Mapping Frost Occurrence Using Satellite Data

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ABSTRACT

Detailed maps of the date of the first and last frost, the length of the frost-free period, and the number of days of frost during spring have been produced for the Otago region of New Zealand. These frost occurrence variables are estimated using a combination of channel-5 (11.5–12.5 μm) infrared brightness temperature data and the normalized difference vegetation index (NDVI) from the Advanced Very High Resolution Radiometer (AVHRR) satellite instrument. It is shown that a generalized linear model with quasi-likelihood estimation is best suited to the estimation of these frost occurrence variables. The maps show that frosts occur earlier in the autumn and later in the spring with increasing distance away from the coast and from major rivers and lakes. Frost is most prevalent on the top of high mountain ranges where the air temperature is coldest and is shown to be more common near the bottom of inland basins as compared with the sides of the surrounding hills because of cold-air drainage and ponding.

1. Introduction

Many agricultural and horticultural crops in New Zealand have their production potential lowered by frost damage (Hewett 1973). In frost-susceptible areas, such as the Otago region shown in Fig. 1, a thorough knowledge of the frequency and timing of frosts is necessary to minimize the risk of frost damage. Minimum air temperature data recorded in standard Stevenson screens at climate stations can be used to assess frost risk. However, the frost risk may be significantly different at a location only a few kilometers away from a climate station location because of a change in altitude, aspect, slope, or land cover. In this study, we use Advanced Very High Resolution Radiometer (AVHRR) data from National Oceanic and Atmospheric Administration (NOAA) polar-orbiting satellites, combined with minimum air temperature data from climate stations, to produce maps of several frost variables at 1-km spatial resolution. We also describe a method of downscaling these frost maps to 50-m spatial resolution using altitude data from a Digital Elevation Model (DEM).

There are two definitions of frost: air and ground; and two types of frost: radiation and advection. An air frost occurs when the air temperature in a standard meteorological screen at a height of 1.3 m above a level grass surface falls below 0°C, while a ground frost occurs when the grass temperature is less than or equal to −1°C (Goulter 1981). For the purposes of this study, only air frosts have been mapped. Radiation frosts are caused by the radiative loss of heat from the earth’s surface (Hewett 1973). They often occur on cold, clear nights with little or no wind; in New Zealand, they are frequently associated with slow-moving anticyclones during autumn, winter, and early spring. Frosts of this type are more common on slopes with a southerly aspect (in the Southern Hemisphere), at high altitudes where the temperatures are colder and in broad inland valleys where cold nocturnal air pools, through the process of cold-air drainage. Advection frosts are caused by the influx of cold polar air accompanied by strong winds and low humidity. While advection frosts are common in continental areas of the Northern Hemisphere, they are extremely rare in New Zealand.

In the Otago region, and more specifically in inland areas, frost damage to fruit trees is a significant concern. Although different species have different tolerances to frost (e.g., apples and pears are more frost-resistant than peaches and nectarines, which in turn are more hardy than apricots), early frosts in autumn and late frosts in spring can be devastating to all fruit. In autumn, an earlier-than-normal frost can damage actively growing shoots and the trees can become susceptible to damage from the bacterium Pseudomonas syringae, causing stone fruit blast. In spring, a later-than-normal frost can cause a variety of damage depending upon the developmental stage of the fruit. Susceptibility to damage progressively increases from bud-break through the bloom period to the stage of small green fruit, resulting in malformation, discoloration, or death.

Isochrone maps of the extreme first and last air frost...
date have been produced for all of New Zealand by Goulter (1981), based on minimum air temperature data from standard meteorological screens at climate stations throughout the country. These maps show broad-scale patterns only but clearly indicate that there is a large difference in frost occurrence (by as much as 3 months over distances of only 100 km) between the coastal and inland regions of both the North and South Islands. This dependence on distance to the sea is by far the dominant feature of the maps. The difference in frost dates between the north and south of the country (approximately 12° of latitude or around 1400 km), by contrast, is on the order of only one month.

