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Fire–climate relationships and long-lead seasonal wildfire prediction for Hawaii

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Abstract. We examined statistical relationships between the seasonal Southern Oscillation Index (SOI) and total acreages burned (TAB) and the number of fires in the Hawaiian Islands. A composite of TAB during four El Niño/ Southern Oscillation (ENSO) events reveals that a large total of acres burned is likely to occur from spring to summer in the year following an ENSO event. The correlation is most significant between the TAB in summer and the SOI of the antecedent winter. This relationship provides a potential for long-lead (i.e. 2 seasons in advance) prediction of wildfire activity in the Hawaiian Islands.

Logistic regression is applied to predict events of large acreages burned by wildfires. The goodness of predictions is measured by specificity, sensitivity, and correctness using a cross-validation method. A comparison of prediction skill for four major islands in Hawaii is made using the summer TAB as the response variable and the preceding winter SOI as the predictor variable. For predicting the probability of events (sensitivity), results indicate rather successful skills for the islands of Oahu and Kauai, but less so for Maui and Hawaii. It is more difficult to predict non-events (specificity), with the exception of Oahu. As a result, only Oahu has a high overall correctness rate among the four islands tested.

Introduction

Wildfires have inflicted major damage to life and property in the Hawaiian Islands and posed a great ecological threat to numerous flora and fauna found nowhere else in the world. In recent years, the number of fire occurrences (NFO) as well as the total acres burned (TAB) in Hawaii has increased as a result of increased population density and climate variations associated with strong and recurrent El Niño events. These damages could be reduced with accurate long-lead prediction provided to wildfire control agencies. The El Niño phenomenon is manifested as the anomalous warming of the east and central equatorial Pacific. This study investigates relationships between fire activity and short-term climate variations, which can be used to estimate fire potential for long-range fire planning and management.

In recent years, strong El Niño events, such as 1982–1983 and 1997–1998 events, have caused violent climate variations worldwide (e.g. severe drought in Indonesia). Numerous studies (Chu 1989, 1995) have established a linkage between local rainfall anomalies in the Hawaiian Islands and El Niño. However, few studies have been conducted on fire–climate relationship in Hawaii, let alone on long-lead seasonal fire prediction.

Brenner (1989) investigated how variations in sea surface temperatures in the eastern and central Pacific and sea level pressure anomalies in Darwin in the Northern Territory of Australia are related to fire activity in Florida. His study revealed that, during La Niña years, the acres burned in Florida by wildfires were anomalously high, and the converse was true during El Niño years. Fujioka *et al.* (1991) and Klein and Whistler (1992) developed a long-range fire weather forecasting system for Alaska and the contiguous U.S. The system consists of regression models that predict monthly mean fire weather variables, with demonstrated skill, from the predicted anomalous 700-mb monthly mean height field (Klein *et al.* 1996). The dependent variable is chosen on the basis of its correlation with historical fire activity.

In the Hawaiian Islands, the climate variation and fire behavior in response to El Niño are different from those in other states of the USA. Drought or deficiency of rainfall occurs frequently from winter to spring in the year following

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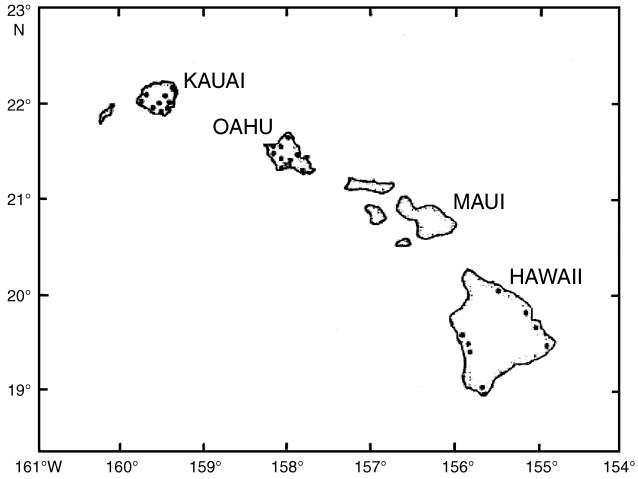

Fig. 1. Map of the major Hawaiian Islands.

