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A method for improving landscape scale temperature predictions and the implications for vegetation modelling

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Abstract

Understanding how environmental factors influence the spatial distribution of vegetation allows environmental managers to plan for issues such as climate change, ecological restoration and intensified land use. Elevation is often used as an indirect predictor of temperature, but this limits the applicability of environmental models to other study areas and introduces errors in mountainous terrain where variations in slope, aspect, and radiation can significantly alter the relationship between elevation and temperature. Some studies have developed estimates for temperature that also consider factors such as radiation, but these usually estimate the temperature for each location without considering the surrounding environment. In this study, average summer maximum and minimum temperatures were recorded at various locations on the Illawarra Escarpment, near Sydney, Australia. It was hypothesised that wind and air movements would average out large differences in elevation and radiation in mountainous terrain and cause the temperatures to be more strongly correlated with local averages of elevation and radiation than they are with the actual elevation and radiation where the temperatures were recorded. The use of local averages improved the estimate of average summer maximum temperature from a regression r2 of 0.185 using elevation alone, to an r2 of 0.685 when using canopy cover, local average elevation and local average radiation. In contrast, average summer minimum temperatures were better predicted using the elevation of each location without averaging. The results were applied to vegetation modelling by comparing a generalised additive model using the predicted average temperatures with a model using elevation. The overall classification accuracy for vegetation communities in the study area was improved from 46.4% to 61.8%. Therefore, improved temperature estimates also improved the explanatory performance of vegetation models.

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A method for improving landscape scale temperature predictions and the implications for vegetation modelling

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Abstract

Understanding how environmental factors influence the spatial distribution of vegetation allows environmental managers to plan for issues such as climate change, ecological restoration and intensified land use. Elevation is often used as an indirect predictor of temperature, but this limits the applicability of environmental models to other study areas and introduces errors in mountainous terrain where variations in slope, aspect, and radiation can significantly alter the relationship between elevation and temperature. Some studies have developed estimates for temperature that also consider factors such as radiation, but these usually estimate the temperature for each location without considering the surrounding environment. In this study, average summer maximum and minimum temperatures were recorded at various locations on the Illawarra Escarpment, near Sydney, Australia. It was hypothesised that wind and air movements would average out large differences in elevation and radiation in mountainous terrain and cause the temperatures to be more strongly correlated with local averages of elevation and radiation than they are with the actual elevation and radiation where the temperatures were recorded. The use of local averages improved the estimate of average summer maximum temperature from a regression r^2 of 0.185 using elevation alone, to an r^2 of 0.685 when using canopy cover, local average elevation and local average radiation. In contrast, average summer minimum temperatures were better predicted using the elevation of each location without averaging. The results were applied to vegetation modelling by comparing a Generalised Additive Model using the predicted average temperatures with a model using elevation. The overall classification accuracy for vegetation communities in the

study area was improved from 46.4% to 61.8%. Therefore, improved temperature estimates also improved the explanatory performance of vegetation models.

1 Introduction

Understanding the relationship between environmental factors and the distribution of vegetation can provide a meaningful contribution to environmental planning and management (Austin 2002, Ferrier *et al*. 2002). This is especially true at the landscape scale where environmental decisions are often made (Lookingbill and Urban 2003, Chuanyan *et al*. 2005). Quantifying the environmental niche of different species and communities can provide evidence as to what would occur if the land were used differently (Guisan and Zimmermann 2000), allows the estimation of past climate from fossils (Arundel 2005), can be used to aid ecological restoration (Chuanyan *et al*. 2005), and can be used to predict how future climate change will alter the distribution of vegetation (Hörsch 2003).

A common way of explaining the distribution of vegetation is through the static modelling of survey data (see Guisan and Zimmermann 2000 for a review). These models capture the realised niche of vegetation in terms of environmental variables, but are based on the assumption that the vegetation is a result of, and in equilibrium with, the current environment and not a relict from the past (Austin 2002).

Static models require detailed maps of the environmental factors that influence the vegetation, the majority of which are based on Digital Elevation Models (DEMs) and contain some level of error (Van Niel *et al*. 2004). For example, the DEM can be used to estimate the slope, aspect, hydrology and radiation for the study area.

Elevation is often used as an indirect predictor of temperature (Lookingbill and Urban 2003), or is used in techniques (e.g. BIOCLIM) that interpolate data from

weather stations (Hughes *et al*. 1996, Lindenmayer *et al*. 1999, 2000, Dymond and Johnson 2002). These methods are prone to error when predicting local temperature variations because there is often a lack of weather stations on which to base the interpolation, they ignore the influence of the local topography (Guisan and Zimmerman 2000), and they fail to account for effects such as cold air drainage and evaporative cooling (Lookingbill and Urban 2003).

Mountainous terrain can be especially difficult to model because the high spatial variability of environmental factors leads to a complex mosaic of vegetation (Hörsch 2003). In Australia, there can be ten species of eucalypt (Myrtaceae: *Eucalyptus* spp.) in a small area (Florence 2004). Whilst it is accepted that there are changes in dominant canopy species associated with slope and aspect, the exact relationship with direct predictors is uncertain (Bell and Williams 1997). Environmental factors such as climate, phosphorus (Beadle 1954, Beadle 1966), fire (Florence 2004), and moisture (Wardell-Johnson *et al*. 1997) have been associated with the distribution of Australian vegetation, but no vegetation models have yet been able to satisfactorily explain the distribution of eucalypts (Austin *et al*. 1997), possibly because some scientists assume that the same environmental factors are limiting all the species (Arundel 2005). In addition, most studies have ignored the interaction between environmental factors at a location and those of neighbouring areas.

The complexity of Australian vegetation is well illustrated by the Illawarra Escarpment, approximately 80km south of Sydney, Australia (Figure 1). There is a complex mosaic of eucalypt forests, woodlands, and rainforests on the Woronora Plateau and the slopes of the escarpment. The city of Wollongong lies on the coastal plain and foothills to the south and east, but there are also some remnants of native vegetation. The climate of the Illawarra region is humid and mild, with average daily

minimum temperatures of 9 to 18^{o}C and maximum temperatures of 17 to 26^{o}C throughout the year (Fuller 1995). Annual rainfall ranges from 1000-1200mm on the coastal plain to 1500-1600mm on the escarpment, with slightly more rain falling in February-May than in August-November (Fuller 1995).

Preliminary modelling of the study area using Generalized Additive Models (GAMs, Hastie and Tibshirani 1990) has confirmed that it is difficult to quantitatively explain the current distribution of vegetation using the available predictors. It has been suggested that obtaining better quality predictor variables would be a good first step to address this problem (Guisan and Zimmermann 2000, Austin 2002). This could include replacing the elevation predictor with more accurate and/or direct maps of average maximum and minimum temperatures.

The aims of this study were to develop more accurate maps of average summer maximum and minimum temperatures, and to quantify the improvement in vegetation modelling performance when these are used instead of elevation. Whilst estimates of temperature have been developed for other study areas, this study aimed to determine whether the estimates could be improved by considering the interaction between a location and its surrounding environment.

