The Predictive Performance of Multi-level Models of Housing Submarkets: A Comparative Analysis

Abstract

Much of the housing submarket literature has focused on establishing methods that allow the partitioning of data into distinct market segments. This paper seeks to move the focus on to the question of how best to model submarkets once they have been identified. It focuses on evaluating effectiveness of multi-level models as a technique for modelling submarkets. The paper uses data on housing transactions from Perth, Western Australia, to develop and compare three competing submarket modelling strategies. Model one consists of a citywide "benchmark", model two provides a series of submarket-specific hedonic estimates (this is the 'industry standard') and models three and four provide two variants on the multi-level model (differentiated by variation in the degrees of spatial granularity embedded in the model structure). The results suggest that greater granularity enhances performance, although improvements in predictive accuracy will not necessarily offer compelling grounds for the adoption of the multi-level approach.

Key words: Housing economics, hedonic models, multi-level models, submarkets, prediction accuracy

1. Introduction

Housing submarkets arise as a result of the co-existence of a high degree of heterogeneity of preferences in relation to house types, sizes and locations on the demand-side of the market and an extremely variegated and indivisible stock of properties on the supply-side (see Grigsby, 1963; Maclennan, 1982; Watkins, 2008). The way in which segmented demand is matched on to the differentiated stock gives rise to identifiable submarkets. Each submarket is quasi-independent and exhibits an equilibrium price that remains distinct from that of other market segments even in the long run.

This pervasiveness and durability means that the existence of submarkets is of considerable analytical significance. As Galster (1996) explains submarkets provide a framework from which to understand market dynamics and the way in which policy interventions work through the housing system. He argues that changes in one submarket have important but predictable repercussions for price changes and migration flows in other submarkets. It is argued that an understanding of the submarket structure can assist decision-making of a variety of housing sector stakeholders. This might include improving the effectiveness of public sector expenditure (Bates, 2006), directing the use of tax instruments (Berry et al, 2003), enhancing private sector investment and mortgage lending strategies by allowing more robust risk pricing (Goodman and Thibodeau, 2007), enriching estate agents marketing strategies (Palm, 1978) and helping refine housing consumers search strategies (Maclennan et al, 1987). Significantly, it is also clear that failure to adequately accommodate housing submarkets can undermine the performance of housing market models by limiting predictive accuracy. This has important practical implications for the methods used in constructing house price indices (Spinney et al, 2011), applying mass appraisal techniques (Adair et al, 1996), undertaking environmental impact assessment (Michaels and Smith, 1990) and measuring the implicit value of public infrastructure programmes (McGreal et al, 2000).

Watkins (2011) suggests that the literature concerned with housing submarkets has emerged in three waves. The first wave occurred in the 1950s and 1960s and was led by a group of institutional economists who identified the potential of the submarket as an analytical construct that could be used to track housing market change (see, for instance, Fisher and Winnick, 1952; Fisher and Fisher, 1954; Grigsby, 1963). This work was motivated by a desire to engage in debates about efficiency and equity of housing policy interventions and, to date, continues to frame most conceptual discussions. The second wave, during the 1970s and early to mid 1980s, saw the development of a series of standard econometric tests for submarket existence (Schnare and Struyk, 1976; Ball and Kirwan, 1977; Goodman, 1978; 1981). This was motivated largely by concerns that the coefficients in market-wide hedonic models were subject to aggregation bias (Straszheim, 1975). The third wave has been the most voluminous in terms of published outputs largely as a result of improvements in the availability of impressively detailed micro datasets. This work has focused on how best to use statistical methods to reveal clusters in the data (see below for a more detailed discussion). This has seen an emerging consensus around two ways of partitioning data to reveal submarket formulations: the first uses statistical methods, including for example techniques such as principal components and cluster analysis (exemplified by Bourassa et al, 1999) and the estimation of isotropic semi-variograms (see Tu et al, 2007) while the second uses markets experts, such as estate agents and valuers, to define segments (see for instance Keskin, 2010; Bourassa et al, 2003).

This paper seeks to contribute to the development of a fourth phase in the evolution of the submarket literature. It seeks to build on the emerging consensus about how best to partition data by shifting the focus on to how best to accommodate the submarkets revealed within house price models. As Costello et al (2010) note, to date, there have been few attempts to systematically appraise alternative ways of modelling submarkets. The dominant approaches has been based on simply including submarket dummies within hedonic models (e.g. Fletcher et al, 2000; Butler, 1982) or estimating a set of submarket-specific hedonic equations (e.g. Bourassa et al, 2003; Goodman and Thibodeau, 2003). The former has been criticised for failing to allow the implicit price of individual attributes (such as a parking space) to vary between submarkets (Maclennan et al, 1987). The latter addresses this but suffers from an inability to differentiate between the effects of hard boundaries such as school catchment areas and softer and more fluid spatial influences such as neighbourhood quality (see Clapp and Wang, 2006; Kauko et al, 2002 on this issue). As we argue later in this paper, in operational terms the utility of both of these methods is highly constrained by the need to impose hard submarket boundaries that draw on pre-determined partitions.

This has spawned an interest in the application of multi-level modelling strategies as an alternative basis for modelling housing submarkets and capturing the fluidity of submarket boundaries over time (Leishman, 2009; Orford, 1999; Goodman and Thibodeau, 1998). Multi-level models are advised when the observations being analysed are clustered and correlated, the causal processes underlying the relationships operate simultaneously at multiple spatial scales and there is value in seeking to disentangle the spatial effects (Subramanian, 2010). Their use has begun to expand within the quantitative human geography literature the technique has been used to explore a range of complex spatial impacts and interactions including the composition of public health outcomes and measurement of social well-being (see Moon et al, 2005; and Ballas and Tranmer, 2008 respectively). This clearly resonates with the challenges associated with modelling housing submarkets.

Thus the main aim of this paper is to undertake an appraisal of the performance of multi-level models of housing submarkets. Specifically the paper analyses the outputs of two different variants of a multi-level house price model and compares the results to those generated by employing the more standard approach of estimating a series of individual house price functions for each separate submarket. Both modelling strategies employ agent-based definitions of submarkets that have been shown to be superior to other partitioning schemes (see AUTHORS, 2011 for evidence; and Watkins (2001) and Keskin (2010) for further support). The empirical analysis is designed as a comparative experiment. It applies different methods to data from Perth, Western Australia covering the one year period between mid

2007 and mid 2008. The research design is adapted from a series of previous studies that explore the empirical performance of competing submarket formulations (Costello et al, 2010; Bourassa et al, 2003; Goodman and Thibodeau, 2003; Watkins, 2001). There are three stages to our performance evaluation. The first stage seeks to develop a robust hedonic house price model to act as an 'industry-standard' benchmark against which the performance of the alternative submarket modelling strategies can be compared. The second stage parameterises the competing models: specifically it estimates the set of submarket-specific hedonics and the two variants on the multi-levels model. The third stage explores the predictive accuracy of the models. It considers 'average' errors and also the distribution of the differences between actual values and model-based estimated values.

