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Statistical forecast modeling for San Francisco International Airport

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STATISTICAL FORECAST MODELING FOR SAN FRANCISCO
INTERNATIONAL AIRPORT

A Thesis

Presented to

The Faculty of the Department of Meteorology

San Jose State University

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

by

Aaron Dale Daly

May 2004

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ABSTRACT

STATISTICAL FORECAST MODELING FOR SAN FRANCISCO INTERNATIONAL AIRPORT

by Aaron D. Daly

During the summer at San Francisco International Airport (SFO), the presence of low stratus in the final approach zone reduces visibility and prevents the airport from operating at full capacity. Data from 1996 through 2000 were collected at San Jose State University (SJSU) and used to build nonlinear models that forecasted for the 2001 stratus season. Their performances are compared to five operational forecasting models developed by MIT Lincoln Laboratory (MIT/LL). The SJSU nonlinear models were more reliable and had smaller overall error than the MIT/LL models. For each forecast hour, the SJSU nonlinear models matched or exceeded the performance of every MIT/LL model except at 1500 UTC and 1800 UTC. This indicates that the SJSU models, which were developed using only local SFO area data, may not represent the major factors that affect stratus dissipation at those times.

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A. Marine Stratus in San Francisco Bay Area

1. Synoptic-Scale Influences

From late spring throughout the summer, the synoptic-scale wind circulation in the northeastern Pacific Ocean is typically controlled by a high-pressure area that creates a northwesterly flow of air along the west coast of the USA. This persistent airflow along the coast also causes a southeastward transport of surface water, which in turn results in the upwelling of cold water just off the California coast. The cold water chills the air above it, and thus produces marine fog offshore of the western U.S. coast (Fig. 1). The high-pressure system also produces large-scale subsidence as the air flowing along the coast sinks and warms. A temperature inversion is thus established with cool air below and warm air above. This layer of cool marine air trapped below the warm air is called the marine boundary layer, or more simply the "marine layer". The base of the warm air layer, which is the base of the temperature inversion, acts as a capping lid atop the marine layer.

Since the warm air layer is the result of high-pressure subsidence, changes to this large-scale pressure field influence the height and extent of the marine layer. The height of the marine layer generally varies slowly over a period of a few days as the high-pressure system persists, but an alteration of this synoptic feature, such as the passing of a pressure trough with an associated front, can cause a rapid change in height. In this scenario, the height of the marine layer can increase substantially, and can even reach the height of the entire troposphere as the passing shortwave energy mixes the warm and cold air layers, eroding the capping inversion in the process. The extent of the marine layer depends on the distribution of the synoptic-scale pressure field. If the pressure field is favoring onshore flow, then it is very likely that the marine layer will also migrate onshore. Likewise, an offshore flow will act to prevent the marine layer from advancing onshore (Fig. 2).

Figure 1: Average sea level pressure (mb) in July (Mazur, 1991).

Figure 2: Offshore and Onshore forcing scenarios (Wilson et. al., 1996).

2. Mesoscale Influences

From May through September, horizontal gradients of surface temperature affect mesoscale circulations in the San Francisco Bay Area. As the interior California valleys are heated throughout the day, significant land-sea temperature gradients cause onshore circulations known as seabreezes. If the synoptic-scale pressure field is not favoring an offshore flow, then the seabreeze circulation can push the marine layer into the Bay, where the cool air lowers the inland air temperature (Fig. 3). As the marine layer cools further after sunset, the Lifting Condensation Level (LCL) drops below the inversion base thus allowing elevated stratus to form in this well-mixed layer.

Nighttime radiative cooling at the top of the stratus deck destabilizes the marine layer, which allows more vertical mixing within it and strengthens the inversion by lowering the temperature of the inversion base (Fig. 4). Typical heights of the cloud tops, which are the top of the marine layer and the base of the subsidence inversion, vary from 1000 feet to 2500 feet, and the cloud bases can vary from 700 feet to 1500 feet.

Figure 3: Seabreeze circulation forcing marine layer onshore (courtesy of Robert Tardif, Department of Earth Sciences at UQAM).

Figure 4: Nighttime development of stratus.

3. Topographic Influences

Local topography is a significant factor in the behavior of the marine layer. The Santa Cruz mountain range is located west of the San Francisco International Airport (SFO) and runs southward along the coastline, ranging from 1000 to 1900 feet in height. These mountains prevent the onshore advancement of the marine layer when the inversion base height is below them; however, there are two major gaps in this mountain range that allow the cool air to move onshore even when the inversion base height is low. The Crystal Springs gap, where the elevation drops to 850 feet, is located about seven miles SSW of SFO. The San Bruno gap is about five miles NW of SFO, and the elevation drops to 150 feet (Fig. 5). This extreme drop in elevation makes the San Bruno gap the primary gateway for the marine layer to advect towards SFO when the inversion base height is below the coastal mountains.

Figure 5: Locations of SFO, Crystal Springs Gap, and San Bruno Gap.

When the predominant circulation is onshore and the marine layer height exceeds that of the coastal mountains, they cease to be an effective barrier and the cool air

spills over them into the Bay Area. After the marine layer has moved into the Bay Area, both the coastal mountain range to the west and the Diablo range to the east act as barriers that confine this air in the Bay Area. As described in the previous section, radiative cooling occurs after sunset, and stratus begins to fill the Bay Area, usually starting in the Oakland area first, and filling the remainder of the Bay overnight. This is the most common scenario, but sometimes an onshore rush of a deep marine layer in the late afternoon or early evening can provide enough cooling so that SFO is covered by stratus when the evening rush of air traffic begins.

4. The Daily Cycle

Figure 6 shows a typical summer marine stratus daily cycle. The figure depicts a west-to-east cross section of California. Figure 6A begins the cycle at mid-day with the foggy marine layer still offshore. Downward arrows represent the large-scale subsidence that caps the marine layer. The horizontal arrows represent the onshore flow, and the upward arrows represent the warm air rising from the heated interior valley. In the late afternoon (Fig.

6B), the seabreeze circulation described in section 1.b. begins to drive the marine layer onshore. Then the radiational cooling of the cool marine air causes a stratus cloud deck to cover the Bay Area overnight (Fig. 6C). After sunrise, the air warms by solar insolation, and the cloud deck in the Bay Area dissipates (Fig. 6D).

Figure 7 expands Figure 6D into more detail. This figure shows more detail of the Bay Area, with the SFO approach zone and Oakland added to the picture. The vast majority of stratus over the approach zone is dissipated by 11:00 a.m. local time. Advection is represented in the figure by the horizontal arrows. Cool advection is occurring where the stratus is still present, but when there is sufficient radiative warming to overcome the cool advection and evaporate the stratus, the exposed land becomes heated. This heats the air above it, and this warm air flows from the coastal range eastward into the bay. This warm advection helps dissipate any lingering stratus in the approach zone.

