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Hierarchical forecasts for Australian domestic tourism

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Abstract

In this paper we explore the hierarchical nature of tourism demand time series and produce short-term forecasts for Australian domestic tourism. The data and forecasts are organized in a hierarchy based on disaggregating the data according to geographical regions and purposes of travel. We consider five approaches to hierarchical forecasting: two variations of the top-down approach, the bottom-up method, a newly proposed top-down approach where top-level forecasts are disaggregated according to the forecasted proportions of lower level series, and a recently proposed optimal combination approach. Our forecast performance evaluation shows that the top-down approach based on forecast proportions and the optimal combination method perform best for the tourism hierarchies we consider. By applying these methods, we produce detailed forecasts of the Australian domestic tourism market.

Keywords: Australia; Exponential smoothing; Hierarchical forecasting; Innovations state space models; Optimal combination forecasts; Top-down method; Tourism demand

1. Introduction

Quarterly tourism demand is measured by the number of "visitor nights", the total nights spent away from home. The data is disaggregated by geographical region and by purpose of travel, thus forming a natural hierarchy of quarterly time series. In this paper we take advantage of this hierarchical structure, and use hierarchical forecasting methods to produce forecasts of the Australian domestic tourism market for several levels of disaggregation.

Australia can be divided into six states: New South Wales (NSW), Victoria (VIC), Queensland (QLD), South Australia (SA), Western Australia (WA) and Tasmania (TAS), and the Northern Territory (NT). (For the purposes of this analysis, we treat the Australian Capital Territory as part of NSW and refer to the Northern Territory as a "state".) Business planners require forecasts for the whole of Australia, for each state, and for smaller regions.

In Section 2 we present two hierarchical time series structures for Australian domestic tourism data. In the first hierarchy, we initially disaggregate the data by

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purpose of travel and then by geographical region. The purposes of travel we consider are: holiday, visiting friends and relatives (VFR), business, and other. In the second hierarchy, we disaggregate the data by geographical region alone.

The most common approaches to forecasting hierarchical time series are the top-down and bottom-up approaches. The majority of the literature on hierarchical forecasting has focused on comparing the performances of these two methods, with some favouring the top-down approaches (see for example Fliedner (1999), Fogarty, Blackstone, and Hoffman (1990), Grunfeld and Griliches (1960) and Narasimhan, McLeavey, and Billington (1994)), while others favour the bottom-up approaches (see for example Dangerfield and Morris (1992), Edwards and Orcutt (1969), Kinney (1971), Orcutt, Watt, and Edwards (1968) and Zellner and Tobias (2000)), and still others find neither method to be uniformly superior (see for example Fliedner and Mabert (1992), Shing (1993) and Weatherby (1984)). In Section 3 we introduce a notation which neatly generalises hierarchical forecasting approaches. We then present two new hierarchical forecasting methods. First, we propose a new top-down approach which is based on disaggregating the top-level forecasts according to forecasted proportions, rather than the conventional historical (and therefore static) proportions. Second, we present the newly proposed "optimal combination" approach of Hyndman, Ahmed, and Athanasopoulos (2007). The optimal combination approach is based on forecasting all series at all levels, and then using a regression model to obtain the minimum variance unbiased combination of the forecasts. The resulting revised forecasts display some desirable properties not found in forecasts from other approaches.

We present our modelling procedure in Section 4. For each series, and at each level of the hierarchies, we obtain forecasts using a single source of error (or innovations) state space model (see Aoki (1987)). These models have been very successful when applied to data from forecasting competitions (e.g., Hyndman, Koehler, Snyder, and Grose (2002) and Makridakis and Hibon (2000)). Considering regional tourism demand and tourism demand by purpose of travel allows specific characteristics and dynamics in the data to surface at different levels of the hierarchy. We believe that the greatest advantage of the two new approaches we consider, compared to the conventional methods, is that with these approaches we are able to capture the various characteristics through the individual modelling of all of the series. Both the innovations state space models we use to forecast the individual series, and the hierarchical forecasting approaches we apply to combine these forecasts, are novel to the tourism literature. Neither appeared in the comprehensive reviews of Li, Song, and Witt (2005) and Song and Li (2008), which jointly cover tourism forecasting studies from 1990 to 2006. The only exception is Athanasopoulos and Hyndman (2008), who also use innovations state space models as a time series alternative to econometric modelling approaches, and forecast Australian domestic tourism demand at an aggregate level, and also by purpose of travel.

In order to evaluate the performance of the alternative hierarchical approaches, we perform an out-of-sample forecast evaluation in Section 5. We also test for significant differences in predictive accuracy between the approaches by applying the Diebold–Mariano test. We conclude that the best performing hierarchical approach for this application is our newly proposed top-down method, followed by the optimal combination approach.

We apply the two new approaches in Section 6, where we forecast tourism demand for Australia and the states from both hierarchies. Our forecasts show a decline in the aggregate domestic tourism demand for Australia over the next two years. This decline is mainly driven by a decline in tourism demand in the states of New South Wales and Victoria. Continuing with the top-down approach based on forecasted proportions, we produce forecasts for all levels of the hierarchies and draw some useful conclusions for policy makers. We present a summary of our findings and concluding remarks in Section 7.

2. Hierarchical time series

Consider the hierarchical structure of Fig. 1. We denote the completely aggregated "Total" series as level 0, the first level of disaggregation as level 1, and so on down to the bottom level K, which comprises the most disaggregated series. Hence, the hierarchy depicted in Fig. 1 is a $K = 2$ level hierarchy. Let $Y_{X,t}$ be the tth observation ($t = 1, \ldots, n$) of series Y_X, which corresponds to node X on the hierarchical tree.

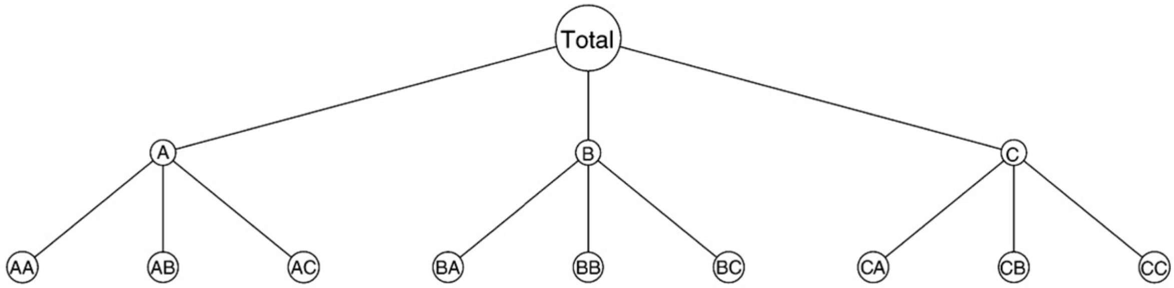

Fig. 1. A two level hierarchical tree diagram.

We use a sequence of letters to denote the individual nodes, as depicted in Fig. 1. For example, $Y_{\mathrm{A},t}$ denotes the tth observation of the series corresponding to node A at level 1, $Y_{\mathrm{AB},t}$ denotes the tth observation of the series corresponding to node AB at level 2, and so on. Notice that the actual letter sequence indicates the individual node and the length of the letter sequence denotes the level. For the totally aggregated level, the tth observation is denoted by Y_t. We let m_i denote the total number of series for level i, and $m = m_0 + m_1 + \cdots + m_K$ is the total number of series in the hierarchy.

We study two hierarchical time series structures for the Australian domestic tourism market. The structures of the hierarchies are presented in Tables 1 and 2. Each hierarchy allows for different dynamics to surface, which we then attempt to capture in our modeling process.

For each domestic tourism demand time series, we have quarterly observations of the number of visitor nights, which we use as an indicator of tourism activity. The sample begins with the first quarter of 1998 and ends with the final quarter of 2006. The series are obtained from the National Visitor Survey, which is managed by Tourism Research Australia. The data were collected using computer-assisted telephone interviews from approximately 120,000 Australians aged 15 years and over on an annual basis (Tourism Research Australia, 2005).

3. Alternative approaches to hierarchical forecasting

In order to generalise the notation for the various approaches to hierarchical forecasting, we let vector $\boldsymbol{Y}_{i,t}$ contain all the observations in level i at time t. We stack all observations of all series at time t in a column vector defined as $\boldsymbol{Y}_t = [Y_t, \boldsymbol{Y}'_{1,t}, \ldots, \boldsymbol{Y}'_{K,t}]'$. Now we can write

Table 1
Hierarchy 1.

Level	Number of series	Total series per level
Australia	1	1
Purpose of travel	4	4
States and Territories	7	28
Capital city versus other	2	56

For more details on this structure refer to Appendix A.1.

$$\boldsymbol{Y}_t = \boldsymbol{S}\boldsymbol{Y}_{K,t}, \tag{1}$$

where $\boldsymbol{S}$ is a "summing" matrix of order $m \times m_K$ that aggregates the bottom level series all the way up the hierarchy. For example, for the hierarchy of Fig. 1 we have

$$\underset{(13\times 1)}{\begin{bmatrix} Y_t \\ Y_{\mathrm{A},t} \\ Y_{\mathrm{B},t} \\ Y_{\mathrm{C},t} \\ Y_{\mathrm{AA},t} \\ Y_{\mathrm{AB},t} \\ \vdots \\ Y_{\mathrm{CB},t} \\ Y_{\mathrm{CC},t} \end{bmatrix}} = \underset{(13\times 9)}{\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ & & & & \boldsymbol{I}_9 & & & & \end{bmatrix}} \underset{(9\times 1)}{\begin{bmatrix} Y_{\mathrm{AA},t} \\ Y_{\mathrm{AB},t} \\ Y_{\mathrm{AC},t} \\ Y_{\mathrm{BA},t} \\ Y_{\mathrm{BB},t} \\ Y_{\mathrm{BC},t} \\ Y_{\mathrm{CA},t} \\ Y_{\mathrm{CB},t} \\ Y_{\mathrm{CC},t} \end{bmatrix}}$$

where $\boldsymbol{I}_k$ denotes an identity matrix of order $k \times k$.