It was hypothesised that wind and air movements would average out large differences in radiation and elevation over small distances and cause temperatures to be more strongly correlated with the average elevation and radiation in the surrounding area than they are with the actual elevation and radiation where the temperature was recorded. This was tested by comparing the linear regression of temperature against the local average radiation and elevation with the linear regression of temperature against the actual elevation and radiation where temperature sensors were located. A stronger relationship would indicate that the local averages

were better correlated with temperature, and would therefore be more appropriate for any temperature prediction method including linear regression and elevation sensitive interpolation methods such as ANUSPLIN and GIDS (Price *et al*. 2000).

Chuanyan et al. (2005) have also suggested that elevation is an unsatisfactory predictor for capturing the environmental niche of vegetation, and recently compared a number of other temperature estimation techniques. It is hoped that using the locally averaged elevation and radiation will further increase the accuracy of any of these methods, and lead to more ecologically realistic vegetation models.

2 Materials and methods

2.1 Environmental predictor variables

Elevation data for the Illawarra Escarpment was available in the form of a digital elevation model (DEM) with a 10m cell size. Whilst it is unknown how the DEM was created, it appears to have been derived from the contours of a topographic map and contains some noticeable imperfections. Airborne Laser Scanning (ALS) data that is available for a subset of the study area (courtesy of AAMHatch Pty Ltd) suggest that the errors in elevation are generally in the order of 5-10m for most of the study area, but may be up to 30m near the steep cliffs around Mt Keira.

Three maps were also obtained. A map of vegetation communities was available courtesy of the Department of Environment and Conservation (NPWS 2002). Spatial errors for community boundaries are within 24m for 93% of the map area, but may be up to 70m in some areas on the escarpment. Communities are described in terms of species composition, and the canopy cover of each structural layer is estimated. Cultural data (roads, walking trails, powerlines, and gas pipelines) was provided by the Department of Infrastructure, Planning and Natural Resources (DIPNR). A

comparison with high-resolution aerial photos (courtesy of AAMHatch Pty Ltd) suggests that spatial errors for the cultural data may be up to 50m in the vicinity of the escarpment. A geology map was available for part of the study area courtesy of Phil Flentje at the University of Wollongong. This was in the form of categorical data, with one value for each of the 20 geological units. An extra categorical value, ‘unknown’, was added for those areas outside the geological map. The geology map was used as a surrogate for soil properties (such as phosphorus) that are known to influence the distribution of vegetation.

Streamlines were calculated from the DEM where the flow accumulation (as determined using ESRI ArcMap hydrology functionality) was greater than 500 cells. The distance to the streams was calculated using Euclidean distance, with values less than one being rounded up so that the log transformation would produce values greater than zero and the output would be more sensitive to areas that are near streams. Lookingbill and Urban (2003) used a similar log transformation of distance to streams in their estimations of temperature.

The distance to disturbance was estimated by calculating the minimum distance to either the lines in the cultural data or the ‘Cleared’ polygons in the vegetation data. Values less than one were rounded up and the data was also log transformed.

Exposure to winds was estimated by calculating the angle to the horizon for each azimuth that is a multiple of 15. This was done in ArcGIS using an AML script to calculate the shadow using ‘hillshade’ at altitudes of 0.125, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 2, 2.5, 3, 3.5, 4, 5, 6, 7, 8, 9, 11, 13, 15, 18, 21, 25, 29, 34, 39, 45, 51, 58, 65, 73, and 81 degrees. The cells in the resulting raster grid contained the minimum angle that resulted in no shadow. This grid was incremented by one and log transformed so that the output was more sensitive to changes near low altitudes.

Exposure to warm and dry westerly to northwesterly winds was estimated by averaging the log-transformed angles for azimuths of 255, 270, 285, 300, 315, and 330 degrees. Exposure to cold, moist southerly winds was estimated by averaging the log-transformed angles for azimuths of 150, 165, 180, 195, and 210 degrees. Exposure to moist northeasterly winds was estimated by averaging the log-transformed angles for azimuths of 30, 45, and 60 degrees. These azimuths were chosen based on preliminary modelling and existing literature on the area. Dry westerly winds are dominant in winter and moist south and northeasterly winds are common in spring and summer (Erskine 1984, Bywater 1985, Mills 1986, Fuller 1995). Northwesterly winds are not as common, but are dry and warm in summer and can have a desiccating influence on the local rainforests (Fuller 1995).

Averages were employed to the wind directions because it had the effect of allowing wind to ‘bend’ around mountains, thus avoiding the long wind-shadows that stretch across the entire coastal plain when considering only one direction. Kramer *et al*. (2001) used the EXPOS model for a similar effect, but their model also allows wind to bend over the top of mountains. In any event, these are still approximations for exposure to wind, as wind is also influenced by valleys, mountaintops, and elevation (Raupach and Finnigan 1997, Finardi *et al*. 1998, Uchida and Ohya 1999, Ruel *et al*. 2001).

Incoming solar radiation was calculated using the DEM and the Solar Analyst (USDA Forest Service) extension for ESRI ArcView. The total direct radiation was calculated for January 18th 2005, and is referred to in this paper as simply ‘radiation’. The 18th January was selected because it is near the middle of the observation period.

2.2 Predicting maximum and minimum temperatures

Geographic Information System (GIS) data was used to stratify the study area according to elevation, radiation, and distance to streams, as these factors have been identified as influencing maximum and/or minimum temperature (Moore *et al*. 1993, Lookingbill and Urban 2003). Forty locations for temperature loggers were selected based on the stratification results to overcome a number of problems with random sampling. These problems include the clustering of high elevation and low radiation sites which would cause random sites to be so close that they may be spatially auto-correlated, access restrictions to privately owned lands, and other access problems caused by the steep topography and dense vegetation that could not be identified until the sites were visited.

Whilst it is recognised that non-random sampling can lead to bias, attempts were made to minimise this risk by ensuring the full range of each predictor was sampled, and by ensuring the environmental predictors were poorly correlated for the sampled locations. Radiation was poorly correlated with both elevation (r^2 = 0.009) and distance to streams (r^2 = 0.015) due to the stratification, whilst elevation was moderately correlated with distance to streams (r^2 = 0.306) because there were fewer streams near the drainage divides at high altitudes.

Temperatures were recorded using DS1921G iButton temperature loggers (Dallas Semiconductor/MAXIM). Recordings where made every 30 minutes from 29th November 2004 to 9th January 2005, and from 15th January 2005 to 25th February 2005. Sensors were placed on the surface of the ground with as much shelter from direct radiation as possible given the vegetation at each location. Each sensor was pinned to the ground inside a small, coarse meshed bag, however three sensors moved

by 1-2m during the study period due to disturbance from falling trees, erosion, and possibly lyrebirds.