Figure 6: Bay Area stratus cycle (Clark and Wilson, 1996).

Figure 7: Detailed depiction of clearing of approach zone (MIT/Lincoln Labs).

5. Major Factors in Stratus Dissipation

This study is focused on forecasting the dissipation of stratus for the scenarios depicted in Figures 6C, 6D, and 7. These are days where the Bay Area is covered by a stratus deck overnight, and then this stratus clears after sunrise. It is necessary to identify the most important processes contributing to stratus dissipation so that one has a guide for collecting appropriate data to build forecast models. Farley (2000) described the meteorology behind the stratus "burn-off" as a heat-budget problem. Stated very simply, heat added to the marine layer (i.e., solar heating) acts to evaporate clouds, and any impedance to this heating will slow down or reverse the evaporation process. Clark and Wilson (1996) developed a conceptual model that agrees with Farley's idea, and they describe the important processes involved with stratus dissipation. These processes, which are described in the following sections, serve as a guide for the data collection in this study.

a. Temperature Advection

Temperature advection is the transport of cooler or warmer air into an area, which causes the temperature of that area to change. Following Farley's reasoning, cool air advection slows down the clearing of stratus, while warm air advection accelerates the stratus burn-off. The type and amount of temperature advection depends both the wind speed and the temperature gradient between the local area and the area upwind. For example, if cool marine air is blowing from the northwest through the San Bruno gap towards SFO, advective cooling occurs. However, if southerly wind is blowing towards SFO, this wind could be warmer and drier due to the transport over heated land, and this may speed up stratus dissipation. How the wind varies can play a large role in the dissipation of Bay Area stratus, and therefore wind speed and direction data for the SFO area should be analyzed for building forecast models.

b. Cloud Layer Characteristics and Water Budget

Another assumption in the conceptual model is that the total water content in the marine layer stays constant

during the dissipation process. Clark and Wilson state that this is a reasonable assumption since dew point temperature in the Bay Area stays nearly constant in the morning. Dew point temperature is a proxy measure of water vapor content, and since over 95% of the water mass in the marine layer is vapor, a nearly constant dewpoint temperature implies nearly constant total water content. The removal of water from the marine layer as precipitation is ignored in this simple conceptual model because SFO averages only about one half inch of rain during the summer stratus season. The model therefore treats the stratus burn-off process a phase change of water from liquid to vapor (Fig. 8).

Another assumption of the model is that the density of liquid water in a stratus cloud increases linearly with height, from zero at the base of the cloud to a maximum value at the top of the cloud (Goodman, 1977). Figure 9 illustrates this assumption in the graph on the left, while the graph on the right shows that the total water content remains almost constant in the cloud. Figure 10 shows the liquid water profile of a stratus cloud schematically, and

we can see that the total liquid water content (LWC) can be calculated by finding the area of the shaded right triangle (A). D is the depth of the cloud layer, which is (cloud top height - cloud base height), so we can estimate the total liquid water of the cloud by this expression:

$$A = \frac{1}{2}(D)(LWC_{\max}) \quad (1)$$

$LWC_{\max}$ (LWC at top of cloud) is proportional to D because the liquid water profile increases linearly with height. Therefore the total liquid water content of the stratus cloud is proportional to the square of the depth of the cloud layer. Or in other words, the total liquid water content of a stratus layer increases quadratically with its thickness. This model considers the dissipation of stratus to be the phase change of liquid water to water vapor, so if one can estimate the amount of liquid water in the stratus cloud using the cloud thickness, this should help in forecasting the stratus burn-off. For this reason, the top and bottom of the stratus layer should be considered when building forecast models.

Figure 8: Conservation of total liquid water during stratus evaporation (Clark et. al., 1996)

Figure 9: Liquid water and total water profiles in marine layer (Duynerke et. al. 1995)

Figure 10: Total liquid water in a stratus cloud (Zwack and Tardif, 1998)

c. Radiative Processes

Section 1.b. describes how stratus forms overnight through radiative cooling and the lowering of the LCL. Stratus dissipation can be viewed as the warming of the marine layer through solar insolation until the LCL rises to the top of the marine layer. The marine layer has considerable turbulent kinetic energy (TKE), and therefore any absorbed energy is evenly dispersed through the layer in a short time. After the sun rises and incoming short-wave radiation reaches the top of the stratus deck, a fraction of the short-wave solar radiation is transmitted through the stratus layer and is absorbed by the ground. The ground is heated and emits long-wave radiation. This

surface heat flux heats the air above the ground, raises the LCL, and evaporates the cloud in the process. Other components of the radiative heat budget of the marine layer are the absorption of atmospheric long-wave radiation by the cloud, absorption of a portion of incoming short-wave radiation by the cloud, reflection of a portion of the incoming short-wave radiation by the cloud, and the emission of long-wave radiation from the top of the cloud. After sunset, the long-wave emission of radiation from the top of the cloud causes significant cooling as described in section 1.b. During the dissipation process however, the long-wave emission of the cloud decreases with decreasing cloud thickness, and the absorption of incoming short-wave radiation increases as the sun elevation angle increases. The heat budget of the marine layer is summarized in Figure 11.

At the time of this study, there were no historical measurements of all of these components of the heat budget. What were available were the times of sunrise at SFO and radiometer measurements, which report the ratio of incoming solar short-wave radiation (I_{inc}) to transmitted solar

short-wave radiation at the surface (I_{sfc}). This ratio increases from zero to one after the sun rises and the stratus dissipates. This ratio should be considered in building forecast models because the ratio of I_{inc} to I_{sfc} is proportional to the liquid water content in the cloud (Fig. 12).

Figure 11: Marine layer heat budget.

Figure 12: Liquid water path and amount of surface short-wave radiation (Zwack and Tardif, 1998)

d. Changing Inversion Base Height

An assumption of the conceptual model is that the top of the stratus layer is the same height as the inversion base (Clark and Wilson, 1996). The inversion base is the result of synoptic-scale subsidence of the high-pressure area described in section 1.a. The height of this inversion will therefore depend on the characteristics of the high-pressure area. As described in section 1.a., the high-pressure area is generally very stable, but there are some phenomena that can change the inversion height significantly in a period of hours.

On the synoptic scale, this can be passing of fronts, troughs, or vorticity maxima. The arrival of these features results in a rising of the inversion base, and the inversion base lowers after they pass. Mesoscale processes that cause short-term changes in the inversion base height include the passing of gravity waves and local divergence. Atmospheric gravity waves typically have a period of 30-90 minutes and manifest themselves as a fluctuation in the inversion base height that can possibly impact the dissipative process. Divergence of surface

winds caused by horizontal gradients of friction or topography along with horizontal pressure gradient changes can lower the inversion base and impact the dissipation of stratus (Fig 13). The trend of inversion height should therefore be considered when building the forecast model.

