



National Centre for Social and Economic Modelling
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Urban and Rural Estimates of Poverty

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About NATSEM

The National Centre for Social and Economic Modelling was established on 1 January 1993, and supports its activities through research grants, commissioned research and longer term contracts for model maintenance and development with the federal departments of Family and Community Services, Employment and Workplace Relations, Treasury, and Education, Science and Training.

NATSEM aims to be a key contributor to social and economic policy debate and analysis by developing models of the highest quality, undertaking independent and impartial research, and supplying valued consultancy services.

Policy changes often have to be made without sufficient information about either the current environment or the consequences of change. NATSEM specialises in analysing data and producing models so that decision makers have the best possible quantitative information on which to base their decisions.

NATSEM has an international reputation as a centre of excellence for analysing microdata and constructing microsimulation models. Such data and models commence with the records of real (but unidentifiable) Australians. Analysis typically begins by looking at either the characteristics or the impact of a policy change on an individual household, building up to the bigger picture by looking at many individual cases through the use of large datasets.

It must be emphasised that NATSEM does not have views on policy. All opinions are the authors' own and are not necessarily shared by NATSEM.

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Abstract

This paper reports on NATSEM's spatial microsimulation methodology and shows how it can be used to estimate poverty in urban areas.

The methodology is first described, and then maps of poverty are shown for Australia and capital cities. Further analysis of poverty rates in capital cities is then conducted. We find that poverty rates tend to be higher in Adelaide, Perth, Hobart and Darwin compared to Sydney, Melbourne, Canberra and Brisbane. Poverty rates within urban areas show how areas of poverty congregate. We also find that areas of high poverty are frequently 'buffered' by areas of moderate poverty. This is not always the case, as in some areas we find high poverty neighbouring a low poverty area but, generally, there tends to be a moderate poverty small area 'buffer'.

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General caveat

NATSEM research findings are generally based on estimated characteristics of the population. Such estimates are usually derived from the application of microsimulation modelling techniques to microdata based on sample surveys.

These estimates may be different from the actual characteristics of the population because of sampling and nonsampling errors in the microdata and because of the assumptions underlying the modelling techniques.

The microdata do not contain any information that enables identification of the individuals or families to which they refer.

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1 Introduction

Until recently, Australian researchers have found it difficult to produce neighbourhood level estimates of household characteristics of great relevance to social policy makers, such as the small area incidence of poverty or housing stress. This is because the key source of small area data, the five yearly Australian Census, contains estimates of only the gross income of households and individuals and then only in income ranges. More sophisticated national measures of relative advantage and disadvantage have typically relied upon disposable (after-income-tax) measures of cash income, adjusted for the number of people each household's income has to support (Saunders and Bradbury, 2006).

For the past five years, the National Centre for Social and Economic Modelling (NATSEM) at the University of Canberra has been working on techniques for reweighting an Australian Bureau of Statistics Confidentialised Unit Record File (CURF) to small area Census data. This allows small area estimates of a number of variables to be calculated (Chin and Harding 2006; Chin et al. 2006a). In the literature, such techniques are often referred to as spatial microsimulation. There are also international examples of work in this field (Williamson 2001; Ballas et al. 2003)

So far, we have concentrated on estimates of poverty (defined as half median equivalised disposable income) and housing stress (defined as households where more than 30% of their disposable income is spent on housing costs and they are in the bottom two income quintiles) (Chin et al. 2006b; Phillips et al. 2006; Tanton et al. 2007). In addition, we have linked the synthetic small area household database to NATSEM's STINMOD model (which replicates the rules of tax and social security programs), so that we can also analyse the local impact of changes in taxes and transfers (Chin et al. 2005; Lloyd 2007).