In previous studies, temperature sensors have been placed at a variety of heights including 10cm and 5cm below the surface, and 15cm, 30cm, 1.3m and 2m above the surface (Lookingbill and Urban 2003, Lemenih *et al*. 2004, Porte *et al*. 2004, Ritter *et al*. 2005). Some have used radiation screens to avoid direct radiation (Ritter *et al*. 2005), whilst others used the shade of the trees (Lookingbill and Urban 2002). It is not evident which height provides the most useful predictor for the distribution of vegetation, but it has been shown that both soil and air temperatures influence the growth rate of eucalypts (Bell and Williams 1997). It is also not clear how well the surface temperature correlates with either the subsurface soil temperatures or canopy air temperatures, but it has been suggested that surface temperatures have the maximum diurnal variation and may be 5-10^{o}C different from the air temperature at 1.5m – where meteorological measurements are made (Campbell and Norman 1998). Surface temperatures may be more spatially variable, because they are less subjected to the winds and advection that can mix air (Porte *et al*. 2004), and are obviously more exposed to solar radiation than subsurface measurements.

When the sensors were reprogrammed in mid January 2005, the percentage canopy cover of each site was visually estimated to the nearest 10% and recorded. The full range of canopy covers were observed (0-100%), and canopy cover was poorly correlated with elevation (r^2 = 0.065), radiation (r^2 = 0.117) and distance to streams (r^2 = 0.072). Therefore, canopy cover was considered for inclusion in models for predicting temperature. It should, however, be noted that the visual assessment of canopy cover is prone to error. The relative importance of different canopy and sub-

canopy layers is not obvious, and it is unknown how much the canopy cover varies temporally, or whether measurements should be biased towards the path of the sun.

One site had to be discarded because the data on the temperature logger was lost. For each of the remaining 39 sites the daily maximum and minimum temperatures were recorded, and then averaged to determine the mean maximum and minimum temperatures for each of the 39 sites. Linear regression was used to determine how well elevation explained the average maximum and minimum temperatures, as done by Lookingbill and Urban (2003). The results of the regression were compared with the regression using elevation in combination with the other predictors (radiation, log distance to streams, and percentage canopy cover).

Partial response graphs and residuals were examined to ensure that the regression was, as expected, linear, and that the residuals appeared to be normally distributed. Linear relationships have already been established (Lookingbill and Urban 2003).

In order to establish whether or not the relationship between elevation and temperature varies during the course of the day, the average temperature for each 30-minute period was calculated for each site. Regression was used to calculate the relationship for each 30-minute interval, and the correlation coefficients recorded. The regression was conducted using elevation alone, and elevation in combination with radiation and canopy cover. The lapse rate was estimated from the coefficient of the elevation parameter in the regression.

2.3 Using a low pass filter to improve estimates

It was hypothesised that wind and air movements would cause the maximum temperature at a given site to be more strongly correlated with the average elevation and radiation over the surrounding area than with the actual elevation and radiation where the temperature was recorded. For example, a site surrounded by areas of

consistently high radiation would be warmer than a site surrounded by a mosaic of low and high radiation.

In order to test this hypothesis, the radiation and elevation predictors were transformed using low pass filters. This process averaged the values of each predictor over a circular region around each pixel in the predictor map, and calculated the moving average of elevation and radiation. The low pass filters were performed using the neighbourhood functionality of ESRI ArcMap, with radii of 100m, 200m, 500m, 750m, 1000m, 1250m, and 1500m.

For each radius, linear regression was used to examine the effect of the low pass filter on the correlation coefficient between maximum temperature and elevation and/or radiation (in comparison to the regression with the unfiltered predictors). The radius that maximised the r^2 of the regression was used to estimate the optimal radius for the low pass filter. The low pass filter was also used to examine the effect on the correlation coefficient of the regression for the average temperature for each 30-minute period during the day.

As the minimum radius (100m) is ten times the cell size of the DEM (10m), the resolution of the DEM is not expected to have a significant influence on the optimal radius. As averaging will cancel out random errors, it is also expected that DEM accuracy will become less significant once the low pass filter is used. Problems may be encountered in future if the cell size approaches the radius of the filter, but there is no reason to believe that the optimal radius in terms of distance would change, even though the radius would obviously be less in terms of the number of cells.

2.4 Vegetation modelling

A dataset of random points (defined by an easting and northing in the study area) was created and the vegetation community was determined for each point from the

NPWS vegetation map. Rare and non-vegetated communities were discarded, which left 23 different communities. There were also a small number of points (<1%) that had to be discarded because there were spatial or other inconsistencies between the different data layers. For each remaining point, the environmental predictors were extracted from the appropriate themes in ArcMap, and the data set was randomly split into a training data set of 4995 points and a validation data set of 2306 points.

A GAM was produced in SPlus (Insightful Corp.) for each of the 23 communities using the training dataset and the predictors (see Section 2.1 for more details) of elevation, geology, log distance to streams, log distance to disturbance, and exposure to the three wind directions (EGWD models). Each of the models was then applied to the validation data set and each point classified into one of the 23 communities according to the model that produced the highest predicted probability of occurrence.

The GAMs were then repeated using the predicted average summer maximum and minimum temperatures instead of elevation. In the first instance, the maximum was predicted using the filtered elevation and radiation (ER model), and in the second instance the maximum was predicted using the filtered elevation and radiation and the canopy cover (CER model). It was necessary to estimate the canopy cover from the vegetation map, with each community assumed to have a constant summer canopy cover of between 30% and 90%, estimated according to the community descriptions by the NPWS (2002). This is in contrast with the visual estimates of canopy cover that were used to derive the formula for maximum temperature. In future, the canopy cover could be estimated more accurately using remote sensing (Wang *et al*. 2003).

No attempts were made to trim insignificant predictors from any of the GAMs, or to vary the degrees of freedom for each predictor. This ensures that the comparison between models is only comparing the effect of the maximum temperature predictor,

but runs a risk of over-fitting. It has also been suggested that excessive absences past the recorded distribution of a species need to be culled (Austin and Meyers 1996, Leathwick *et al*. 1996). This was not done because the output was the “most probable entity” rather than the “probability of occurrence” (Guisan and Zimmermann 2000). Whilst it is recognised that a GAM can predict a non-zero probability of occurrence outside the observed range, this will not result in it being the most probable entity as long as another community it more likely to occur in that location.

3 Results

3.1 Predicting minimum temperature

Elevation was highly significant for predicting the average summer minimum temperatures ($r^2 = 0.763$, $t = -10.92$, d.f. = 37, $P<0.001$). Distance to streams was also significant ($r^2 = 0.196$, $t = -3.000$, d.f. = 37, $P<0.01$), but this must be treated with caution due to the moderate correlation between elevation and distance to streams. This is emphasised by the fact that when distance to streams and elevation were both used to model the average minimum temperature, the distance to streams was no longer significant ($r^2 = 0.766$, $t_{elev} = -9.355$, d.f. = 36, $P_{elev} < 0.001$, $t_{stream} = 0.603$, d.f. = 36, $P_{stream} > 0.05$), and there was negligible improvement in correlation from the regression with elevation alone. The average minimum temperature was not significantly influenced by either radiation ($r^2 = 0.006$, $t = -0.461$, d.f. = 37, $P > 0.05$) or canopy cover ($r^2 = 0.015$, $t = 0.754$, d.f. = 37, $P > 0.05$), nor were they significant when combined with elevation and/or distance to streams.

