

Statistical-empirical forecasting guidance for the occurrence of fog at Mount Gambier Airport

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A statistical-empirical decision aid for forecasting morning fogs at Mount Gambier Airport based on pre-dawn data is presented. Of main concern are those fog events significantly impacting on aviation operations, although the model is applicable to other fog events of lesser impact. The aid is restricted to precipitation-absent fogs.

The probability of fog occurrence was modelled on a ten-year dependent dataset using the logistic equation. By converting probabilistic forecasts to categorical forecasts of fog events, skill scores of Probability of Detection, False Alarm Rate and Critical Success Index were determined based upon three years of independent data. For operationally significant fogs, the Probability of Detection, False Alarm Rate and Critical Success Index were 73%, 23% and 60% respectively on the independent data. These scores were very similar to those obtained from the dependent dataset of ten years. When fog events were defined less stringently as either fogs *per se* or shallow fogs, the respective skill scores on the independent data were 84%, 20% and 70%; again with similar scores on the dependent data.

Introduction

The forecasting problem

Mount Gambier Airport, in the southeast of South Australia, is one of the most fog-prone aerodromes in South Australia. At Mount Gambier Airport, the occurrence of fog has greater impact on aviation operations than does any other weather phenomenon. On

average, fog occurs at Mount Gambier Airport on about 40 days each year and can occur in any month although the mid-year months are more susceptible. In 1961, there were 96 days when fog was reported. (In that year too, many other locations in southeast Australia, such as Canberra, East Sale, and Launceston, experienced an abnormally high number of fog days.) In May 1991, fog was reported on 14 consecutive days at Mount Gambier.

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Mount Gambier Airport is classified as a regional airport and typically carries 10,000 aircraft movements per year. Early morning and evening flights to Mount Gambier during winter and near-winter months may suffer delays with subsequent passenger and cargo off-loading due to either the presence of fog or to the forecast of fog. Accurate and reliable forecasts of fog are of obvious economic and general benefit to the relevant airlines in particular and to the Mount Gambier community in general.

Forecasts for Mount Gambier Airport are provided to the aviation industry routinely by the South Australian Regional Forecasting Centre. In practice, fog forecasting relies on the subjective expertise of generally very experienced meteorologists. Within the Forecasting Centre, Mount Gambier Airport has a notoriety for its susceptibility to fog. No objective decision aid based on empirical rules-of-thumb is available although there have been several attempts to produce a decision aid in the past. Currently, little practical guidance for fog forecasting is available from microphysical numerical models although recently Wright and Thomas (1998) reported on the development in the UK of the Visibility Analysis/Forecast System (VAFS) which uses prognoses of temperature and moisture parameters from a mesomodel blended with satellite imagery. Numerical modelling of fog formation is extremely difficult since it is a highly non-linear process sensitive to local surface texture, type, roughness and thermal conductivity and to the local variations in concentrations of large condensation nuclei (Roach 1995a, b). Until such models or systems such as VAFS are developed and operational, the authors have sought to combine simple statistical techniques with their own forecasting experience, and that of their colleagues, to produce an operationally useful aid, preferably with the potential for extension to other locations. The purpose of an aid such as this is to provide non-prescriptive guidance for forecasters, especially inexperienced forecasters, and to provide a benchmark of skill for other models and techniques. In particular, knowing the conditions at and up to 1730 UTC (3 am local) and assuming that precipitation is not imminent, the aid answers the question: if there is no fog present at 1730 UTC, what is the probability of a fog forming in the period between 1730 and 2330 UTC? Local time is UTC + 9.5 hours: there is a daylight-saving regime in summer but this is not relevant here.

Aids at other locations

Objective aids for forecasting fogs at other locations typically incorporate input variables, or proxies, such as:

- (a) humidity (usually wet-bulb depression or dew-point depression);
- (b) surface wind;
- (c) wind at gradient level (that is, radar-balloon wind at approximately 600 m);
- (d) cloud cover;
- (e) past trajectories (although in light wind situations this is often somewhat subjective);
- (f) hydrolapse;
- (g) past precipitation;
- (h) location of anticyclones; and
- (i) time of sunrise or duration of radiational cooling.

Petterssen (1956) provided a graphical methodology for composing such aids. Most aids, albeit using more advanced computational and statistical techniques, are similar to Petterssen's scheme. Wright and Thomas (1998) provide a concise account of fog formation and visibility reduction. The state of fog forecasting in practice is given by Leipper (1995) and Roach (1994 and 1995a, b, c). The skill (or luck) in composing a useful aid in general lies in selecting and combining the 'best' predictor variables such that over-forecasting and under-forecasting are minimised. In our opinion, there also seems to be a necessary skill in suitably limiting the type of events, e.g., by time of day, by season or by mesoscale or synoptic type. In our case, we have limited the forecast aid to those situations without present weather of rain or drizzle between 1730 and 2330 UTC; also excluded are those cases with fog present at 1730 UTC. Approximately 10 per cent of fog events and 50 per cent of non-fog events are thereby excluded from consideration.

Any introduced aid should be demonstrably superior to climatology, persistence and the operational forecasts, albeit for the limited subset of application. For relatively infrequent events of the yes/no type, measures of skill commonly used in the aviation and meteorological community are: Probability of Detection (POD) or Hit rate, False Alarm Rate (FAR) and Critical Success Index (CSI). These are defined below with reference to Table 1.

Let X be the number of occurrences of forecast events that were verified (hits), Y the number of forecast events that were not verified (false alarms), Z the number of events which were not forecast (misses), and W the number of correctly forecast non-events, then:

Table 1. Contingency table of forecast and observed events and non-events.