The method has implications for Australian cities because it allows estimates at below the Capital City/Rest of State split normally used by the ABS in reporting results from surveys. The reason this split is used is that, for many ABS surveys, this is the smallest geographic area for which the survey can provide reliable estimates across Australia. In some capital cities, like Sydney and Melbourne, the larger Statistical Regions may have sufficient sample size to provide reliable estimates – but, in many capital cities, this is not the case. The spatial microsimulation method we use allows estimates to be produced for all capital cities, down to the Statistical Local Area.

This paper starts by outlining the method we use for the regional microsimulation (Section 2). The next section describes some of the applications of our model (Section 3). The final section discusses the future of the method and possible avenues for further research.

2 Method

Producing regional weights

The first step in producing regional poverty estimates involves combining information from two sources – the Australian Census of Population and Housing 2001, and data from recent income surveys conducted by the Australian Bureau of Statistics. The census has limited information on poverty and housing stress, but includes variables that broadly relate to poverty and housing stress at a very detailed regional level. The ABS Survey of Income and Housing Costs, on the other hand, provides the detailed information about income needed to calculate income poverty and housing stress, but at a very low level of spatial disaggregation. To produce a set of household weights for each small area included in the modelling, we benchmark the Survey of Income and Housing Costs to the census, using variables that are available in both data sources. The census benchmark variables used to produce the regional estimates depend on what we want to estimate, and we decide on the benchmarks based on what is available in both the Census and the survey, and what is highly correlated with the variable of interest. Recently, we have experimented with using a logistic regression to identify benchmarks that are correlated with our variable of interest (in this case, poverty), but the logistic regression identified only five benchmarks, and we found that poverty rates calculated using only five benchmarks were not as robust as poverty rates using ten benchmarks. This paper reports on poverty rates using ten benchmarks.

The available benchmarks are shown in Table 1, along with the benchmarks which the regression analysis showed to be correlated with poverty rates and housing stress.

Table 1 Benchmarks used in the reweighting algorithm

Census XCP ⁽¹⁾ table	Poverty	Housing Stress	Used in this paper
Dwelling tenure by weekly household rent		Y	Y
Labour force status by sex and age	Y	Y	Y
Dwelling tenure by household type			Y
Dwelling tenure by household income	Y	Y	Y
Non-private dwelling			Y
Monthly mortgage by household Income		Y	Y
Dwelling structure by household family composition			Y
Number of persons usually resident	Y	Y	Y
Weekly household rent by weekly household income			Y
All household types			Y

Note: (1) XCP refers to the Census 2001 Expanded Community Profile Tables

To maximise our sample size, and thus improve our estimates, we combined data from two separate years of the Survey of Income and Housing Costs – 2002/03 and 2003/04. In order to combine these two separate survey years with 2001 Census data, we first merged the two income surveys, then converted all dollar amounts in each of these surveys to 2001 values. We then re-coded the benchmarking variables where necessary to ensure that variable definitions were categorised identically across the income surveys and the census. Finally, we used the GREGWT reweighting program to reweight the combined income surveys, using the census benchmark variables (Chin and Harding 2006).

The GREGWT algorithm is a generalised regression routine written in the SAS programming language, and developed by the ABS (Bell 2000). It conducts iterative calculations to derive an optimal set of household weights for each SLA, using a regression approach to minimise the difference for each benchmark class between the census count and the estimated count. When the difference between the two counts – known as the residual – is at or close to zero, the iterations stop (Chin and Harding 2006) – a process known as convergence. The output from the GREGWT run is a set of household weights for each SLA in Australia, with these weights closely matching the characteristics of households in each SLA as recorded in the census data.

In the calculation of poverty rates for this paper, the GREGWT residuals (that is, the difference between the census count and the estimated count for each of the benchmark variables) for some areas were very large. This is common for non-representative areas like industrial areas or areas with low populations (Chin and Harding 2006). A summary of the non-convergent SLAs is shown in Table 2.