Based on these results, the minimum temperature was predicted based on elevation, with the equation:

$$T_{min} = 17.3 – 0.0052 * \text{Elevation}$$

Where T_{min} is the predicted average summer minimum temperature (^oC) at each location, and the Elevation (m) is taken from the DEM. The graph of the predicted average minimum temperature against the recorded average minimum temperature is shown in Figure 2a.

3.2 Predicting maximum temperature

Linear regression with each predictor individually showed that both canopy cover ($r^2 = 0.303$, $t = -4.014$, d.f. = 37, $P < 0.001$) and elevation ($r^2 = 0.185$, $t = -2.896$, d.f. = 37, $P < 0.01$) were significantly correlated with maximum temperature, but radiation ($r^2 = 0.055$, $t = 1.473$, d.f. = 37, $P > 0.05$) and distance to streams ($r^2 = 0.005$, $t = -0.433$, d.f. = 37, $P > 0.05$) were not. When both elevation and canopy cover were used in the regression the correlation improved significantly ($r^2 = 0.651$, $t_{canopy} = -6.934$, d.f. = 36, $P_{canopy} < 0.001$, $t_{elev} = -5.988$, d.f. = 36, $P_{elev} < 0.001$). When all the parameters were included in a multiple regression the r^2 improved to 0.680, but elevation and canopy cover were the only predictors that were significant. The equation for predicting the average maximum temperature using the canopy cover and elevation was:

$$T_{max} = 28.9 – 6.6 * \text{Canopy} – 0.0127 * \text{Elevation}$$

Where T_{max} is the predicted average maximum temperature (^oC), Canopy is the visually estimated canopy cover as a ratio between 0 and 1, and Elevation (m) is taken from the DEM. The graph of the predicted average summer maximum temperature against the recorded average summer maximum temperature is shown in Figure 2b.

3.3 The effects of low pass filters

When a low pass filter was used to average the radiation over various radii, the correlation with the average maximum temperature increased substantially, reaching a

maximum value at a radius of 1000m ($r^2 = 0.199$, $t = 3.029$, d.f. = 37, $P < 0.01$, Figure 3a). It can also be seen that the relationship became more significant, and transformed radiation from an insignificant parameter ($P > 0.05$) into a significant one ($P < 0.01$).

There was also an improvement in the significance of the relationship between maximum temperature and elevation when using a low pass filter, with the best result also at a radius of 1000m ($r^2 = 0.248$, $t = -3.493$, d.f. = 37, $P < 0.01$, Figure 3b). Elevation was significant at every radius ($P < 0.01$), but there were slight improvements in the correlation coefficient and significance.

The correlation coefficient was also improved when average summer maximum temperature was regressed against both filtered elevation and filtered radiation (Figure 3c). In this case, there was a slight degradation in correlation with radii of 100m to 200m, but the best results were once again with a radius of 1000m ($r^2 = 0.379$, $t_{elev} = -3.236$, d.f. = 36, $P_{elev} < 0.01$, $t_{rad} = 2.760$, d.f. = 36, $P_{rad} < 0.01$). This represented a substantial improvement from when the unfiltered elevation was used alone (r^2 from 0.185 to 0.379). Elevation was significant for each radii ($P < 0.01$), but radiation was only significant for radii between 750m and 1500m ($P < 0.05$).

When canopy cover was included as a predictor in the linear regression, along with the low pass filtered elevation and radiation, the best correlation was at a radius of 750m ($r^2 = 0.699$, $t_{canopy} = -6.233$, d.f. = 35, $P_{canopy} < 0.001$, $t_{elev} = -5.517$, d.f. = 35, $P_{elev} < 0.001$, $t_{rad} = 2.617$, d.f. = 35, $P_{rad} < 0.05$, Figure 3d). Both elevation and canopy cover were highly significant at every radii ($P < 0.001$), but radiation only became significant with radii greater than 500m ($P < 0.05$). There was a marginal improvement in correlation between the low pass filtered result and the unfiltered result (r^2 from 0.654 to 0.699).

3.4 Intra-day trends

Regression of the average temperature for each 30-minute period against elevation emphasised the poor relationship between elevation and daytime temperatures. Not only is elevation an inadequate predictor of the average maximum temperature (r^2 = 0.185), but it is also a poor predictor of the average temperature for every time interval from 10:00am to 4:30pm inclusive ($r^2 < 0.4$). In contrast, the estimate using the low pass filtered elevation and radiation maintained a reasonable correlation throughout the day ($r^2 > 0.43$). The result using the filtered predictors was higher than the result based on unfiltered elevation for every time interval from 8:00am to 9:00pm inclusive (Figure 4a).

When canopy cover, radiation and elevation are included in a multiple linear regression, then once again the low pass filtered results for day time average temperatures (10:30am to 5:00pm inclusive) are an improvement over the unfiltered results, but the night-time temperatures are substantially better using the unfiltered elevation (Figure 4b).

The intra-day results emphasise that whilst the low pass filtered radiation and elevation improve daytime temperature predictions, they are not as good at predicting the nighttime temperatures. This is consistent with using unfiltered elevation to predict the minimum temperature, but using the low pass filtered elevation and radiation to predict the maximum temperature.

3.5 Vegetation modelling

The overall accuracy of the GAM model using elevation, geology, distance to streams, distance to disturbance, and exposure to the 3 wind directions (EGWD model) was quite poor at 46.4%. When the average summer maximum temperatures

were predicted using the low pass filtered elevation and radiation (ER model), the overall accuracy of the GAM model improved to 49.0%. The formula used was:

$$T_{max} = -32.7 + 0.01327 * Rad1000 – 0.0115 * Elev1000,$$

where T_{max} is the predicted average summer maximum temperature (^{o}C), Rad1000 is the radiation (W/m^2) averaged over a 1000m radius, and Elev1000 is the elevation (m) averaged over a 1000m radius.

Alternatively, when the maximum temperature was predicted using the canopy cover and the low pass filtered radiation and elevation (CER model), the overall accuracy improved significantly to 61.8%. The formula used was:

$$T_{max} = -13.3 + 0.00955 * Rad1000 – 0.0137 * Elev1000 – 5.3 * Canopy,$$

where T_{max} is the predicted maximum temperature (^{o}C), Rad1000 is the radiation (W/m^2) averaged over a 1000m radius, Elev1000 is the elevation (m) averaged over a 1000m radius, and Canopy is the canopy cover as a fraction between 0 and 1.

Figure 5 illustrates the estimated average summer maximum temperature based on the low pass filtered elevation and radiation. The distributional patterns of maximum temperatures are shown to be vastly different to the distributional patterns of the average summer minimum temperature that are based on elevation alone. These differences are maintained when the average summer maximum temperatures are predicted based on canopy cover, and the low pass filtered elevation and radiation.

4 Discussion

4.1 Temperature prediction

The average summertime maximum temperature could not be accurately predicted using elevation alone (r^2 = 0.185), but a much better estimate could be made using the percentage canopy cover, the low pass filtered elevation and the low pass filtered

radiation ($r^2 = 0.685$). The estimates based on the low pass filtered predictors also outperformed elevation for predicting the average temperature for each 30-minute period from 8:00am to 9:00pm inclusive. In all cases the optimal radius for the low pass filter was between 750m and 1000m. Elevation was a better predictor for the average summer minimum and overnight temperatures.