In hierarchical forecasting we are interested in working with the forecasts rather than the actual observations of each series. Suppose that we have generated h-step-ahead forecasts for each individual series Y_X, denoted by $\hat{Y}_{X,n}(h)$. We should clarify that these forecasts are based on a sample of $t =$

Table 2
Hierarchy 2.

Level	Total series per level
Australia	1
States and Territories	7
Zones	27
Regions	82

For more details on this structure refer to Appendix A.2.

$1, \ldots, n$, and hence they are the forecasts for time $n + h$. Therefore, $\hat{Y}_{\mathrm{AB},n}(h)$ denotes the h-step-ahead base forecast of series Y_{AB} using the sample $Y_{\mathrm{AB},1}, \ldots, Y_{\mathrm{AB},n}$. For level i, all h-step-ahead base forecasts will be represented by $\hat{\boldsymbol{Y}}_{i,n}(h)$, and the h-step-ahead base forecasts for the whole hierarchy are represented by the vector $\hat{\boldsymbol{Y}}_n(h)$, which contains all of the base forecasts stacked in the same order as $\boldsymbol{Y}_t$.

Using this notation, all existing hierarchical methods can be represented by the general form

$$\tilde{\boldsymbol{Y}}_n(h) = \boldsymbol{S}\boldsymbol{P}\hat{\boldsymbol{Y}}_n(h), \tag{2}$$

where $\boldsymbol{S}$ is the $m \times m_K$ summing matrix, as in Eq. (1), and $\boldsymbol{P}$ is a matrix of order $m_K \times m$. The role of $\boldsymbol{P}$ differs depending on the hierarchical approach. This will become clear in subsequent sections. This general representation shows that the final revised forecasts $\tilde{\boldsymbol{Y}}_n(h)$ produced by any hierarchical forecasting approach are the result of linearly combining the independent base forecasts, $\hat{\boldsymbol{Y}}_n(h)$.

3.1. The bottom-up approach

Arguably the most commonly applied method to hierarchical forecasting is the bottom-up approach (see for example Dangerfield and Morris (1992), Dunn, Williams, and DeChaine (1976), Orcutt et al. (1968), Shlifer and Wolff (1979), Theil (1954) and Zellner and Tobias (2000)). To represent this approach using the general form of Eq. (2), we write

$$\boldsymbol{P} = [\boldsymbol{0}_{m_K \times (m-m_K)} | \boldsymbol{I}_{m_K}], \tag{3}$$

where $\boldsymbol{0}_{i \times j}$ is the $i \times j$ null matrix. The role of $\boldsymbol{P}$ here is to extract the bottom level forecasts, which are then aggregated by the summation matrix $\boldsymbol{S}$ to produce the revised forecasts for the whole hierarchy. The greatest advantage of this approach is that, by modelling the data at the most disaggregated bottom level, we do not lose any information due to aggregation. Hence, we can better capture the dynamics of the individual series. However, bottom level data can be quite noisy, and is therefore more challenging to model.

3.2. Top-down approaches based on historical proportions

The other commonly applied method in hierarchical forecasting is the top-down approach (see for example Fliedner (1999), Grunfeld and Griliches (1960), Lütkephol (1984) and McLeavey and Narasimhan (1985)). The most common form of the top-down approach is to disaggregate the forecasts of the "Total" series and distribute these down the hierarchy based on the historical proportions of the data. In terms of the general form of Eq. (2), we write

$$\boldsymbol{P} = [\boldsymbol{p} | \boldsymbol{0}_{m_K \times (m-1)}], \tag{4}$$

where $\boldsymbol{p} = [p_1, p_2, \ldots, p_{m_K}]'$ are a set of proportions for the bottom level series. So the role of $\boldsymbol{P}$ here is to distribute the top level forecasts to forecasts for the bottom level series.

In this paper we consider two versions of this approach which performed quite well in the study by Gross and Sohl (1990). For the first one

$$p_j = \sum_{t=1}^{n} \frac{Y_{j,t}}{Y_t} \Big/ n \tag{5}$$

for $j = 1, \ldots, m_K$. We label this "Top-down HP1" in the tables that follow. Each proportion p_j reflects the average of the historical proportions of the bottom level series $\{Y_{j,t}\}$ over the period $t = 1, \ldots, n$ relative to the total aggregate $\{Y_t\}$; i.e., vector $\boldsymbol{p}$ reflects the *average historical proportions*.

In the second version we consider

$$p_j = \sum_{t=1}^{n} \frac{Y_{j,t}}{n} \Big/ \sum_{t=1}^{n} \frac{Y_t}{n} \tag{6}$$

for $j = 1, \ldots, m_K$. We label this "Top-down HP2" in the tables that follow. Each p_j proportion here captures the average historical value of the bottom level series $\{Y_{j,t}\}$ relative to the average value of the total aggregate $\{Y_t\}$; i.e., vector $\boldsymbol{p}$ reflects the *proportions of the historical averages*.

The simplicity of the application of these top-down approaches is their greatest attribute. One only needs to model and produce forecasts for the most aggregated top level series. These approaches seem to produce quite reliable forecasts for the aggregate levels, and they are very useful with low count data. On the other hand, their greatest disadvantage is the loss of information due to aggregation. With these top-down approaches, we are unable to capture and take advantage of individual series characteristics such as time dynamics, special events, etc. For example, in the empirical application with tourism data that follows, the data are highly seasonal. The seasonal pattern of tourism arrivals may vary across series depending on the tourism destination. A ski resort will have a very different seasonal pattern to a beach resort. This will not be captured by disaggregating the total of these destinations based on historical proportions. Finally, with these methods we base the disaggregation of the "Total" series forecasts on historical and static proportions, and these proportions will miss any trends in the data.

3.3. Top-down approach based on forecasted proportions

To improve on the above historical and static nature of the proportions used to disaggregate the top level forecasts, we introduce a top-down method for which the proportions for disaggregating the top level forecasts are based on the forecasted proportions of lower level series.

To demonstrate the intuition of this method, consider a one level hierarchy and only 1-step-ahead forecasts, which we initially produce for all series independently. At level 1 we calculate the proportion of each individual forecast to the aggregate of all the individual forecasts at this level. We refer to these as the forecasted proportions, and use them to disaggregate the top level forecast. For a K-level hierarchy, this process is repeated for each node, going from the top level to the very bottom level.

We label this "Top-down FP" in the tables that follow. As the results will show, this method has worked well with the tourism hierarchies we consider in this paper. The greatest disadvantage of this method, which is in fact a disadvantage of any top-down approach, is that these approaches do not produce unbiased revised forecasts, even if the base forecasts are unbiased (refer to the discussion of Eq. (5) in Hyndman et al. (2007)).

As with the two previous top-down approaches,

$$\boldsymbol{P} = [\boldsymbol{p}|\boldsymbol{0}_{m_K\times(m-1)}], \tag{7}$$

where $\boldsymbol{p} = [p_1, p_2, \ldots, p_{m_K}]'$ are a set of proportions for the bottom level series. In order to present a general form for the bottom level proportions we need to introduce some new notation. Let $\hat{Y}^{(\ell)}_{j,n}(h)$ be the h-step-ahead forecast of the series that corresponds to the node which is ℓ levels above j. Also let $\hat{S}_{j,n}(h)$ be the sum of the h-step-ahead forecasts below node j which are directly connected to node j. The two notations can be combined. For example, in Fig. 1, $\hat{S}^{(2)}_{\mathrm{AA},n}(h) = \hat{S}_{\mathrm{Total},n}(h) = \hat{Y}_{\mathrm{A},n}(h)+\hat{Y}_{\mathrm{B},n}(h)+\hat{Y}_{\mathrm{C},n}(h)$.

If we generate h-step-ahead forecasts for the series of the hierarchy in Fig. 1, the revised final forecasts moving down the farthest left branch of the hierarchy will be

$$\begin{aligned}\tilde{Y}_{\mathrm{A},n}(h) &= \left(\frac{\tilde{Y}_{\mathrm{A},n}(h)}{\hat{S}^{(1)}_{\mathrm{A},n}(h)}\right)\hat{Y}_{\mathrm{Total},n}(h)\\ &= \left(\frac{\hat{Y}^{(1)}_{\mathrm{AA},n}(h)}{\hat{S}^{(2)}_{\mathrm{AA},n}(h)}\right)\hat{Y}_{\mathrm{Total},n}(h)\end{aligned}$$

and

$$\begin{aligned}\tilde{Y}_{\mathrm{AA},n}(h) &= \left(\frac{\hat{Y}_{\mathrm{AA},n}(h)}{\hat{S}^{(1)}_{\mathrm{AA},n}(h)}\right)\tilde{Y}_{\mathrm{A},n}(h)\\ &= \left(\frac{\hat{Y}_{\mathrm{AA},n}(h)}{\hat{S}^{(1)}_{\mathrm{AA},n}(h)}\right)\left(\frac{\hat{Y}^{(1)}_{\mathrm{AA},n}(h)}{\hat{S}^{(2)}_{\mathrm{AA},n}(h)}\right)\tilde{Y}_{\mathrm{Total},n}(h).\end{aligned}$$

Consequently,

$$p_1 = \left(\frac{\hat{Y}_{\mathrm{AA},n}(h)}{\hat{S}^{(1)}_{\mathrm{AA},n}(h)}\right)\left(\frac{\hat{Y}^{(1)}_{\mathrm{AA},n}(h)}{\hat{S}^{(2)}_{\mathrm{AA},n}(h)}\right).$$

The other proportions are obtained similarly. The general result can be written as follows:

$$p_j = \prod_{\ell=0}^{K-1}\frac{\hat{Y}^{(\ell)}_{j,n}(h)}{\hat{S}^{(\ell+1)}_{j,n}(h)} \tag{8}$$

for $j = 1, 2, \ldots, m_K$.

3.4. The optimal combination approach

The final approach to hierarchical forecasting we consider is the "optimal combination approach" introduced by Hyndman et al. (2007). This approach optimally combines the base forecasts to produce a set of revised forecasts that are as close as possible to the univariate forecasts, but also meet the requirement that forecasts at upper levels in the hierarchy are the sum of the associated lower level forecasts. Unlike any other existing method, this approach uses all of the information available within a hierarchy; allows for correlations and interactions between series at each level of the hierarchy; accounts for ad hoc adjustments of forecasts at any level; and, provided that the base forecasts are unbiased, produces unbiased forecasts which are consistent across all levels of the hierarchy. Furthermore, this approach can also produce estimates of forecast uncertainty that are consistent across levels of the hierarchy (forecast intervals produced by the optimal combination approach are the subject of our current research).