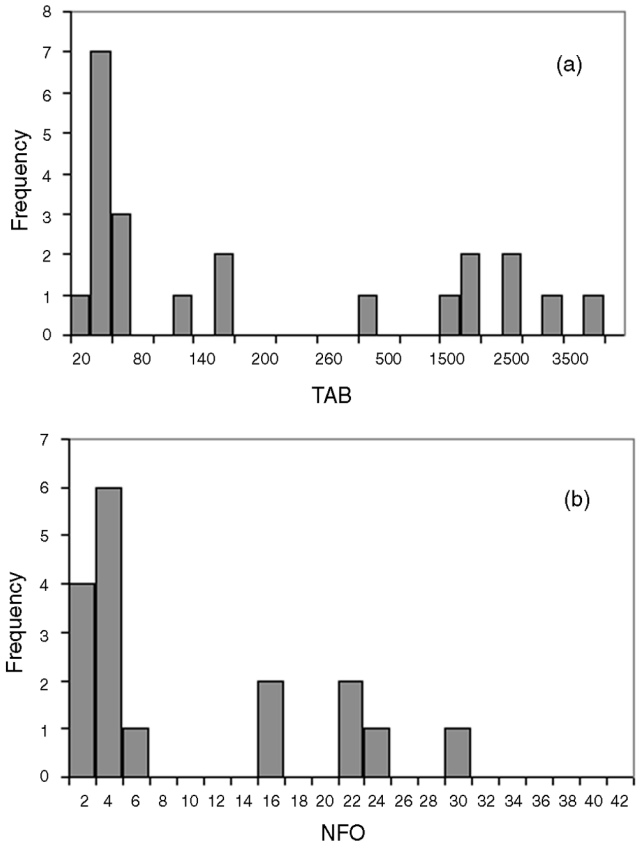

Fig. 2. Histogram of summer (*a*) Total Acres Burned (TAB) and (*b*) Number of Fire Occurrences (NFO) for Oahu. Note that the *x*-axis in (*a*) is on a log scale.

an El Niño (Chu 1995), possibly promoting favorable conditions for wildfire occurrence. This study explores the relationship between the El Niño phenomenon and wildfire activities in the Hawaiian Islands. A simple statistical fire–climate model is also developed to test feasibility of long-lead seasonal fire prediction.

Data processing

The Hawaii Department of Land and Natural Resources, Division of Forestry and Wildlife, supplied wildfire records for the islands of Hawaii, Maui, Oahu, and Kauai for the period July 1976 to December 1997 (Fig. 1). From these, we tabulated monthly and seasonal TAB and NFO by island. The Southern Oscillation Index (SOI) is the difference in normalized sea level pressure between Darwin (Australia) and Tahiti, and has been used in previous studies (e.g. Chu and Katz 1985, 1989). This index is representative of large-scale atmospheric circulation patterns. The El Niño phenomenon is linked with the Southern Oscillation, and both events are labeled together ENSO. The monthly SOI data from 1976 to 1997 are obtained from the National Centers for Environmental Predictions of the National Oceanic and Atmospheric Administration.

The fire data are highly skewed, as typified by the summer TAB statistics for Oahu (Fig. 2). For instance, more than 2400 acres were burned in a single wildfire that occurred on Oahu on 18 June 1983, while the yearly total TAB in 11 of the total 22 years (50% of the data) is less than 1000 acres. Table 1 lists median and interquartile range (lower quartile to upper quartile) of seasonal TAB values for the four major islands in Hawaii. For the seasonal TAB, winter is defined from December of the preceding year to February of the current year (e.g. winter of 1997 runs from December 1996 through February 1997). The other three seasons are defined as: spring (March to May), summer (June to August), and fall (September to November). Given the small land size for Oahu, Kauai, and Maui, the median is expected to be small. For the island of Hawaii, which has the largest land area among the four islands, the 'middle value' of the seasonal TAB is relatively large (238.5 acres) and the central 50% of the data lie between 36.4 and 1310.9 acres. However, when the median TAB is divided by land area, the island of Maui has the highest rate.

