA from the cohort component model. Discrepancies between the AU-based population total and the TA-level projection were eliminated by applying a common scaling factor to the AU populations for each TA, calculated as the ratio of the projected TA-level population to the sum of the unconstrained AU populations.

Evaluation Method

The performance of the approach was evaluated in two ways. First, the in-sample performance of the model was examined. Specifically, the four alternative regression models for projecting non-residential population (and the resulting estimates of the AU-level populations) in 2006 were compared with those estimated with actual populations. Second, the out-of-sample forecast accuracy was evaluated by doing a post-hoc comparison

of the small area forecasts with data from the 2013 estimated usually resident populations (based on the 2013 Census). The forecast accuracy of the four models was compared with that of two naïve models: (1) a linear extrapolation, that takes the population change from 2001 to 2006, and extrapolates this to 2013; and (2) a CSG+ (modified constant share of growth) model, which assumes a constant share of TA growth for each AU that experienced positive population growth between 2001 and 2006, and no growth for areas that declined in population between 2001 and 2006 (White, 1954; Wilson, 2015a). Rather than using a population projection model in the CSG+ model, the change between actual 2006 and 2013 estimated usually resident populations was used. This provides an over-conservative estimate of the degree of error and bias in the CSG+ model.

Multiple measures of forecast error and bias were estimated. Following Wilson (2015b), the primary measure of forecast accuracy is weighted mean absolute percentage error (WMAPE). This measure is a weighted mean of the absolute percentage errors, with the weights being the size of the actual populations in the year projected (Siegel, 2002). WMAPE is preferable to other measures (such as Mean Absolute Percentage Error) when there is a wide range of population sizes. The AU populations in the study area range from zero to 7 750 in 2006, which makes WMAPE the most suitable measure.

The median absolute percentage error (MedAPE), the median algebraic percentage error (MedALPE), and the root mean square error (RMSE) are also reported. MedAPE and RMSE both measure forecast precision because the direction of the error does not affect these measures, while MedALPE measures forecast bias. Although Mean Absolute Percentage Error (MAPE) and Mean Algebraic Percentage Error (MALPE) are the most commonly used measures of forecast accuracy and bias respectively (Tayman, 1996), MedAPE and MedALPE are preferable over MAPE and MALPE. This is because using the median error reduces the impacts of extreme outliers (i.e. unusually large, or small, errors) and the skewed nature of the distribution of error in small populations, on the overall measures of error and bias (Tayman and Swanson, 1999). For instance, Tayman (1996) shows that MAPE tends to overstate the error, and that the degree of overstatement is largest for areas with the smallest population size. In contrast to these other measures, RMSE penalises the forecaster for forecasts that are further from the actual population (Stoto, 1983), which may be helpful for risk averse planners adopting a minimax approach, i.e. where forecasts will provide the planner with greater utility if the largest errors are minimised.

4. RESULTS

Table 2 shows the results of the evaluation of the in-sample (2006) and out-of-sample (2013) performance of the four model and data specifications (I-IV), using all four error measures (WMAPE, MedAPE, MedALPE, and RMSE). Two out-of-sample comparisons are included: (1) using the raw statistical model described in the previous section; and (2) using the statistical model, but carrying forward the 2006 in-sample residual and using it to modify the 2013 projection.

Table 2. In-Sample and Out-of-Sample Model Performance.

Error Measure	Model I	Model II	Model III	Model IV
<i>In-sample</i>				
WMAPE (%)	19.0	19.0	16.2	16.3
MedAPE (%)	17.5	17.6	14.8	14.3
MedALPE (%)	-2.7	-2.9	-0.7	-0.1
RMSE (%) [*]	26.6	26.5	23.3	22.8
<i>Out-of-sample</i>				
WMAPE (%)	20.8	20.5	19.0	18.2
MedAPE (%)	19.3	19.1	16.2	16.5
MedALPE (%)	-0.6	-0.6	-1.9	2.1
RMSE (%) [*]	28.3	28.4	27.0	25.9
<i>Modified Out-of-sample</i> ^{**}				
WMAPE (%)	7.5	6.7	9.0	6.7
MedAPE (%)	5.7	4.8	6.7	4.8
MedALPE (%)	-0.8	0.0	-1.4	0.0
RMSE (%) [*]	14.3	14.0	15.8	14.0

Note: ^{*} As a percentage of the mean AU population; ^{**} Modified out-of-sample measures include a correction, whereby the in-sample residual is carried forward to form part of the forecast.