Figure 13: Local divergence resulting in lowering of stratus over the Bay (Wilson, et. al., 1996)

6. Impact of Stratus on SFO

SFO is located on the western shore of the San Francisco Bay (Figure 14, left). All air traffic arriving at SFO is merged into an approach corridor or "zone" that begins where the runways end and extends about 15 miles ESE of the airport (Figure 14, right).

Due to the mountainous terrain to the east and west of SFO, the air traffic merges into the approach zone at an altitude of about 3500 feet. When visibility is excellent, arriving aircraft are permitted to enter the approach zone

in side-by-side pairs and make parallel, or "side-by" (SBY) landings simultaneously on runways 28L and 28R, which are spaced about 750 feet apart (Figure 15). During periods of excellent visibility, SFO can land a maximum of about 60 aircraft per hour using parallel visual approaches (VAPS). If the visibility is not excellent, but still sufficient for aircraft to see each other during a SBY approach, SBY landings are permitted, but visual flight rules (VFR) are in effect, and the landing rate drops to about 45 aircraft per hour. When visibility is very poor, i.e., the slant-range visibility is less than 5 miles, instrument flight rules (IFR) are in effect and SFO can no longer accept SBY approaches. During IFR, arriving aircraft must land one at a time, and this reduces the landing rate to a maximum of 35 planes per hour.

Figure 14: SFO airport and Approach Corridor.

Figure 15: SFO Runways 28R, 28L and Approach Trajectory.

SFO has the greatest annual number of IFR events of any US airport, and Figure 16 shows that low cloud ceilings cause most of these events. Low cloud ceilings at SFO usually result from the lowering of stratus cloud bases as shown in Figure 4. For SFO, IFR is in effect for cloud ceilings less than 2500 feet. If the cloud ceiling is less than 3000 feet and not less than 2500 feet, SBY approaches are permitted under VFR. The minimum cloud ceiling for VAPS is 3000 feet.

Figure 16: Number and Type of IFR events by airport (Clark, 1995).

Figure 17 (upper) shows the typical summer weekday traffic at SFO, and one can see the impact of IFR conditions. The air traffic exceeds the IFR capacity several times during the day, especially between 10:00 a.m. and 1:00 p.m. PDT. Figure 17 (lower) shows the typical summer hourly transitions between VFR and IFR. IFR to VFR represents stratus dissipation, while VFR to IFR represents the development of low stratus bases. One can see that the most frequent time of stratus development is between midnight and 6:00 a.m. PDT, which corresponds with light traffic at SFO. The most frequent period of stratus burn-off is between 8:00 a.m. and 12:00 p.m. PDT, which corresponds with the heavy morning traffic. The most frequent burn-off time occurs around 10:00 a.m. PDT.

Figure 17: Hourly SFO Traffic and Ceiling Transitions.

The Traffic Management Unit (TMU) at the Oakland Air Route Traffic Control Center (ARTCC) makes decisions that affect SFO air traffic. TMU anticipates the available SFO capacity and communicates with the national Air Traffic Control System Command Center to help regulate the incoming flow of traffic. If the airport capacity is reduced due to weather, delay programs go into effect, which usually result in flights being held at airports further upstream. TMU's goal is to correctly match anticipated demand with available capacity so that any delay time is minimized. The Oakland Central Weather Service Unit (CWSU) provides

the TMU with forecasts of when weather conditions will improve or worsen so that changes in capacity can be estimated.

During the summer, the CWSU is very busy forecasting the morning stratus burn-off time so that the rush of traffic after 10:00 a.m. can be handled appropriately by the TMU. It is hoped that the results of this study can aid CWSU in making improved forecasts. Improved forecasts of stratus burn-off will result in fewer delay hours, and since SFO is a major hub for both national and international air traffic, reductions in delays can translate to savings on the order of millions of dollars annually.

B. Statistical Forecasting Models

1. Previous Studies

There have been several studies that involve forecasting the dissipation of summer stratus at SFO. The most recent studies at the time of this work were John Farley (Farley, 2000), MIT/Lincoln Laboratory (MIT/LL, ongoing), and Hilliker & Fritsch (H&F, 1999). These studies presented objective statistical forecast models for SFO that were developed using historical data. Each study used regression methods to develop their forecast models, but each used different types of regression, different sets of historical data, and different methods of predictor selection.

a. John Farley

Farley's models used predictors derived from ceiling heights and acoustic radar (sodar) data at both SFO and San Carlos Airport (SQL), and used digitized visible satellite data for the Bay Area. MIT/LL produced inversion heights (Z_i) from the raw sodar data using a special algorithm. The sodar measurements are discussed further in section B.3.a.

Farley's models forecasted the time after sunrise when Side-By landings (SBY) began at SFO, i.e., the transition from IFR to VFR. He developed models that gave hourly forecasts from 14Z (7:00 AM PDT) through 16Z (9:00 AM PDT).

Farley's models were developed using ordinary linear regression, which produces models of the following form:

$$Y = C_0 + C_1X_1 + C_2X_2 + \dots + C_{p-1}X_{p-1} \quad (2)$$

In (2), Y is the response variable (for Farley, hours to SBY after sunrise), X_i are the predictors, and C_i are the derived coefficients. The model has a total of p terms: $(p-1)$ predictors and one constant term C_0 . The number of historical stratus burn-off cases used to derive the coefficients is the sample size n . When using statistical methods like regression, having large degrees of freedom (df) is desirable because it means more information will be used in making our forecasts. In this case, df is simply the following:

$$df = n - p \quad (3)$$

If one wants large df for models, one should use as many historical cases as possible (large n), but one should

strive to keep the number of predictors in the model at a minimum (small p).

The linear regression procedure finds the set of coefficients that minimize the model's Mean Squared Error (MSE). To find MSE for a model, one uses the model to make forecasts for each of the cases that were used in developing the model. Then these forecasted values are compared to the actual observed values by calculating the error for each case:

$$Error_i = (Forecast_i - Observed_i), \text{ where } i = 1 \text{ to } n \quad (4)$$

Then one finds the Sum of Squared Errors (SSE), and finally the MSE. Note that a large df produces a small MSE:

$$SSE = \sum_1^n (Error_i)^2 \quad \text{and} \quad MSE = \frac{SSE}{df} \quad (5)$$