According to the fire control agencies, NFO is more easily affected by human activity than is TAB (Brenner 1989). For example, a record high number of fires was reported (NFO = 122) in Oahu in 1980 but there was no unusual climate forcing in the Pacific Ocean (i.e. ENSO event) in this year. Moreover, the annual rainfall totals measured at most gauges in 1980 were above normal (e.g. 1980 was not a dry year). Because of the potential problems in NFO, only TAB is employed as the fire index in the subsequent analysis.

Background climate and variations of TAB

Background climate and annual cycle of TAB

The annual cycle of rainfall and temperature in Hawaii is broadly characterized by two seasons: summer, which extends approximately from May to October, and winter, from November to April. Summer is a dry and warm season

Table 1. Median and interquartile range of seasonal TAB (acres), and the ratio of median TAB per land area (acres/km^2) for various islands in Hawaii

	Kauai	Oahu	Maui	Hawaii
Median	3.3	25	79.7	238.5
Interquartile range	(0.8, 15.8)	(6.1, 126.6)	(8.3, 504.7)	(36.4, 1310.9)
Median/land area	0.0023	0.0162	0.0423	0.0229

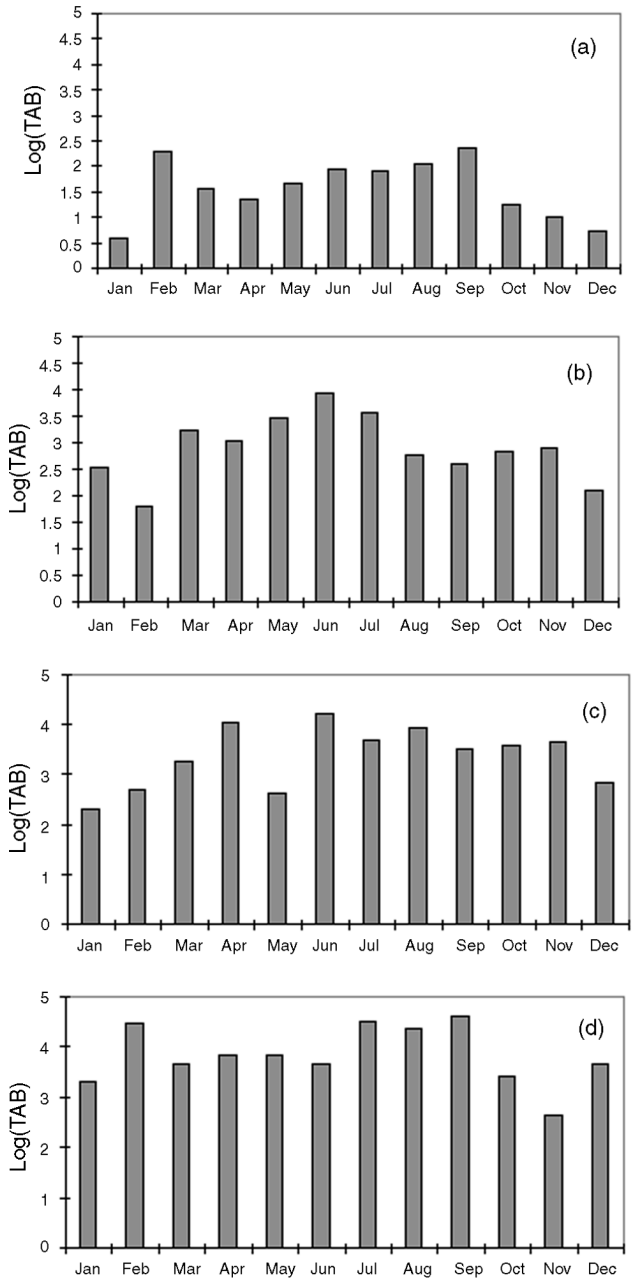

Fig. 3. Monthly mean Total Acres Burned (TAB) for (*a*) Kauai, (*b*) Oahu, (*c*) Maui and (*d*) Hawaii.