Source: Authors' calculations

Overall, the models exhibit a moderate degree of accuracy, with in-sample errors of between 14.3 and 19.0 per cent. There is an overall downward bias in the models, as the MedALPE values are consistently negative. Unlike Wilson and Rowe (2011) the estimates of WMAPE here are larger than MedAPE, which probably reflects that absolute errors are largest for the AUs with larger populations. In terms of in-sample

performance, Models I and II perform similarly, but are clearly dominated by Models III and IV (the spatial regression models), which exhibit smaller degrees of both error and bias. Comparing Models III and IV, both are similar in terms of error, but Model IV exhibits a smaller degree of bias. The median extent of bias in Model IV is 0.1 per cent under-projection, compared with 0.7 per cent under-projection for Model III. The comparison between the four models is similar in the two out-of-sample comparisons.

Comparing the in-sample with the first out-of-sample results demonstrates that the land-use-based projection model performs nearly as well at seven years after baseline as it does in the baseline year. There is little degradation of performance over time for any of the models, with WMAPE increasing by between 1.5 and 2.8 percentage points between the in-sample and out-of-sample measures.

In the modified out-of-sample measures, Model III is clearly worse than other models, and Models II and IV perform best and nearly identically. There is no evidence of forecast bias in either of these models, and WMAPE is just 6.7 per cent. Comparing the out-of-sample and modified out-of-sample results demonstrates the substantial performance improvement that is obtained by carrying forward the in-sample residual. Across all models this reduces the WMAPE by between one half and two thirds.

Table 3 shows the results of the out-of-sample comparison between the four land-use-based models and the two naïve models (linear extrapolation, and CSG+). To ensure comparability, the models were used to allocate the 2013 estimated usually resident population, rather than the 2006-base projected TA-level populations for 2013. Thus the error measures differ slightly from those reported in Table 2. As with the last comparison in Table 2, Models II and IV perform the best of the four land-use-based models. They also perform better than the naïve linear extrapolation on three out of the four error measures (i.e. all except RMSE). However, the CSG+ model performs the best on all error measures, with a WMAPE of 5.6 per cent, 1.1 percentage points better than Models II and IV.

Table 3. Comparative Out-Of-Sample Model Performance.

Error Measure	Model I	Model II	Model III	Model IV	Linear	CSG+
WMAPE (%)	7.3	6.7	8.7	6.7	7.6	5.6
MedAPE (%)	5.6	5.0	6.4	5.0	6.4	4.5
MedALPE (%)	-1.7	-1.7	-0.8	-1.7	-2.3	-0.3
RMSE (%)*	14.1	13.6	15.6	13.6	12.6	10.3

Source: the Authors

5. DISCUSSION AND CONCLUSION

This paper reported results of new land-use-based models for small area population projections, and compared those models' forecast accuracy with that of naïve projections based on linear extrapolation and a modified constant-shares-of-growth model. The land-use-based approach can readily be employed to projections in other areas, but necessarily requires a land use model. However, the land use model need not be as detailed as that employed here.

To date, few studies have compared the forecast accuracy of combined projection models with that of simpler models. The preferred model (Model II) uses the WISE land use model to derive the residential population of each AU, and a spatial Durbin model using absolute non-residential land use (in hectares) as explanatory variables to derive the non-residential population of each AU. Model II was preferred over the similar Model IV because of the ease of interpretation of coefficients for end-users. The preferred model has an out-of-sample WMAPE of 6.7 per cent over a seven-year projection horizon.

The error in the preferred model compares favourably with previous studies that use a variety of models (and measures of error). Wilson and Rowe (2011) found WMAPEs after five years varied from 6.0-7.3 per cent for areas with a population of 2 000-4 999, and 5.0-6.7 per cent for populations of 5 000-14 999, for projections of the population of Queensland, Australia. These WMAPEs increased to 8.2-11.3 per cent and 6.7-9.5 per cent respectively for a ten-year projection horizon. Tayman *et al.* (1998) report that MAPE is a decreasing function of population size, based on San Diego data and a projection model that uses land use to allocate populations to small areas. They show MAPEs for a ten-year

projection that range from 72 per cent for populations of 500, to 39 per cent for populations of 5 000, and to 10.5 per cent for populations of 50 000. Tayman and Swanson (1996), using a land-use-based model for census tracts in Detroit, Dallas-Fort Worth, and San Diego, found MAPEs of between 18.6 and 28.5 per cent for a 10-year forecast horizon. For comparison, the unweighted out-of-sample MAPE for the preferred Model II is 10.9 per cent for a seven-year projection, which is substantially lower than those reported in these previous studies. Census tracts typically have larger population sizes than the area units projected here, which further demonstrates the efficacy of the approach.