Table 2 Non-convergent SLAs

State/territory	Total number of SLAs	Number of non-convergent SLAs	Percent of non-convergent SLAs	Percent of all households in that State/Territory living in non-convergent SLAs
New South Wales	199	4	2.0%	2.1%
Victoria	200	6	3.0%	0.3%
Queensland	454	13	2.9%	0.4%
Australian Capital Territory	107	19	17.8%	0.9%

Source: ABS Census of Population and Housing 2001; Survey of Income and Housing Costs 2002/03; Survey of Income and Housing Costs 2003/04; authors' calculations

It can be seen that the proportion of people lost because of these non-converging SLAs is very small. Many of these non-converging SLAs are industrial areas or office areas, so there are not many people living there.

One of the reasons that we did not calculate poverty rates for South Australia, Western Australia, Tasmania and the Northern Territory was because we could not get many SLAs in these States to converge. We are now experimenting with reducing the number of benchmarks from ten, but not down to five where the poverty rates became unusable, to get convergence for some areas in these States.

Applying the weights

The weights produced through the above process can then be applied to variables that are highly correlated with the benchmarks used. In the case of this paper, we applied them to the creation of poverty rates for each small area. Following the existing consensus among poverty researchers in Australia, the poverty rates were calculated using half median equivalised household disposable income (Saunders and Bradbury 2006). The poverty rates were calculated for persons, rather than for households (that is, they were 'person-weighted'). The estimates of the equivalent disposable incomes of households were taken from NATSEM's STINMOD/06B model, which takes the 22,000 households captured in the 02/03 and 03/04 ABS income surveys as its base data; inflates their earnings, housing costs and other private income sources to December 2006 levels; and then imputes the rules of income tax and cash transfer programs as they applied in December 2006. Because the STINMOD estimates were for 2006, we also inflated the (2001 Census based) population weights to 2006 levels, using the projected increases between 2001 and 2006 in the ABS Population Projections by Statistical Local Area.

Apart from producing estimates of the number of persons or households with particular characteristics within each small area of Australia, the other interesting application of the technology is to estimate the local impact of policy change. If

STINMOD is used to model a policy change, like tax cuts, then the regional weights can be applied to the STINMOD output, and the effect of the policy change on small areas can be calculated.

3 Applications

This section shows some of the applications of the spatial microsimulation model being used by NATSEM. The first application shown is Australia-wide poverty rates. The next application is the regional effect of tax changes.