To decide which predictors were included in his models, Farley used an approach developed by MIT/LL: a forward-stepwise procedure that added one predictor at a time to a model. Starting with a historical record of SBY

times for SFO, he calculated the average SBY (climatological SBY) that occurred after each forecast hour. He then used this conditional climatology to predict SBY over the historical period, and calculated the forecast error for each stratus burn-off event. Next, he calculated a Pearson correlation coefficient (r) between the errors and every potential predictor X for the n stratus cases:

$$r = \frac{\sum_1^n (X_i - \bar{X})(Error_i - \overline{Error})}{\sqrt{\left(\sum_1^n (X_i - \bar{X})\right)\left(\sum_1^n (Error_i - \overline{Error})\right)}}, \text{ where}$$

$$\bar{X} = \frac{\sum_1^n X_i}{n} \quad \text{and} \quad \overline{Error} = \frac{\sum_1^n Error_i}{n} \quad (6)$$

The value of r can vary from -1 to 1. An r value close to 1 or -1 means that the two variables are highly correlated, and a value of r close to zero means that the variables have a low correlation. The predictor with the largest magnitude of correlation was Farley's first predictor in his model. Using MS Excel's Solver function, he created a model with this one predictor and a constant term. He then used this model to forecast SBY over the historical period, and he correlated the forecast errors

with all of the remaining predictors. The next predictor he chose for his model had the highest magnitude of correlation with the new forecast errors. This process was repeated until Farley had a model with several predictors.

Farley used historical data for the months of May through October in 1996 and 1997, and evaluated his models on stratus burn-off events in May through October of 1998. He had three types of models: a "Zi-Ceiling" model that used Z_i (cloud tops) and lowest ceiling heights (cloud bases) as predictors, a "Cloud" model that used satellite data as predictors, and a "Combo" model that used Z_i , lowest ceiling heights, and satellite data as predictors.

b. MIT Lincoln Laboratories

MIT/LL's predictors were derived from digitized visible satellite data for the Bay Area, and also derived from the following data at SFO, SQL, and the San Mateo Bridge (SMB): lowest cloud ceiling heights, sodars, radiometers, and winds. MIT/LL derived Z_i from the raw sodar data. They also maintained their own anemometers at

SFO and SQL that reported instantaneous wind data every five minutes. This historical data set was used to create a Local Model that made a forecast using only the data from SFO, SQL, and SMB, and a Satellite Model that only used satellite data for a forecast.

For their predictor selection, MIT/LL used an iterative process where the first step has all potential predictors in the model, and each successive step results in one or more predictors being set to zero ("nulled") until a satisfactory model with a small set of predictors is found.

MIT/LL developed Local and Satellite models for each forecast hour from 13Z through 18Z using this nulling method. They used historical data for the months of May through October for 1996 through 2000, and their models gave hourly real-time operational forecasts from 13Z through 18Z for the summer of 2001. These forecasts were available to the Oakland CWSU to aid them in making their own forecasts. The MIT/LL Local Models used predictors similar to Farley's Zi-Ceiling model, but they had

additional predictors for wind and radiometer data. Their Satellite model used predictors similar to Farley's satellite model.

MIT/LL improved upon the ordinary linear regression techniques used by Farley by using a method developed by Wes Wilson of MIT/LL that is dubbed "Pre-Scaled Additive Modeling" (PAM). It is a variation of an established statistical technique called Generalized Additive Modeling (GAM). GAM produces models with predictors that are allowed to exhibit nonlinear behavior. It does this by developing "structure functions" that scale the predictors nonlinearly; i.e., the forecast can be more sensitive to certain ranges of a predictor, and some ranges might not influence the forecast at all. In ordinary linear regression, the forecast is equally sensitive to all values of a predictor. The nonlinear predictor behavior can reduce MSE even more than ordinary linear regression; however, large amounts of historical data are needed to develop the structure functions because the total number of terms in the model increases by orders of magnitude. Wilson estimated that at least 16 years of historical data

would be needed if conventional GAM were used to develop stratus-forecasting models in the Bay Area (Wilson, personal communication).

Wilson developed the PAM procedure so that a similar nonlinear scaling method could be employed without such a large data requirement. PAM produces structure functions that rescale predictors, but these functions are greatly simplified from the GAM functions. Figure 18 shows an example of linear scaling versus a PAM nonlinear scaling with a structure function, using the time of sunrise at SFO as a predictor. The dots represent values of SFO sunrise time (UTC) for the historical stratus burn-off days from May through October, for the years 1996-2000. Steeper slopes of line segments mean that the forecast is more sensitive to changes in predictor values in that range. Line segments with zero slope mean that changes to values of the predictor in these ranges don't influence the forecast. The PAM method is discussed in more detail in section B.3.d.

Figure 18: Linear scaling (left) and Nonlinear scaling (right).

c. Hilliker & Fritsch

H&F used hourly Surface Aviation Observations (SAO) in the Bay Area and radiosonde data from Oakland from 1982-1993 to develop their models. The SAO consist of surface measurements of temperature, dew point, wind speed and direction, cloud cover, ceiling height, visibility, and precipitation. The radiosonde data set is a record of heights, humidity, and wind data at eight standard pressure levels between 1000mb and 500mb. The H&F study used logistic regression to develop their models. This is another method of scaling each predictor X_n nonlinearly, but

it was completed using the specialized software S-PLUS, and the details of how the predictors were scaled were not reported. Their final model has the following form:

$$Y = \{1 + \exp[-(C_0 + C_1X_1 + C_2X_2 + \dots + C_{p-1}X_{p-1})]\}^{-1} \quad (9)$$

Logistic regression reduces the MSE more than ordinary linear regression because the response variable Y is restricted to a number in the interval $[0,1]$. This restriction makes logistic regression the standard method for producing probability forecasts (Wilson, personal communication). For example, a model output close to zero means that an event is very unlikely to occur, and an output close to one means an event is very likely to occur. For H&F, the event is a low cloud ceiling at SFO. H&F developed models that forecast the probability of a low SFO ceiling (≤ 3000 ft) existing within given time intervals from the forecast hours 12Z through 17Z, when IFR conditions at SFO already existed at the time of the forecast.

H&F differs significantly from the previous two studies in their use of binary variables as predictors and their method of predictor selection. Their binary variables were derived from the surface and upper-air observations, and below is an example of a binary variable V_3 derived from visibility:

$$\begin{aligned} V_3 &= 1 \text{ if (Visibility} \leq 3 \text{ miles)} \\ V_3 &= 0 \text{ otherwise} \end{aligned} \quad (10)$$

Their predictor selection method focused on the strength of the contribution of each predictor in a model. The measure of this strength is a standard statistic known as an F-ratio (F). To compute F for a predictor, one first calculates forecasts with that predictor in the model, and then calculates forecasts with that predictor removed from the model, and then one calculates the differences in these forecasts. These differences are individually squared and then added together to produce a Regression Sum of Squares (SSR) :

$$SSR = \sum_1^n (Y_i - \hat{Y}_i)^2, \text{ where}$$

Y_i = Forecast with the predictor

$\hat{Y}_i$ = Forecast without the predictor

(11)

SSR represents the information that a predictor is contributing to the forecast, so SSR should be "large" for every predictor in the model. One decides how large SSR is by comparing it to the MSE with all predictors in the model:

$$F = \frac{SSR}{MSE} \quad (12)$$

A large F-ratio means that the predictor is contributing meaningful information to the forecast, while a small F-ratio means that the predictor is not contributing to the forecast.