Satellite-obtained thermal infrared radiance data have been used to map frost variables in southeastern Australia (Kalma et al. 1983) and in the Pampean region of Argentina (Kerdiles et al. 1996). Kalma et al. (1983) showed that nighttime thermal infrared data in the wavelength band 10.25–12.5 µm from the Heat Capacity Mapping Mission (HCMM) satellite were in general agreement with a priori frost risk maps derived from terrain and land cover information for four relatively cloud-free nights in 1978 and 1979. No atmospheric corrections were applied to the satellite data and no estimates of surface emissivity were made for the Kalma et al. (1983) study. Kerdiles et al. (1996) examined AVHRR thermal infrared brightness temperature data for three nights in 1992 when severe frosts were present over the whole of the Pampean region of Argentina. Several split-window (channel 4 minus channel 5) land surface temperature (LST) models were intercompared and related to minimum air temperatures from climate stations. Surface emissivity was estimated from the normalized difference vegetation index (NDVI) based on the methods of van de Griend and Owe (1993) and Coll et al. (1994). The Kerdiles et al. (1996) study found that the relationships between brightness temperature and minimum air temperature were statistically more significant than those between estimated LST and minimum air temperature, resulting in correlations of 0.81, 0.44, and 0.90 for the three winter nights.

Platt and Prata (1993) discussed the retrieval of LST from satellite measurements on cold, clear winter nights for an area in northern Victoria, Australia. They concluded that on these cold cloud-free winter nights, the normal attenuation of infrared brightness temperature due to water vapor absorption is reversed because of emission from the relatively warmer atmospheric layer at the top of the temperature inversion. This additional emission may also compensate for emissivity effects, which tend to suppress the magnitude of the surface emission because land surfaces rarely behave as perfect blackbodies. The net result of this extra emission is that the infrared brightness temperature measured by the satellite is very similar to the actual land surface temperature during these special conditions. Further, they concluded that on cold clear winter nights, LST can be effectively estimated from only one AVHRR infrared channel, without the need for a split window method, an estimation of emissivity, or knowledge of the water vapor content.

In this study, six frost variables are mapped for the Otago region of New Zealand using AVHRR data from 1999 and 2000 together with climate station minimum air temperature data. The first two frost variables are the 20th-percentile date of the first frost to occur in autumn and the 80th-percentile date of the last frost to occur in spring. The dates of the first and last frost have often been used to assess frost risk (Goulter 1981). However, because most growers in frost-susceptible regions use some form of frost protection (e.g., firespots, wind machines, or sprinkler systems) the average date of these frosts is not as important as the relatively rare events that occur once in every five years. For this reason, the 20th- and 80th-percentile dates have been mapped. Another useful indicator of frost risk is the mean length of the frost-free period, which is the number of days between the last frost in spring and the first frost in the following autumn. This frost variable has also been mapped. Last, because frost occurrences in spring can be particularly damaging, the mean number of frosts in
TABLE 1. AVHRR data used in this study. The first 12 dates are nighttime images used to calculate the mean winter channels (Ch) 3, 4, and 5 brightness temperature ($T_b$) for the Otago region. The next six dates are daytime images used to estimate the mean winter emissivity based on the NDVI, and the last two dates are a daytime image in autumn and a daytime image in spring used to calculate the NDVI in these two seasons.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time (NZST)*</th>
<th>Satellite</th>
<th>Orbit No.</th>
<th>Derived variables</th>
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<tr>
<td>5 Jun 1999</td>
<td>0235</td>
<td>NOAA-14</td>
<td>22817</td>
<td>Ch 3, 4, and 5 $T_b$</td>
</tr>
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<tr>
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<td>NOAA-14</td>
<td>23748</td>
<td>Ch 3, 4, and 5 $T_b$</td>
</tr>
<tr>
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<td>28040</td>
<td>Ch 3, 4, and 5 $T_b$</td>
</tr>
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* NZST = New Zealand standard time.

each of September, October, and November was also mapped.

2. Data

a. Frost variables

The six frost variables were derived from daily minimum air temperature measurements from standard Stevenson screens at 48 climate stations throughout the Otago and neighboring regions (Fig. 1). For each station and for each year, the first and last frost day (i.e., in the Southern Hemisphere, the first and last yearday of the year when frosts occurred), the frost-free period (i.e., the number of consecutive days from the date of the last frost with minimum air temperatures greater than 0°C), and the number of days of frost in September, October, and November were identified. The record lengths at the 48 stations varied between 3 and 71 yr, with the mean record length equal to 17.5 yr. From these annual time series, the six frost variables were derived for each station location.

b. Geographical variables

The geographical variables used in this study are altitude, latitude, longitude, and distance to the sea. These variables, which have previously been used as predictors of minimum air temperature (Zheng and Basher 1996), were determined at each of the 48 climate station locations and at 1-km and 50-m grids for the whole Otago region. In this study, we investigate whether they can also be used as predictors of the frost variables listed above.