The paper has four main sections. The next section explores the existing literature to outline the nature of submarkets. It establishes the need for modelling strategies to accommodate submarkets and, if possible, be able to deal with dynamic change within submarket structures. Section three describes the data and methods of estimation used in the paper. Section four presents the main modelling results and discusses the comparative performance. The final section sets out some conclusions.

2. The nature of submarkets and the case for multi-level modelling strategies

Research on housing submarkets has, hitherto, focused on the development of consistent methods of identifying their boundaries. This reflects concerns by some commentators that the lack of a common approach to the definition and identification of submarkets contributed to lack of a consensus about their importance in the analysis of metropolitan housing markets (see Rothenberg et al, 1991; Watkins, 2001). The explanation for submarket existence set out in the opening paragraph of this article, based implicitly on the contribution of Grigsby (1963), emphasises that potential submarkets are clusters of dwellings that are relatively close substitutes in the view of those who demand housing, though not necessarily in close spatial proximity (see Galster, 1996 for a detailed discussion).

Maclennan and Tu (1996) emphasise the fact that neighbourhood and environmental attributes are traded with housing, alongside physical attributes. They point to the indivisibility of some housing attributes, and impossibility of replication of others, as a root cause of submarket creation. Examples of non-divisible attributes include those typically measured by researchers using dummy variables, such as property type. Non-replicable attributes are more likely to relate to a property vintage. For example, stone-built properties were constructed at lower cost in the past than they can be today, hence the existing stock of such properties is difficult to replicate.

From these facts, Maclennan and Tu (1996) develop an argument first articulated clearly by Schnare and Struyk (1976), that consumers' demand for non-divisible, non-replicable attributes may be price inelastic. This may give rise, in essence, to a two stage housing choice in which consumers restrict their potential choices to those possessing a particular attribute, or bundle of attributes. This might reflect an overriding desire to locate in the catchment area of a highly ranked school, as in the Schnare & Struyk example, or an overriding desire to consume a desirable bundle of environmental and neighbourhood attributes. The result, in either case, is that consumers seek to maximise utility from the available bundles of physical attributes only after restricting the potential options to exclude those that do not reflect their overriding desires (those for which their demand is relatively price inelastic).

Despite increasing clarity about the conceptual basis for submarket existence, there is no evident consensus about the appropriate approach for identifying or testing for submarkets. This has spawned considerable investment in studies that explore different mechanisms for partitioning house price datasets, driven in part by a desire to move beyond the imposition of submarket structures based on prior notions or pre-existing administrative boundaries. Bourassa et al (1999), for instance, demonstrate one widely accepted approach to testing for spatial submarkets: the use of a combination of principal component analysis and hedonic regressions. Chow tests and weighted standard error tests related to the latter are used to ensure that the existence of spatial submarkets is accepted only when parameter estimates vary across the metropolitan area *and* stratification leads to greater predictive accuracy. The paper concludes that further research directions might include an exploration of methods to determine the optimal number of submarkets in a metropolitan area.

Interestingly, several studies (including later work by the same authors, see Bourassa et al, 2003) found that spatial submarkets based on real estate agents' definitions led to models with greater predictive accuracy compared with those based on statistically derived submarkets. Michaels and Smith (1990) asked five agents to cluster 85 locations within suburban Boston into between five and ten submarkets. These returns were amalgamated to give three competing classifications. Despite the difficulties reconciling the agents' views, the expert-defined boundaries produced house price estimates that substantially reduced standard errors when compared with a market-wide hedonic formulation.

Similarly, in a study of the Glasgow housing market, Watkins (2001) overcame the problems encountered using agents' views by adopting the sub-area boundaries used in listing service publications. This produced a set of house type submarkets nested within agent-defined partitions. This submarket formulation proved superior, in terms of reducing standard error to the alternative produced using the standard PCA and Cluster analysis methods. In Bourassa et al's (2003) contribution, they used a combination of principal component analysis and cluster analysis to identify non-contiguous clusters of similar properties. They set the initial number of clusters at 34 – the number of real estate agent 'submarkets', but reduced this to 18 by incorporating a minimum cluster size to more easily in order to facilitate subsequent hedonic regressions[1].

Several of these contributors identify the instability of the boundaries generated by these approaches as ongoing problems. It is clear that irrespective of the quality of data and analytical rigour underlying some previous cross-sectional analyses of the metropolitan housing market structure, the findings of such studies have limited value if submarket structures are subject to significant or rapid change.

A series of studies has explored the stability of submarket boundaries with respect to migration and, specifically, the concept of filtering (see Jones et al, 2003, 2004; Rothenberg, 1991; Galster and Rothenberg, 1991). An important argument implicit in these studies is that while intra-metropolitan differences in housing attribute prices may be interpreted as evidence of submarkets, there is no reason to suppose that these price differences are stable over time. Differential rates of new housing supply and migration between submarkets may act to break down submarket boundaries, effectively smoothing attribute price differences spatially through arbitrage processes (see Jones et al, 2004). Indeed, Jones et al (2003) tested the temporal stability of previously identified spatial submarket boundaries, finding evidence of significant change in several submarket boundaries over time.

[1] In fact, their analysis considered three samples of data that varied either in terms of the types of property included, or the number of explanatory variables available. Their cluster analysis identified 14, 15 and 18 clusters for these three samples, with the number rising with sample size.

One way of remedying this problem is to develop a modelling strategy that can reveal, (rather than impose) then test, submarket structures. Bourassa et al, (2007) compare traditional hedonic models that incorporate submarket variables with lattice models and geostatistical approaches. Their main finding is that a traditional hedonic model with submarket dummies has superior predictive performance compared with their comparative models. However, they also note the potential for further comparison with the approach demonstrated by Pavlov (2000) and Fik et al (2003) which included x/y co-ordinates in the hedonic models. The latter also used interactions between x/y co-ordinates and location dummies. These studies were motivated by the objective of hedonic estimation in the absence of prior knowledge of submarket boundaries.

This has also provided the context for the emerging interest in the potential of multi-level models that has appeared (apparently) independently in the UK and the US. The initial contributions developed from the notion that hedonic specification could be better contextualised by applying the expansion method (Can, 1992). In other words, a more complex model can be developed by expanding the parameters of the simple hedonic equation (see section 3 for more formal mathematical notation that illustrates this point). In the UK, Jones and Bullen (1993) developed an expanded multi-level hedonic with two tiers: the property level and the submarket level. This formulation captures the market-wide influences on property values but also allows parameters to vary between submarkets. Thus, the price of a property is a function of the market-wide price and a submarket-specific differential. The approach was applied to data on individual properties drawn from the 5% Survey of Building Society Mortgages collected by the Department of the Environment (DoE) (see Jones and Bullen, 1994). The DoE data captured the price, physical and locational attributes of properties in 33 Local Authority districts in London. The structure of the dataset limited the scope of fine grained spatial analysis. With as few as 20 observations within each district there was little scope to analyse submarkets at the micro level employed by other analysts (see Orford, 2000; 2002). The results did, however, establish the presence of significant local/submarket differentials.