Using a low pass filter is a crude method to consider the interaction between a site and its neighbours, but appears to be effective for this study area. This is possibly because it reflects the movement of hot and cold air to and from surrounding locations, and allows locations where there is consistently higher radiation to be hotter than those locations where there is a mosaic of high and low radiation. It remains to be tested whether this local phenomenon can be replicated at other sites, and how the relationship varies according to latitude and relief. In areas with more constant canopy cover and radiation it would be expected that elevation would become more dominant.

Likewise, as the diurnal variation in temperature decreases at locations deeper into the soil or higher off the surface (Campbell and Norman 1998), it is possible that the influence of radiation and/or canopy cover may be reduced when the temperature sensors are placed at different locations, or if radiation screens are used. Under these circumstances, it is also possible that the effect of the surrounding environment is reduced, and hence the effect of low pass filtering may be diminished or absent.

It is possible that the filtering method could be improved by weighting the elevation/radiation in the surrounding locations according to distance from the centre (similar to Price *et al*. 2000, Ferrier *et al*. 2002), predominate wind directions, or the shape of the topography. It also needs to be confirmed that the low pass filtered elevation and radiation would also improve the results of other temperature estimation techniques such as ANUSPLIN and GIDS (Price *et al*. 2002). At the continental scale

where the pixel size is roughly the size of the filter used in this study (e.g. 1000m in Price *et al*. 2000), a low pass filter may not have any effect. At the regional scale where the pixel size is 100m or less (e.g. Ferrier et al. 2002), filtering the elevation used by ESOCLIM may slightly improve the accuracy of the model, but this also depends on whether the effect is valid for non-surface temperatures, and whether it is valid for other study areas.

The pixel size is obviously important for studies in mountainous areas, because the elevation may vary by hundreds of meters within one pixel when the pixel size is 100-1000m. This could translate to a within pixel temperature variations of 2-3^{o}C. It is also worth noting that in the Illawarra region, there are many vegetation patches that occupy small areas that could not be captured using a pixel size of 100-1000m, and so a landscape level model is necessary to capture to fine scale changes in temperature and vegetation. It is at the landscape scale that low pass filtering probably has the greatest potential to improve temperature estimates and modelling results.

Previous studies have shown that the lapse rate of temperature is in the order of 6^{o}C/1000m, with daily variations from 3.8^{o}C/1000m near the minimum temperature to 7.0^{o}C/1000m near the maximum (Lookingbill and Urban 2003). In this study, the lapse rate varied from a minimum of 4.9^{o}C/1000m at 6am to a maximum of 8.4^{o}C/1000m during the day. A lapse rate of 5.2^{o}C was determined for the minimum temperature based on elevation alone, and values of approximately 9-13^{o}C/1000m were used in the various formulas for maximum temperature, depending on the parameters that were included in the regression. Therefore, the results of this study appear to be consistent with previous research.

The relationship between canopy cover and temperature is also consistent with previous studies, with the effect ranging from 2^{o}C to 10^{o}C depending on the location

of the sensor and the range of canopy cover examined (Porte *et al*. 2004, Lemenih *et al*. 2004, Ritter et al. 2005). In this study, a 50% difference in canopy cover accounted for a 2.6^{o}C to 3.3^{o}C difference in maximum temperature, depending on the other parameters included in the regression.

The effect of radiation is more difficult to compare with previous studies because it was not significant as a predictor unless the low pass filter was used. Lookingbill and Urban (2003) found that radiation slightly improved the estimation of the maximum temperature for their mountainous area (r^2 from 0.41 to 0.48), but the effects may vary according to latitude and the time of year.

It is possible that the predictions of maximum temperature could be improved further. Qualitatively, moist sites appeared to be cooler than dry sites. This is consistent with a study by Bywater (1985), which suggested that diurnal variations are lower during rainy periods, and the study by Ritter *et al*. (2005), which considered soil moisture as one factor leading to lower temperatures.

Note that temperatures were only recorded for the summer period from December 2004 until February 2005. These recordings may not be representative of the long-term average for this time of year, and may differ from the temperatures recorded at any other height. Therefore, all temperatures discussed in this article should be treated as relative temperatures rather than absolute temperatures. In addition, it is unknown whether this time of year and these sensor locations have the most predictive power for modelling species distribution. It is possible that another season or sensor height may be more biologically important.

4.2 Vegetation modelling

When the vegetation on the Illawarra Escarpment (Figure 1) is modelled, using a GAM for each of the 23 communities, and the validation data set classified according

to which community has the highest probability of occurrence, the results are quite poor. Using the predictors of elevation, radiation, distance to streams, distance to disturbance, and exposure to 3 wind directions the overall accuracy is only 46.4%. If the elevation predictor is replaced with the predicted average summer minimum temperature (using elevation) and the predicted average summer maximum temperature (using canopy cover, and the low pass filtered elevation and radiation at a radius of 1000m) the overall accuracy improves significantly to 61.8%.

Caution must be used, however, since this improvement may be artificially high because the vegetation map was used to estimate canopy cover and therefore predict maximum temperature. This may have introduced feedback into the system when the maximum temperature was subsequently used to predict the vegetation community.

There are still improvements in the overall GAM accuracy from 46.4% to 49% when canopy cover is not used, and the maximum temperature is predicted using the low pass filtered elevation and radiation alone. Therefore, the better estimates of maximum temperature improve vegetation models regardless of whether or not canopy cover is used. Whilst the improvement without canopy cover is not large, this would be expected given that the estimate of maximum temperature is much poorer than when canopy cover is included (r^2 = 0.379 versus r^2 = 0.685).

In this study, the standard deviation of the regression residuals decreased from 2.8^{o}C in the formula for maximum temperature using elevation alone, to 2.5^{o}C in the formula that also included radiation, to 1.8^{o}C in the formula that also included canopy cover. Whilst these may not be indicative of the whole study area due to the stratification and selection of sensor locations, they imply the prediction errors are reduced by possibly 30-40%. Errors of this magnitude cannot be ignored as it has been suggested that 41% of eucalypts have a mean annual temperature range of less

than 2°C (Hughes *et al*. 1996). Including the canopy cover feedback into the prediction of maximum temperatures and vegetation is not ideal, but it may be necessary to include canopy cover in the models if the errors are going to be reduced to a satisfactory level. The best solution might be to obtain the canopy cover from alternative sources such as remote sensing (Wang *et al*. 2003).

Qualitative analysis of the GAM partial response graphs from this study suggests that the actual improvement in modelling results depends on which environmental factors are limiting each community. If a community is being limited by minimum temperature then including maximum temperature into the model may have less effect than a community that is being limited by maximum temperature. Also, the improvement depends not only on the predictive power for that community, but also on the degree to which that community can be distinguished from other communities, and which factors are limiting their distribution.

Previous studies have suggested that eucalypt communities and species may be significantly influenced by summer maximum temperatures (Passioura and Ash 1993) and/or winter minimum temperatures (Moore *et al*. 1993). These studies, and the results of this research, suggest that the limiting factors vary from species to species and community to community, and it is unlikely that any one temperature predictor can differentiate the 23 communities found in this study area.