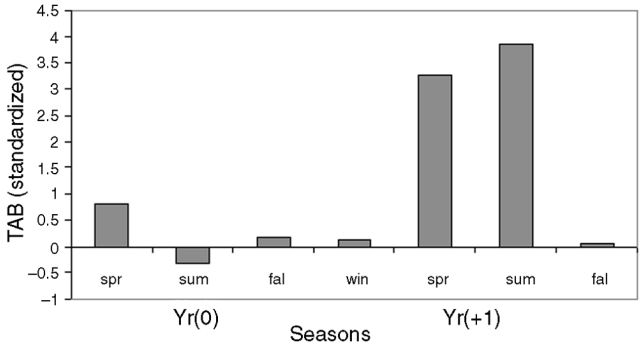

Fig. 4. Seasonal composite of Total Acres Burned (TAB) for Oahu during the four ENSO events (1976–1977, 1982-1983, 1986–1987 and 1991–1992.

with persistent north-easterly trade winds from the sea. As cumulus-cloud clusters from the North Pacific Ocean are advected into the islands, they are forced to rise along the mountain barriers. The upward displacement of air, caused by orographic effects, is known as orographic uplift which produces clouds and rains. Thus, areas of maximum rainfall are generally found on windward slopes where uplifting is predominant. On the leeward side of the mountains where air descends the slope and warms by compression, low rainfall occurs. This phenomenon is known as a rain-shadow effect, which occurs on the downwind side of the mountain ridges. Because of the rain-shadow and uplifting effects, large rainfall gradients over short distances are not uncommon in Hawaii. High mountain tops well above 3000 m (e.g. Mauna Kea on the island of Hawaii) are dry because low-level moisture-laden trade flows are capped by the subsidence inversion, which usually occurs at an elevation of about 1500 m.

During the cooler and rainy winter season, trade winds are often interrupted by mid-latitude frontal rainband systems and kona storms (Ramage 1962; Chu *et al.* 1993). A kona storm occurs when Hawaii appears to be under the influence of the circulation of a subtropical cyclone; it can last for a week or more and occasionally brings flooding to the islands. Frontal passages generally bring light to moderate rainfall to the islands. However, because of its southernmost location, the island of Hawaii experiences less frontal-induced rainfall than the island of Kauai.

The warmer and drier weather in summer naturally increases the potential for fire occurrence. Consequently, TAB in the four islands is expected to be high during the summer months. Indeed, the peak month of TAB for Maui and Oahu is June, while the peak for Kauai and Hawaii occurs in September (Fig. 3). Note that the log(TAB) is used in the vertical axis. The percentages of TABs during summer

Table 2. Spearman Rank correlation coefficients between SOI and TAB for Oahu
* correlations significant at the 10% level; # correlations significant at the 5% level; @ for correlations significant at the 1% level

	Same year as the SOI				Following year of the SOI			
SOI/TAB	Winter	Spring	Summer	Fall	Winter	Spring	Summer	Fall
Winter	–0.214	–0.345	–0.631@	–0.189	0.073	–0.312	–0.058	–0.309
Spring		–0.330	–0.369	–0.397*	–0.237	–0.482#	–0.288	–0.175
Summer			0.102	–0.248	–0.342	–0.264	–0.337	–0.007
Fall				–0.251	–0.432*	–0.348	–0.586@	–0.161

months (June, July, and August) to the total annual amounts are 39%, 60%, 57%, and 31% for Kauai, Oahu, Maui, and Hawaii, respectively.

From October to January, TAB generally decreases, probably because more rainfall occurs during these four months. The larger value of TAB in February (April) for Hawaii (Maui) might be related to the increase in human outdoor activities, such as hiking and camping during these months. We focus the analysis and prediction modeling of TAB on Oahu during summer mainly, because population pressure on the island puts a premium on fire management and because of the large acres burned in summer (i.e. 60% of the total annual amount occurs in summer).

Fire activity during ENSO cycle

A composite of the seasonal standardized anomaly of TAB on Oahu during four El Niño events (1976–1977, 1982–1983, 1986–1987, 1991–1992) is shown in Fig. 4. The original, 3-consecutive-months TAB data are summed to produce a seasonal value. Standardization is achieved by taking the difference between the original seasonal data and the long-term average seasonal mean and then dividing this departure by the standard deviation for each season. The year in which El Niño occurred is denoted as Yr (0), while the following year is Yr (+1).