To build their models, H&F added one predictor at a time to their model in a stepwise fashion that is similar to Farley's method. However, they used values of F instead of correlations as their criteria: predictors that were selected for their models have F-ratios of at least 10.

d. Motivation

The purpose of this study is to build on the previous studies' methods and create a method for building more accurate forecasting models. The first step taken towards this goal was to critique each study and determine if the historical data, methods of predictor selection, and model building techniques were appropriate or could be improved.

As discussed in Section A.5, the primary physical processes that contribute to stratus burn-off are cloud layer features, radiation, advection, and inversion base height. The H&F models lack predictors that are direct measures of radiation and inversion height, and Farley's models lack predictors related to radiation and advection. MIT/LL uses predictors related to all four processes to develop their models. Therefore, this study follows MIT/LL's example and considers predictors related to all four processes.

Farley's predictor selection method using correlations is a useful way of finding strong candidates for inclusion

in a model, but a more statistically rigorous method is needed for deciding which predictors actually go in the model and which should not. Correlation coefficients are the basis for his predictor selection, but there is no accounting for the sample size. For example, a correlation using a sample of 100 has much less error and is more useful than one using only 10 numbers. He states that he added predictors to a model until additional predictors had no "meaningful" contribution. He doesn't present an objective method for deciding when this point is reached. It is also possible that when new predictors are added to the model, previously-added predictors are no longer useful. He does not check this when he develops his models.

MIT/LL's nulling method for predictor selection overcomes these shortcomings of Farley's approach, but there are many subjective steps in its operation. Two individuals working with the same set of predictors could produce two different models with small MSE. In this case, it would be difficult to determine which model's predictors represent the most important physical processes

contributing to stratus dissipation at a given forecast time.

Meteorologists need to understand the physical processes contributing to stratus dissipation, and a forecast model should contain predictors that contribute useful information to the forecast and have a meaningful physical interpretation. MIT/LL's nulling procedure and H&F's F-ratio approach both attempt to find predictors that contribute the most information to the forecasts. At the time of this study, H&F's F-ratio approach seemed more objective than the nulling procedure, so this study used an F-ratio criterion similar to H&F's.

Farley and MIT/LL's models were developed to forecast the number of hours after sunrise until SBY at SFO. This means that the sunrise time is always a linear predictor with a coefficient of one in all of their models. It's possible that the contribution of the sunrise time may be nonlinear, or the sunrise time may not be a useful predictor for some forecast hours. This study treats sunrise time the same as every other predictor candidate:

it has to pass an F-ratio test to be included in the forecast models.

The nulling method of MIT/LL resembles a backward-stepwise procedure, where all predictors are included in the model in the first step, and then they are systematically eliminated. The drawback to this type of procedure is that one cannot have any missing values of predictors over the historical period. The entire historical sample of stratus dissipation events is thus reduced to a smaller sample of days where each potential predictor had a value. Farley's and H&F's methods were forward-stepwise procedures that are more appropriate for real-world meteorological data sets that frequently have gaps in the record. This study used a forward-stepwise procedure for this reason.

Meteorological phenomena can be highly nonlinear, so a forecast model should include some nonlinear predictors. The H&F nonlinear method restrained the forecast to the interval $[0,1]$, which was interpreted as the probability of low ceilings at SFO. This probability can be useful, but

the actual approach zone is 5-15 miles from SFO. It's possible that stratus is burned off at SFO while stratus still lingers in the approach zone. This study follows Farley and MIT/LL's example and forecasts the time of SBY at SFO, which is exactly what the TMU needs to know in order to manage the air traffic. The MIT/LL PAM method allows predictors to behave nonlinearly, but does not restrain the forecast to $[0,1]$. Also, PAM does not require specialized software or a lot of historical data. For these reasons, the PAM method was used to scale the model predictors. This study applies PAM to the sunrise time when it was used as predictor, while MIT/LL does not. This study also follows H&F's example and uses some binary variables as predictors.

In conclusion, this study uses a nonlinear-scaling regression approach with a forward-stepwise F-ratio criterion for all potential predictors to produce models that forecast SBY at SFO. This method is practical for the model builder who deals with real-world meteorological data, practical for the end user who manages air traffic at SFO, and useful to the meteorologist who is interested in

the most significant factors that contribute to stratus dissipation at a certain time.

2. SJSU Methodology

a. Historical Data and Potential Predictors

Historical data related to the four previously discussed processes of stratus dissipation were gathered from the three closest stations to the SFO approach zone: SFO, SQL, and SMB. For the years 1996 through 2000, hourly surface observations for the months of May through October (the summer stratus season) were used to develop forecast models for every hour from 13Z through 18Z.

The years 1996-2000 were chosen since these are the years that MIT/LL's acoustic radars (sodars) and radiometers at SFO and SQL were collecting data. The sodar emits a vertical pulse of sound, and some of the sound waves are reflected at the inversion base, where the speed of sound changes rapidly with air temperature from the cool marine layer below to the warm dry air above. The reflected sound is received at the sodar, and the elapsed

time between the emitted and reflected signal is used to calculate the inversion base height Z_i using an algorithm developed by MIT/LL.

The 5-minute anemometer wind observations and radiometer readings from MIT/LL's stations at SFO and SQL were also used in the historical database, and the data recorded at 55 minutes past the hour were used in order to match the time of the hourly SAO data at SFO, which were recorded at 56 minutes past the hour. The u and v components of all wind data were extracted as additional potential predictors, and the hourly trends of all the potential predictors became potential predictors as well. The complete list of potential predictors is in Appendix A.

b. Response Variable and Predictor Selection

The forecasted value in this study was the time of SBY occurring at SFO. The historical values of SBY for the period of May through October, 1996-2000, were provided by the CWSU and were used in the model development. This study uses the F-ratio for predictor selection, but it is

more lenient than H&F and allows predictors into the model with F-ratios of 9 or greater (rounded to the whole number). This was done because the number of potential predictors and historical cases is much smaller than in the H&F study. The steps for predictor selection are similar to Farley's (forward-stepwise), but an F-ratio is used instead of a correlation coefficient. Predictors with the largest F-ratios greater than 9 were selected one at a time, and if two or more potential predictors had similar F-ratios, the predictor that gave the most sample cases was chosen.