c. Satellite variables

Channel-3 (3.55–3.93 μm), channel-4 (10.5–11.5 μm), and channel-5 (11.5–12.5 μm) AVHRR brightness temperature data were obtained for 12 nights in the winters of 1999 and 2000 for the lower South Island of New Zealand (Table 1). The data are at the Local Area Coverage (LAC) spatial resolution, yielding an instantaneous field of view of 1.1 km at nadir. The AVHRR data were remapped onto Lambert conformal projections at 1-km resolution and registered by aligning the images with a coastal outline. The registration error using this method is less than 1 km over the whole area. Scan angles were between 30° and 45° from nadir over the Otago region on the selected dates, and radiance calibration details can be found in Uddstrom and Gray (1996). The 12 nights were chosen because they were anticyclonic, had minimum air temperatures less than 0°C at most of the climate stations in the region, and were cloud-free over the entire region. Checks for cloud were made by visually inspecting the satellite images and by analyzing the differences in the spectra at the three channels (i.e., channel 4 – channel 3, and channel 4 – channel 5) for any suspicious areas. Before calculating the mean winter brightness temperatures, each of the 12 nights was normalized by dividing by its areal standard deviation. This normalization minimizes the internight variability that exists because of some nights being colder than others. The split window difference, that is, the mean winter channel-4 minus channel-5 brightness temperature, was subsequently calculated and also used as a potential predictor of frost occurrence.

Last, the NDVI was calculated for the region [using
Calculate the 20\textsuperscript{th} percentile first frost date, 80\textsuperscript{th} percentile last frost date, mean frost-free period, and mean number of frosts in September, October and November from minimum air temperature data at each of the 48 climate stations.

Find the best set of predictors of these frost variables from the geographical variables (latitude, longitude, altitude and distance to the sea) and the satellite variables (winter channel 3, channel 4 and channel 5 AVHRR data, winter emissivity, and spring and autumn NDVI).

Map each of the frost variables at 1 km grid resolution (the resolution of the satellite data) for the Otago region using the results from the generalized linear model.

Estimate the frost variables at 50 m grid resolution using linear interpolation and locally-derived lapse rates of frost occurrence with altitude.

Fig. 2. Box diagram showing the general methodology used to estimate the six frost variables at 1-km and 50-m grid resolutions from the predictor geographical and satellite variables.

3. Methodology

Figure 2 is a box diagram that outlines the methodology used to estimate the six frost variables at 1-km and 50-m grid resolutions from the predictor geographical and satellite variables. The second box of Fig. 2 refers to finding the best set of predictor variables, which are determined using a generalized linear model with quasi-likelihood estimation. Section 3a describes the generalized linear model in detail since it is not commonly used in meteorological studies. The procedure for interpolating the frost variables from the resolution of the satellite data (1 km) to a 50-m grid resolution (the fourth box of Fig. 2) is described in section 3b.

a. The generalized linear model with quasi-likelihood estimation

In the generalized linear model, the mean and variance of a response variable $y$ are assumed to have the following relationship:

$$\text{var}(y) = \phi V(m),$$

where $\mu$ is the mean of the response variable $y$, $V$ is the variance function characterizing how the mean of $y$ relates to the variance of $y$, and $\phi$ is the scatter parameter to be estimated. A strictly monotonic link function $g$ is assigned to describe how the mean of $y$ depends on the linear predictors $x_1, \ldots, x_m$:

$$g(\mu) = \beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m,$$

where $m$ is the number of predictors and $\beta_0, \ldots, \beta_m$ are the regression coefficients (Chambers and Hastie 1992). For continuous response variables, the link functions $g(\mu)$ can be $\mu$, $1/\mu$, $1/\mu^2$, $\ln(\mu)$, and $\sqrt{\mu}$, and the variance functions $V(\mu)$ can be $1$, $\mu$, $\mu^2$, and $\mu^3$. If $g(\mu) = \mu$ and $V(\mu) = 1$, the generalized linear model is the traditional linear regression model.