One problem with using multiple temperature predictors is that they can be highly correlated with each other – leading to problems in the GAMs. Lehmann *et al*. (2003) solved this problem by utilising the difference between the mean annual temperature and the winter average, however, in the Illawarra the average summer minimum and maximum temperatures were poorly correlated and could both be included in the models without introducing any problems with the GAMs. Moore *et al*. (1993)

suggest that the relative contributions of elevation and radiation vary from summer to winter, and therefore it is possible that winter temperatures could be included as well if they are poorly correlated with the summer temperatures.

Austin (2002) suggests that it is difficult to determine whether poor vegetation models result from an unidentified environmental variable, or from other factors such as competition or poor dispersal. This study highlights that it could also be due to using inaccurate predictors, as suggested by Ferrier *et al*. (2002). This study has shown that the performance of vegetation models can be improved by developing more accurate estimates of seasonal maximum and minimum temperatures.

Whilst the improvement in prediction from using direct predictors has been noted (Austin and Meyers 1996, Guisan and Zimmermann 2000), it has also been suggested that they allow the model to be applied to wider areas (Guisan and Zimmermann 2000, Austin 2002). Two possible issues were seen during this study that may cause this to not always be the case. Firstly, the temperature range of each community and the overlap between them varied according to which formula was used to predict the maximum temperature. Clearly, it would be dangerous to apply the models to another area unless the maximum temperature had been calculated in the same manner as when the model was developed – especially if the temperatures were based around air, soil, or canopy temperatures at a different height, taken during a different year, or during a different season. This is similar to the findings of Weiss and Hays (2005).

Secondly, the relationships in this study area are not necessarily applicable to the broader region. For example, *Eucalyptus sieberi* is known to be dominant on the Hawksbury sandstone (Fuller 1995), which is found along the top of the escarpment in this study area. The models produced in this study area suggest it can only occur where the minimum temperature is low (due to high elevation), however it does grow

where the Hawksbury sandstone occurs at lower elevations to the north of the study area. It is unknown how many of the models reflect the ‘local’ rather than the ‘global’ environment, or whether other factors such as competition with new species would change the relationship in other areas.

5 Conclusions

Using the low pass filtered radiation and elevation for temperature predictions improved the estimates of maximum temperature for all combinations of elevation, radiation and/or canopy cover. The low pass filter also improved the temperature estimates for all 30-minute periods during the day from 8am to 9pm inclusive. The optimal radius was 750m to 1000m in all cases, but this may change in other study areas, in other seasons, or for other temperature sensor locations.

Including the improved estimates of maximum temperature in vegetation community models significantly improved the overall classification accuracy from 46.4% to 61.8%. This suggests that the effort spent to produce more direct or accurate predictors can reap large rewards, and it should not always be assumed that elevation is a good surrogate for temperature.

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Figure Captions:

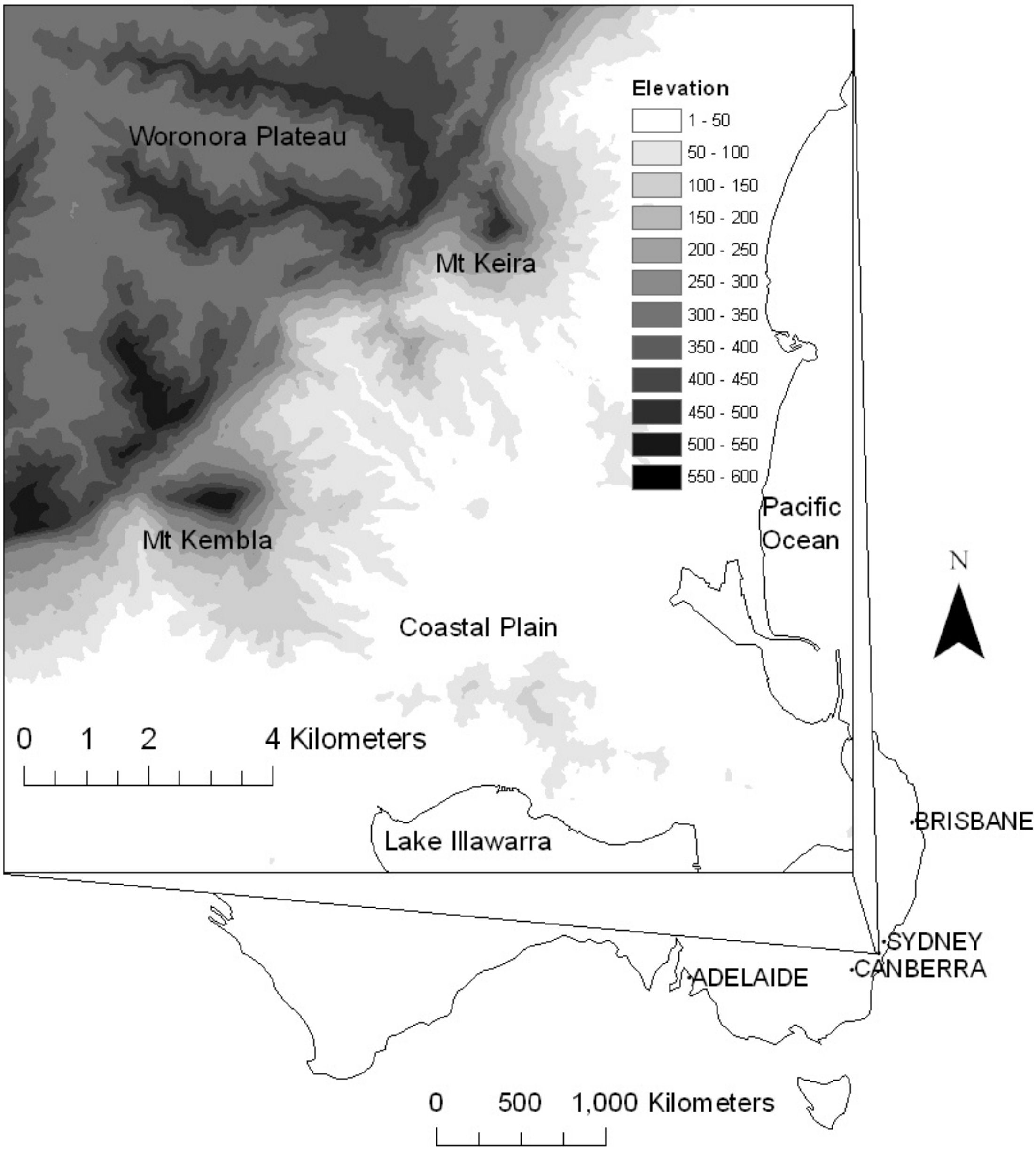

Figure 1: The topography of the Illawarra Escarpment in the vicinity of Wollongong, Australia. The inset is a Digital Elevation Model showing the rising elevation from the coastal plain to the Woronora Plateau, with Mt Keira and Mt Kembla protruding eastward.