c. Binary Variable Predictors

The H&F study used binary variables derived from continuous meteorological variables like visibility, wind speed, and ceiling height. This SJSU study added binary variables to the potential predictor list, but they were based on the presence or absence of a cloud ceiling in the hourly observation at SFO and SMB (SQL did not report ceiling data). This was done because during a review of historical stratus cases, cases where a ceiling existed at these stations tended to have models with a lower MSE than

cases without a ceiling. The regression technique becomes more sophisticated for models that use both continuous and binary variables, so the statistics software JMP was used as a tool for developing the models. JMP gave F-ratios for both the binary and continuous variables, and all of the F-ratios and other statistics from building the models are listed in Appendix B.

d. Nonlinear Scaling (PAM)

The PAM procedure starts with a historical record of SBY times for SFO. If one is building a model that forecasts at 13Z, one calculates the average SBY (climatological SBY) that occurred after 13Z. This climatology is used to predict SBY over the historical period, and the forecast error is calculated for each case. Then one lets the PAM method scale the predictors to maximize the magnitude of correlation between each predictor and the climatological forecast error. There are four types of structure functions for rescaling the predictor: a function with zero, one, two, or three "knots". The function with zero knots is the most simple, and three knots is the most complex. The goal in PAM is to

use the simplest structure function that gives the greatest magnitude of correlation. The zero-knot and one-knot functions are used first for scaling, and there is a check to see if there is a significant increase in the magnitude of correlation when a knot is added to the function. If there is, the one-knot function is retained, and the procedure is repeated with the one-knot and two-knot functions. If the two-knot function doesn't give a significant increase in correlation, the one-knot function is kept.

As a brief example, consider the time of sunrise at SFO. The values of sunrise time in the historical record of 1996-2000 vary from 12.78Z to 14.74Z. Figure 19 shows two graphs that show a linear scaling of sunrise time to $[0,1]$, and a zero-knot structure function nonlinear scaling of the sunrise time to $[0,1]$, using the climatological SBY residuals at 13Z:

Figure 19: Linear scaling (left) and Nonlinear scaling (right).

The nonlinear scaling example in Figure 19 (right) uses a structure function with no "knots", i.e., there is only one straight-line segment that has a slope greater than zero. Functions with more knots did not improve the correlation between sunrise and the climatological forecast errors. Figure 19 (right) gives us a physical interpretation of the sunrise time. The sunrise time doesn't contribute any information to the forecast when it is earlier than 13.67Z, which corresponds to the months May through August. The forecast is very sensitive to the time of sunrise as it varies between 13.67Z and 13.94Z (most of September), and the maximum contribution to the forecast is for sunrise at 13.94Z or later (late September through

October). Figures 20 and 21 show examples of PAM that give structure functions with 1 and 2 knots respectively, and they were developed by correlating the predictors to 15Z SBY residuals.

The structure functions displayed in Figures 19-21 are the only types of functions that were used to scale the predictors: the three-knot function was not needed. When scaling the predictors with these structure functions, it was important to check that each line segment piece had a fairly even distribution of data. Extremely large or small data points ("outliers") can distort the PAM analysis, and were removed before developing the structure functions. A physical interpretation of the final predictors and their structure functions is given in section C.2.c., the final SJSU model equations are listed in Appendix C, and the structure functions for every predictor are listed in Appendix D.

Figure 20: Linear scaling (left) and Nonlinear scaling with 1 knot (right).

Figure 21: Linear scaling (left) and Nonlinear scaling with 2 knots (right).

C. 2001 Model Performance

1. MIT Lincoln Laboratories Stratus Forecast Models

During the 2001 stratus season (May through October), MIT/LL operated forecasting models that gave real-time forecasts at 13Z through 18Z. Along with their Local and Satellite models, there were several other models in operation: the COBEL, Regional, and Consensus models. The SJSU models in this study were developed from the same historical data and used the same set of potential predictors used by MIT/LL when they developed their Local model, and these models both gave forecasts for the same hours. This means that the SJSU models' 2001 performance can be compared directly to the MIT/LL Local models' performance to evaluate the effectiveness of the SJSU methodology versus MIT/LL. However, it is also useful to compare the performance of all stratus-forecasting models during 2001, since the best performing models may give some insight into important physical processes contributing to stratus burn-off.

a. COBEL Model

COBEL is a high-resolution 1-dimensional (column) numerical model of the planetary boundary layer that simulates the development and dissipation of marine stratus. This model is unique in the 2001 group because it is developed using the underlying physics of fog instead of statistics from historical data. A team from the University of Quebec at Montreal headed by Peter Zwack adapted COBEL for forecasting stratus dissipation from a model developed in Toulouse, France for forecasting fog behavior (Wilson and Clark, 2000).

COBEL is initialized at 12Z each morning with a vertical profile of temperature, humidity, and wind at San Francisco International Airport (SFO). The initialization uses a combination of the 12Z Oakland sounding and lower atmosphere measurements at SFO. This profile characterizes the total vertically-integrated liquid water content of the SFO stratus cloud layer.

As the model iterates, the model's physical processes simulate the decrease of the cloud liquid water with time. The COBEL forecast of the stratus dissipation is reported as the time when the liquid water content above SFO reaches zero. Since the model is adapted for a single point location, the forecast for that location (SFO) is then adjusted to account for the distance from the approach zone. This is done by correlating the historical cloud coverage data at SFO with the historical SBY records, and the final forecast reported by COBEL is the expected time of SBY at SFO.

COBEL is re-initialized hourly with updated measurements of surface temperature, humidity, wind, and solar radiation. This re-initialization adjusts the model's liquid water content so that it's consistent with the amount of solar radiation transmitted through the cloud layer. The model is re-run, and it provides a new forecast of SBY each hour.

COBEL includes most of the previously discussed physical processes involved in the dissipation of marine

stratus, as well as turbulence (with a 1.5 order closure of TKE), cloud, and drizzle parameterizations. What is missing from the current operational version of COBEL are dynamics for advection. Also, the model uses a Boussinesq approximation with constant subsidence (~ 1 cm/s), and a constant geostrophic wind (~ 2 m/s) is applied over the entire model domain (0 to 1.5 km). This makes COBEL inadequate for simulating stratus when there is significant mesoscale advection or synoptic-scale forcing at SFO.

b. Local Model

MIT/LL adapted Farley's Z_i -Ceiling models into operational models called the Local Statistical Forecast Model (LSFM), which were discussed in section B.1.b. As mentioned in sections B.1.a. and B.1.d., these models were developed in terms of the elapsed time after sunrise, so sunrise is included as a linear predictor with a coefficient of one in every model. The LSFM was developed to give forecasts from 13Z through 18Z. One drawback to the LSFM is a predictor set drawn from data only from the local SFO and approach zone area. This means that although synoptic-scale events could be reflected in time through

the hourly trends of local meteorological variables, the events would not be represented well in space due to the closeness of the stations used for the LSFM. Another drawback of the LSFM is that only a four-year sample of historical cases is used for model development.

c. Regional Model

MIT/LL combined their regression approach with the predictor strategy of Hilliker & Fritsch to produce the operational model called the Regional Statistical Forecast Model (RSFM). Unlike the LSFM, the RSFM uses surface and upper air data from the entire Central California region. There are two stages to the model. In the first stage, these weather observations are used as predictors for forecasting the probability of low cloud ceilings at both SFO and SQL. In the second stage, these probabilities are correlated with the historical database of SBY times to determine the most likely time for SBY at SFO. The RSFM forecast is the time when the probability of no overcast or broken cloud layers $\leq$ 4000 feet at both SFO and SQL is 50%.