In this paper, the response variables are the frost variables described in section 2a, and the predictor variables are the geographical variables and satellite variables described in sections 2b and 2c, respectively. The quasi-likelihood estimation, which is a generalization of the least squares estimation for linear regression, is applied to estimate the regression coefficients. That is, the regression coefficients are estimated by minimizing the deviance:

$$D(\hat{\beta}_0, \ldots, \hat{\beta}_m)$$

$$= \sum_{r=1}^R w(r) \int_{a_1(\gamma)}^{r(\gamma)} \frac{y(r) - u}{V(u)} du,$$

where $R$ is the number of locations, $y(r)$ is the observation of $y$ at location $r$, $x_1(r), \ldots, x_m(r)$ are the observations of the predictors at location $r$, and $w(r)$ are weights normalized to the total number of locations. From Eq. (3) it can be seen that the deviance is similar to the variance of the standardized residuals. The iteratively reweighted least squares estimation, which is similar to the Newton–Raphson algorithm (Chambers and Hastie 1992), is applied to search for the minimum deviance. The estimates are denoted as $\hat{\beta}_0, \ldots, \hat{\beta}_m$. Then
\[
\hat{\phi} = \sum_{r=1}^{n} w(r) \left[ \frac{\{y(r) - g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)]\}^2}{V[g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)]]} \right]
\]

(4)

is the estimated scatter parameter,

\[
g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)]
\]

(5)
is the prediction of \( y \) at the location \( r \), and

\[
\hat{\phi}V[g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)]]
\]

(6)
is the estimated error variance at the location \( r \). The routine “glm” in the statistical package SPLUS (Chambers and Hastie 1992) is an implementation of the generalized linear model.

To achieve the best estimation, the predictors, link functions, and variance functions must be carefully selected. In this study, they are selected by the Akaike Information Criteria (AIC). That is, the best selection of models (i.e., predictors, link functions, and variance functions) corresponding to the lowest Akaike information

\[
\text{AIC} = D(\hat{\beta}_0, \ldots, \hat{\beta}_m) + 2\hat{\phi}(m + 1).
\]

(7)

Computationally, this can be achieved in three steps. First, for each frost variable the values are normalized by dividing by their median, ensuring that the data are equally separated about unity. Otherwise, higher- (lower) order variance functions are selected if more of the data values are above (below) unity. Second, predictors with the lowest AIC are automatically selected by applying the routine “step.glm” in the statistical package SPLUS with a specific link function and a specific variance function. Last, the second step is repeated for all possible link functions and variance functions, and the combination of link function, variance function, and predictors that results in the lowest AIC is selected as the best model.

Once the best set of model parameters has been determined, the regression coefficients \( \hat{\beta}_0, \ldots, \hat{\beta}_m \) and the scatter parameter \( \hat{\phi} \) are estimated by fitting the selected generalized linear model to \( y(r)/\text{median}(y), r = 1, \ldots, R \). Then, the frost variables at 1-km grid resolution are estimated as

\[
g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)] \times \text{median}(y),
\]

(8)

where \( m' \) is the number of predictors left in the model. Last, the associated error variance at 1-km grid resolution is estimated as

\[
\hat{\phi}V[g^{-1}[\hat{\beta}_0 + \hat{\beta}_1 x_1(r) + \cdots + \hat{\beta}_m x_m(r)]]
\]

\[
\times \text{median}(y)^2 + CV(r),
\]

(9)

where the first term is the estimated residual variance and the second term is the prediction error variance of the frost variable at location \( r \) calculated by cross validation (CV). This is the process of removing a climate station from the analysis, calculating the prediction error at that location, repeating the procedure for every cli-

| Station name   | Length of record (yr) | Alt (m MSL) | Lon (E) | Dist to the sea (km) | Mean No. FFP | Mean No. LFD | Mean No. FPP | Mean No. LFD | Mean No. FFP | Mean No. LFD | Mean No. FFP | Mean No. LFD | Mean No. FFP | Mean No. LFD | Mean No. FFP | Mean No. LFD | Mean No. FFP | Mean No. LFD | Mean No. FFP |
|----------------|-----------------------|-------------|--------|----------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| Nugget Point   | 11                    | 109.800     | 169.33 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Taieri Head    | 10                    | 170.333     | 45.783 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Omarama        | 8                    | 170.095     | 170.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Dunedin        | 6                    | 170.034     | 170.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Dunedin Airport| 6                    | 170.633     | 170.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Livingstone    | 6                    | 169.250     | 170.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Tapanui        | 6                    | 167.103     | 169.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Ranfurly       | 6                    | 167.234     | 169.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |
| Alexandra      | 6                    | 169.383     | 169.971 | 0.1                  | 31           | 11           | 12            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            | 1            |