In the US, Goodman and Thibodeau (1998) introduced a similar two level (property and submarket) specification. The approach involved identifying spatial submarket areas using data on housing transaction that took place in a single school district in Dallas, Texas between early 1995 and 1997. The housing data were augmented with information on the performance of public elementary schools and the results showed that significant price differentials existed between school catchment areas. This approach was developed further in future papers and, with access to a larger dataset covering the entire metropolitan area, the researchers were able to establish a hierarchical model with multiple levels (Goodman and Thibodeau, 2003; 2007). The rationale for the model is that all dwellings share the amenities available within their locality and thus the determinants of house prices are nested within multiple geographies: properties are located within neighbourhoods, neighbourhoods within school districts, and school catchment within municipal boundaries. The analysis showed evidence of differentials at a variety of spatial scales.

The potential of this approach has been explored further elsewhere. Orford (2000) uses around 1,500 housing observations collected from estate agents in Cardiff, Wales to examine how a multilevel approach might explicitly incorporate spatial market segments. The paper showed evidence of price differentials for submarkets that reflected segmentation associated with particular communities, reinforced by institutional factors including the influence of agents, and the significance of structural heterogeneity within the housing stock. More recently, Leishman (2009) develops a multi-level approach that demonstrates the possibility of modelling a unitary metropolitan housing market, but allowing coefficients to vary between small, census derived geographies within the city. The paper shows that, using a multi-level hedonic estimation approach, submarket boundaries in Glasgow changed significantly within a relatively short time period (of 3 to 4 years). It is this basic model structure that provides the general framework for the empirical analysis that follows in this paper.

3. Research questions and approach

The empirical analysis is motivated by a number of research questions that emerge from our review of the literature:

- Is it appropriate to model the metropolitan housing market without accounting for the possibility of spatial divisions?

- Does a spatially segmented model based on real estate agents' definitions of 'submarkets' out-perform a unitary model?

- Does a multi-level hedonic model out-perform the spatially segmented model? and

- How do different variants of the multi-level approach perform?

To determine the empirical performance of a number of conceptual approaches to defining housing submarkets, we estimate a number of empirical models. We then proceed to measure prediction error, both in an aggregate sense and in terms of underlying spatial patterns, for each of these models. We place particular focus on prediction errors greater than 20% and demonstrate spatial clustering of these particularly high errors using GIS (see Fik et al, 2003 for another example of this approach).

Model (1) is a simple hedonic model estimated using OLS. Its specification includes a set of continuous predictors including X and Y coordinates, and distance from the CBD. This model provides a benchmark with which to compare statistical performance and predictive accuracy of the later models as well as embodying the 'unitary housing market' hypothesis. However, we do not directly test for the existence of spatial submarkets at this point.

$$P_i = \alpha + \sum_k \beta_k X_i + \varepsilon_i \qquad (1)$$

Where:

P_i Transaction price of the *i*th dwelling

X_{ki} Physical and neighbourhood housing attributes for the *i*th dwelling in the *j*th potential submarket

ε_i Error term or residual

Model (2) is really a set of hedonic models estimated separately according to pre-defined spatial divisions in the data. By adopting this approach, implicitly these subdivisions are taken as a representation of *a priori* submarkets. Model (2) is also estimated by OLS and follows the same specification as model (1). The spatial subdivisions are derived from market analysis published by the Real Estate Institute of Western Australia (REIWA). In these regular statistical publications and market commentaries, the Perth Metropolitan housing market is divided, in spatial terms, into 22 sub-regional areas.

$$P_{ij} = \alpha_j + \sum_k \beta_{kj} X_{ij} + \varepsilon_{ij} \qquad (2)$$

Where:
P_{ij} Transaction price of the *i*th dwelling in sub-region *j*
ε_{ij} Error term

Models (3) and (4) represent full random coefficients multilevel estimations in which all continuous hedonic variable parameters are permitted to vary spatially, between pre-defined spatial units. In model (3) we adopt the subregions or potential spatial submarkets defined by REIWA, as discussed earlier in the paper. In model (4) we adopt postcodes, a considerably smaller unit of geography.

$$P_{ij} = \alpha + \sum_k \beta_k X_i + \sum_j \mu_{0j} + \sum_j \sum_k \mu_{kj} X_i + \varepsilon_i \qquad (3 \text{ and } 4)$$

Where:

P_{ij} Log of transaction price of the *i*th dwelling in the *j*th spatial area

μ_{0j} Random intercept for the *j*th spatial area

μ_{kj} Random slope parameters for the *k* attributes, specific to the *j*th spatial area

The multi-level models are estimated using restricted log likelihood. The estimation approach essentially allows the decomposition of residuals to reveal random intercepts and hedonic slope parameters that are specific to each defined spatial area. A city-wide intercept and set of hedonic parameters are estimated as fixed effects. For a given observation, the predicted price can be obtained by multiplying out the physical attributes with the city-wide coefficients and summing with the product of attributes and the coefficients or random effects specific to the spatial area in which the dwelling is located.

The estimations are carried out using a one year sample of housing transactions in the Perth metropolitan area, Western Australia. A period extending from the middle of 2007 to the middle of 2008 was chosen as a study period after a preliminary analysis (not reported in this paper) to determine a period of relative stability in the Perth metropolitan housing market.

The hedonic data used for the estimations in this study were supplied on license by Landgate, the Western Australian Land Information Authority. These data benefit from considerable detail in terms of hedonic attributes. There are dummy variables describing the presence of ensuite and other bathrooms, dining, family, living and games rooms as well as swimming pool and study or home office variables. Additional variables describe wall and roof construction, location and property age. However, previous empirical work involving this particular dataset has highlighted significant collinearity between many of these attribute variables and location. This is, of course, a common problem in hedonic studies but it is particularly problematic in the context of this study since the main empirical objective is to construct possible spatial submarkets from smaller geographical building blocks. The hedonic analyses therefore focus on a reduced set of explanatory variables with descriptive statistics provided in table 1.

(Table 1 here)

4. Estimation results

4.1 The benchmark model

The empirical performance of the city-wide hedonic model is, unsurprisingly, relatively poor. The adjusted R square is 0.40 (see table 1), although almost all of the physical attribute variables are statistically significant at the 1% level. The 'house' property type is implicit in the constant. Distance from the CBD is significant at 1% and negative, in line with prior theoretical expectations. Despite the careful choice of a comparatively stable study period, the time dummy variables indicate significant variation in transaction prices from the base period.

(Table 2 here)

4.2 Models segmented by real estate agents' submarkets

The subregional spatial units defined by REIWA are illustrated in Figure 1. Segmenting the data by the subregional spatial units defined by REIWA and re-estimating the hedonic model, including distance from the CBD, leads to a substantial improvement in empirical performance, as shown in Table 3.

(Figure 1 here)

(Table 3 here)

For two sub-regions, adjusted R squares are below 0.50 (Wanneroo North East and Wanneroo North West). In the other 20 cases, adjusted R squares range from 0.54 to 0.87. The sample sizes range from 1,144 (Fremantle) to 5,313 (Rockingham). Table 4 sets out descriptive statistics for the sub-region model coefficients.