The RSFM uses information about the inversion height and strength based on the 12Z Oakland sounding, but does not include the hourly Z_i measurements from sodars or radiometer data as predictors. However, the large spatial extent of its predictor locations can account for synoptic-scale phenomena, and the large historical database (16 years) provides enough stratus cases for building a model with many scaled predictors using a standard GAM technique. MIT/LL developed an operational Data Quality Analysis (DQA) that was used for the training (historical) data and is being used for the real-time data used for forecasting (Wilson, personal communication). There is a drawback to having a model with many predictors like the RSFM. As more predictors are used to make a forecast, the chance increases that data for at least one predictor will be unavailable, and the model will not forecast. The potential reliability of the model is therefore reduced.

d. Satellite Model

MIT/LL adapted Farley's Cloud models into the Satellite Statistical Forecast Model (SSFM). This model is based on the correlation between GOES-10 visible satellite

imagery for the Bay Area and the historical record of SBY times at SFO. A major limitation of the SSFM is that it cannot forecast before sunrise or when the sun angle is too low. This prevents a forecast at 13Z for the entire season, and prevents a forecast at 14Z as well for late August through October. Therefore, the SSFM forecast is only used from 15Z to 18Z.

There are three major steps involved in the generation of the SSFM forecasts. The first is a data pre-processing step to optimize the quality of the data being used for analysis. For example, the data are normalized for sun angle so that changes in brightness correspond to changes in cloudiness rather than the changing sun angle. The second step is a grouping of the gridded satellite data points into "sectors" that are geographically homogeneous (Figure 22). In the final step, the evolution of the cloudiness within each sector is correlated with the SBY times. The SSFM allows a large aerial perspective of the behavior of clouds in the Bay Area, but it is also sensitive to the availability and calibration of the GOES satellite data. The predictors of the SSFM are statistics

for the sample of data within each sector, and include the mean and standard deviation of the brightness values, and the percent of cloud coverage within a sector.

Figure 22: Potential predictive sectors for the SSFM.

e. Consensus Model

The Consensus Model is derived from the forecasts of the previous four models, and it provides a single unified forecast of the time of SBY at SFO. Generation of the Consensus Forecast is a three-step process. First, specific weather observations are examined to classify the

day as a particular meteorological "type". The day type is classified at 13Z from the quality of the inversion height estimates, which is computed by MIT/LL from the 12Z Oakland sounding and sodar data, and from the 925mb wind speed from the Oakland sounding. The day type is classified again at 15Z using the "texture" of SFO cloudiness. This texture is quantified by examining the standard deviation of the brightness values in the satellite sectors over the Pacific Ocean (Fig. 22). Low standard deviations correspond to smooth texture, and the texture becomes more ragged with increasing standard deviation.

The second step is a calculation of the Consensus Forecast by weighting each of the four component forecasts based on their historical performance on each of the day types. If a model cannot give a forecast, its weight is zero. The final step is to quantitatively assess the Confidence in the resulting forecast. This is done by first using the current forecast weights to compute a hypothetical Consensus Forecast for each similar day type in the historical database and then comparing this forecast with the actual SBY time on those days. The Confidence is

computed as the fraction of days that the Consensus Forecast would have fallen within an "acceptable" range of error. A forecast is acceptable to the CWSU if the true time of SBY occurs no more than 30 minutes later than the forecast time and no more than 60 minutes before the forecast time.

MIT/LL claims that the best days for stratus forecasting (highest confidence) have high quality estimates of inversion heights, low 925mb winds, and smooth cloud layer textures. This corresponds with no synoptic-scale events, low advection, and no high cloud decks. The Consensus Model should be very reliable since it will give a forecast if at least one of the four component models gives a forecast.

2. Results

a. Measuring Model Performance

The performance of the 2001 models was evaluated by measuring their reliability and forecast error on the stratus days when there was a transition from IFR to VFR.

Days where IFR conditions lasted all day were not included since they are beyond the scope of this study. Note that after the 2001 stratus-forecasting season, days where IFR conditions lasted all day were combined with days where stratus burnoff occurred after 21Z, and classified as "late" burnoff days. On these days, a forecast was considered successful if it was after 21Z (Sinton, personal communication).

The reliability is estimated by counting the number of forecasts made by a model (n), and the forecast error is estimated by using the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE):

$$MAE = \frac{\sum_{i=1}^n |Error_i|}{n} \quad \text{and} \quad RMSE = \sqrt{\frac{\sum_{i=1}^n (Error_i)^2}{n}} \quad (13)$$

MAE assumes that the seriousness of the error increases linearly with the error, and the RMSE assumes that the seriousness of the error increases quadratically with the error. Forecasters often use the MAE, but the RMSE has a useful property: it takes into account both the bias and precision of the model's forecasts. Bias is

measured by the average of the forecast errors, and precision is measured by the standard deviation of the forecast errors. Below are formulas for Bias, Precision, and their relationship to RMSE:

$$Bias = \frac{\sum_1^n Error_i}{n}, \quad Precision = \sqrt{\frac{\sum_1^n (Error_i - Bias)^2}{n}}$$

and $RMSE = \sqrt{(Bias)^2 + (Precision)^2} \quad (14)$

Ideally unbiased and precise models are desirable, which correspond to a low RMSE. In this study, the RMSE is the primary measure of a model's error, but the MAE is also included for completeness.

Figure 23 compares the RMSE and MAE of the unscaled and scaled SJSU models (red and green, respectively) using all 398 forecasts for 2001. The PAM scaling reduced total RMSE by 20% and total MAE by 15%. This shows that the PAM procedure is an effective tool for reducing forecast error.

2001 Model Performance for all 398 SJSU Forecasts

Figure 23: RMSE (top) and MAE (bottom) for SJSU (red) and SJSU-Scaled Models (green).

b. SJSU Nonlinear models vs. MIT/LL Models

The SJSU PAM-scaled model errors were compared to the five operational MIT/LL model errors using RMSE and MAE as measures of error. For the period of May through October of 2001, there were a total of 85 stratus days with a reported time of SBY occurring (IFR to VFR).