Table 2. Geographical and frost variables at a sample of the 48 climate stations used in this study (listed according to distance to the sea). FFP = frost first frost date, LFD = last frost date.
is estimated as the mean of the lapse rates between that grid points. Then the mean lapse rate at each grid point divided by the difference of altitudes between the two grid points. The lapse rate between any grid point and its eight neighboring grid points. Second, the estimated lapse rates, the satellite variables, and the altitude at 1-km resolution are linearly interpolated onto the 50-m grid. Last, the satellite variables at the grid points of the 50-m grid are estimated as the interpolated satellite data plus the interpolated lapse rate times the difference between the actual altitude (obtained from a 50-m DEM) and the interpolated altitude.

4. Results

a. Frost occurrence at the climate stations

Table 2 shows values of the geographical and frost variables for a sample of the 48 climate stations. In general, the greater the distance to the sea is, the earlier the 20th-percentile date of the first frost, the later the 80th-percentile date of the last frost, the shorter the mean frost-free period, and the greater the number of frosts in September, October, and November. This result is consistent with the broad-scale frost maps produced by Goulter (1981). However, there are some obvious exceptions to this relationship, for example Ranfurly and Dunedin Airport.

Ranfurly is higher in altitude than other stations at similar distances away from the sea; hence, it is prone to earlier frosts in autumn and later frosts in spring. The data from this station indicate the general linear relationship between altitude and frost occurrence, where the number of frosts generally increases with altitude. Whereas, despite being only 8.1 km from the sea and only 1 m above mean sea level (MSL), Dunedin Airport (and the surrounding area known as the Taieri Plains) receives many more frosts than would be expected based on geographic variables alone. This is because the Taieri Plains are surrounded by hills and mountains on all sides, so that the area is highly susceptible to nocturnal cold-air drainage and pooling. This process results in a nonlinear response of frost occurrence to geographic variables, in which frost occurrence decreases from the floor of the basin to the lower slopes of the surrounding hills and then increases from those intermediate slopes to the higher altitudes.
b. Determination of the best models for estimating frost occurrence

As stated in section 3a, the first step for mapping the frost variables is to describe the relationships between the frost variables and the geographical variables and satellite data. The generalized linear model with quasi-likelihood estimation is fitted to the data at the 48 climate stations to achieve this objective. The response variables are the six frost variables. The predictors are the geographical variables (latitude, longitude, altitude, distance to the sea) and the satellite-based measurements (means of channel-3, -4, and -5 brightness temperatures over the 12 nights, the mean split window difference, mean surface emissivity over the 12 winter nights, mean channel 3 divided by emissivity, mean channel 4 divided by emissivity, spring NDVI, and autumn NDVI). The link functions are \( \mu, 1/\mu, 1/\mu^2, \ln(\mu), \) and \( \sqrt{\mu} \), and the variance functions are \( 1, \mu, \mu^2, \) and \( \mu^3 \), because others are not available in the SPLUS routine glm. The weights in the analysis are the climate station data record lengths normalized by the mean record length over all 48 stations, with stations with longer records receiving more weight than those with shorter records.

The AIC is applied to select the generalized linear models. The best combinations of predictors, the link function, the variance function, and the percentage-explained deviance (unity minus the ratio of deviance associated with the selected predictors over deviance associated with intercept only, as a percentage) for each of the six frost variables are listed in Table 3.

Table 3 shows that the best predictors are the AVHRR channel-5 (11.5–12.5 \( \mu \)m) brightness temperature for all six frost variables and NDVI in spring or autumn for three of the six frost variables. The percentage-explained deviance is around 60% for five of the six frost variables, and around 45% for the remaining one.

The three satellite brightness temperature predictors
(channels 3, 4, and 5) are highly correlated with each other; hence, the need for only one channel, and channel 5 is preferred by the AIC over the other two. Mean emissivity over the 12 nights, as a separate variable and in combination with the brightness temperature data (e.g., channel 5 divided by emissivity), was not included in the best combination of predictors. Also, the split window difference was not kept in the model once the channel-5 data were included. This result is consistent with the studies that have stated that a single AVHRR channel will suffice for the estimation of frost parameters and LST during cold winter nighttime conditions.