		Observed	
		Fog	No-Fog
Forecast	Fog	X	Y
	No-Fog	Z	W

$$\begin{aligned} \text{POD} &= X / (X+Z) \\ \text{FAR} &= Y / (X+Y) \\ \text{CSI} &= X / (X+Y+Z) \end{aligned}$$

Mason (1982) proposed an assessment model, which unfortunately seems to be neglected, using the ROC curve (Relative, or Receiver, Operating Characteristic curve) from signal detection theory. The ROC curve concept has been much used to assess the quality of medical diagnostic systems (Swets 1996) and in a number of other fields such as quality assurance and object detection in remote sensing. In signal detection theory, the same definition for POD applies but an alternatively defined False Alarm Rate, FAR* (starred here to avoid confusion) is used. The FAR* of signal detection theory as used by Mason is:

$$\text{FAR}^* = Y / (Y + W)$$

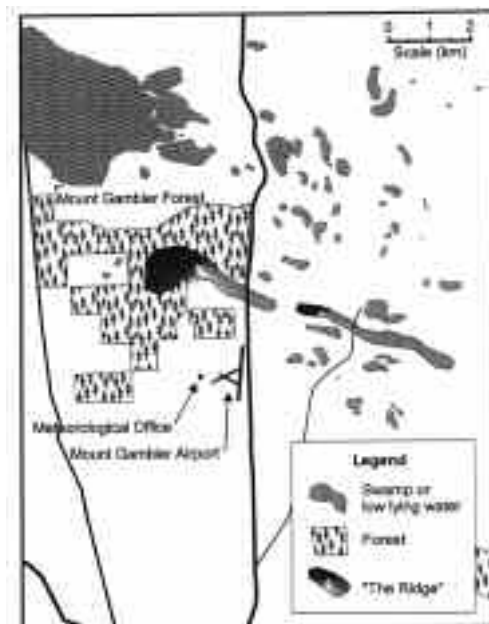
For a binary type event, if one has a model that provides a probability of occurrence of the event then one can decide on a decision criterion or threshold probability P_C at which to forecast the event. The graph of POD against FAR* as the decision criterion for a probabilistic predictive model varies is called the ROC. The resulting curve for a particular model gives an immediate comparison with the skill of climatology and can be compared to other relevant models. Although we will not use it here, it is worth noting that the Hanssen-Kuipers Score is equal to POD minus FAR* (Kok 2000).

Within the Bureau of Meteorology's South Australian Office, decision aids for the occurrence of fog and/or stratus have been devised for airports at Adelaide, Port Lincoln, Woomera and Broken Hill. (Broken Hill is actually in the State of New South Wales but the South Australian Regional Forecasting Centre has responsibility for aviation forecasts.) Typical skill scores for these aids are POD: 90%, FAR: 40-50% and CSI: 50-60%. In the UK, Wright and Thomas (1998) report that for fogs of 1000 m visibility, VAFS has scored POD, FAR and CSI respectively at 82%, 20% and 68%, but deteriorating to 23%, 50% and 19% for fogs of 200 m visibility.

Location

Mount Gambier Airport is situated at 37° 45' South and 140° 47' East at an elevation of 63 m above mean sea level and about 33 km from the Southern Ocean shoreline which runs approximately east-west in this region (Fig. 1). A narrow ridge with altitude of approximately 80 m is located about 3 km from the airport and runs WNW/ESE. Nearby there are forests and perennial swamps – some with names rather evocative of fog, such as Dismal Swamp!

Fig. 1 Mount Gambier Airport and environs.



Purpose

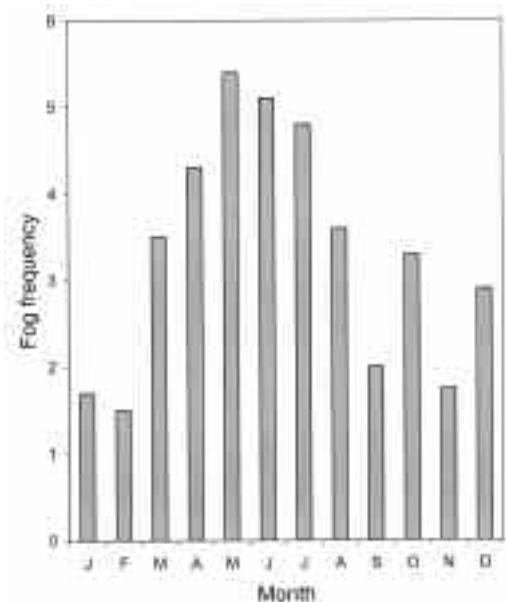
The purpose of this paper is to describe the formulation and verification of an objective aid for forecasting at 1730 UTC the occurrence during the period 1730 to 2330 UTC of precipitation-absent fog at Mount Gambier Airport (that is, excluding all situations with present weather of rain or drizzle). Situations with fog pre-existing at 1730 UTC were also excluded: the aid as subsequently developed would in practice always predict fog to persist in such cases. The aid is based on data from the period 1130 UTC and 1730 UTC and provides an estimate of the subsequent probability of fog forming during the period 1730 UTC to 2330 UTC. In the dependent dataset no fogs formed after 2330 UTC except in association with precipitation. Midnight local time corresponds to 1430 UTC (1330 UTC in summer). We describe the data and the preliminary analyses used to identify candidate predictors; present a statistical-empirical model based upon the logistic equation followed by some verification details and finally, the conclusions.

Data analysis

Data

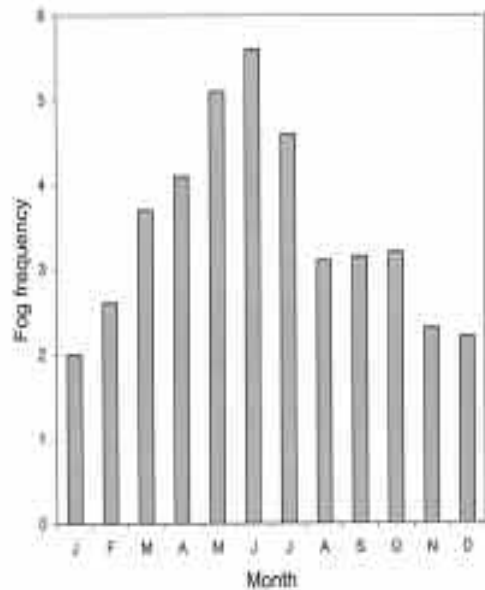
All available microfiche data (1942-1993) from the Bureau of Meteorology were used to prepare a preliminary climatology of fog occurrence (Fig. 2). These fog events are for any time of day, provided observers are

Fig. 2 Monthly fog occurrence (fog days) at Mount Gambier Airport 1942 – 1993.