The general idea is derived from the representation of the h-step-ahead base forecasts of a hierarchy by the linear regression model

$$\hat{\boldsymbol{Y}}_n(h) = \boldsymbol{S}\boldsymbol{\beta}_h + \boldsymbol{\varepsilon}_h, \tag{9}$$

where $\boldsymbol{\beta}_h = \mathrm{E}[\hat{\boldsymbol{Y}}_{K,n}(h)|\boldsymbol{Y}_1, \ldots, \boldsymbol{Y}_n]$ is the unknown mean of the base forecasts of the bottom level K, and $\boldsymbol{\varepsilon}_h$ has zero mean and covariance matrix $V[\boldsymbol{\varepsilon}_h] = \boldsymbol{\Sigma}_h$. The term $\boldsymbol{\varepsilon}_h$ represents the error in the above regression, and should not be confused with the h-step-ahead forecast error. If we know $\boldsymbol{\Sigma}_h$ then we can use generalised least squares estimation to obtain the minimum variance unbiased estimate of $\boldsymbol{\beta}_h$. In general, this is not known, but Hyndman et al. (2007) show that under the reasonable assumption that $\boldsymbol{\varepsilon}_h \approx \boldsymbol{S}\boldsymbol{\varepsilon}_{K,h}$, where $\boldsymbol{\varepsilon}_{K,h}$ contains the forecast errors in the bottom level, the best linear unbiased estimator for $\boldsymbol{\beta}_h$ is $\hat{\boldsymbol{\beta}}_h = (\boldsymbol{S}'\boldsymbol{S})^{-1}\boldsymbol{S}'\hat{\boldsymbol{Y}}_n(h)$. This leads to the revised forecasts given by $\tilde{\boldsymbol{Y}}_n(h) = \boldsymbol{S}\hat{\boldsymbol{\beta}}_h$, and hence, in the general form of Eq. (2),

$$\boldsymbol{P} = (\boldsymbol{S}'\boldsymbol{S})^{-1}\boldsymbol{S}'. \tag{10}$$

In some circumstances, simpler forecasting equations can be obtained. Note that hierarchy 1 is balanced, which means that the same degree of disaggregation takes place at each node within a level; i.e., the number of series at each node varies across levels, but not within a level. Therefore the simple ANOVA method presented in Eqs. (12) and (13) of Hyndman et al. (2007) can be applied to produce the revised forecasts for the optimal combination approach. We label this approach "Optimal" in the tables that follow.

Table 3
Classification of exponential smoothing methods.

Trend component	Seasonal component		
	N (None)	A (Additive)	M (Multiplicative)
N (None)	N, N	N, A	N, M
A (Additive)	A, N	A, A	A, M
A_d (Additive damped)	A_d, N	A_d, A	A_d, M
M (Multiplicative)	M, N	M, A	M, M
M_d (Multiplicative damped)	M_d, N	M_d, A	M_d, M

4. Forecasting individual series

The classification of the exponential smoothing methods in Table 3 originated with the Pegels (1969) taxonomy, which was further advanced by Gardner (1985), Hyndman et al. (2002) and Taylor (2003). Each of the fifteen methods listed has a trend and a seasonal component. Hence, cell (N, N) describes the simple exponential smoothing method, cell (A, N) Holt's linear method, and so on. We model and forecast all series in the hierarchy individually at all levels for each hierarchical structure using exponential smoothing based on innovations state space models. Hyndman et al. (2002) developed a statistical framework for most of the exponential smoothing methods presented in Table 3. The statistical framework incorporates stochastic models, likelihood calculations, prediction intervals and procedures for model selection. We extend their framework here to include Taylor (2003) multiplicative damped method.

For each method, there are two possible state space models, one corresponding to a model with additive errors and the other to a model with multiplicative errors. Table 4 presents the fifteen models with additive errors and their forecast functions. The multiplicative error models can be obtained by replacing ε_t by $\mu_t\varepsilon_t$ (for further details see Hyndman, Koehler, Ord, and Snyder (2008)). Empirically, we have found that the purely additive models (models with additive error, trend and seasonality) give better forecast accuracy. Consequently, we selected models

Table 4
State space equations for each additive error model in the classification.

Trend component	Seasonal component		
	N (none)	A (addictive)	M (multiplicative)
N (none)	$\mu_t = \ell_{t-1}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t$	$\mu_t = \ell_{t-1} + S_{t-m}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t + s_{t-m+h_m^+}$	$\mu_t = \ell_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/\ell_{t-1}$ $\hat{Y}_{t+h\mid t} = \ell_t s_{t-m+h_m^+}$
A (addictive)	$\mu_t = \ell_{t-1} + b_{t-1}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t + hb_t$	$\mu_t = \ell_{t-1} + b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t + hb_{t-m+h_m^+}$	$\mu_t = (\ell_{t-1} + b_{t-1})s_{t-m}$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + b_{t-1})$ $\hat{Y}_{t+h\mid t} = (\ell_t + hb_t)s_{t-m+h_m^+}$
$\mathrm{A_d}$ (additive damped)	$\mu_t = \ell_{t-1} + \phi b_{t-1}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t + \phi_h b_t$	$\mu_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t + \phi_h b_t + s_{t-m+h_m^+}$	$\mu_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = \phi b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + \phi b_{t-1})$ $\hat{Y}_{t+h\mid t} = (\ell_t + \phi_h b_t)s_{t-m+h_m^+}$
M (multiplicative)	$\mu_t = \ell_{t-1}b_{t-1}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t/\ell_{t-1}$ $\hat{Y}_{t+h\mid t} = \ell_t b_t^h$	$\mu_t = \ell_{t-1}b_{t-1} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t/\ell_{t-1}$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t b_t^h + s_{t-m+h_m^+}$	$\mu_t = \ell_{t-1}b_{t-1}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t/(s_{t-m}\ell_{t-1})$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1}b_{t-1})$ $\hat{Y}_{t+h\mid t} = \ell_t b_t^h s_{t-m+h_m^+}$
$\mathrm{M_d}$ (multiplicative damped)	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t/\ell_{t-1}$ $\hat{Y}_{t+h\mid t} = \ell_t {b_t}^{\phi h}$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi} + s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t/\ell_{t-1}$ $s_t = s_{t-m} + \gamma\varepsilon_t$ $\hat{Y}_{t+h\mid t} = \ell_t {b_t}^{\phi h} + s_{t-m+h_m^+}$	$\mu_t = \ell_{t-1}b_{t-1}^{\phi}s_{t-m}$ $\ell_t = \ell_{t-1}b_{t-1}^{\phi} + \alpha\varepsilon_t/s_{t-m}$ $b_t = b_{t-1}^{\phi} + \beta\varepsilon_t/(s_{t-m}\ell_{t-1})$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1}b_{t-1})$ $\hat{Y}_{t+h\mid t} = \ell_t {b_t}^{\phi h} s_{t-m+h_m^+}$

Multiplicative error models are obtained by replacing ε_t with $\mu_t\varepsilon_t$. In each case, ℓ_t denotes the level of the series at time t, b_t denotes the slope at time t, s_t denotes the seasonal component of the series at time t, and m denotes the number of seasons in a year; α, β, γ and ϕ are constants with $0 < \alpha, \gamma, \phi < 1$ and $0 < \beta < \alpha$; $\hat{Y}_{t+h|t}$ denotes the h-step-ahead forecast based on all the data up to time t; $\phi_h = \phi + \phi^2 + \cdots + \phi^h$; $\hat{Y}_{t+h|t}$ denotes a forecast of Y_{t+h} based on all the data up to time t, and $h_m^+ = [(h-1) \bmod m] + 1$.

by minimising the AIC amongst all additive models. In a few cases, the forecasts from the additive models did not have face validity (e.g., the forecasts were negative), and the models for these series were then replaced by models with multiplicative components. The models selected for each series are given in Appendix A.

5. Forecast performance evaluation

In order to evaluate the forecasting performance of each of the hierarchical approaches presented in Section 3, we perform an out-of-sample forecast evaluation for each of the Australian domestic tourism hierarchies considered in this paper. We initially select models (as in Section 4) using the whole sample of 36 quarterly observations. We then re-estimate the models based on the first 12 observations (1998:Q1-2001:Q4), and produce 1- to 8-step-ahead forecasts. We increase the sample size by one observation, re-estimate the models, and again produce 1- to 8-step-ahead forecasts. This process is iterated until 2005:Q3, and produces 24 1-step-ahead forecasts, 23 2-step-ahead forecasts, 22 3-step-ahead forecasts, and so on, up to 17 8-step-ahead forecasts. We use these forecasts to evaluate the out-of-sample forecast performance of each of the hierarchical methods considered. We calculate the mean absolute percentage error (MAPE) for each forecast horizon and for each of

Table 5
Out-of-sample forecasting performance: Hierarchy 1.