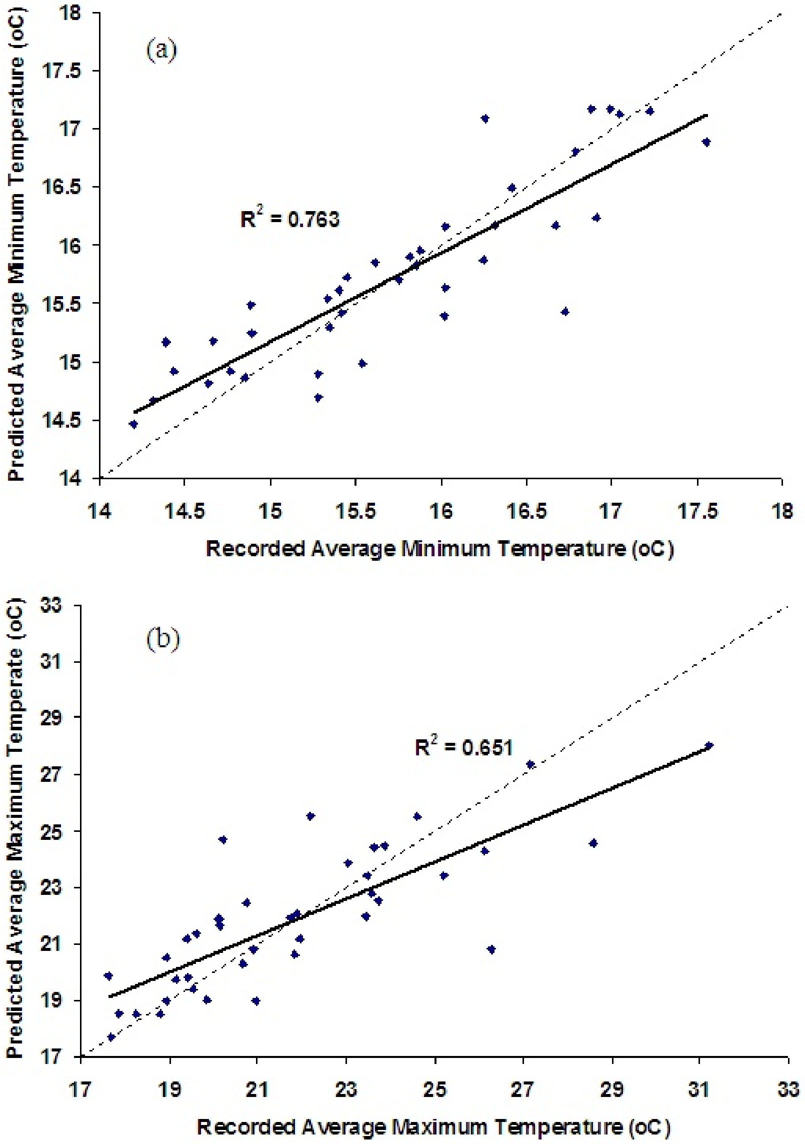

Figure 2: The relationship between the predicted average summer minimum (a) and maximum (b) temperatures and the corresponding minimum and maximum temperatures that were recorded by 39 temperature sensors placed at ground level on the Illawarra Escarpment. The predicted average minimum temperature is based on the regression of the actual recorded minimum temperatures against the elevation of each site, whilst the predicted average maximum temperature is based on the regression of the actual recorded maximum temperature against the elevation and canopy cover of each site.

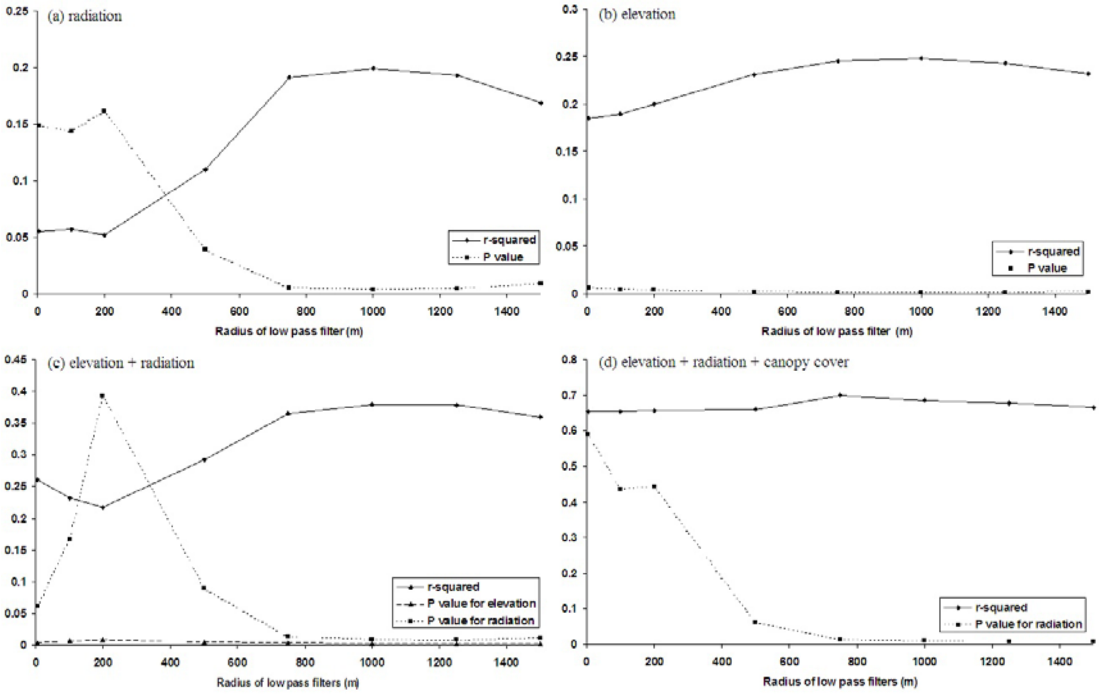

Figure 3: The r^2 and P values that resulted from the regression of the average summer maximum temperature against various predictors for 39 temperature sensors placed at ground level on the Illawarra Escarpment. Predictors were the low pass filtered radiation (a), the low pass filtered elevation (b), the low pass filtered radiation and the low pass filtered elevation (c), and the canopy cover, low pass filtered radiation and low pass filtered elevation (d).