on duty, and include those events associated with rain. METARS (Meteorological Aerodrome Reports) and SPECIS (Special Meteorological Aerodrome Reports) are performed half-hourly and as required respectively at Mount Gambier Airport from 1730 UTC to 1130 UTC. Radar wind findings are performed at 0530, 1130, 1730 and 2330 UTC and radiosondes are released irregularly at 1130 UTC and regularly at 2330 UTC. Data covering ten years (1980-1989) were collated – this is the dependent data. All days with precipitation during the period 1730 UTC and 2330 UTC were discarded. Of the remainder, all cases were classified as either a (precipitation-absent) fog event or non-event. A fog event was defined to occur if fog formed by 2330 UTC. Such events were defined as Alternate Fogs if fog, or those shallow fogs with visibility below the aviation authority's designated 'Alternate Minima' (< 7700 m) occurred, implying an operational restriction. In practice, this aviation term means that aircraft must have sufficient fuel to be able to divert to another airport with suitable weather or to wait until the fog is forecast to clear. The observing site is located several metres above the runway: experienced observers note that some events officially recorded as fog patches with visibility greater than the minima, could well have been a fog on the runway with the visibility in that sector reduced to below the minima criteria. Thus the number of operationally significant fogs is in reality probably higher than indicated by the recorded number of Alternate Fogs. A less stringent

Fig. 3 Monthly fog occurrence (fog days) at Mount Gambier Airport 1980 – 1989.



definition of a fog event – any fog or shallow fog in the vicinity – was also adopted and this classification termed All Fogs. Being more numerous, the All Fogs data were expected to be less 'noisy' and thus easier to analyse and interpret. The METAR and SPECI data were then used to compile monthly histograms of occurrence of All Fogs which is seen to peak in May or June (Fig. 3).

Since the September to March period contains relatively fewer fogs, the study concentrates on the fog-prone period April to August. However, the aid is extendible to the months of March, September and October although with fewer fogs in these months, it is more difficult to verify, and this is not attempted here.

As stated, those fog events and non-events associated with precipitation between 1730 and 2330 UTC were excluded. Further, all fog events during 1800 UTC to 2330 UTC with pre-existing fogs at 1730 UTC were also excluded in both model formulation and verification. This reduced the dataset to about half, leaving, for April to August, 676 cases of fog or no-fog at 1800 to 2330 UTC and no pre-existing fog at 1730 UTC. Approximately 30 per cent were Alternate Fogs and nearly 50 per cent were All Fogs. All likely predictor parameters up to 1730 UTC were collated. The pre-existing fogs were excluded since they almost certainly lead to a subjective operational forecast of fog occurrence at 1800 UTC. In retrospect, it was found that the aid always correctly forecast these events too but these are not included in skill

assessment of the aid. For the forecaster, forecasting the fog in these situations is usually trivial: the forecaster's concern immediately moves on to the next difficult question: when will the fog clear? This question is not addressed here although it could probably be pursued with the technique presented.

At this stage, a dataset for the years 1990, 1991, and 1994 was obtained for independent verification. All formulation of the aid was performed without the independent data. The ratios of fogs to total fog and no-fog cases, both for All Fogs and Alternate Fogs, are similar for the dependent and independent datasets. At the time of developing this aid, the post-1992 data were in various formats and stages of actual and planned digitisation. All the data in the dependent and independent sets were keyed in by the authors from manual records: thus the number of years of data used to develop and to verify was kept to a practical minimum. A secondary consideration affecting the size of the independent dataset was that for the period of the independent data, operational forecasts effectively used a probability of 20 per cent as the threshold for predicting fog but this has changed to 30 per cent in recent years (see section entitled 'Verification').

Analysis

Immediate findings were that

- (a) no fog formed after 2300 UTC;
- (b) fog often formed without rain in 12 and 24-hour periods prior – this was true even in summer;
- (c) wind speed was important in that with 600 m wind speeds in excess of 15 m/s at 1730 UTC no fog formed;
- (d) the pressure was unrelated to fog occurrence;
- (e) the synoptic situation did not seem to provide any guide as to subsequent fog formation;
- (f) as expected, dew-point depression tended to be associated inversely with fogs. This was so at 1730 UTC and less so at 1130 UTC (Figs 4 and 5);
- (g) low cloud amount tended to be inversely related to fog occurrence (see Fig. 6);
- (h) gradient wind components were found to relate to fog occurrence. Figure 7 shows the decrease in fog likelihood as the absolute value of the southerly component, $|v|$, increases. The fog likelihood decreases with westerly component u (Fig. 8). This behaviour will be unremarkable to the reader. However, fog likelihood increases with increasing easterly component, at least up to 10 m/s. Remember that there were no instances of fog subsequent to a 1730 UTC gradient wind speed in excess of 15 m/s.

To perform regression analysis, fog events were assigned the value 1, and non-events zero. As a preliminary practical step, multiple linear regression was

Fig. 4 Probability of occurrence of All Fogs for dew-point depression at 1730 UTC. Vertical bars represent 95% confidence intervals. Curve represents single parameter curve derived from the logistic equation.

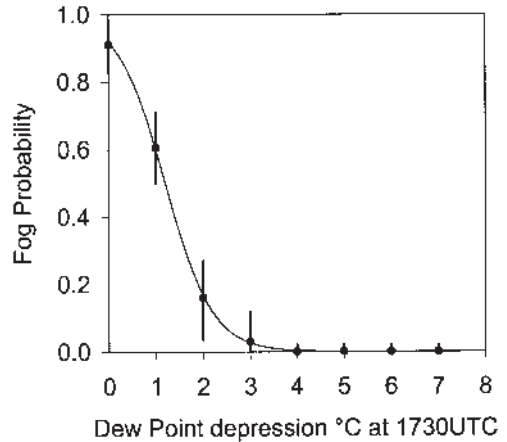
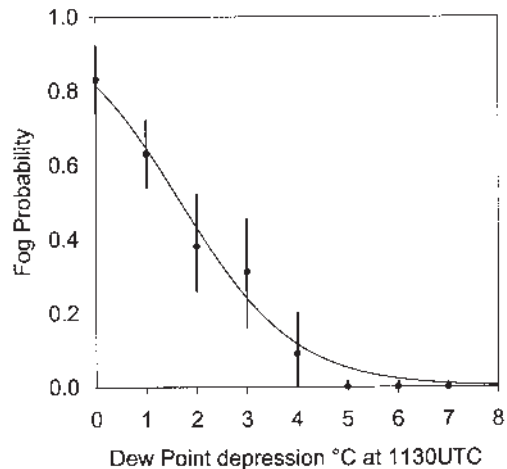


Fig. 5 As for Fig. 4 but for dew-point depression at 1130 UTC.



used with a very large suite of potential candidate predictors for the purpose of short-listing the candidates. Common software packages have easy-to-use linear regression routines to quickly narrow down the candidates. The same is not usually the case for non-linear regression. A multiple linear regression with independent variables of temperature, dew-point depression, gradient and surface wind components and their absolute values, pressure, low cloud amount, all at

Fig. 6 As for Fig. 4 but for low-level cloud at 1130 UTC.