MAPE	Forecast Horizon (h)								
	1	2	3	4	5	6	7	8	Average
Top Level: Australia									
Bottom-up	**3.48**	**3.30**	3.81	4.04	3.90	4.56	4.53	4.58	4.03
Top-down HP1	3.89	3.71	**3.41**	**3.90**	3.91	**4.12**	**4.27**	**4.27**	**3.93**
Top-down HP2	3.89	3.71	**3.41**	**3.90**	3.91	**4.12**	**4.27**	**4.27**	**3.93**
Top-down FP	3.89	3.71	**3.41**	**3.90**	3.91	**4.12**	**4.27**	**4.27**	**3.93**
Optimal	3.80	3.64	3.48	3.94	**3.85**	4.22	4.34	4.35	3.95
Level 1: Purpose of travel									
Bottom-up	8.14	8.38	8.38	9.02	9.31	9.39	9.44	9.52	8.95
Top-down HP1	13.11	12.49	12.62	13.21	13.33	13.08	13.37	13.35	13.07
Top-down HP2	13.14	12.56	12.70	13.24	13.34	13.13	13.43	13.36	13.11
Top-down FP	7.98	7.97	**8.02**	**8.52**	**8.86**	8.74	8.85	**9.20**	**8.52**
Optimal	**7.94**	**7.91**	8.16	8.66	8.88	**8.66**	**8.81**	9.29	8.54
Level 2: States									
Bottom-up	**21.34**	**21.75**	**21.81**	**22.39**	**23.76**	23.26	23.01	23.31	**22.58**
Top-down HP1	32.63	30.98	31.49	31.91	32.23	30.11	30.51	30.91	31.35
Top-down HP2	32.92	31.23	31.72	32.13	32.47	30.32	30.67	31.01	31.56
Top-down FP	22.15	21.96	21.94	22.52	23.79	23.18	22.96	**23.07**	22.70
Optimal	22.17	21.80	22.33	23.53	24.26	**23.15**	**22.76**	23.90	22.99
Bottom Level: Capital city versus other									
Bottom-up	**31.97**	31.65	31.39	32.19	33.93	33.70	32.67	33.47	32.62
Top-down HP1	42.47	40.19	40.57	41.12	41.71	39.67	39.87	40.68	40.79
Top-down HP2	43.04	40.54	40.87	41.44	42.06	39.99	40.21	40.99	41.14
Top-down FP	32.16	31.30	31.24	**32.18**	34.00	**33.25**	**32.42**	**33.22**	**32.47**
Optimal	32.31	**30.92**	**30.87**	32.41	**33.92**	33.35	32.47	34.13	32.55
Total									
Bottom-up	**64.93**	65.07	65.39	67.62	70.90	70.91	69.65	70.89	68.17
Top-down HP1	92.10	87.37	88.10	90.14	91.18	86.98	88.03	89.21	89.14
Top-down HP2	92.99	88.04	88.70	90.71	91.78	87.55	88.58	89.64	89.75
Top-down FP	66.17	64.94	**64.60**	**67.12**	**70.55**	**69.29**	68.51	**69.76**	**67.62**
Optimal	66.22	**64.28**	64.84	68.54	70.90	69.37	**68.38**	71.67	68.03

the alternative hierarchical approaches. The results for hierarchy 1 are presented in Table 5, and the results for hierarchy 2 are presented in Table 6. The first four panels in each table are self-explanatory. In these we present the MAPEs for the alternative hierarchical approaches for each of the four levels in the hierarchy. In the final panel labeled “Total” we present the aggregate MAPEs across the whole of the hierarchy. Finally, the last column of each table, labeled “Average”, shows the average MAPE across all the forecast horizons for each approach.

For each hierarchy it can be seen that the two top-down approaches based on static historical proportions are only useful for forecasting the very top level of the hierarchies. This is not surprising. With the top-down strategies, no disaggregation takes place at the top level. All we do here is to model the time series at the top level independently of the hierarchical structure. However, as we move down the hierarchy the performance of the top-down approaches is shown to deteriorate. These two methods are easily identified as the overall worst performing methods, and are not recommended.

Of the three remaining alternative approaches, it seems that the overall best performing method for both hierarchies is the top-down approach based on forecasted proportions. This approach is clearly the best performer for hierarchy 2. For hierarchy 1 the optimal combination approach seems to also perform well. The surprising feature of this analysis is the

Table 6
Out-of-sample forecasting performance: Hierarchy 2.

MAPE	Forecast Horizon (h)								
	1	2	3	4	5	6	7	8	Average
Top Level: Australia									
Bottom-up	**3.79**	**3.58**	3.92	4.01	4.12	4.55	4.30	**4.24**	4.06
Top-down HP1	3.89	3.71	3.41	3.90	3.91	4.12	4.27	4.27	**3.93**
Top-down HP2	3.89	3.71	**3.41**	3.90	**3.91**	**4.12**	**4.27**	4.27	**3.93**
Top-down FP	3.89	3.71	**3.41**	3.90	**3.91**	**4.12**	**4.27**	4.27	**3.93**
Optimal	3.83	3.66	3.46	**3.88**	3.92	4.19	4.30	4.25	3.94
Level 1: States									
Bottom-up	10.70	10.52	10.68	10.85	11.37	11.46	11.43	11.27	11.03
Top-down HP1	19.30	18.63	19.00	18.94	19.48	18.68	19.27	19.85	19.14
Top-down HP2	19.17	18.57	18.90	18.78	19.34	18.60	19.13	19.67	19.02
Top-down FP	**10.58**	**10.29**	**10.20**	**10.54**	**10.94**	**10.90**	**11.08**	**11.18**	**10.71**
Optimal	11.07	10.58	10.67	11.13	11.60	11.62	11.89	12.21	11.35
Level 2: Zones									
Bottom-up	14.99	14.97	14.88	14.98	15.73	15.69	15.63	15.65	15.32
Top-down HP1	24.14	23.55	23.84	23.94	24.46	23.66	24.28	24.33	24.03
Top-down HP2	24.32	23.77	24.07	24.11	24.60	23.88	24.53	24.51	24.22
Top-down FP	**14.82**	**14.83**	**14.58**	**14.78**	**15.44**	**15.36**	**15.51**	**15.54**	**15.11**
Optimal	15.16	15.06	14.78	15.27	15.85	15.74	15.87	16.15	15.48
Bottom Level: Regions									
Bottom-up	33.12	32.54	31.86	32.26	33.97	33.74	34.01	33.96	33.18
Top-down HP1	41.95	40.36	40.87	41.09	41.77	40.51	41.43	41.76	41.22
Top-down HP2	42.50	40.96	41.45	41.61	42.28	41.03	41.97	42.23	41.75
Top-down FP	**31.82**	**31.50**	**30.80**	**31.53**	**32.58**	**32.50**	**33.16**	**33.29**	**32.15**
Optimal	35.89	33.86	33.04	34.26	36.22	36.06	36.64	37.49	35.43
Total									
Bottom-up	62.59	61.61	61.34	62.11	65.18	65.44	65.37	65.13	63.60
Top-down HP1	89.28	86.25	87.12	87.86	89.62	86.96	89.26	90.21	88.32
Top-down HP2	89.88	87.02	87.83	88.40	90.12	87.62	89.90	90.68	88.93
Top-down FP	**61.11**	**60.33**	**58.98**	**60.74**	**62.87**	**62.87**	**64.03**	**64.28**	**61.90**
Optimal	65.96	63.16	61.94	64.54	67.59	67.61	68.70	70.10	66.20

better-than-expected performance of the bottom-up approach. We believe that the good performance of this approach can be attributed to the nature of the data. Even at the very bottom level the data is well behaved, with a prominent seasonal component for most series.

Furthermore, this method is also advantaged by the short-term forecasts we are producing in this forecast evaluation exercise. If the forecast horizon was longer the performance of this method would deteriorate, as it misses the trends in the series. For example, for hierarchy 2, none of the selected bottom level models include a trend, so that the bottom-up approach produces flat forecasts for all series at all levels. However, at level 1 there is a strong downward trend for the New South Wales series, which comprises 33% of the total tourism demand for Australia. This trend is captured by both the top-down FP method and the optimal combination approach.

In Table 7 we summarise the results of Diebold–Mariano (DM) tests (Diebold & Mariano, 1995) for comparing the forecast accuracy between the bottom-up method and either the top-down FP method or the optimal combination approach. The results presented are for the DM test calculated for differences between squared errors. We have also calculated the same DM tests for the differences in absolute errors. The results were qualitatively no different.

For each level, the results show the percentage of times the top-down FP forecasts and the optimal

Table 7
Diebold–Mariano (DM) tests for comparing the predictive accuracy of the bottom-up method with that of either the top-down FP (TDFP) method or the optimal combination approach.

	Hierarchy 1				Hierarchy 2			
	TDFP better	TDFP worse	Optimal better	Optimal worse	TDFP better	TDFP worse	Optimal better	Optimal worse
Level 0	12.50	0.00	12.50	0.00	37.50	0.00	50.00	0.00
Level 1	34.38	9.38	28.13	9.38	16.07	7.14	14.29	8.93
Level 2	15.18	11.61	16.52	8.48	11.11	9.26	12.50	6.94
Level 3	16.29	11.83	16.74	9.60	16.16	12.96	12.96	13.87

The entries show the percentage of times the TDFP and optimal combination forecasts are significantly better or worse than the bottom-up forecasts at each level over all $h = 1$- to 8-step-ahead forecast horizons; i.e., the percentage of times the DM test statistic falls in the lower or upper 2.5% tail of a standard Normal distribution.

Table 8
Forecast average rate of growth/decline per annum over 2007 and 2008.

	Australia	NSW	VIC	QLD	SA	WA	TAS	NT
Top-down FP hierarchy 1	−0.29	−2.03	−0.61	1.05	2.22	−0.04	−2.21	5.32
Optimal hierarchy 1	−0.24	−1.84	−0.80	0.78	2.76	−0.10	−1.22	6.46
Top-down FP hierarchy 2	−0.29	−2.29	0.06	1.07	2.70	0.00	−1.15	0.15
Optimal hierarchy 2	−0.35	−2.22	−0.19	0.59	3.03	0.11	−0.28	1.16
Proportion		*0.33*	*0.19*	*0.26*	*0.10*	*0.07*	*0.03*	*0.02*

The *proportion* entry denotes the historical proportion of tourism in the corresponding area relative to total Australian tourism.

combination forecasts are significantly better or worse than the bottom-up forecasts, over all $h = 1$- to 8-step-ahead forecast horizons. In other words, for each level and over all forecast horizons we present the percentage of times the DM test statistic falls in the lower or upper 2.5% tail of a standard Normal distribution. For example, at level 1 of hierarchy 1, the forecasts produced by the top-down FP method (for all forecast horizons) were significantly more accurate than the forecasts produced by the bottom-up method, 34% of the time. On the other hand, the bottom-up method produced significantly more accurate forecasts than the top-down FP method only 9% of the time. For the same hierarchy and the same level, these percentages are 28% and 9% when comparing the optimal forecasts with those from the bottom-up method.

In general, the results show that, for all levels, the number of times the top-down FP method significantly outperforms the bottom-up method is greater than the reverse. The same is also true for the optimal combination approach. We should note here that we also tested for significant differences between the top-down FP method and the optimal approach. The results for these were mixed, with neither method consistently outperforming the other.