(Table 4 here)

The magnitudes of standard deviations to their respective means suggests remarkable stability for the intercepts and for coefficients on bedrooms, total number of rooms, car parking, land area and the ratio of bathrooms to bedrooms. There is much more variation in the coefficients for property type variables, as might be expected given that their incidences are likely to exhibit strong spatial patterns. Perhaps most interesting is the evident variation in the coefficient of distance from the CBD (the standard deviation is more than twice the size of the mean). The descriptive statistics therefore give some mixed messages. There is evidence of some variation in slope parameters for ubiquitous attributes and much stronger evidence for those that are likely to cluster spatially. The substantial variation in slope parameters for the distance variable is perhaps the most compelling casual evidence in support of the submarkets hypothesis.

4.3 The multi-level models

As described in the previous section, we estimated two full random effects multi-level models. In the first model, hedonic attribute parameters are estimated on a city-wide basis (as fixed effects) and a full specification of random effects allows estimation of differences in slopes between different spatial units in the metropolitan area. In the first model we use the REIWA defined subregions as the second of the two levels. In the second model we use postcodes, a more finely spatially-grained administrative unit of geography. Figure 2 depicts these boundaries.

(Figure 2 here)

Given the volume of estimation results, providing a summary is challenging. We proceed by summarising the fixed effects and model fit statistics for each of the two models in Table 5. In Table 6 we provide a set of descriptive statistics for the estimated random effects. In other words, the coefficients shown in Table 6 are analogous to hedonic coefficients from an OLS estimation and the descriptive statistics give an indication of the variation in these (the adjustment resulting from application of the random effects) between the defined spatial units.

(Table 5 here)

(Table 6 here)

The 'townhouse' property type is not significant in the first multi-level model, but is significant at 1% in the second. The 'terrace' property type variable is significant only at 10% in the first model, but is significant at 1% in the second. The results are supportive of the idea that spatial aggregation in the presence of spatially varying attribute parameters gives rise to misleading results. In the second model, the specification permits estimation of attribute parameters at a much smaller scale. One of the benefits is that the city-wide parameter estimates appear to be more stable.

For most of the other variables, the results are generally stable between the two multi-level estimations. Differences in parameter estimates seem to affect primarily the property type variables. Interestingly, the coefficient on distance from the CBD is very stable between the two estimations. This result may appear surprising given its apparent instability in the earlier hedonic estimations (models 1 and 2). In both cases the LR and Wald Chi square tests suggest strong explanatory power, but at this stage little more can be said about the relative performance of models 3 and 4 given that the likelihood ratios cannot be compared directly (since model 4 is specified with a greater number of random effects parameters).

Given the impracticality of presenting coefficients for all defined spatial units, Table 6 summarises the mean and standard deviation of the estimated random effects. As discussed in the previous section, these can be interpreted as location-specific differences in attribute parameters (compared with the corresponding city-wide coefficients).

The descriptive statistics in Table 6 reveal instability in parameter estimates between the two estimation approaches. In particular, in moving from a multi-level model with relatively large spatial units (REIWA sub-regions), to that with smaller spatial units (postcodes) reveals:

- The mean and standard deviation of the random effects differ noticeably for the ‘group house’, ‘villa’, ‘home unit’ and ‘flat’ property type variables.

- The mean random effect for ‘terrace’ is almost the same between the two estimations, but the standard deviation is much larger in the finer spatially-grained model.

- The mean random effects for bedrooms, car parking, the ratio of bathrooms to bedrooms and distance from the CBD seem stable between the two models.

- Random effects for land area and total number of rooms appear to have much more variation in the second model than the first.

4.4 Predictive performance of the models

We now turn to the predictive performance of the five models examined in the empirical analysis. Table 7 summarises the mean, standard deviation, lower and upper quartile prediction errors. The figures are percentages.

(Table 7 here)

The figures show an improvement in predictive accuracy between models 1 and 2 (the city-wide and sub-region models respectively). The first multi-level model (model 3), with larger spatial units, has poorer predictive power than the sub-region models. This is interesting because, of course, models 2 and 3 are conceptually similar, despite the different estimation approaches. Both models are designed to allow hedonic parameters to vary between subregional spatial units as defined by real estate agents. While model 2 achieves this through separate estimation of the hedonic model for each spatial unit, model 3 does so through a combination of city-wide effects and subregional effects. On the basis of predictive power, the multi-level approach used for model 3 appears to be less efficient, achieving slightly lower predictive accuracy than a simpler segmented OLS model. However, the second multi-level model (model 4) has superior predictive accuracy in comparison with the other three models. Mean prediction error is -1.61% with a standard deviation of 19.18%. Figures 3 to 6 (see annex) depict the spatial patterns of prediction errors.

(Figure 3 here)

(Figure 4 here)

(Figure 5 here)

(Figure 6 here)

For ease of reference, prediction errors between -10% and +10% are shown in green and greater prediction errors are shown in red. The progressive improvement between models 1 & 2 and between 2 & 3 are evident visually. Similarly, the lower incidence and more random spatial distribution of large (more than 10%) prediction errors is evident in a comparison of models 1 and 5 (the worst and best in terms of predictive power). However, it is also notable that even the best empirically performing model leads to a spatial pattern of prediction errors that is far from random. Transacted properties in waterfront locations, either facing the Indian Ocean or the substantial frontage of Swan River, are associated with much higher incidence of high prediction error.

5 Conclusions

This paper set out to examine the utility of applying multi-level strategies to modelling spatial housing submarkets. The empirical analysis was designed to compare the predictive performance of several models. Setting up a simple, city-wide OLS hedonic model, with a simple distance variable, allowed us to establish a basic benchmark with which to compare several alternative approaches. We found that separate estimation of the hedonic models for potential submarkets (or subregions) defined by real estate agents led to a model that was superior to the benchmark in terms of predictive power.

Estimation of multi-level hedonic models also led to improvement beyond the benchmark OLS model. Here however, the predictive performance for one of the models (model 3) was slightly below that of the sub-region models on average. This is an important and interesting finding in that it implies that a spatially segmented OLS estimation approach is acceptable when there is certainty about spatial submarket boundaries, and would be appropriate when submarket boundaries are expected to remain stable over time.

However, as we argue earlier, the best modelling strategy is not just that which produces the greatest predictive accuracy. The best approach to modelling submarkets must also be able to capture the fluidity in submarket boundaries over time. Where the spatial extent of submarket boundaries is less certain, or when there is an expectation of change in these boundaries over time, our analysis suggests that a multi-level approach, with more finely spatially grained units of geography, may be preferable to a segmented approach. Our second multi-level model (model 4), defined with smaller spatial units, exhibits predictive performance that exceeded all other estimation approaches examined in this paper. The spatial pattern of prediction errors is less concentrated. The results imply that multi-level models have the capacity to improve predictive power and reduce spatial dependence when compared with standard hedonic methods. In addition, when applied over time, multi-level models appear better able to deal with dynamic change in the composition of submarkets and have the potential to capture the multiple (often nested) geographies that exist within local housing systems. They can be used effectively to differentiate between neighbourhood, local (sub-regional) and regional influences. More applied research is required, however, to exploit this potential.