The composite shows that TAB from fall of Yr (0) to fall of Yr (+1) is positive, suggesting that TAB increases after an El Niño event. The only negative value appears in the summer of Yr (0). From winter to summer of Yr (+1), TAB dramatically peaks in response to a prolonged dry climate associated with El Niño event. Usually, El Niño-related drought in Hawaii occurs in winter and spring of Yr (+1) (Chu 1995). Apparently, TAB follows the El Niño–rainfall cycle with a lag of one season (Fig. 4). The above results suggest that the El Niño effect on wildfire is persistent, lasting for at least 6 months, and is likely to cause a large TAB event in the following spring and summer.

Correlation between Fire Index and SOI

We calculated lag correlations between the seasonal TAB and the seasonal SOI using the entire dataset to identify the time-dependence of this relationship. Because of the skewness and variability of the TAB data, Spearman correlations, rather than Pearson correlation, are calculated. A Spearman rank correlation is simply a Pearson correlation coefficient computed using the ranks of the data. It is more robust and resistant than the Pearson product-moment correlation coefficient.

Table 2 shows the result of Spearman rank correlation coefficients between SOI and TAB for Oahu. These correlations are either concurrent or between TAB and SOI several seasons previously. All statistically significant correlation coefficients are negative, suggesting that a negative SOI is followed by a larger TAB in the following seasons. Note that the two highest correlations occurred for winter SOI and summer TAB of the same year (–0.631), and for fall SOI and summer TAB of the following year (–0.586). The third largest correlation value (–0.482) shows a strong relationship between the SOI in spring and TAB in the following spring. This result indicates that the influence of ENSO on the fire activity on Oahu could persist for a year. The lag correlations between the SOI and TAB on Kauai and Hawaii are also strong but in different seasons from Oahu (not shown). Besides the difference in microclimate among the islands, the data used in this study are based on fire records reported only on state land, and the state land size varies from island to island. In fact, this feature is reflected in Table 1, in which the medians and interquartiles for each island are quite different. It is likely that these factors account for the difference in lag correlations from island to island. In summary, it is important to note that the significant correlations between SOI and TAB in Table 2 indicate a potential for long-lead fire forecasting for Oahu using a statistical model.

Long-lead prediction models

Logistic regression is used to model and predict the conditional probability, y, of an event, given that the odds ratio of the event to the non-event is log-linear in a set of independent variables, $\{x_i\}$ (Sharma 1995):

$$\ln \frac{y}{1-y} = \beta_0 + \sum_1^n \beta_i \mathrm{x}_i . \tag{1}$$

Inverting the ratio and solving for y, we obtain

$$y = \frac{1}{1+\exp(-(\beta_0 + \sum_1^n \beta_i x_i))} . \tag{2}$$

As the sum in the argument of the exponent function ranges from negative infinity to positive infinity, y assumes values from 0 to 1.

In this study, we defined y as the probability of a large TAB event and modeled the log odds by a simple linear equation ($n = 1$):

$$y = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_1))}, \quad (3)$$

where x is the SOI in the pre-season used to predict the TAB event. We estimated parameters using the LOGISTIC procedure in SAS. Regression parameters in equation (3) are fitted by a non-linear equation. A check of the TAB series shows a weak autocorrelation pattern from year to year, suggesting that the underlying data are nearly independent. The dependent variable of each datum consisted of a binary number, either a 1 for a large TAB event in the season targeted for prediction or a 0 for a TAB event not classified as large. Specifically, an observation is classified as an event if a TAB value exceeds a specified threshold value; otherwise it is classified as a non-event. We used three different thresholds prior to the analysis, corresponding to the 50th, 75th and 90th percentiles of seasonal TAB.

Table 3. Logistic parameter of β_1 and its *P* value with different criteria at the median, 75th, and 95th percentiles (Q75, Q95)
The predicted variable is summer TAB for Oahu and the predictor is SOI in the antecedent winter

	Parameter β_1	*P* value (β_1)
Median	–1.031	0.086
Q75	–1.850	0.035
Q90	–1.367	0.066

In the setting of the logistic regression, we tested the statistical significance of the parameter, under the null hypothesis that $\beta_1 = 0$, that is, no relationship between TAB and SOI exists; the alternative hypothesis is $\beta_1 \neq 0$, meaning a relationship between TAB and SOI does exist. The standard error of the parameter (β_1) can be used to compute the t-test value. The square of the t-test value gives the Wald χ^2 statistic, which can be used to assess the statistical significance of the independent variable. The estimates of the parameter, β_1, and P value of χ^2 statistics were calculated using the entire 22 data points. Results with three criteria being set at the median, 75th (i.e. upper quartile) and 90th percentiles are shown in Table 3. As can be seen, the null hypothesis for β_1 can be rejected at the 5% significance level for the 75th percentile ($P < 0.05$). The null hypothesis is also close to rejection for the 90th percentile.