6. Forecasts

From the forecast evaluation analysis we can conclude that the approach that performed best was our proposed top-down approach based on forecasted proportions. The next-best performing method was the optimal combination approach.

In this section we use these two methods to forecast tourism demand for Australia and the Australian states from both hierarchical structures. The large number of series in each hierarchy prevents us from presenting the raw data forecasts. In order to summarise our forecast results in a useful manner, we present the average forecasted rate of growth/decline per annum, as calculated over the next two years for each series.

6.1. Forecasts for Australia and the states

In Table 8 we present the forecast average rate of growth/decline for tourism demand for Australia and the Australian states (refer to Fig. 2 for a map

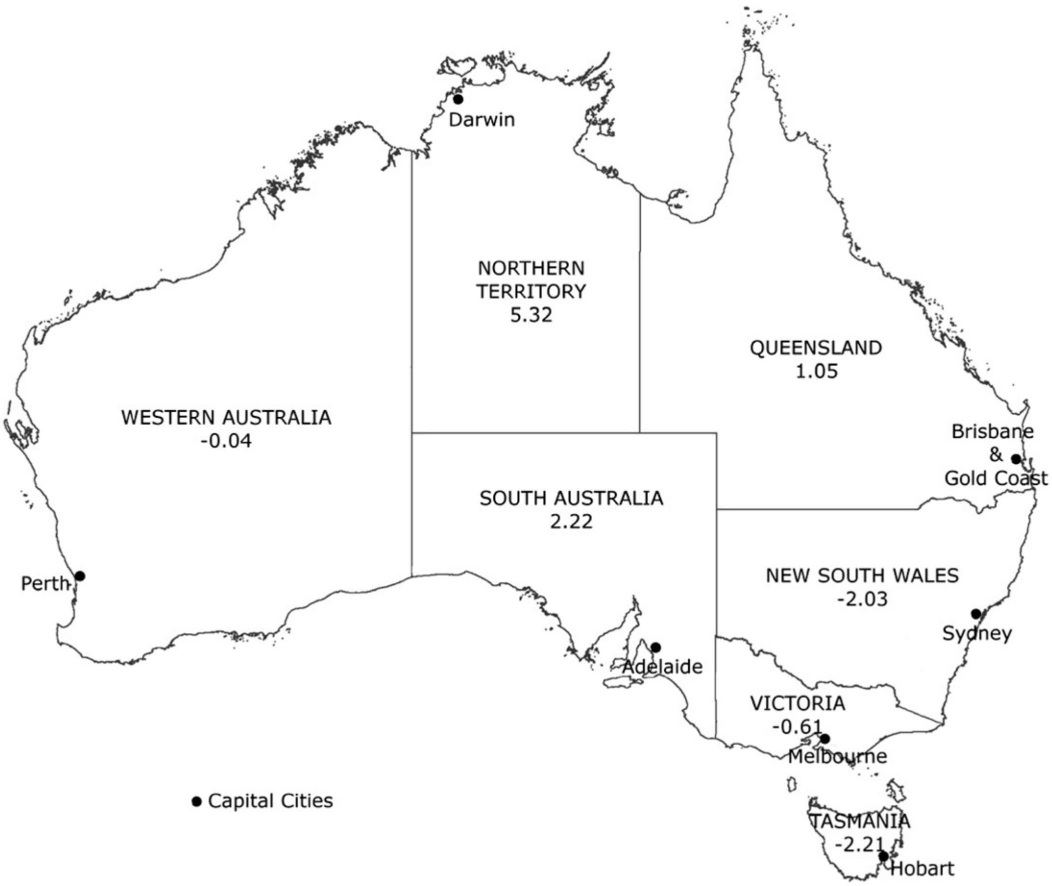

Fig. 2. Average forecast rates of growth/decline per annum over 2007 and 2008 for the states of Australia. The rates are produced by the top-down approach based on forecasted proportions from Hierarchy 1.

of Australia). The forecasted rates from the top-down approach based on forecasted proportions are labeled "Top-down FP", and the optimal combination forecasted rates are labeled "Optimal". The forecasted rates from all sources seem to be consistent in terms of direction. There are only two exceptions: the case of Victoria, where the top-down forecasted rate from hierarchy 2 is positive (although very small) in contrast to the decline shown by all of the other sources; and the case of Western Australia, where the forecasted rates from hierarchy 1 for both the top-down and optimal approaches are negative, in contrast to the forecasts from hierarchy 2 which are positive for both approaches.

The consensus from the methods is that there will be a decline in domestic tourism demand for Australia over the next two years. The most conservative rate of decline of 0.24% p.a. is produced by the optimal combination approach from hierarchy 1. The least conservative rate of decline of 0.35% p.a. is given by the optimal combination approach from hierarchy 2. This rate of decline seems to be driven mainly by the decline in the states of New South Wales and Victoria, which make up approximately 52% of Australia's aggregate domestic tourism demand. The areas showing some signs of growth are the states of Queensland, South Australia and the Northern Territory.

In the left panel of Fig. 3, we plot the quarterly data for the aggregate Australian domestic tourism demand. The plot reveals the nature of the data (a prominent seasonal component), and the nature of

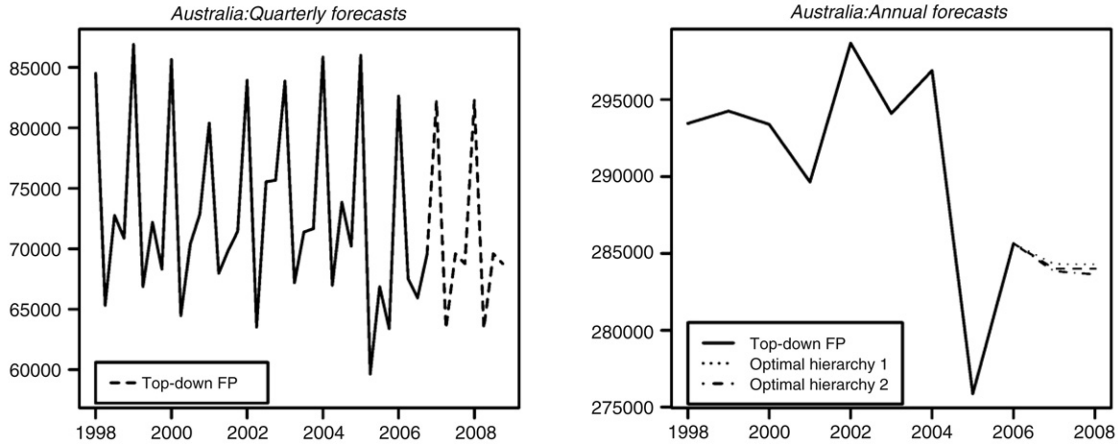

Fig. 3. Quarterly and annual forecasts for Australian tourism demand for the period 2007 and 2008.

Table 9
Average forecast rate of growth/decline per annum over 2007 and 2008 by purpose of travel.

	Holiday	VFR	Business	Other	Total	Proportion
NSW	−4.39	−1.00	0.32	5.38	−2.03	0.33
VIC	−0.46	−1.40	1.32	−1.36	−0.61	0.19
QLD	1.82	−0.17	−3.80	14.87	1.05	0.26
SA	0.74	1.19	4.94	10.45	2.22	0.10
WA	−0.84	1.08	−4.89	14.27	−0.04	0.07
TAS	−4.38	−0.92	8.98	−5.53	−2.21	0.03
NT	−2.60	−4.32	22.40	56.35	5.32	0.02
Total	−1.20	−0.61	−0.20	9.25		
Proportion	*0.47*	*0.31*	*0.15*	*0.07*		

The *proportion* entry denotes the aggregate historical proportion of the corresponding purpose of travel to total Australian tourism.

the forecasts produced by the innovations state space models. We plot only the top-down forecasts here, as the forecasts from the optimal combination approach are not very different. In the right panel of Fig. 3, we plot the annual data and the forecasts from the three alternative approaches. As the methods give such similar forecasts, we will only present forecasts from the top-down forecasted proportions approach for lower levels of the hierarchies.

6.2. Further forecasts from hierarchy 1

The structure of hierarchy 1 allows us to model tourism demand based on the four purposes of travel. The forecasted growth rates by purpose of travel presented in the “Total” row in Table 9 show a decline in three of the four components. The only component showing an increase is “Other”, which is a relatively small component and has little impact on the aggregate domestic tourism demand. The two main components are “Holiday” and VFR travel, which make up 78% of domestic tourism. We forecast an increase in “Holiday” travel for the states of Queensland and South Australia, and an increase in VFR for the states of South Australia and Western Australia. For all other areas at this level, our forecasts show a decline in these two main components. Note that the only state for which we forecast growth over the next two years for all four components is South Australia.

The largest growth shown in Table 10 in terms of “Holiday” travel comes from the state of Queensland, and in particular its capital city. It should be noted that we consider both Brisbane and the Gold Coast as the capital city of this state. (Refer to Fig. 2 for a map of Australia showing the capital city for each state.) The Gold Coast (and Queensland in general) is arguably the most developed and most promoted Australian holiday destination, which explains its forecasted growth over the next two years.

For the other two main states (New South Wales and Victoria), our forecasts show a decline in “Holiday” travel for their respective capital cities, Sydney and Melbourne. For the rest of New South Wales we forecast a significant decline, and we forecast moderate growth for the rest of Victoria. For the remaining areas, the results are mixed in terms of “Holiday” travel. For South Australia we forecast a

Table 10
Average percentage growth/decline per annum over 2007 and 2008 for the capital city versus the rest of the state.