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Table 1 Descriptive statistics for key hedonic variables

Variable	N	Mean	Median	Minimum	Maximum	St. Dev.
Transaction price		521,022	435,000	105,000	23,000,000	362,993
Bedrooms		3.14	3	1	7	0.85
Number of rooms		8.53	8	4	23	2.43
Car parking		1.34	1	0	6	0.76
Distance from CBD (km)		15.45	13.10	0.20	54.27	10.21
Land area (square metres)		599.98	603	42	4946	402.2
Ratio of bathrooms to bedrooms		0.50	0.50	0.17	2	0.17
Property type (dummies):						
House	41,346					
Group house	5,187					
Villa	3,272					
Home unit	2,502					
Duplex	2,418					
Flat	1,924					
Townhouse	1,740					
Triplex	366					
Quadruplex	220					
Terrace	137					
Total N	60,699					

Table 2 City-wide hedonic model with distance variable

Variable	Coefficient	t statistic	
Constant	12.493	1195.204	***
Group house	-0.128	-24.988	***
Villa	-0.189	-28.956	***
Home unit	-0.22	-29.18	***
Duplex	-0.054	-7.395	***
Flat	-0.459	-51.64	***
Townhouse	0.012	1.427	
Triplex	-0.088	-5.012	***
Quadruplex	-0.104	-4.602	***
Terrace	0.11	3.853	***
Bedrooms	0.041	9.555	***
Car parking	0.084	37.903	***
Distance from CBD (km)	-0.018	-124.452	***
Land area (square metres)	0	59.346	***
Ratio of bathrooms to bedrooms	0.387	34.519	***
Number of rooms	0.039	26.822	***
Q2, 2007	-0.013	-2.536	**
Q3, 2007	0.007	1.411	
Q4, 2007	0.03	5.546	***
Q5, 2008	0.011	2.037	**
Q6, 2008	-0.024	-4.389	***
Q7, 2008	-0.054	-10.175	***
Q8, 2008	-0.091	-16.731	***
Adjusted R Square	0.403		
Std. Error	0.333		
F	1861.927		

Figure 1 **Perth, Western Australia submarkets as defined by REIWA**

Table 3 Summary of sub-region hedonic models

Sub-region	Adjusted R Square	Std. Error of the Estimate
ARMADALE/SERPENTINE	0.646	0.184
BASSENDEAN/BAYSWATER	0.716	0.182
BELMONT	0.623	0.188
CANNING	0.544	0.193
COCKBURN	0.521	0.195
FREMANTLE	0.559	0.319
GOSNELLS	0.567	0.15
HILLS	0.566	0.195
JOONDALUP NORTH	0.504	0.226
JOONDALUP SOUTH	0.526	0.249
MELVILLE	0.686	0.25
PERTH CITY	0.742	0.209
ROCKINGHAM/KWINANA	0.518	0.207
SOUTH PERTH/VICTORIA PARK	0.723	0.242
STIRLING EAST	0.716	0.187
STIRLING WEST	0.666	0.235
SWAN	0.515	0.178
VINCENT/STIRLING SE	0.865	0.195
WANNEROO NORTH EAST	0.482	0.153
WANNEROO NORTH WEST	0.349	0.233
WANNEROO SOUTH	0.773	0.132
WESTERN SUBURBS	0.841	0.293

Table 4 Descriptive statistics –sub-region model coefficients

Variable	Mean	Median	Minimum	Maximum	St. Dev.
Constant	12.275	12.216	11.027	13.562	0.539
Group house	-0.098	-0.081	-0.278	0.046	0.087
Villa	-0.138	-0.117	-0.426	0.088	0.134
Home unit	-0.210	-0.172	-0.542	0.068	0.162
Duplex	-0.044	-0.046	-0.226	0.129	0.081
Flat	-0.394	-0.358	-0.888	-0.125	0.228
Townhouse	-0.007	-0.046	-0.279	0.689	0.219
Triplex	-0.104	-0.074	-0.431	0.204	0.174
Quadruplex	-0.109	-0.093	-0.488	0.217	0.19
Terrace	-0.026	-0.067	-0.232	0.379	0.178
Bedrooms	0.05	0.053	0.016	0.096	0.021
Car parking	0.061	0.063	0.016	0.11	0.027
Distance from CBD (km)	-0.019	-0.006	-0.119	0.087	0.047
Land area (square metres)	0.001	0	0	0.003	0
Ratio of bathrooms to bedrooms	0.294	0.294	0.052	0.549	0.142
Number of rooms	0.041	0.037	0.007	0.08	0.018
Q2, 2007	0.01	0.007	-0.023	0.073	0.02
Q3, 2007	0.026	0.024	-0.03	0.078	0.021
Q4, 2007	0.041	0.035	-0.033	0.115	0.035
Q5, 2008	0.04	0.031	-0.035	0.151	0.043
Q6, 2008	0.017	-0.004	-0.085	0.168	0.059
Q7, 2008	-0.01	-0.015	-0.108	0.094	0.041
Q8, 2008	-0.038	-0.037	-0.128	0.045	0.036