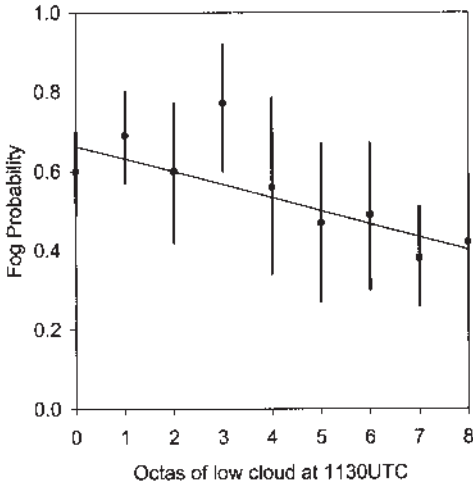
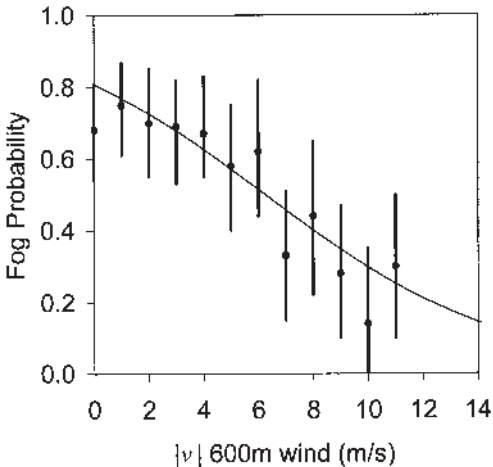


Fig. 7 As for Fig. 4 but for absolute southerly component of 600 m wind at 1730 UTC.

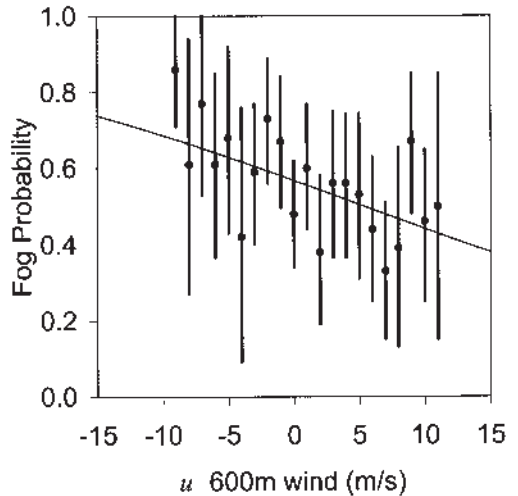


1130 UTC and at 1730 UTC, and with various cross-products, with backward elimination of variables with significance level >0.05 showed a correlation coefficient squared, r^2 of 0.39 for the following linear model:

$$P = a_0 + a_1d + a_2d_{12} + a_3|v| + a_4c_{12} + a_5u \quad \dots 1$$

where P is the likelihood of fog. The variables d , u , v and c signify dew-point depression, westerly component of the gradient wind, southerly component of the gradient wind, and cloud cover and refer to 1730 UTC

Fig. 8 As for Fig. 4 but for westerly component of 600 m wind at 1730 UTC.



unless subscripted otherwise such that, for example, c_{12} refers to cloud cover at 1130 UTC. The coefficients are a_0, a_1, a_2, a_3, a_4 and a_5 . The value of this linear model is that it is easy to calculate and indicates potential candidates for predictor variables. One obvious drawback of this linear model is that P could be calculated as greater than one or less than zero, although one may of course perform suitable, albeit inelegant, truncations. A second is that, although Figs 6, 7 and 8 exhibit quasi linearity, Figs 4 and 5 clearly do not. Another criticism is that the implicit assumptions of multiple linear regression models are that the predictors are independent of each other and that the predictors and the predictand are normally distributed.

The model

The linear model at Eqn 1 established d, d_{12}, u, c_{12} , and $|v|$ as potential predictors of fog. Initially we confine the model formulation to the classification of All Fogs; later the classification for Alternate Fogs is described. The reason for investigating the All Fogs first is that since the events in this classification are more numerous, it was expected that any relations uncovered would be statistically more reliable and could then be used to provide insight into the relations likely to be pertinent to Alternate Fogs. The first two drawbacks of the linear model (the possibility of modelled probabilities outside the range zero to one and the patent non-linearity) can be avoided by using a logistic model of the form:

$$P = \frac{1}{(1 + e^y)} \quad \dots 2(a)$$

where

$$y = a_0 + \sum_{i=1}^n a_i x_i \quad \dots 2(b)$$

where x_i represents the i th of n independent variables with a_i being the corresponding coefficient and a_0 a constant. This model is proposed primarily on the grounds of its relative simplicity and pragmatism. Note that P is now bounded between zero and one.

To determine the a_i coefficients, the best fit to Eqn 2 using various merit or loss functions was obtained. For common merit functions such as least squares, maximum log likelihood, least absolute deviation and least χ^2 statistic, the calculated values of the a_i coefficients differed only in the third significant figure. For brevity, we report only on the least squares fit. Also tried were models of the types:

$$P = e^{-y^2} \quad \text{and} \quad P = \frac{1}{(1 + y^2)}$$

and these also produced good fits but not quite as good as the logistic model.

In the interest of consistency, we check the model for each variable one at a time. Thus firstly, we use as a single-predictor model:

$$P = \frac{1}{(1 + e^{a_0 + a_j x_j})} \quad \dots 3$$

where j refers to the j th variable in Table 2.