	Holiday		VFR		Business		Other		Total	
	Cap City	Other	Cap City	Other	Cap City	Other	Cap City	Other	Cap City	Other
NSW	−2.74	−4.68	−0.50	−1.21	−3.09	2.90	−1.60	10.72	−1.78	−2.12
VIC	−2.59	0.54	−1.93	−0.93	5.39	−4.16	−3.23	0.59	−0.96	−0.36
QLD	2.63	1.25	2.36	−2.09	−6.31	−2.01	13.17	16.23	1.81	0.49
SA	0.06	−1.24	2.33	−0.51	−0.28	−7.09	8.88	20.25	1.70	−1.18
WA	0.74	0.74	2.81	−0.63	4.53	5.41	17.78	2.23	4.01	1.02
TAS	−7.81	−2.46	2.35	−3.20	8.20	9.77	6.98	−12.00	−2.07	−2.29
NT	2.36	−7.08	4.21	−13.97	22.48	22.33	70.62	47.25	9.87	1.17

Note that Brisbane and the Gold Coast are considered the combined capital city for the state of Queensland.

slight increase for Adelaide and a decrease for the rest of the state. We forecast “Holiday” travel to increase uniformly across the state of Western Australia, and decrease uniformly across the state of Tasmania, with quite a large decline for Hobart. For the Northern Territory, we forecast an increase for Darwin and a decline for the rest of the territory.

Travel for VFR is forecast to decline for all of the states outside their respective capital cities. A decline is forecast for Sydney and Melbourne, but we forecast moderate growth for the rest of the capital cities.

The forecasted growth rates for “Business” travel show an increase for both New South Wales and Victoria. Our forecasts show that this increase will come from different sources. “Business” travel will grow in New South Wales due to an increase outside the city of Sydney. In contrast, for Victoria, the growth in “Business” travel will come from an increase within the Melbourne area. For the rest of Australia, “Business” travel will either uniformly decline across the states (in Queensland and South Australia), or will uniformly grow (in Western Australia, Tasmania and the Northern Territory).

6.3. Further forecasts from hierarchy 2

Hierarchy 2 allows us to analyse our top level Australian forecasts in more depth in terms of location. In Table 11 and Fig. 4, we present the forecasted growth rates for the tourism zones of Australia, as classified in Appendix A.2.

The decline forecasted for the state of New South Wales is mainly driven by a decline in the coastal zones. In particular, the Metro, North Coast and South Coast zones, which comprise approximately 70% of the tourism demand in New South Wales, all show a significant decline. The only zone which shows some growth is the inland South zone. For the state of Victoria, the major contributors to the forecasted decline are the Metro, the East Coast, and the North West inland zones, which make up approximately 75% of Victoria’s tourism demand.

The state of Queensland is the second largest contributor to domestic tourism. The overall moderate forecasted growth is driven by the growth in the Metro and Central Coast zones. These zones comprise approximately 73% of the state’s domestic tourism. As we have mentioned previously, these areas are arguably the most well-known and well-developed tourist destinations in Australia. In the North Coast region of the state, a significant decline is forecasted. The other state for which we forecast growth is South Australia. Moderate to high growth is shown for most of the state, with the exception of the South Coast, for which we forecast a decline.

Consider the coastal areas of the three main states: New South Wales, Victoria and Queensland. The zones that comprise these areas are (starting from the south coast of Victoria—see Fig. 4): West Coast (BB), Metro (BA) and East Coast (BC) Victoria; South Coast (AC), Metro (AA) and North Coast (AB) New South Wales; Metro (CA), Central (CB) and North Coast (CC) Queensland. Based on the historical data, tourism demand in these areas comprises approximately 60% of the aggregate Australian tourism. For these areas combined, we forecast a decline of 0.74% per annum over the next two years. If we exclude the growth forecasted for Metro and Central Coast Queensland, the decline drops to 1.93% per annum for the next two years. For the rest of Australia (i.e., excluding the east coast zones), we forecast growth of 0.39% per annum for

Table 11
Average forecasted rate of growth/decline per annum over 2007 and 2008 for the Australian tourism zones, as classified in Appendix A.2.

NSW			π
AA	Metro	−4.61	*0.32*
AB	Nth Coast	−2.45	*0.27*
AC	Sth Coast	−1.02	*0.10*
AD	Sth	0.45	*0.11*
AE	Nth	−0.37	*0.14*
AF	ACT	−0.13	*0.06*
VIC			π
BA	Metro	−0.05	*0.47*
BB	West Coast	2.05	*0.09*
BC	East Coast	−0.88	*0.13*
BD	Nth East	0.32	*0.16*
BE	Nth West	−0.20	*0.15*
QLD			π
CA	Metro	2.97	*0.57*
CB	Central Coast	0.39	*0.16*
CC	Nth Coast	−3.17	*0.18*
CD	Inland	0.02	*0.09*
SA			π
DA	Metro	2.69	*0.46*
DB	Sth Coast	−1.57	*0.18*
DC	Inland	5.56	*0.20*
DD	West Coast	4.35	*0.16*
WA			π
EA	West Coast	0.06	*0.75*
EB	Nth	−3.23	*0.14*
EC	Sth	4.83	*0.11*
TAS			π
FA	Sth	−2.41	*0.47*
FB	Nth East	−0.51	*0.33*
FC	Nth West	1.03	*0.21*
NT			π
GA	Nth Coast	−0.79	*0.59*
GB	Central	1.59	*0.41*

The π entries denote the aggregate historical proportion of the corresponding zone relative to the aggregate historical tourism of the state the zone belongs to.

the next two years. These results show the importance of the east coast areas to Australian domestic tourism, which implies that the tourism authorities should pay significant attention to these areas.

In Table 12, we present the average forecasted rates of growth/decline per annum over the period 2007–2008 for the series at the bottom level of hierarchy 2, which are the tourism regions as classified in Appendix A.2. In Fig. 5 we colour-code the forecasted rates and plot them in the corresponding regions on the map of Australia. The darkest shade of grey is given to the regions for which our forecasted rate shows a severe decline, i.e., an average decline of more than 3% per annum over the next two years. As the forecasted rates improve, i.e., less of a decline and moving into growth, the shaded grey gets lighter. The lightest shaded regions, i.e., the white regions, show a significant average growth of more than 3% per annum over the next two years.

These results present a plethora of information for local governments and tourism authorities. We will only highlight some general observations. Fig. 5 allows us to recognise the spatial correlations that exist around Australia. For example, consider the state of New South Wales. There is a clear clustering of inland regions (ADA, ADB, ADD, AEA and AEC) with an average positive forecasted growth rate over the next two years. On the other hand, there is a clustering of coastal regions (AAA, AAB, AAC, AED and ABA) with a very pessimistic average forecasted rate of decline of more than 3% per annum over the next two years. The same conclusions can be drawn for the state of Queensland. A clustering of regions with a positive forecasted growth rate can be found around Brisbane and the Gold Coast (CAA, CAB, CAC, CBA and CBB), while a clustering of regions with an average forecasted decline over the next two years can be found further north (CBC, CBD, CCA, CCB and CCC).

In a recent report by Tourism Australia (Tourism Research Australia, 2008), the aggregate decline of Australian domestic tourism has been recognised, and policy recommendations based on expert opinions have been put forward in order to reverse this trend. The first key challenge identified in this report is the development of a "vision" for domestic Australian tourism. Arguably, Queensland, and in particular the Gold Coast, is the most developed and most promoted domestic holiday destination in Australia. In this paper we have identified these as the areas with the highest predicted growth. We believe that this is a direct result of the high quality tourism infrastructure in these areas, complemented by the vigorous communication of the product to

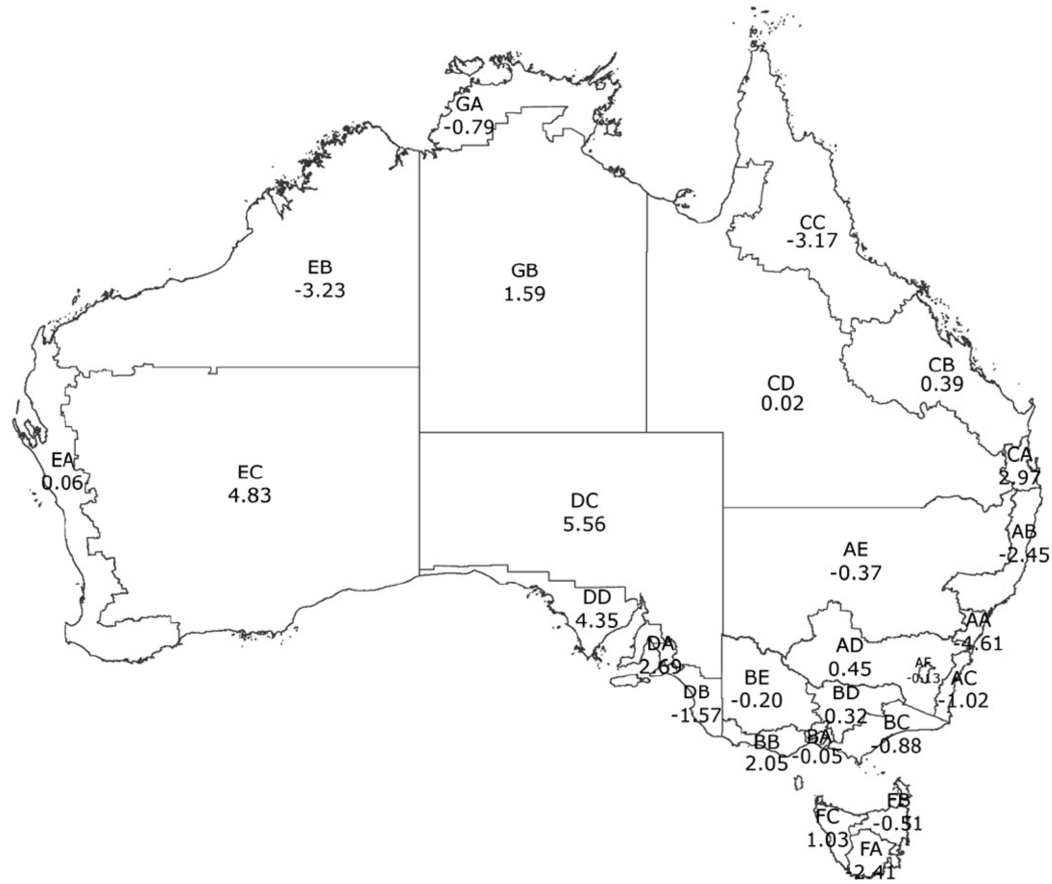

Fig. 4. Average forecast rate of growth/decline per annum over 2007 and 2008 for the tourism zones of Australia.

the Australian market. This combination is something that the tourism authorities should aspire to when developing the Australian domestic tourism vision, if the predicted decline in domestic tourism is to be reversed.