In testing prediction skill, cross-validation is used. Cross-validation is a technique of repeatedly omitting one or more observations from the data, reconstructing the model, and then making estimates for the omitted cases (Chu and He 1994). For the fire data in this study, only 22 years of TAB are available. Therefore, 22 logistic models are set up, each omitting one point. By doing so, cross-validation uses the entire data sample as independent data and thus produces a more robust test result. Then the forecasted TAB is classified as an event or non-event using the aforementioned three given criteria.

As an example of summer TAB prediction, Table 4 shows the number of observed and predicted events and non-events, sensitivity, specificity, and overall correctness for the median, upper quartile and the 90th percentile criterion for Oahu. Sensitivity, specificity and correctness are three measures for prediction accuracy. Sensitivity is a ratio of the total number of correctly classified events to the total number of events, while specificity is a ratio of the total number of correctly classified non-events to the total number of non-events. Correctness simply gives the probability that the model correctly classified the sample data for each criterion when events and non-events are considered together.

Referring to equation (3), y is the summer TAB for Oahu and x is the SOI of the preceding winter. In this study if the predicted probability is 0.7, which exceeds the specified cut-off (e.g. median), then this prediction is called an event. This can be compared with the actual observation, which is also classified as an event or non-event based on the same cut-off point as the prediction. If the corresponding actual observation also indicates an event, then the prediction is deemed to be correct. In Table 4, the forecast with the upper quartile has the highest correctness (86.4%) and sensitivity

Table 4. Logistic classification table for the summer TAB prediction for Oahu using SOI of the preceding winter as predictor
Q75 and Q95 are the same as Table 3. The cut-off values for summer TAB (acres) are also indicated in the first column

	Observed Event	Correctly classified event	Observed non-event	Correctly classified non-event	Sensitivity (%)	Specificity (%)	Correctness (%)
Median 98.5	11	6	11	9	54.5	81.8	68.2
Q75 1025	6	5	16	14	83.3	87.5	86.4
Q90 2200	3	2	19	14	66.7	73.7	72.7

Table 5. Logistic classification table of TAB prediction for Oahu with the 75th percentile for winter, spring, summer, and fall using SOI in various pre-seasons as predictors

Target season (Predictor season)	Observed event	Correctly classified event	Observed non-event	Correctly classified non-event	Sensitivity (%)	Specificity (%)	Correctness (%)
Winter (SOI preceding fall)	6	2	14	9	33.3	64.3	52.4
Spring (SOI preceding spring)	5	3	14	6	60.0	42.9	42.1
Summer (SOI preceding fall)	6	4	16	11	66.7	68.8	68.2
Fall (SOI preceding spring)	5	2	14	8	40.0	57.1	57.9

Table 6. Logistic classification table for the summer TAB prediction for various islands in Hawaii with the 75th percentile (Q75) as the cut-off

The SOI of the preceding winter is the predictor variable

	Observed event	Correctly classified event	Observed non-event	Correctly classified non-event	Sensitivity (%)	Specificity (%)	Overall correctness (%)
Kauai	5	5	12	4	100	33.3	52.9
Oahu	6	5	16	14	83.3	87.5	86.4
Maui	6	3	16	5	50	31.3	35.4
Hawaii	6	3	16	7	50	43.8	45.4

(83.3%). For the six observed events, five events are correctly classified and 14 out of 16 non-events are also correctly forecasted two seasons in advance using the cross-validation method. The logistic model performs reasonably well with the criteria of the median and the 90th percentile; the correctness reaches 68.2% and 72.7%, respectively. As shown in Table 2, in addition to the strong correlation between the summer TAB and the SOI of the preceding winter, strong correlations are found elsewhere. For example, a pronounced correlation is noted between the spring TAB and the spring SOI of the antecedent year (–0.482). To test the overall usefulness of the model, we apply the logistic equation to forecast TAB in winter, spring, summer, and fall using the SOI in various pre-seasons as predictors. The classification table given in Table 5 shows moderate overall correctness for winter, summer and fall (52.4%, 68.2% and 57.9%). These correctness rates are consistent with the results of lag correlations shown in Table 2; in general, a larger lag correlation coefficient between the SOI and the TAB corresponds to higher classification correctness.