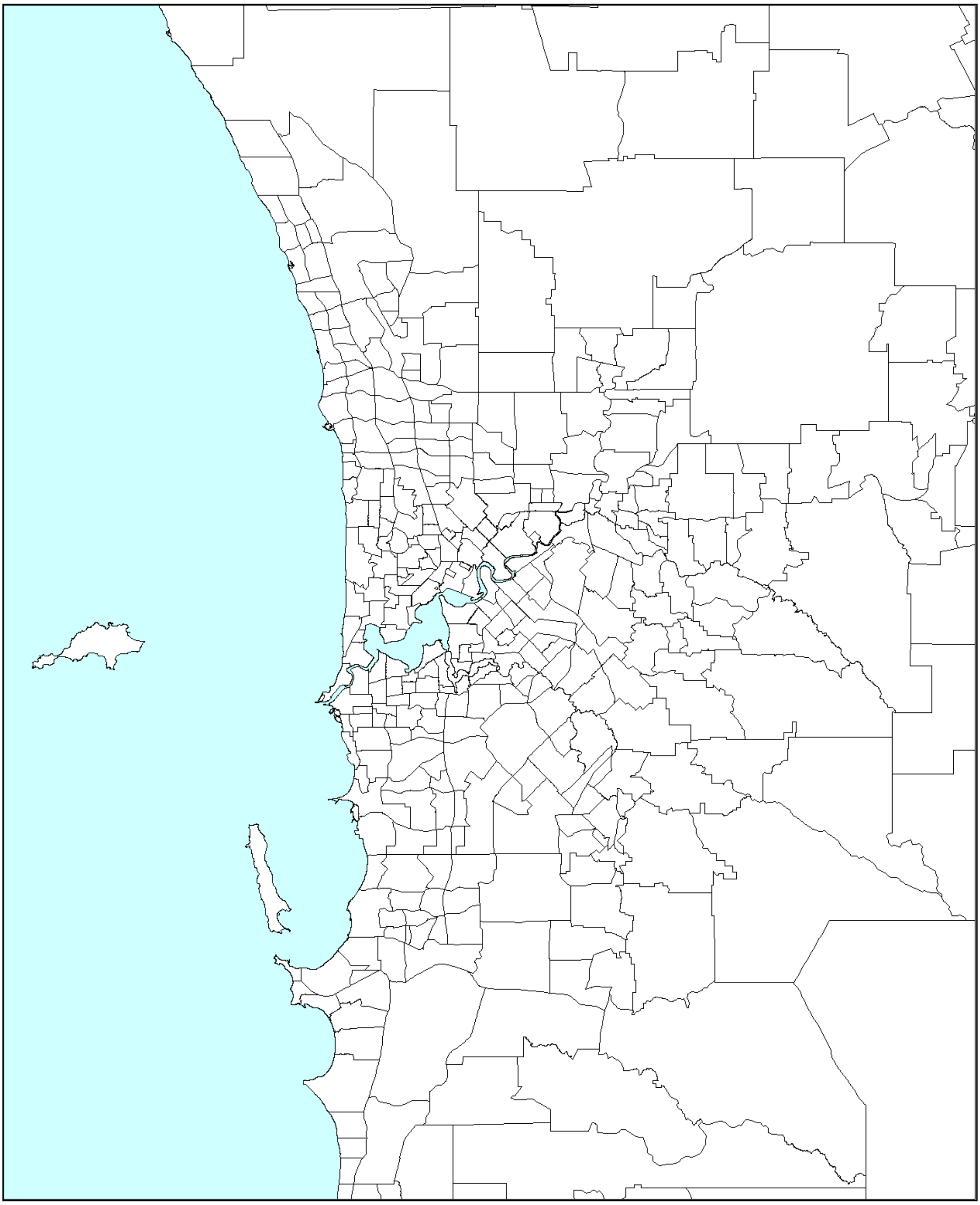

Figure 2 **Postcode regions for Perth, Western Australia**

Table 5 Multi-level model - fixed effects and model fit statistics

Variable	Real estate agents' subregions		Postcodes	
	Coefficient		Coefficient	
Constant	12.2802	***	12.4637	***
Group house	-0.0972	***	-0.1043	***
Villa	-0.1394	***	-0.1815	***
Home unit	-0.2169	***	-0.2743	***
Duplex	-0.0450	***	-0.0911	***
Flat	-0.3939	***	-0.4356	***
Townhouse	-0.0188		-0.1253	***
Triplex	-0.1332	***	-0.1840	***
Quadruplex	-0.1324	***	-0.1991	***
Terrace	-0.0675	*	-0.1473	***
Bedrooms	0.0494	***	0.0513	***
Car parking	0.0609	***	0.0474	***
Distance from CBD (km)	-0.0183	*	-0.0183	**
Land area (square metres)	0.0005	***	0.0005	***
Ratio of bathrooms to bedrooms	0.2936	***	0.2549	***
Number of rooms	0.0406	***	0.0365	***
Q2, 2007	0.0078	**	0.0131	***
Q3, 2007	0.0239	***	0.0305	***
Q4, 2007	0.0364	***	0.0375	***
Q5, 2008	0.0333	***	0.0375	***
Q6, 2008	0.0062	*	0.0098	***
Q7, 2008	-0.0161	***	-0.0127	***
Q8, 2008	-0.0435	***	-0.0377	***
Wald Chi2	1,447.28	***	3,490.96	***
Log restricted likelihood	7,238.77		15,815.96	
Groups	22		22	
Total N	60699		60699	
LR test	53,451.41	***	70,605.78	***

Table 6 Multi-level model - estimated random effect statistics

Random effects	Subregions		Postcodes	
	Mean	St. Dev.	Mean	St. Dev.
Constant	0.007	0.080	0.014	0.061
Group house	0.009	0.113	0.030	0.115
Villa	-0.004	0.133	0.039	0.151
Home unit	0.001	0.060	0.011	0.063
Duplex	0.021	0.181	0.023	0.137
Flat	0.010	0.186	0.043	0.148
Townhouse	0.012	0.127	0.008	0.06
Triplex	0.011	0.106	0.006	0.048
Quadruplex	0.004	0.063	0.007	0.058
Terrace	0	0.014	-0.001	0.031
Bedrooms	0.003	0.024	0.005	0.025
Car parking	-0.003	0.045	0	0.073
Distance from CBD (km)	0	0	0	0
Land area (square metres)	0.012	0.127	0.004	0.142
Ratio of bathrooms to bedrooms	-0.002	0.016	0	0.018
Number of rooms	0.004	0.526	-0.061	1.014

Table 7 Predictive accuracy of the models

Summary of models	Mean	St. Dev.	Percentile 25	Percentile 75
Model 1 (city-wide OLS)	-3.28	29.37	-13.06	13.57
Model 2 (REIWA sub-regions)	-2.32	23.86	-10.44	10.96
Model 3 (ML /REIWA sub-regions)	-2.38	24.22	-10.59	11.06
Model 4 (ML / postcodes)	-1.61	19.18	-8.98	9.00