NDVI in autumn significantly increases the percentage-explained deviance of the 20th-percentile date of the first frost by approximately 20%. This is because the first frost date occurs in autumn, and it is likely that differences in vegetation cover at this time influence the occurrence of frosts. Using similar reasoning, NDVI in spring significantly increases the percentage-explained deviance of the 80th-percentile date of the last frost (by approximately 10%). Autumn NDVI also increases the percentage-explained deviance of the mean frost-free period by approximately 10%.

Geographical variables do not enhance the estimation of the frost variables as much of the variability present in these geographical variables is captured by the satellite data (i.e., brightness temperature generally decreases with altitude and distance from the sea under winter clear-sky night conditions). To demonstrate this point, each geographical variable was regressed against the channel-5 data using linear regression. The results showed that about 40% of the variability of each geographical variable could be explained by the channel-5 data.

The optimal link functions are linear for the first three frost variables and are nonlinear \((1/\mu^2)\) for the last three frost variables, indicating that a standard linear model is not sufficient to achieve our objectives and the generalized linear model is necessary. Unfortunately, the link functions available in the SPLUS routine \texttt{glm} are still limited. As a result, some transformations of the frost variables may be necessary for more physically reasonable fitting. In this study, a constant (shown in the first column of Table 3) is added to the mean number of frosts in September, October, and November. These constants are selected on the basis that the fitted surface is close to zero at the Taiaroa Head climate station. Here, the observed mean number of frosts is virtually zero during spring season. This is physically reasonable, because the station is by the ocean and low in altitude (see Table 2 for station details). On the other hand, the fitted surface is an inverse function of the channel-5 bright-
ness temperature and reaches its highest value (1.28°C) at this station. Therefore, it is justified to set a value of zero at the station as a boundary condition of the fitting. Without adding these constants to the mean number of frosts in September, October, and November, no link function can satisfy this boundary condition.

The optimal variance functions for the 20th percentile of first frost dates and the mean frost-free period is $\mu^2$. This implies that the lower the channel-5 brightness temperature is, the lower the estimation errors of these two frost variables. However, this is not the case for the 80th percentile of last frost dates. This may be due to the different sign in the slope of the relationship (lower brightness temperatures correspond to later last frost dates), as compared with the first frost date (lower brightness temperatures correspond to earlier first frost dates) and frost-free period (lower brightness temperatures correspond to shorter frost-free periods). To check this point, the generalized linear model was fitted to 365 minus the 80th percentile of last frost dates so that the sign of the slope is the same as the sign of the other two variables. Despite this change, the optimal variance function is still unity, implying that a variance function of unity is an inherent feature of the 80th percentile of last frost dates. The optimal variance function is also unity for the mean number of frosts in September and October but is $\mu$ for the mean number of frosts in November. All the selected nonunity variance functions imply the need for the generalized linear model.

c. Maps of the frost variables at 1-km grid resolution

Each of the six frost variables was mapped at 1-km grid resolution following the method described in section 3a. However, since there are no climate stations situated above 600 m and since the selected link functions for the mean number of frosts in September, October, and November are nonlinear, the proposed fitting in the area above 600-m altitude is not physically reliable for these variables. Therefore, for these variables the following piecewise fitting approach is applied for a more physically realistic full fitting. When the mean channel-5 brightness temperature over the 12 winter nights is greater than $-0.60°C$ (the minimum mean winter channel-5 brightness temperature at the 48 stations), the selected generalized linear models are fitted. When the mean channel-5 brightness temperature is less than a critical temperature, however, the mean number of frosts in the three spring months is set to the total number of days in that month and the estimated variance is set to zero. When the mean channel-5 brightness temperature is between $-0.60°C$ and the critical temperature, the fitted mean number of frosts and their estimated variances are linearly interpolated.

The critical channel-5 brightness temperature for each month is listed in Table 4. These temperatures are the mean channel-5 brightness temperatures in an altitude band that is also shown in Table 4. These altitude bands were selected because the mean minimum air temper-
ature within the band in the corresponding month is around $-1.0^\circ C$ [calculated using the lapse rate derived by Zheng and Basher (1996), their Table VI], which is suggestive of continuous or near-continuous frost occurrence for the month.