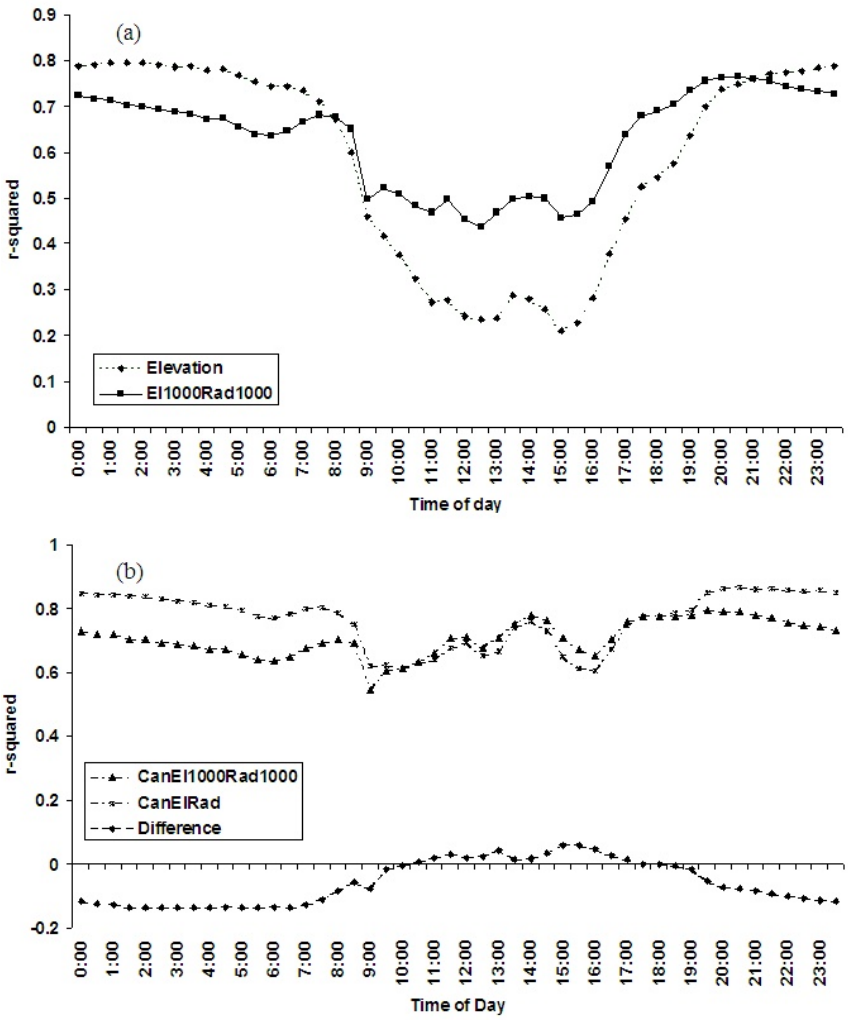

Figure 4: A comparison between the r^2 values for the different regressions predicting the average temperature for each 30-minute period throughout the day (based on 39 temperature sensors at ground level). Elevation refers to the regression using the unfiltered elevation (m) taken directly from the DEM. El1000Rad1000 refers to the regression using the elevation (m) and radiation (W/m^2) as averaged over a radius of 1000m. CanElRad refers to the regression using the canopy cover, unfiltered elevation (m) and unfiltered radiation (W/m^2). CanEl1000Rad1000 refers to the regression using canopy cover, the low pass filtered elevation (m) and the low pass filtered radiation (W/m^2) as averaged over a radius of 1000m. Difference refers to the difference between the r^2 values of the two regressions involving canopy cover, with positive values indicating that the filtered result is higher.

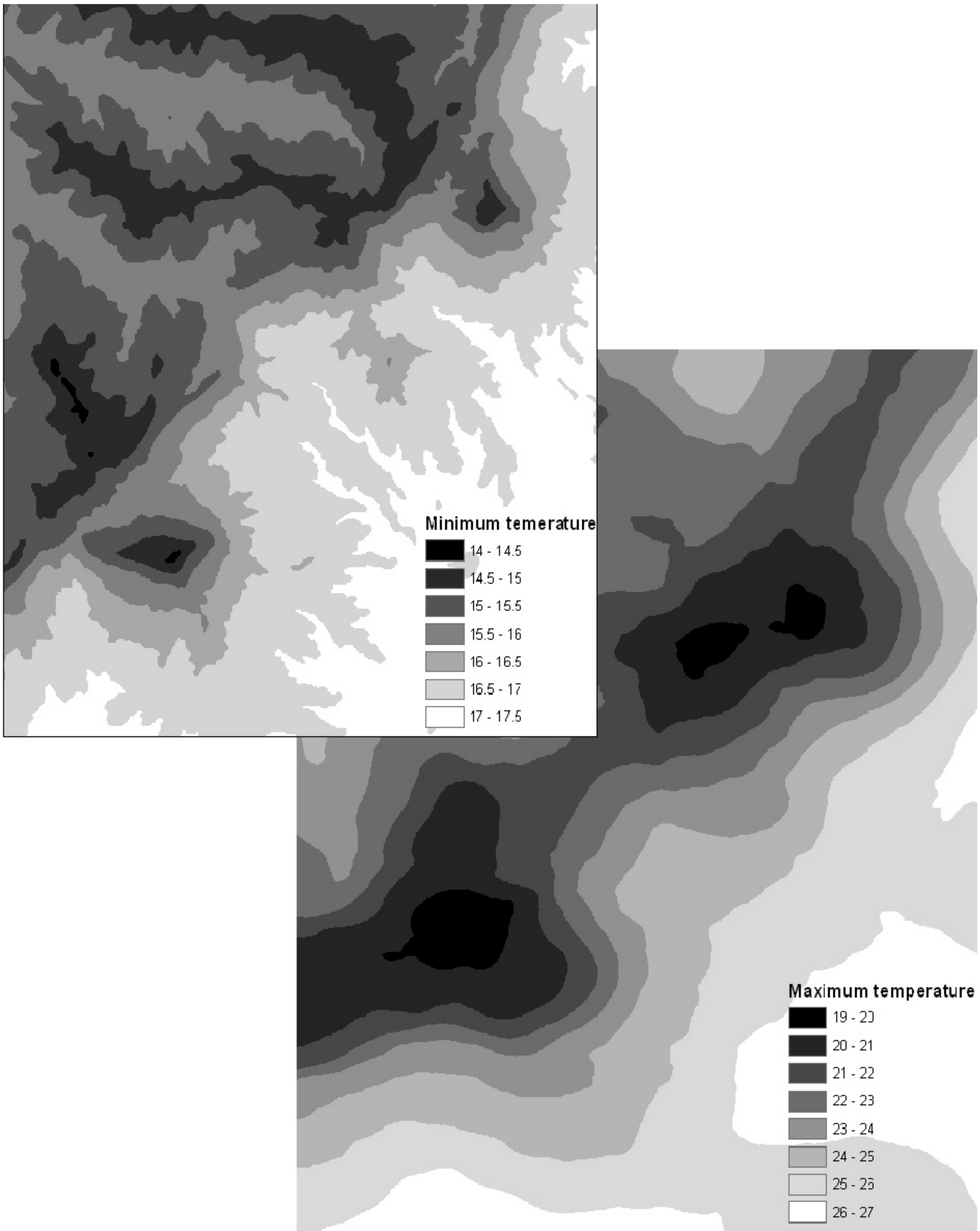

Figure 5: A comparison between the predicted average summer minimum temperature based on elevation (top left) and the predicted average summer maximum temperature based on the low pass filtered elevation and low pass filtered radiation (bottom right). Whilst the minimum temperature south of Mt Kembla is similar to the minimum temperature north of Mt Keira (15.5^{o}C – 16.5^{o}C), the maximum temperature appears to be 1^{o}C – 2^{o}C cooler (20^{o}C – 21^{o}C versus 21^{o}C – 23^{o}C).