The source of the improved projections performance of the land-use-based models, relative to previous projections models, is predominantly generated by the carrying-forward of in-sample residuals. Without carrying forward the residuals, the out-of-sample performance of the models looks much more similar to those of other models. This procedure makes sense for statistical and urban growth models (but not for extrapolation or CCM models). If other studies using statistical models, such as Chi *et al.* (2011), carried forward residuals in their forecasts, then their model performance may look much better.

Land-use-based population models that account for spatial interdependence (Models II and IV) outperform models that ignore these effects (Models I and III). The population density of a given small area reflects a complex interplay of the land use of that particular area, and the land uses of surrounding areas. For instance, urban land uses will have quite different characteristics and population densities than rural land uses, even within the same category of land use. Spatial Durbin models allow us to capture the spatial dependence, and small area population projection models should make more use of spatial models.

However, despite their good performance in comparison with past modelling efforts, the land-use-based forecasts do not outperform the naïve CSG+ model (White, 1954; Wilson, 2015a). The inability of complex models to outperform simple models in projections of small area population is a general finding in the literature on small area population projections (van der Gaag *et al.*, 2003). However, the WISE land use model used here has recently undergone significant improvement, with input from a wide group of local authority planners. This improved model, which operates with a 2013-base land use map, demonstrates substantially better in-sample performance, with a nearly 30 per cent reduction in WMAPE (based on Model I) to 13.5 per cent. Unfortunately, out-of-sample model

testing based on this new land use model will not be possible until after the 2018 Census, but these initial results are extremely promising.

There are a number of limitations to the models presented here. First, the projections do not include an explicit measure of uncertainty. Instead, the AU populations were simply forecasted as point estimates. However, the measures of forecast error could be used to estimate uncertainty (Tayman, 2011). It is worth noting that the degree of uncertainty present in population projections at smaller geographic levels is substantially larger for smaller populations (Cameron and Poot, 2011), so understanding better the uncertainty in the estimates is clearly important. Second, because the forecasts are based on a statistical model at the small-area level, they potentially suffer from the same limitations as statistical models outlined in the introduction. However, because the statistical model is only used to project the non-residential population, rather than the whole population, these problems are somewhat mitigated. Third, the projections were evaluated based on only a single period in time and a single region of New Zealand. It may be that demographic trends fit the land-use-based models particularly well (or not so well) by chance alone. The model will be evaluated further in later periods, but should also be applied to other regions and contexts.

Fourth, it is likely that small area population projections present a problem of endogeneity. If projections are used in planning decisions then they may become somewhat self-fulfilling prophecies. For instance, if population is projected to increase in a given AU, then planners may create infrastructure that supports the expected additional population, leading to more development in that AU and consequently more population. However, if population had been projected to increase elsewhere instead, then infrastructure spending, development and population growth would be directed towards that other area instead. Thus, small area population projections should be used as one tool among many in the planning process.

Finally, despite the forecast accuracy of the land-use-based models being lower than naïve models, the land-use-based models do serve an important purpose. Too often, population projection models are seen by local authority planners and elected officials as ‘black boxes’ or academic curiosities that have little relevance to the real world. As Rainford and Masser (1987) note, bridging the gap between the technical aspects of forecasting and the needs of planners is both important and difficult. Achieving ‘buy-in’ from planners and elected officials is imperative in ensuring that population projections are understood and used effectively to achieve improved planning outcomes. One part of this is to ensure that planners can recognise that planning and policy have demonstrable effects

on the projected populations at the small-area level. The land-use-based models have been very successful in this, and are being used extensively in long term planning processes at the local and regional level. Further enhancements to the model, including the improved land use modelling described above, will likely further increase the acceptance of planners for integrated modelling approaches.

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