Note: figures are percentage prediction errors, e.g. Model 1 mean is -3.28%

Annex – Maps of prediction errors

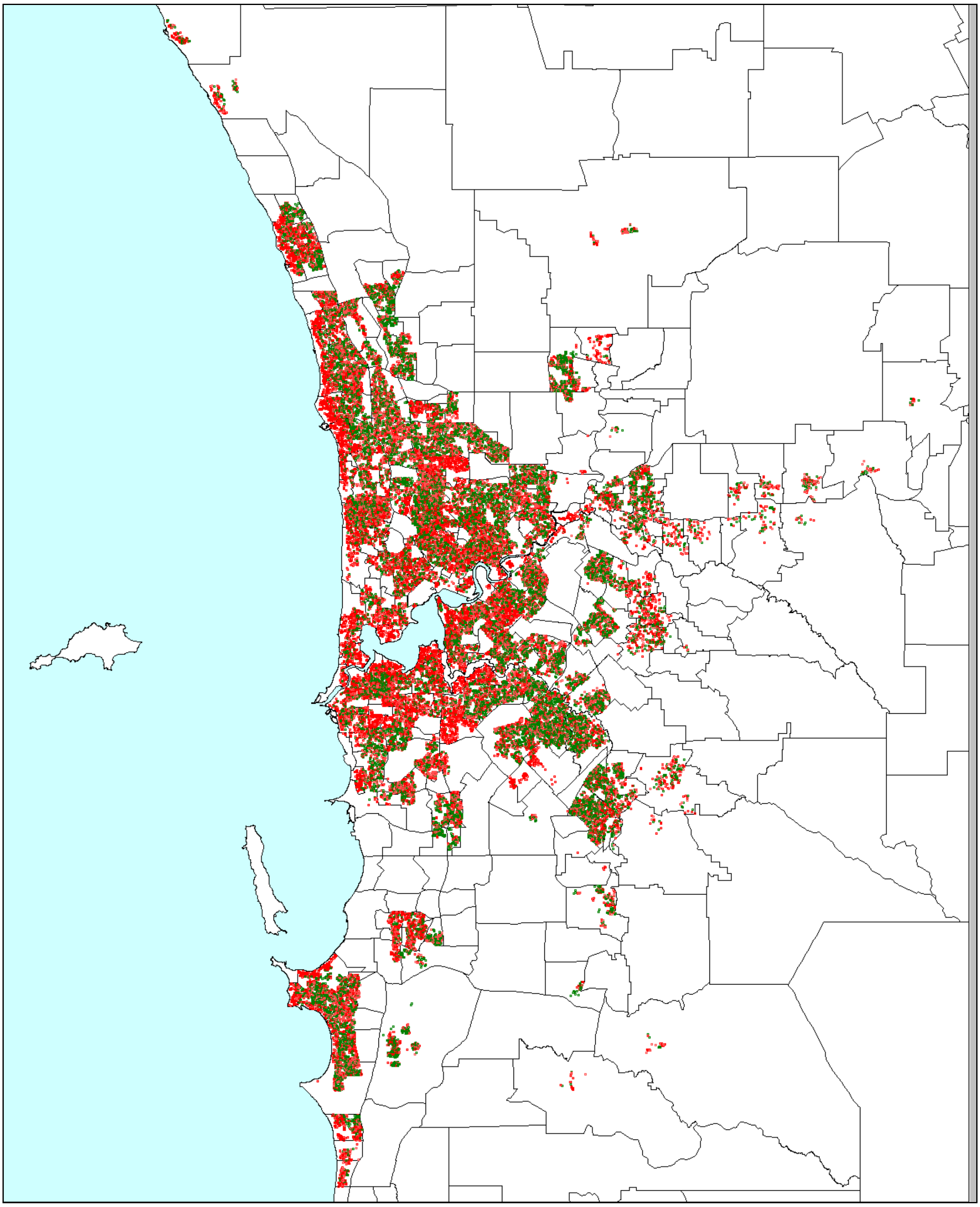

Figure 3 **Prediction errors for model 1**

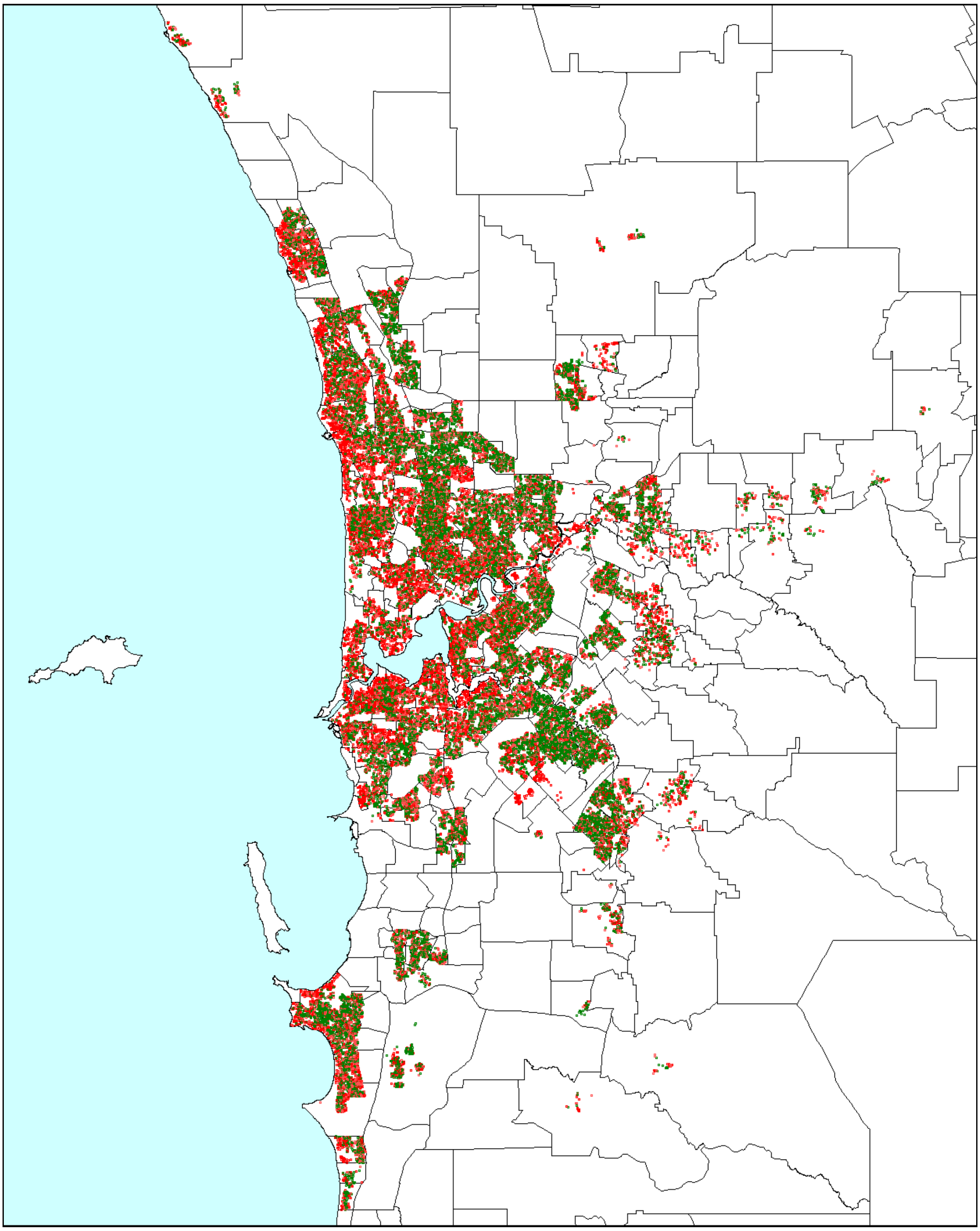