Figures 4 to 8 show the ‘predictions’ of the model of Eqn 3, using the coefficients of Table 2, compared to the observed probabilities denoted by solid circles with bars showing 95 per cent confidence intervals. Overall, the observed probabilities compare reasonably well.

The value of r^2 (the square of the correlation coefficient) in Table 2 is not particularly high and the question arises as to whether r^2 for the model in Eqn 2 (a multiple logistic model) is significantly higher. The question is answered by including predictors until improvements of r^2 are negligible (see Table 3).

We have implicitly assumed that the x_i variables are independent.

Table 2. Values of a_0 , a_j and r^2 determined from Eqn 3 using each x_j input variable one at a time with fog events defined as All Fogs.

j	x_j	a_0	a_j	r^2
1	d_{17}	-2.415	2.010	0.461
2	d_{12}	-1.473	0.875	0.225
3	lv_l	-1.432	0.229	0.153
4	c_{12}	-0.672	0.134	0.113
5	u	-0.273	0.051	0.071

From the five predictors in Table 2, logistic regressions of the best models with 1, 2, 3, 4, and 5 predictors were found. These are shown at Table 3 with the individual r^2 value for each model. Table 3 indicates that the multiple-predictor model of Eqn 2 with $n = 5$ is a suitable model, although it is a matter of judgement as to the size of n . There are of course objective criteria available to choose the value of n , but we choose $n = 5$ on the basis that it incorporates some directional effect which would be consistent with the concept of advection of fogs from local sources.

For the model chosen ($n = 5$) it is necessary to check for any unexpected bias in error and this is done by plotting the error, E , against each of the five x_i variables separately:

$$\text{where } E = P - A \quad \dots 4$$

where P is the probability determined through Eqns 2(a) and 2(b) and A is the assigned value of the actual event (1 for a fog event, 0 for a non-event). Although not shown here, there was no apparent bias. A similar requirement is to assess the reliability of the model. A reliability diagram is constructed by dividing the range of forecast probabilities into discrete intervals and plotting the relative frequency of occurrence in each interval against the interval centre. For perfect reliability all points should lie on the diagonal. Points below (above) the diagonal indicate that the probabilities are over (under) forecast. The reliability as shown in Fig. 9 appears quite good.

Fig. 9 Reliability diagram for five parameter model for All Fogs on the dependent dataset. Perfect reliability is represented by the diagonal.

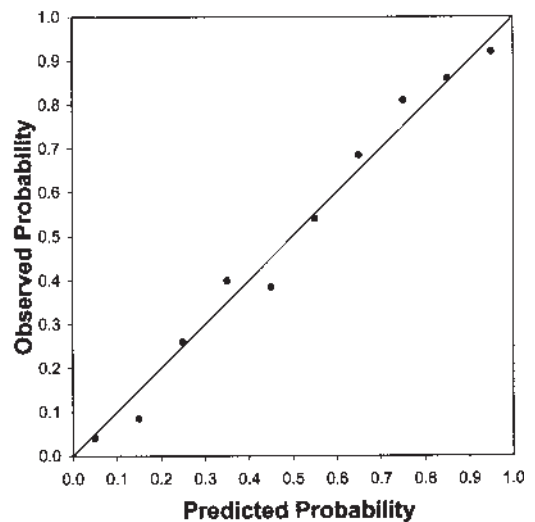


Table 3. Coefficients and r^2 values for the multiple-predictor logistic regression model of Eqn 2 with the number of independent variables $n = 1$ to 5.

n	x_i	a_0	a_1	a_2	a_3	a_4	a_5	r^2
1	d	-2.415	2.010	-	-	-	-	0.461
2	$d d_{12}$	-2.814	1.951	0.354	-	-	-	0.521
3	$d d_{12} \text{lvl}$	-3.168	1.865	0.311	0.102	-	-	0.553
4	$d d_{12} \text{lvl } c_{12}$	-3.893	1.881	0.331	0.128	0.170	-	0.575
5	$d d_{12} \text{lvl } c_{12} u$	-3.835	1.837	0.352	0.119	0.157	0.038	0.591

To obtain a categorical forecast of fog from Eqn 2, we use:

$$C = 0 \text{ if } P < P_c; \quad \dots 5$$

$$C = 1 \text{ if } P \geq P_c$$

where $C = 0$ implies a forecast non-event,
 $C = 1$ implies a forecast fog event and
 P_c is the threshold decision criterion.

Once C is calculated for all the data, values of POD, FAR and CSI as functions of P_c can be determined. The skill scores as a function of P_c are shown at Fig. 10. Clearly POD can be improved by decreasing the value of P_c but at the expense of a deterioration in FAR. CSI has a broad peak between P_c of 0.2 and 0.6.

A ROC curve is composed by plotting POD values against corresponding values of FAR* as shown in Fig. 11 (see Mason (1982) for a detailed description of the assessment using the ROC). The top left-hand corner represents perfect forecasts. The diagonal corresponds to the 'skill' of climatology in the sense that any constant or random forecasts plot on the diagonal. The distance of the ROC from the diagonal is a measure of skill of the model. Swets (1996) recommends using the area between the ROC and the diagonal as a measure of skill for a model. A simpler alternative measure of skill is the distance of the ROC from the top-left corner along the second (unshown) diagonal. The P_c value corresponding to such a point on the ROC is about 0.5 in our case. Since this is compatible with the CSI peak, P_c was set to 0.5. To be clear, we have used the plots of skill scores and the ROC derived from the dependent data to choose subjectively a value of P_c . However, in a rational economic sense, one would expect that the P_c value is selected to optimise the overall cost benefits accruing to the forecasts' end-user. It is quite possible that operational forecasters intuitively allow for the user's cost-benefit structure.

At $P_c = 0.5$, skill scores on the dependent dataset (1980-1989) for All Fogs were:

$$\begin{aligned} \text{POD} &= 91 \% \\ \text{FAR} &= 17 \% \\ \text{CSI} &= 77 \% \\ \text{FAR}^* &= 15\%. \end{aligned}$$

Fig. 10 For All Fogs, skill scores as a function of P_c for dependent data: (a) POD; (b) FAR; (c) CSI; (d) FAR*. 'X' plots the skill of the model on the independent data for $P_c = 0.5$.