Figure 3 shows the mean frost-free period (FFP) for the Otago region at 1-km grid resolution. Maps of the other five frost variables are not shown because the overall pattern is similar. To enhance the map interpretation, a semitransparent hill-shading layer, derived from a 50-m DEM, has been laid over the frost image. The general pattern of a longer FFP near the coasts (mean of around 275 days) and a shorter FFP inland (mean of around 150 days) is clearly apparent. The frostdiest areas are on top of the high interior mountain ranges, which typically have only 30 days of continuous frost-free conditions per year. The land surrounding the lakes and main rivers has its FFP lengthened by the moderating effect of the water on the nighttime temperatures. Last, the effect of cold-air drainage and pooling can be seen in the inland basins. For example, the mean FFP near Middlemarch (which is in a basin) is around 150 days, while on the foothills of the Rock and Pillar Range to the northwest of the town, the mean FFP is around 170 days. On the top of the Rock and Pillar Range, the mean FFP is lower again, at around 90 days.

The FFP standard deviation, derived from Eq. (9), is quite constant over the whole Otago region at a value of about 28.6 days, although it is slightly higher on the top of the mountains and at the coast (around 28.8 days). This standard deviation includes the statistical error caused by the year-to-year variability inherent in the climate station FFP data as well as the error variance related to the density of the climate station network. The mean standard deviations over all of the 1-km pixels within Otago for all the frost variables are listed in Table 3.

d. Maps of the frost variables at 50-m grid resolution

Figure 4 shows the mean FFP at 50-m grid resolution for the area inside the rectangular box shown on Fig. 3. Much more detail can be seen at this resolution. Once again, the shortest FFPs are on top of the high mountains (e.g., the Dunstan Range) and the longest FFPs are near the major rivers and lakes (e.g., Lake Dunstan and the Clutha/Mata-Au River that flows southeast from the lake). The effect of cold-air drainage is clearly visible in the basins to the northwest (Clutha valley) and southeast (Manuherikia valley) of the Dunstan Mountains. Figure 5 shows the altitude above mean sea level and the mean FFP along a transect from the top of the southern Dunstan Mountains north to Lindis Crossing. From this figure, it can be seen that the longest FFP along this transect occurs about 270 m above the valley bottom on the north-facing foothills (middle arrow). In the flat valley bottom, where the cold air pools, the mean FFP is as much as 21 days less than the surrounding hills (right arrow). Right at the valley bottom (far right of plot) the FFP increases again because of the warming effect of the Lindis River. Based on this transect, the effect of cold-air ponding in this basin on the FFP is equivalent to an increase in altitude of about 600 m (left arrow).

5. Discussion and conclusions

This paper introduces a method of mapping frost occurrence variables using satellite infrared data for the Otago region of New Zealand. We show that the timing of the first and last frost, the mean frost-free period, and the average number of frosts in the Southern Hemisphere’s three spring months can be estimated using AVHRR channel-5 infrared data and the NDVI. Geographic variables such as latitude, longitude, altitude, and distance to the sea, although related to frost occurrence, did not significantly enhance the prediction model. This is because much of the geographic variability is captured by the satellite data. Also, the mean split window difference and mean surface emissivity over 12 winter nights failed to improve the model explained deviance. This result is supported by previous research on cold, clear winter nights, which suggests that the land surface temperature can be reliably estimated using data from only one infrared channel.

The generalized linear model with quasi-likelihood estimation is used to predict the frost variables. This method selects the best prediction model based on the minimization of Akaike’s Information Criteria. The generalized linear model is shown to be more suited to the estimation of frost parameters than a linear regression model. This is because some of the frost variables are shown to exhibit nonlinear link functions and/or non-unity variance functions.

The 1-km frost maps show patterns consistent with experience and with a broad-scale map produced by Goulter (1981). That is, frosts occur earlier in the autumn and later in the spring with increasing distance away from the coast and from major rivers and lakes. Also, frost is most prevalent on the top of high mountain ranges where the air temperature is coldest. Furthermore, frosts are shown to be more common near the bottom of inland basins as compared with the sides of the surrounding hills because of cold-air drainage and ponding. Many orchards in Central Otago are situated on the hillsides rather than in the valley bottom for this reason.

Last, a method is described for downscaling the 1-km data to 50-m grid resolution for improved interpretability at the farm scale. Frost maps at this resolution for an area the size of the Otago region have never been produced before in New Zealand. To take into account the sometimes nonlinear relationship between frost occurrence and altitude, local lapse rates were calculated and used to interpolate the 1-km data to the higher-resolution grid. A sample of the 50-m frost maps has been shown to farmers in the central and northeast Otago.
regions for comment, and their reactions to the maps were extremely positive. It is hoped that these maps, in conjunction with maps of other climate variables and of soil properties, will enable farmers to make more informed decisions about current and future farming practices.

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