Australia-wide poverty rates

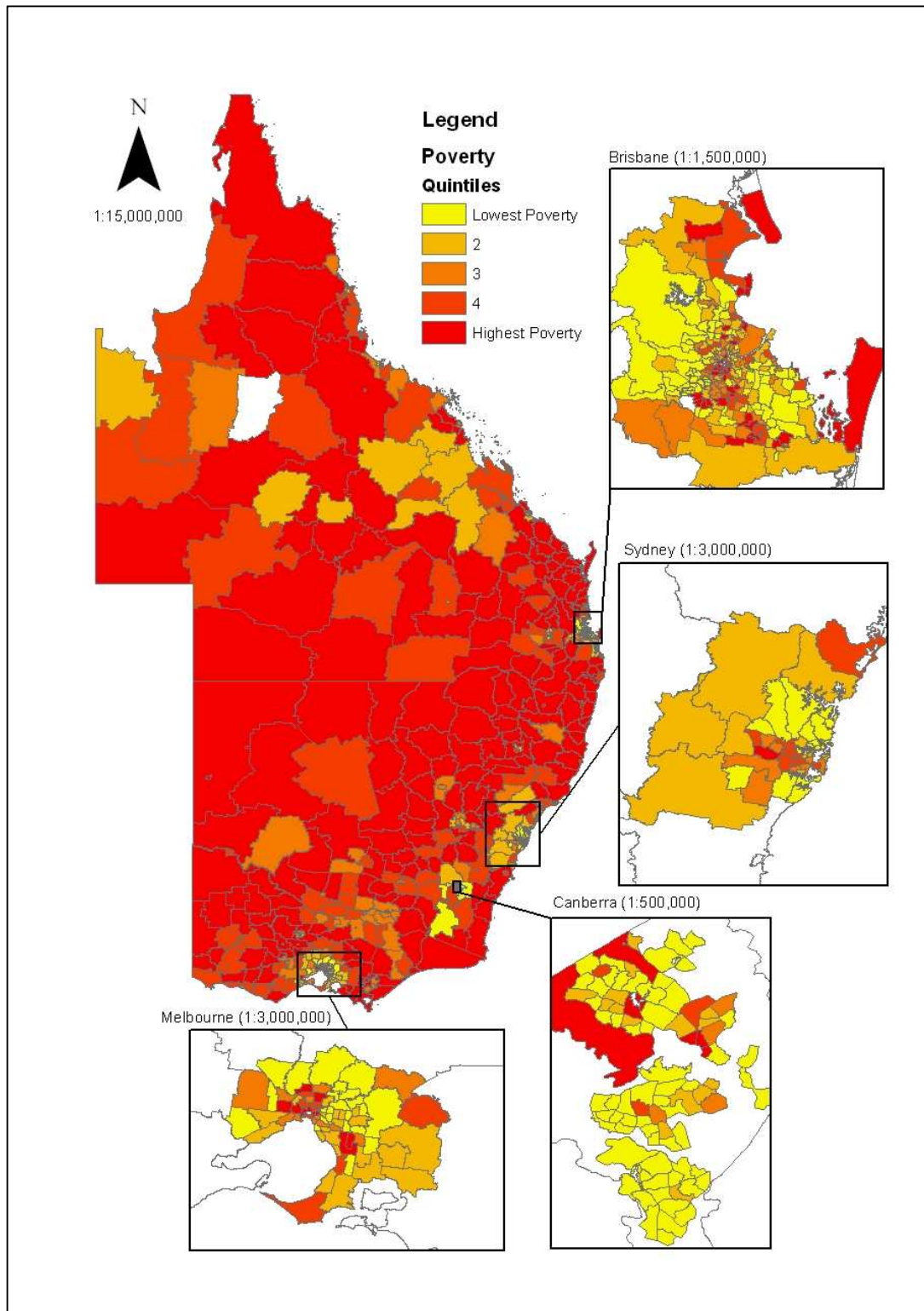
In this study, current disposable household income is used as the basis for measuring poverty. The use of household rather than individual income assumes income-sharing within households. The modified OECD equivalence scale (widely recognised internationally) is used to adjust these household incomes for household size and composition. Persons are then ranked by their household incomes, and the poverty line is set at 50 per cent of the median equivalised household income, so that all persons living in households with incomes falling below this figure are deemed to be in poverty. Further details about the technical issues involved in the choice of income measure, equivalence scale and poverty line can be found in a number of publications (Harding et al. 2001; Saunders 2005).

Poverty rates were calculated for all Australian Statistical Local Areas (SLAs) on the Eastern seaboard. We are still working on poverty rates for WA, SA, Tasmania and the NT. The SLAs vary greatly in size across NSW, Victoria, Queensland and the ACT and, to partly overcome this problem, we present all of our results in population-weighted quintiles of poverty.

It should be noted that these are our first estimates of poverty using a new ABS survey file, and we are still in the process of validating them. Our initial attempts in this area involved the ABS 1998-99 Household Expenditure Survey (which was 'aged' up to 2001 levels to match the 2001 Census data (Chin et al. 2006b)). As noted earlier, these new estimates rely on the ABS 2002-03 and 2003-04 income surveys. While these new estimates appear to be comparable to our previous small area estimates of poverty and, at a national level, are comparable to estimates produced directly from the ABS Surveys, they should still be considered preliminary estimates.

A map of the population weighted quintiles of poverty is shown in Figure 1.