Figure 4 Prediction errors for model 2

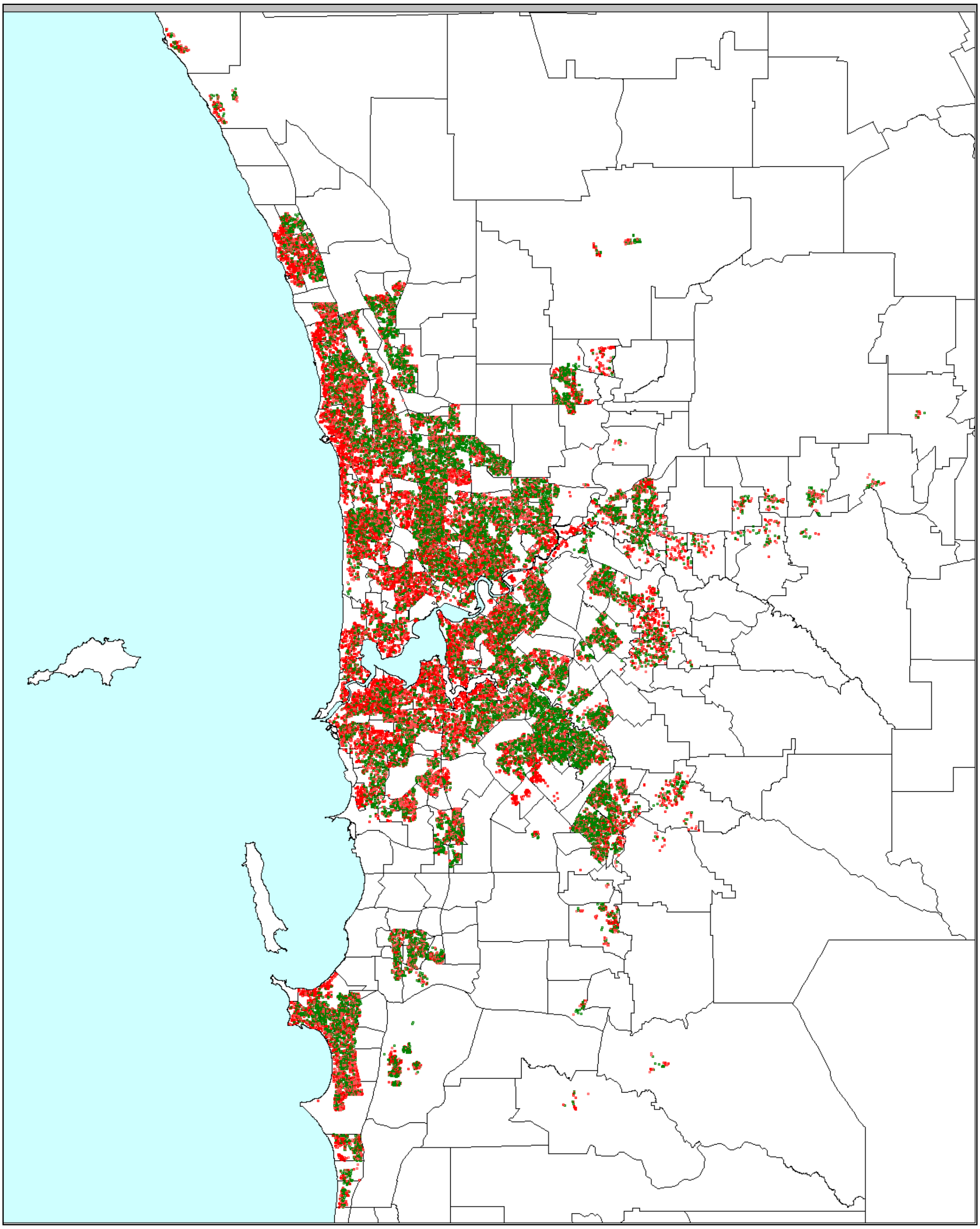

Figure 5 Prediction errors for model 3

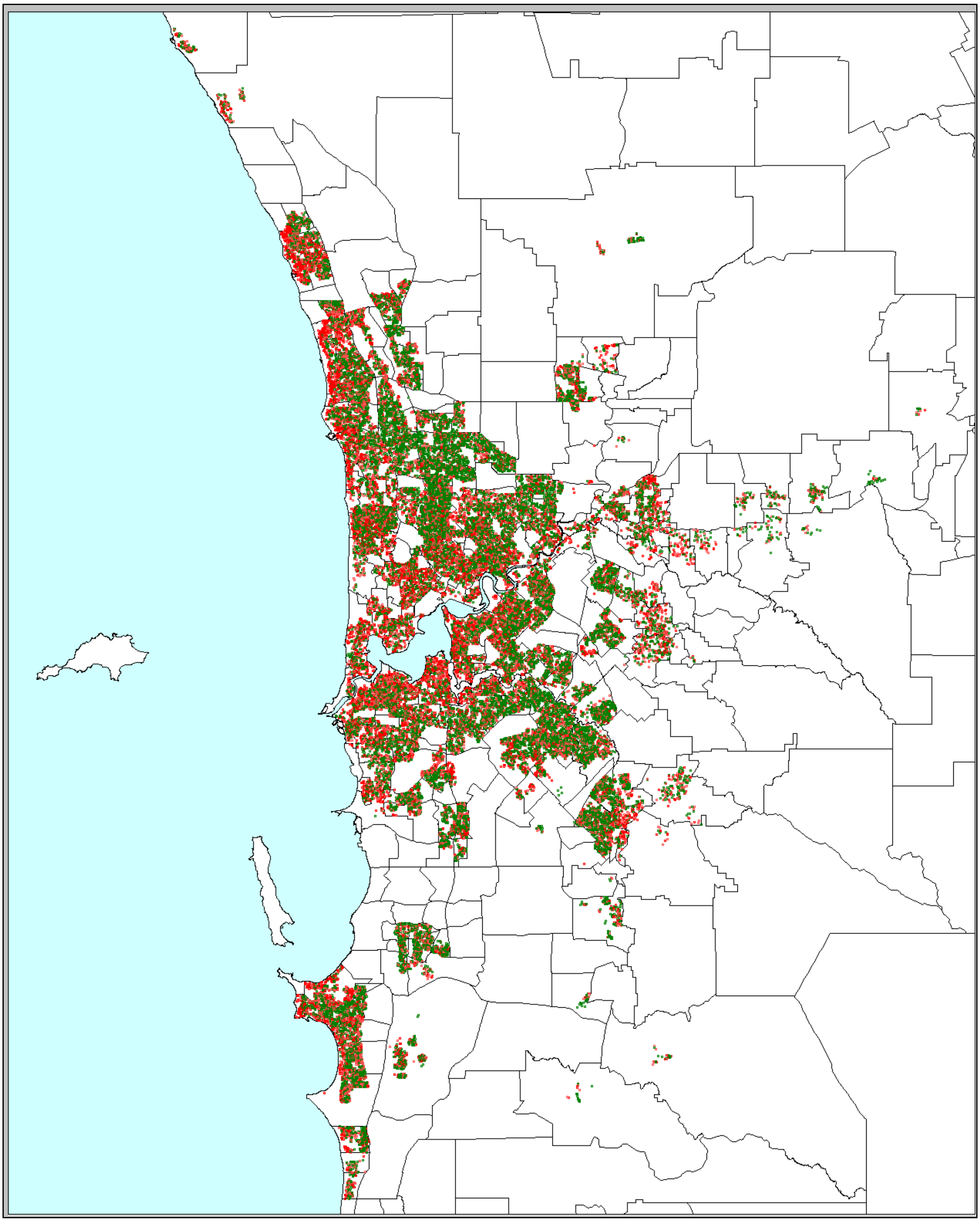

Figure 6 Prediction errors for model 4