Prediction results so far are shown for Oahu. A question arises as to whether other islands also have long-lead predictability. Because the sensitivity and correctness of summer TAB prediction for Oahu are highest with the upper quartile, a similar attempt is made here to predict the probability of large fire events for the other three islands at the same cut-off point as Oahu. A comparison of predicted classification with observation is given in Table 6 based on the cross-validation method. The 75th percentile of summer TAB values for Kauai, Maui, and Hawaii is 697, 1239, and 2307 acres, respectively. Among four islands, the overall correctness is highest for Oahu (86.4%) and disappointingly low for Maui (35.4%).

It is notable that the sensitivity for Kauai is perfect (100%), even though the overall correctness is just 53%. For Hawaii and Maui, the model misses three out of six events, resulting in a sensitivity of 50%. It should be noted that the correct prediction of an event is more important than of a non-event because large acres burned have potentially more impact on fire-fighting agencies (e.g. budget and resource allocations) and local community.

Summary and discussion

The statistics of wildfires reveal that most fires and largest total acreage burned occur in summer. Besides being influenced by climate variability, wildfire activities are also related to many uncertainties such as man-made ignition and problems of control ability. These uncertainties distort fire data from a Gaussian distribution and pose a great difficulty for data analysis and prediction. Total acres burned are less

affected artificially than the number of fire occurrences. Therefore, it was chosen as the index for fire activity in this study.

The ENSO composite chart (Fig. 4) indicates that positive TAB events on Oahu tend to occur from fall of an El Niño year to fall in the year following an El Niño event (extending over five seasons), with the largest anomalies occurring in spring and summer Yr (+1). The total acres burned in summer as a result of wildfires are significantly and negatively correlated with the antecedent winter SOI. Typically, when an El Niño event occurs, the local Hadley cell in the central Pacific becomes more vigorous. Hawaii is located in the subsiding branch of this cell, while the rising branch is found in the central and eastern equatorial Pacific. Consequently, this enhanced subsidence retards formation of rain-producing systems (e.g. frontal rain-band and kona storm) in Hawaii and provides Hawaii with a large potential for wildfires.

The pronounced correlations between TAB and SOI in previous seasons suggest the possibility for a long-lead prediction model. Since the correlation between TAB in summer and SOI in the preceding winter on Oahu is most significant and the year-to-year variability in TAB is large, we focus on modeling the probability of large TAB events using a non-linear logistic regression model. Forecasting the probability of large events would produce properly bounded estimates between 0 and 1 and therefore avoid the problem of dealing with the nearly unbounded TAB values.

Since the fire forecast users are concerned more about abnormally large fire activities, the summer TAB data are classified in a binary format, representing large and not-large events according to three criteria, the median, 75th and 90th percentiles. Prediction skill is measured in terms of the sensitivity, specificity, and correctness. For the island of Oahu, five out of six events are correctly forecasted two seasons in advance. At the same cut-off point, all the fire events on Kauai are correctly forecasted. For Maui and Hawaii, results are less encouraging.

It is more difficult to predict non-events, with the exception of Oahu. As a result, this difficulty degrades the overall correctness sharply. It should be remembered that the model used in this study involves only one predictor, the SOI, which only remotely affects Hawaii's climate variability. In the future, local fire-sensitive data such as the Keetch/Byram drought index (which considers daily maximum temperature and rainfall, and the previous day's drought condition) should be included as additional predictors. This index has been used operationally by fire agencies in the contiguous United States to monitor fire potential. As the Keetch/Byram index is derived from daily meteorological records, the construction of this drought index for various islands in Hawaii requires more time to process and is beyond the scope of the current study.

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