Figure 1 Population weighted Poverty Quintiles, Australia, 2006



Data source: Spatial Microsimulation

It can be seen that remote areas have much higher poverty rates than non-remote areas. Partly this is because many of the less populous remote areas have high poverty rates and, because these high poverty areas are in less populous areas, there are more areas required to get the correct number of people in the bottom quintile. The other reason is that these areas with the highest poverty are very large remote areas in Queensland and NSW, so it only requires a few SLAs to have high poverty rates to make a very large area indeed appear as high poverty.

As part of validating our indexes so far, we compared poverty estimates from the 2005-06 Survey of Income and Housing for each of the States estimated. These results are shown in Table 3. It can be seen Queensland has the lowest poverty rates from both sources. New South Wales and Victoria swap ranks between the SIH and the regional microsimulation, but this could be because the regional microsimulated data is based on data from different years which has then been uprated. Once we benchmark to 2006 Census data, and introduce the 2005-06 SIH, we would expect figures closer to the SIH figures.

Our experience suggests that STINMOD poverty rates are always lower than poverty rates from the Survey of Income and Housing because STINMOD assumes full take up of benefits. So there are people who in the real world do not take up benefits, because they may not know of their full entitlements, who in the STINMOD world would be taking up full benefits, and so would have a higher income.

Table 3 Poverty estimates from the 2005-06 Survey of Income and Housing and spatial microsimulation (STINMOD)

	NSW	Vic	Qld	ACT
Survey of Income and Housing 2005-06	11.1	12.1	10.5	
Spatial Microsimulation	8.0	7.4	6.9	4.6
SIH 2005-06 rank	2	3	1	N/A
Spatial microsimulation rank	3	2	1	

Note: NT and ACT are not available separately from the Survey of Income and Housing CURF used

Source: ABS Survey of Income and Housing 2005-06; NATSEM Spatial microsimulation

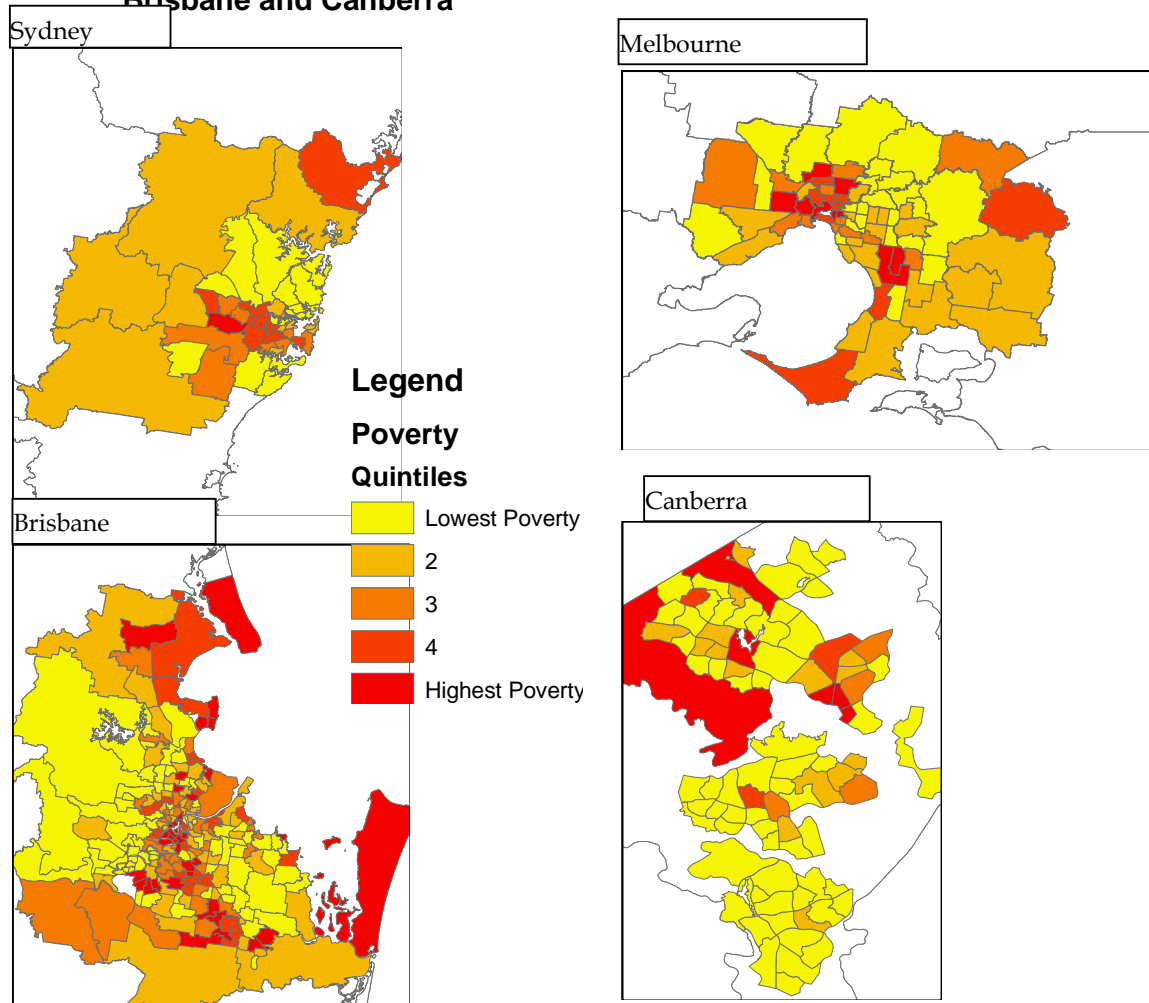
We have also validated our numbers against poverty rates from the ABS 2001 Census, which used gross income rather than equivalised disposable household income, and used a figure close to half median income for the poverty cut off because income on the Census was only available in groups, and found the rankings were similar