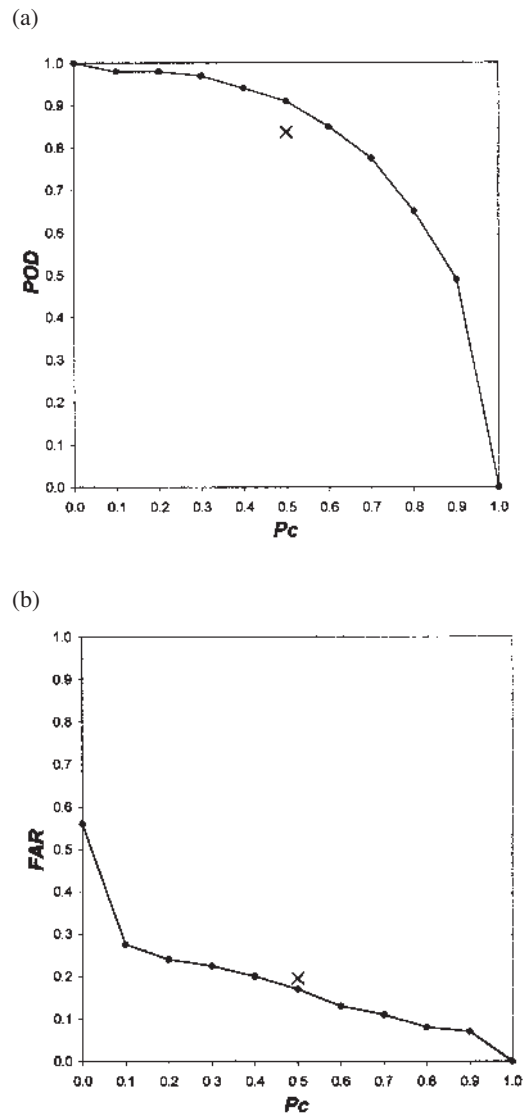


Fig. 10 Continued.

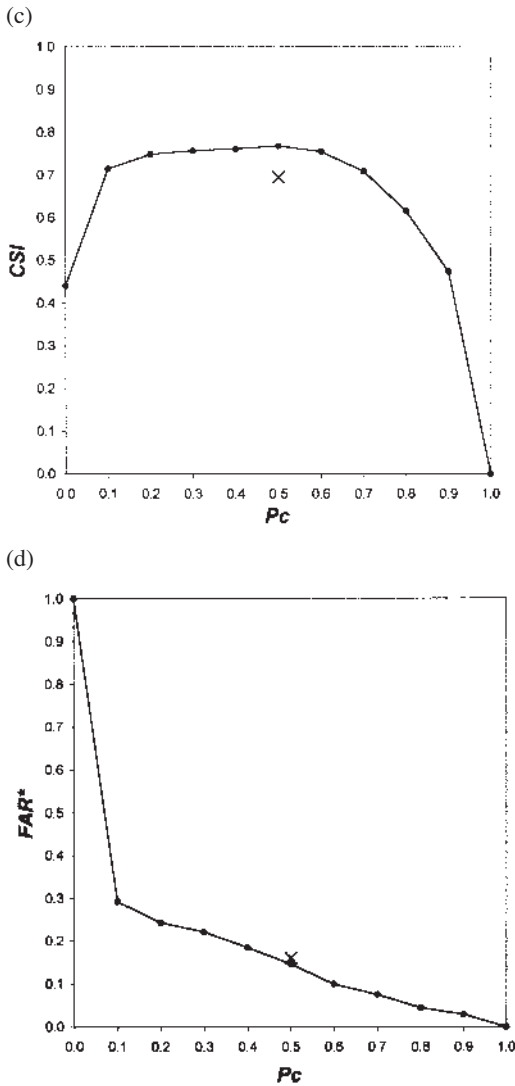
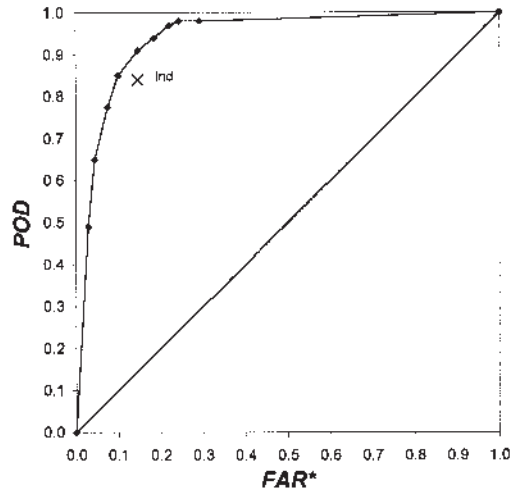


Fig. 11 For All Fogs, the ROC (Relative Operating Characteristic) curve for dependent data. The diagonal represents climatology: the top-left corner represents perfect forecasts. The greater the area between the diagonal and the ROC the better the skill. An optimum trade-off between POD and FAR* may be obtained by selecting a point on the curve at its closest approach to the top-left corner.



coefficients are different. For the same period of dependent data (1980-1989), skill scores were determined as:

- POD = 76 %
- FAR = 20 %
- CSI = 64 %
- FAR* = 11 %.

It remains to verify these encouraging results for the two classifications of fog event (All Fogs and Alternate Fogs) upon independent data and, where possible, to compare results against other forecast methods.

Verification

Essentially, verification involves determining skill scores for independent data, using coefficients previously obtained from the dependent dataset. A reliable model is expected to have similar skill scores for both dependent and independent datasets.