7. Summary and conclusions

In this paper we have applied hierarchical forecasting to Australia's domestic tourism market. We have considered five methods of hierarchical forecasting. The first two are variations of the conventional top-down approach: in the first, the top-level forecasts are distributed to lower levels according to average historical proportions; and in the second, the top-level forecasts are distributed to lower levels according to the proportions of historical averages. The third approach considered is the conventional bottom-up approach. We then consider two new approaches. Our new top-down approach improves on the conventional top-down methods by distributing the top-level forecasts to lower levels according to forecasted proportions of the lower levels, rather than the historical static proportions of the conventional methods. Finally, we consider the optimal combination approach recently introduced by Hyndman et al. (2007). The out-of-sample forecast evaluation performance of the approaches, and the Diebold–Mariano tests for predictive accuracy, lead us to conclude that that the best performing method for the two tourism time series hierarchies we consider is the top-down method based on forecasted proportions, followed by the optimal combination approach.

Our forecasts show a decline in aggregate Australian domestic tourism over the next two years. This is consistent with the findings of Athanasopoulos

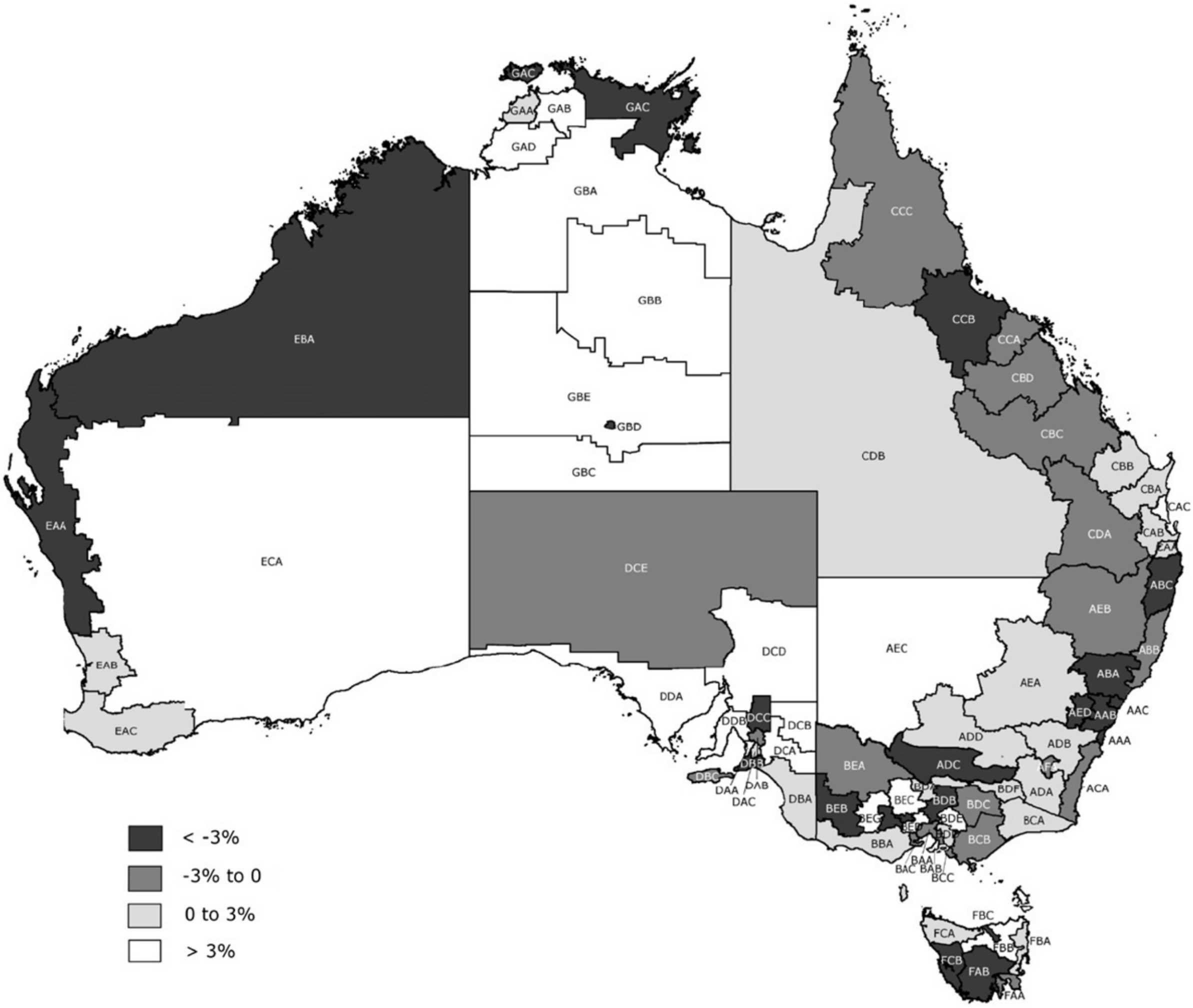

Fig. 5. Average forecast rate of growth/decline per annum over 2007 and 2008 for Australian tourism regions, as classified in Appendix A.2.

and Hyndman (2008), who produce longer-term forecasts of Australian domestic tourism demand. Applying the hierarchical approach has allowed us identify factors that will considerably contribute to this decline. Disaggregating the data by purpose of travel, we forecast a decline in the three main purposes of travel: "Holiday", "VFR" and "Business". Geographically, the aggregate decline is mainly driven by a decline in the states of New South Wales and Victoria. In both hierarchies, Queensland is identified as the state with the highest forecasted growth. Further geographical disaggregation of the data has allowed us to identify the coastal areas in the east coast of Australia, with the exception of the metro and central coast of Queensland, as major contributors to the aggregate decline of Australian domestic tourism.

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We acknowledge valuable comments from Haiyan Song, Fred Collopy (editor), an associate editor, two anonymous referees and participants at the 2008 CAUTHE conference. We thank Andrew Maurer and Claude Calero at Tourism Research Australia for providing data, suggestions and explanations. We acknowledge the financial support of Tourism Research Australia and the Sustainable Tourism Cooperative Research Centre.

Table 12
Average forecast rate of growth/decline per annum over 2007 and 2008 for the Australian tourism regions, as classified in Appendix A.2.

NSW		π
AAA	−3.58	*0.02*
AAB	−4.51	*0.26*
AAC	−5.71	*0.04*
ABA	−3.29	*0.06*
ABB	−0.78	*0.14*
ABC	−4.40	*0.08*
ACA	−1.02	*0.10*
ADA	1.38	*0.03*
ADB	0.34	*0.02*
ADC	−3.13	*0.03*
ADD	0.67	*0.03*
AEA	2.67	*0.06*
AEB	−2.74	*0.04*
AEC	6.52	*0.02*
AED	−3.75	*0.02*
AFA	−0.13	*0.06*
VIC		π
BAA	−0.62	*0.36*
BAB	4.66	*0.06*
BAC	−0.82	*0.05*
BBA	2.05	*0.09*
BCA	0.12	*0.04*
BCB	−1.02	*0.05*
BCC	−1.55	*0.04*
BDA	0.93	*0.04*
BDB	−4.51	*0.02*
BDC	−0.24	*0.06*
BDD	1.29	*0.01*
BDE	10.34	*0.01*
BDF	0.95	*0.02*
BEA	−2.52	*0.05*
BEB	−3.05	*0.01*
BEC	3.17	*0.04*
BED	6.46	*0.01*
BEE	−5.38	*0.01*
BEF	−3.49	*0.02*
BEG	10.46	0.02
QLD		π
CAA	2.39	*0.21*
CAB	1.87	*0.22*
CAC	5.81	*0.14*
CBA	1.20	*0.05*
CBB	2.86	*0.03*
CBC	−0.10	*0.05*
CBD	−2.16	*0.03*
CCA	−2.59	*0.03*

Table 12 (*continued*)

NSW		π
CCB	−7.49	*0.05*
CCC	−1.00	*0.10*
CDA	−0.06	*0.04*
CDB	0.12	*0.04*
SA		π
DAA	3.00	*0.42*
DAB	−1.74	*0.03*
DAC	2.76	*0.01*
DBA	1.76	*0.08*
DBB	−4.02	*0.08*
DBC	−2.89	*0.02*
DCA	10.94	*0.04*
DCB	9.80	*0.04*
DCC	−4.72	*0.02*
DCD	10.04	*0.06*
DCE	−2.28	*0.04*
DDA	4.89	*0.08*
DDB	3.75	*0.07*
WA		π
EAA	−5.54	*0.12*
EAB	0.50	*0.40*
EAC	2.79	*0.23*
EBA	−3.23	*0.14*
ECA	4.83	*0.11*
TAS		π
FAA	−1.51	*0.38*
FAB	−5.56	*0.08*
FBA	0.14	*0.11*
FBB	14.95	*0.05*
FBC	−3.48	*0.17*
FCA	2.19	*0.16*
FCB	−3.44	*0.05*
NT		π
GAA	0.56	*0.47*
GAB	13.73	*0.06*
GAC	−20.33	*0.04*
GAD	7.53	*0.02*
GBA	9.50	*0.12*
GBB	13.55	*0.04*
GBC	12.30	*0.06*
GBD	−6.78	*0.17*
GBE	17.35	*0.03*

The π entries denote the aggregate historical proportion of the corresponding tourism region relative to the aggregate historical tourism of the state the region belongs to.

Appendix. Hierarchies and models

A.1. Hierarchy 1

Table 13
Refer to Fig. 2 on page 11 for a geographical division of Australia into the states, including the capital cities.