Analysis of urban areas

This section shows greater details of poverty in urban areas, and shows how regional microsimulation can be used to conduct an in-depth analysis of poverty in urban areas.

Maps of poverty quintiles are shown for Sydney, Melbourne, Brisbane and Canberra in Figure 2. It can be seen from these maps that, in urban areas, there appears to be clear identifiable areas of poverty risk. One interesting factor appearing in Sydney and Melbourne is the 'peri-urban' areas in the Western suburbs of Sydney and the Western and Eastern suburbs in Melbourne.

Figure 2 Population weighted quintiles of poverty, 2006 Sydney, Melbourne, Brisbane and Canberra



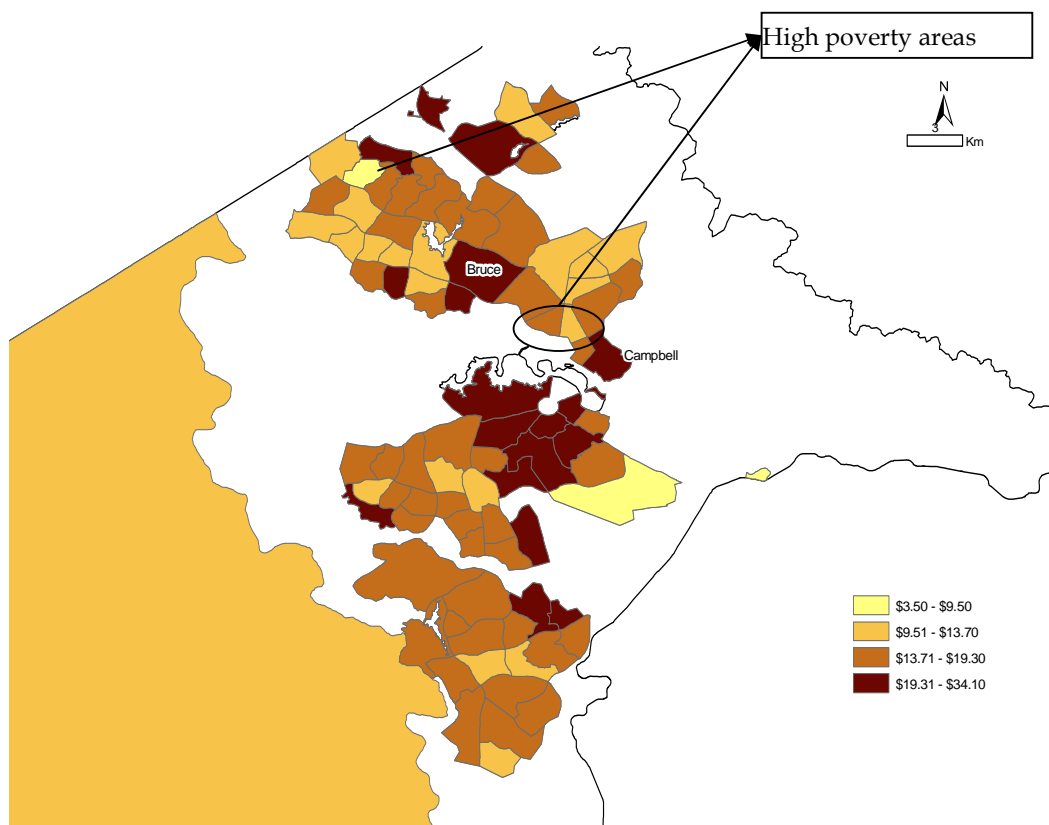
Data source: NATSEM Spatial Microsimulation

Analysis of scenario modelling

By linking the regional weights to NATSEM's STINMOD model, we are able to estimate the effects of policy changes for small areas. This was done recently with the Federal Governments 2005-06 tax cuts (Chin et al. 2005).

The effect of these tax cuts in the ACT is shown in Figure 4. It can be seen that in the ACT, the effect of the tax cuts was greatest in inner city areas and was lower in the outer suburbs. The map of the effect of tax cuts can also be compared to the map of poverty, and it can be seen that generally, in areas of low poverty (mainly the suburbs to the North and South Canberra, but also older suburbs just south of the lake), the tax cuts were moderate – and, in areas of higher poverty (just to the North of Lake Burley Griffin and West Belconnen), the tax cuts were among the lowest.

Figure 4 **Effect of tax cuts in the ACT**



Data source: NATSEM Modelled data: STINMOD and regional microsimulation

Future Work

NATSEM's spatial microsimulation model has now developed enough for us to be able to present results. While we are still validating these results, and have still to calculate estimates that we are happy with for South Australia, Western Australia, Tasmania and the Northern Territory, we are confident that over the next few months, we will be able to present results for most of Australia. We expect to be presenting more results from our spatial microsimulation model over the next few years, and see it as an important tool for policy makers to estimate the regional impact of policy changes. The link to our STINMOD microsimulation model is a major development that will allow us to estimate the effect of Government policy changes at a small area level.

Over the next year, NATSEM has been funded by the ARC to produce estimates of poverty, housing stress and other indicators of advantage and disadvantage for children and for older Australians. We are also investigating what other variables could be estimated using the spatial microsimulation technique, and will be presenting these in 2008. We also expect to be putting much of the output from our model on the ARCRNSISS website.

Conclusions

This paper has illustrated the use of NATSEM's spatial microsimulation method for analysing issues like poverty in urban areas. Over the next year, we expect to be producing many other variables using the spatial microsimulation techniques, including variables for children and for older people.

We have also illustrated how spatial microsimulation can be linked to NATSEM's microsimulation model of the tax/social security system to estimate the effect of policy changes at a small area level. This is particularly useful for estimating the effect of Government policies in urban areas compared to rural areas — but also to see the effect of policies within an urban area.

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