For the fog events All Fogs, the skill scores on independent data (1990, 1991, 1994) with $P_c = 0.5$ were:

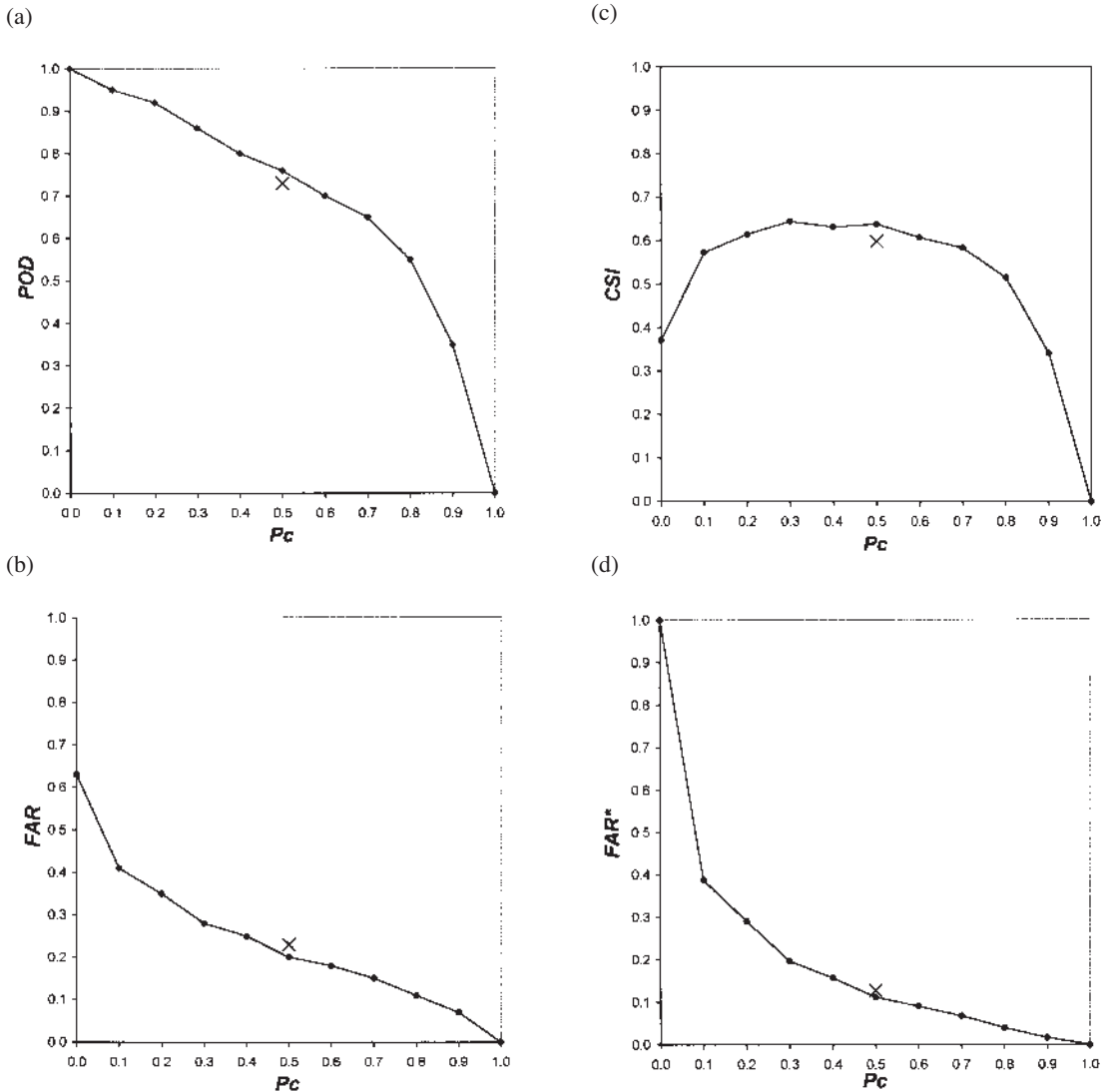
- POD = 84 % (91%)
- FAR = 20 % (17%)
- CSI = 70 % (77%)
- FAR* = 16 % (15%)

with the dependent data scores in brackets.

For the less numerous but operationally more important Alternate Fogs, defined as fogs and/or shallow fogs with visibility reduced such that alternate conditions apply to aviation operations, a similar process was followed. Again, skill scores on the dependent data for values of P_c for Alternate Fogs were plotted (Fig. 12). These curves are basically similar to those of All Fogs with Alternate Fogs' model having less skill: alternatively expressed, Alternate Fogs are more difficult to forecast. The ROC curve for Alternate Fogs at Fig. 13 is consistent with this observation. The value of P_c of 0.5 was again selected to test the model on the independent data.

The predictor variables obtained were again found to be d , lv , d_{12} , c_{12} and u , although of course the coef-

Fig. 12 For Alternate Fogs, skill scores as a function of P_C for dependent data: (a) POD; (b) FAR; (c) CSI; (d) FAR*. 'X' plots the skill of the model on the independent data for $P_C = 0.5$.



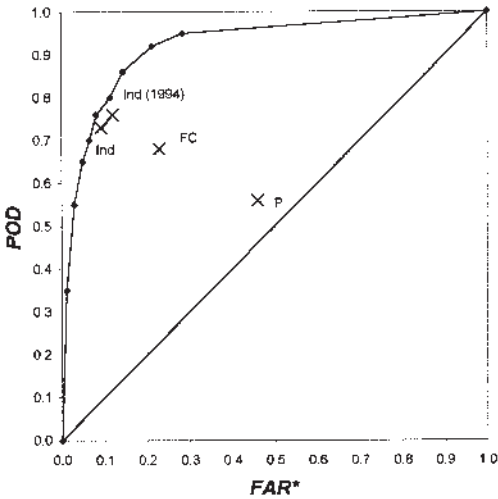
Given that it is usual for such empirical models to exhibit less skill on independent data than on dependent data, then these scores are reasonably close to those for the dependent set (in brackets) and indicate stability in the model.

For the fog events Alternate Fogs, skill scores were calculated for independent data for the whole three-year set and for 1994 alone. Table 4 compares these scores to the dependent dataset. Also included in Table 4 are the skill scores for the routine Regional Forecasting Centre (RFC) forecasts issued at 1800 UTC for the period April - August 1994 and, similar to model verification, excluding those days with pre-

cipitation between 1730 and 2330 UTC. An important caveat, however, is that RFC forecasts at that time were constrained effectively to three options: a categorical forecast of no fog; a probabilistic forecast of fog limited to between 20 and 50 per cent; or a categorical forecast of fog.

Furthermore, the operational forecasters may have forecast fog on the expectation of subsequent rain. If the rain occurred, then that case was excluded from the dataset regardless of whether fog did or did not occur. If no rain occurred, then such a forecast would imply an increase in FAR. To compensate in some measure for this disadvantage, operational forecasts that were

Fig. 13 For Alternate Fogs, ROC for dependent data. The label *P* represents the skill of persistence forecasts based upon the independent data; *FC* represents the official forecast performance for the independent data of 1994; the labels *X* represent the model performance for the independent data of 1994 and of all the independent data.



issued with the knowledge that a fog was in existence at 1730 or 1800 UTC were included – this inclusion would almost certainly act to improve the performance scores. Nevertheless, there is no way that the performance scores can be made directly comparable.