Top level			Model
1	Total	Australia	ANA
Level 1: Purpose of travel			
2	A	Holiday	ANA
3	B	VFR	ANA
4	C	Business	ANA
5	D	Other	ANA
Level 2: States			
6	AA	Hol-NSW	AA_dA
7	AB	Hol-VIC	AA_dA
8	AC	Hol-QLD	ANA
9	AD	Hol-SA	ANA
10	AE	Hol-WA	ANA
11	AF	Hol-TAS	ANA
12	AG	Hol-NT	ANA
13	BA	VFR-NSW	ANA
14	BB	VFR-VIC	ANA
15	BC	VFR-QLD	ANA
16	BD	VFR-SA	ANA
17	BE	VFR-WA	ANA
18	BF	VFR-TAS	ANA
19	BG	VFR-NT	ANA
20	CA	Bus-NSW	ANA
21	CB	Bus-VIC	ANN
22	CC	Bus-QLD	ANA
23	CD	Bus-SA	ANN
24	CE	Bus-WA	ANA
25	CF	Bus-TAS	ANN
26	CG	Bus-NT	ANN
27	DA	Oth-NSW	ANA
28	DB	Oth-VIC	ANN
29	DC	Oth-QLD	ANA
30	DD	Oth-SA	ANN
31	DE	Oth-WA	ANA
32	DF	Oth-TAS	ANN
33	DG	Oth-NT	MNM
Bottom level: Capital city versus other			
34	AAA	Hol-NSW - Sydney	ANA
35	AAB	Hol-NSW - Other	AA_dA
36	ABA	Hol-VIC - Melbourne	ANA
37	ABB	Hol-VIC - Other	AAA
38	ACA	Hol-QLD - Bris + GC	ANA
39	ACB	Hol-QLD - Other	ANA
40	ADA	Hol-SA - Adelaide	ANA
41	ADB	Hol-SA - Other	ANA
42	AEA	Hol-WA - Perth	ANA
43	AEB	Hol-WA - Other	ANA
44	AFA	Hol-TAS - Hobart	ANA
45	AFB	Hol-TAS - Other	ANA
46	AGA	Hol-NT - Darwin	ANA
47	AGB	Hol-NT −Other	ANA
48	BAA	VFR-NSW - Sydney	ANA
49	BAB	VFR-NSW - Other	ANA
50	BBA	VFR-VIC - Melbourne	ANA
51	BBB	VFR-VIC - Other	ANA
52	BCA	VFR-QLD - Bris + GC	ANA
53	BCB	VFR-QLD -Other	ANA
54	BDA	VFR-SA - Adelaide	ANA
55	BDB	VFR-SA - Other	ANA
56	BEA	VFR-WA - Perth	ANA
57	BEB	VFR-WA - Other	ANN
58	BFA	VFR-TAS - Hobart	ANA
59	BFB	VFR-TAS - Other	ANA
60	BGA	VFR-NT - Darwin	ANA
61	BGB	VFR-NT -Other	ANN
62	CAA	Bus-NSW - Sydney	ANA
63	CAB	Bus-NSW - Other	ANN
64	CBA	Bus-VIC - Melbourne	ANN
65	CBB	Bus-VIC - Other	ANN
66	CCA	Bus-QLD - Bris + GC	ANN
67	CCB	Bus-QLD - Other	ANA
68	CDA	Bus-SA - Adelaide	ANN
69	CDB	Bus-SA - Other	ANN
70	CEA	Bus-WA - Perth	ANA
71	CEB	Bus-WA - Other	ANA
72	CFA	Bus-TAS - Hobart	ANN
73	CFB	Bus-TAS - Other	ANN
74	CGA	Bus-NT - Darwin	ANN
75	CGB	Bus-NT - Other	ANN
76	DAA	Oth-NSW - Sydney	ANN
77	DAB	Oth-NSW - Other	ANA
78	DBA	Oth-VIC - Melbourne	ANN
79	DBB	Oth-VIC - Other	ANN
80	DCA	Oth-QLD - Bris + GC	ANN
81	DCB	Oth-QLD - Other	ANA
82	DDA	Oth-SA - Adelaide	ANN
83	DDB	Oth-SA - Other	ANA
84	DEA	Oth-WA - Perth	ANN
85	DEB	Oth-WA - Other	ANA
86	DFA	Oth-TAS - Hobart	ANN
87	DFB	Oth-TAS - Other	ANN
88	DGA	Oth-NT - Darwin	ANA
89	DGB	Oth-NT - Other	MNM

Note: Brisbane and the Gold Coast are considered the combined capital city for Queensland.

A.2. Hierarchy 2

Table 14
Refer to Fig. 4 on page 14 for a geographical division of Australia into zones, and Fig. 5 on page 17 for a geographical division of Australia down to the tourism regions, as shown in this table.

Top level			Model
1	Total	Australia	ANA
Level 1: States			
2	A	NSW	AAA
3	B	VIC	ANA
4	C	QLD	ANA
5	D	SA	ANA
6	E	WA	ANA
7	F	TAS	ANA
8	G	NT	ANA
Level 2: Zones			
9	AA	Metro NSW	ANA
10	AB	Nth Coast NSW	ANA
11	AC	Sth Coast NSW	ANA
12	AD	Sth NSW	ANA
13	AE	Nth NSW	ANN
14	AF	ACT	ANN
15	BA	Metro VIC	ANA
16	BB	West Coast VIC	ANA
17	BC	East Coast VIC	ANA
18	BD	Nth East VIC	ANA
19	BE	Nth West VIC	ANA
20	CA	Metro QLD	ANA
21	CB	Central Coast QLD	ANA
22	CC	Nth Coast QLD	ANA
23	CD	Inland QLD	ANA
24	DA	Metro SA	ANA
25	DB	Sth Coast SA	ANA
26	DC	Inland SA	ANN
27	DD	West Coast SA	ANA
28	EA	West Coast WA	ANA
29	EB	Nth WA	ANA
30	EC	Sth WA	ANN
31	FA	Sth TAS	ANA
32	FB	Nth East TAS	ANA
33	FC	Nth West TAS	ANA
34	GA	Nth Coast NT	ANA
35	GB	Central NT	ANA
Bottom level: Regions			
36	AAA	102 Illawarra	ANA
37	AAB	104 Sydney	ANA
38	AAC	118 Central Coast	ANA
39	ABA	110 Hunter	ANA
40	ABB	112 Nth Coast NSW + 120 Lrd Howe Isl	ANA
41	ABC	113 Northern Rivers Tropical NSW	ANA
42	ACA	101 South Coast	ANA
43	ADA	105 Snowy Mountains	ANA
44	ADB	106 Capital Country	ANA

Table 14 *(continued)*

Top level			Model
45	ADC	107 The Murray	ANA
46	ADD	108 Riverina	ANN
47	AEA	109 Explorer Country	ANN
48	AEB	114 New England North West	ANA
49	AEC	115 Outback NSW	ANN
50	AED	119 Blue Mountains	ANN
51	AFA	117 Canberra	ANN
52	BAA	201 Melbourne	ANA
53	BAB	207 Peninsula	ANA
54	BAC	214 Geelong	ANA
55	BBA	204 Western	ANA
56	BCA	211 Lakes	ANA
57	BCB	212 Gippsland	ANA
58	BCC	221 Phillip Island	ANA
59	BDA	208 Central Murray	ANA
60	BDB	209 Goulburn	ANN
61	BDC	210 High Country	ANA
62	BDD	213 Melbourne East	ANN
63	BDE	219 Upper Yarra	ANA
64	BDF	220 Murray East	ANN
65	BEA	202 Wimmera + 203 Mallee	ANN
66	BEB	205 Western Grampians	ANN
67	BEC	206 Bendigo Loddon	ANA
68	BED	215 Macedon	ANN
69	BEE	216 Spa Country	ANN
70	BEF	217 Ballarat	ANN
71	BEG	218 Central Highlands	ANA
72	CAA	301 Gold Coast	ANA
73	CAB	302 Brisbane	ANA
74	CAC	303 Sunshine Coast	ANA
75	CBA	304 Hervey Bay/Maryborough	ANA
76	CBB	307 Bundaberg	ANA
77	CBC	308 Fitzroy	ANA
78	CBD	309 Mackay	ANA
79	CCA	310 Whitsundays	ANN
80	CCB	311 Northern	ANA
81	CCC	312 Tropical North Queensland	ANA
82	CDA	306 Darling Downs	ANN
83	CDB	314 Outback	ANA
84	DAA	404 Adelaide	ANA
85	DAB	405 Barossa	ANN
86	DAC	408 Adelaide Hills	ANN
87	DBA	401 Limestone Coast	ANA
88	DBB	403 Fleurieu Peninsula	ANA
89	DBC	413 Kangaroo Island	ANA
90	DCA	402 Murraylands	ANA
91	DCB	406 Riverland	ANN
92	DCC	407 Clare Valley	ANN
93	DCD	409 Flinders Ranges	ANA
94	DCE	410 Outback SA	ANA
95	DDA	411 Eyre Peninsula	ANA
96	DDB	412 Yorke Peninsula	ANA
97	EAA	550 Australia's Coral Coast	ANA
98	EAB	553 Experience Perth	ANA

Table 14 *(continued)*

Top level			Model
99	EAC	552 Australia's South West	ANA
100	EBA	551 Australia's North West	ANA
101	ECA	554 Australia's Golden Outback	ANN
102	FAA	601 Greater Hobart	ANA
103	FAB	602 Southern	ANA
104	FBA	603 East Coast	ANA
105	FBB	604 Northern	ANA
106	FBC	605 Greater Launceston	ANA
107	FCA	606 North West	ANA
108	FCB	607 West Coast	ANA
109	GAA	801 Darwin	ANA
110	GAB	802 Kakadu	ANN
111	GAC	803 Arnhem	ANN
112	GAD	809 Daly	ANA
113	GBA	804 Katherine	ANA
114	GBB	805 Tablelands	ANA
115	GBC	806 Petermann	ANA
116	GBD	807 Alice Springs	ANA
117	GBE	808 MacDonnell	ANA

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Corrigendum

Corrigendum to: "Hierarchical forecasts for Australian domestic tourism" [International Journal of Forecasting 25 (2009) 146–166]

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The authors wish to correct two small errors, which have been discovered in the counting observations at the very beginning of Section 5. We state 'We then re-estimate the models based on the first 12 observations (1998:Q1-2001:Q4) and produce 1- to 8-step-ahead forecasts'. The correct quarters are '(1998:Q1-2000:Q4)'.

We also state: 'This process is iterated until 2005:Q3'; this should be 'until 2006:Q3'.

The authors would like to apologise for these errors.

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