Since a forecast of 20 per cent or more of fog implied the same operational effect as a categorical forecast of fog, it was decided to assume that P_c was set at 0.2 for RFC forecasts. (Currently, a similar system applies but with the P_c value of 20% replaced by 30%). It is apparent that the model skill is at least comparable to the operational forecasts. As noted earlier, operational forecasts are possibly influenced by a subjective allowance for the end-user’s cost-benefits.

We investigated the seasonal skill of the models where the coefficients were tuned on a monthly basis on the dependent data. The scores for a composite model, comprising five different sub-models (one applicable to each month), for the winter season, and for the late autumn, are given in Table 5. Overall, the skill scores are superior to the single whole-season model. However, in view of the evident variability in skill scores, a firm conclusion as to the underlying superiority of the composite model comprising five separate sub-models probably ought to wait verification on further independent data. By Occam’s razor, the whole-season single equation model is preferred.

A final comparison for the Alternate Fogs is provided by plotting at Fig. 13 the POD and FAR* scores on the independent data of 1990, 1991, 1994 for:

- (a) the model;
- (b) for a model using persistence where relevant;
- (c) for the operational forecasts; and
- (d) for climatology which is simply presented by the diagonal.

Included for reference is the plot for the dependent data. This plot shows the logistic model is at least

Table 4. Model skill scores (%) for Alternate Fogs on different datasets compared to RFC forecasts. Model compares favourably with operational forecasts.

<i>Skill Scores</i>	<i>Dependent Data</i> 1980 – 1989	<i>Independent Data</i> 1990, 1991, 1994	<i>Independent Data</i> 1994	<i>RFC Forecast</i> 1994
POD	76	73	76	68
FAR	20	23	27	44
CSI	64	60	59	44
FAR*	11	13	17	31

Table 5. Composite model skill scores (%) by season for dependent and independent datasets. There were 39 fog events in AMJJA 1994.

<i>Skill Scores</i>	<i>Dependent</i> 1980 – 1989			<i>Independent</i> 1990, 1991, 1994			<i>Independent</i> 1994		
	<i>AM</i>	<i>JJA</i>	<i>AMJJA</i>	<i>AM</i>	<i>JJA</i>	<i>AMJJA</i>	<i>AM</i>	<i>JJA</i>	<i>AMJJA</i>
POD	77	76	77	79	87	83	75	86	82
FAR	25	24	25	23	32	28	25	24	24
CSI	61	61	61	63	62	63	60	68	65
FAR*	15	14	15	14	24	19	15	16	15

comparable to the other forecasts for the test data and also shows the utility of Mason's assessment method. Mason's recommendation regarding the power of the ROC to discriminate the skills of various probabilistic forecasts is evidently well justified.

Using the entire dataset 1980 - 1994 (April to August) the 'a' coefficients applicable to Alternate Fogs were re-calculated as:

$$\begin{aligned} a_0 &= -2.022 \\ a_1 &= 1.394 \text{ for } d \\ a_2 &= 0.381 \text{ for } d_{12} \\ a_3 &= 0.171 \text{ for } |v| \\ a_4 &= 0.085 \text{ for } u \\ a_5 &= 0.064 \text{ for } c_{12}. \end{aligned}$$

Discussion and summary

Precipitation-absent morning fogs at Mount Gambier Airport commonly occur during the period April to August. The occurrence of such fogs constitutes an operational forecasting problem and was the motivation for this study. An objective statistical-empirical decision aid based on a logistic probability model, developed on 1130 UTC and 1730 UTC site data, for forecasting the probability of precipitation-absent fog forming after 1730 UTC and before 2330 UTC was presented. The aid is applicable to either All Fogs (which includes shallow fogs) or Alternate Fogs (which are those fogs and/or shallow fogs with visibility below a threshold predefined by the aviation regulatory authority). The specified model presented refers to the April to August cool and wet 'season.' The aid appears applicable to the warmer drier months as well but this assertion is difficult to convincingly support since there are far fewer fog events to verify. Verification for both classifications was presented.

The predictors found useful were dew-point depression at 1730 UTC and 1130 UTC, the low-level cloud amount at 1130 UTC, the absolute value of the southerly component of the 600 m wind at 1730 UTC and the (non-absolute) easterly component. The conjunction of the absolute and non-absolute wind components indicates a sensitivity to wind direction probably due to the formation of fog patches over the swamps to the east with these fog patches being advected to the airport on easterly winds.

Categorical forecasts were derived from the probabilistic forecasts. Based on the 1130 UTC and 1730 UTC data, the Alternate Fogs model had skill scores of POD = 73, FAR = 23, CSI = 60 and FAR* = 13% on independent data of 1990-1994. For the 1994 dataset, model skill scores were 76, 27, 59 and 17% respectively, which compared favourably (albeit on a

sample from only one year) to the subjective operational forecasts of 68, 44, 44 and 31%. The comparison is not perfectly direct since the model was tuned to a decision criterion of P_C of 0.5 whereas the operational forecasts effectively used a value of P_C of 0.2 and the assessing dataset was slightly different as discussed earlier. Persistence forecasts were comparatively poor and only marginally better than climatology forecasts.

Finally, model coefficients based on all available years of data were presented. It is suggested that the aid with these coefficients would be a worthwhile adjunct to forecasters' guidance or checklist. Model Output Forecast guidance could relatively easily provide a fog probability from the operational numerical models. Investigation to extend the methodology to the drier months and to other geographically nearby sites is warranted. A further extension (as below) of the model from Eqn 4 by including a time term, where t is the time elapsed since 1730 UTC could also prove useful.

$$P_t = \frac{1}{(1 + e^y)} \quad \dots 6(a)$$

where

$$y = a_0 + \sum_{i=1}^n a_i x_i + a_t t \quad \dots 6(b)$$

and P_t is the probability of a fog forming in the period t after 1730 UTC. It is suggested that with such a model, a probabilistic forecast of fog related to time elapsed since 1730 UTC would be easily obtained.

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