Figure 24 shows that the SJSU Scaled models clearly have the best overall 2001 performance in terms of reliability and error. SJSU has the most forecasts, lowest RMSE, and lowest MAE. The Consensus model is in second place in both reliability and error. The Satellite and COBEL models have the least number of forecasts, and the Satellite model has the most error.

These results show that the SJSU methodology was sound. This methodology was focused on the individual contributions of each predictor to the forecast and included only a minimum amount of predictors in each model. The Regional and Consensus models use a larger number of predictors, but their overall error is larger.

Figure 24: RMSE (top) and MAE (bottom) for all models.

c. SJSU: Physical Interpretations and Structure Functions

(1) 13Z

Below is the equation of the SJSU 13Z Scaled Model,
with the predictors in bold typeface:

$$\begin{aligned} \text{UTC_SBY} = & 17.00 + 1.06 * (\text{UTC_Sunrise}) \\ & + 1.24 * (\text{1300_SFO_Zi}) \\ & + 1.26 * (\text{1300_SQL_U}) \\ & + \begin{cases} -0.37 & \text{if } \text{1300_SFO_Cig} = \\ & \text{"no"}, \\ 0.37 & \text{if } \text{1300_SFO_Cig} = \\ & \text{"yes"} \end{cases} \end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
UTC_Sunrise is the SFO sunrise time (in UTC),
1300_SFO_Zi is the 13Z SFO inversion height (m),
1300_SQL_U is the 13Z SQL U wind component (m/s),
1300_SFO_Cig is the presence/absence of ceiling at
SFO.

(15)

The coefficients of the predictors in (15) indicate how the predictors influence the forecast. Later times of sunrise, higher inversion heights, faster westerly winds, and cloud ceilings at SFO all result in later SBY times. Later times of sunrise mean that the marine layer will take longer on average to heat up and dissipate stratus. A

higher inversion height means a thicker marine layer and a greater volume of air to heat up. Faster westerly winds means that there is more cool advection taking place, which impedes stratus burnoff. A ceiling at SFO means that there's more cloud liquid water to be evaporated, and also means that less solar radiation will reach the ground to heat the marine layer. Figure 25 shows the PAM structure functions for the SJSU 13Z predictors.

Figure 25: PAM structure functions for SJSU 13Z predictors.

The 13Z structure functions all have a similar shape, with zero knots. As was discussed in section B.2.d, the sunrise time doesn't add any time to the forecast when it is earlier than 13.67Z, which corresponds to the months May through August. Forecast time is added very quickly as the time of sunrise increases from 13.67Z and 13.94Z (most of September), and the maximum time added to the forecast is for sunrise at 13.94Z or later (late September through October).

For the 13Z SFO Z_i , the structure function reveals that the forecast is not affected by an inversion height less than 371 meters. Time is quickly added to the forecast as Z_i increases from 371 meters to 746 meters. No additional time is added to the forecast for Z_i greater than 746 meters. This height range is comparable to the elevation range of the coastal mountains to the west of SFO.

A physical interpretation of this is that when Z_i is at the same height as the coastal mountains or below them, they act as a barrier to the cool marine air. When the Z_i begins to rise above the elevation of the mountain range,

it is analogous to slowly opening a "door" and letting cold air enter a room. The resulting cool advection impedes the stratus dissipation. When the Z_i surpasses the mountains by a certain amount, the "door" is fully open and any further rise in Z_i provides no additional effect.

The 13Z SQL U wind is derived from the MIT/LL anemometer data. Its structure function indicates that the forecast is not affected by a U wind with speed less than +2.8 m/s. Time is quickly added to the forecast as the U wind speed increases from +2.8 m/s to +5.2 m/s. No additional time is added for a U wind speed greater than +5.2 m/s.

A physical interpretation is that cool advection adds significant time to the forecast when the U wind exceeds +2.8 m/s. The maximum effect of cool advection is for a wind of +5.2 m/s. Figure 26 shows a windrose analysis of the historical 13Z winds from the MIT/LL SQL anemometer (1996-2000). The most frequent wind direction is W and WNW, with the most frequent wind speeds being 2.8 m/s to 5.2 m/s.

If there is a ceiling reported at 13Z at SFO, an extra 22 minutes are added to the forecast. If there is no ceiling, 22 minutes are removed from the forecast. So the difference between a 13Z SFO ceiling and no 13Z SFO ceiling is 44 minutes. Physically, the presence of a ceiling means that the cloud layer is well developed with more liquid water than if a ceiling is absent. More liquid water will require more time to evaporate, and will also reduce the amount of solar radiation reaching the ground.

Figure 26: Windrose of Historical 13Z MIT/LL Anemometer Data at SQL.

(2) 14Z

Below is the equation of the SJSU 14Z Scaled Model,
with the predictors in bold typeface:

$$\begin{aligned} \text{UTC_SBY} = & 16.44 + 1.24 * (\text{UTC_Sunrise}) \\ & + 1.33 * (\text{1400_SFO_Zi}) \\ & + 1.18 * (\text{1400_SQL_}|\vec{V}|) \\ & + \{-0.50 \text{ if } \text{1400_SFO_Cig} = \\ & \quad \text{"no"}, \\ & \quad 0.50 \text{ if } \text{1400_SFO_Cig} = \\ & \quad \text{"yes"}\} \\ & + \{-0.35 \text{ if } \text{1400_SMB_Cig} = \\ & \quad \text{"no"}, \\ & \quad 0.35 \text{ if } \text{1400_SMB_Cig} = \\ & \quad \text{"yes"}\} \end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
UTC_Sunrise is the SFO sunrise time (in UTC),
1400_SFO_Zi is the 14Z SFO inversion height (m),
1400_SQL_ $|\vec{V}|$ is the 14Z SQL wind speed (m/s),
1400_SFO_Cig is the presence/absence of ceiling at
SFO.
1400_SMB_Cig is the presence/absence of ceiling at
SMB.

(16)

For 14Z, (16) indicates that later times of sunrise,
higher inversion heights, greater wind speeds, and cloud

ceilings at SFO and SMB all result in later SBY times. The physical interpretations of these predictors are similar to those for 13Z. Figure 27 shows the PAM structure functions for the SJSU 14Z predictors.

Figure 27: PAM structure functions for SJSU 14Z predictors.

The 14Z structure functions are similar to those for 13Z except for 14Z SQL wind speed, which is almost linear. Time is added to the 14Z forecast when the wind speed is greater than 1.7 m/s. Figure 28 shows a windrose analysis of the historical 14Z winds from the MIT/LL SQL anemometer (1996-2000).

Figure 28: Windrose of Historical 14Z MIT/LL Anemometer Data at SQL.

The most frequent 14Z wind direction is W, which explains why wind speed was chosen as a predictor and not

the U component. A presence/absence of 14Z SFO ceiling adds/subtracts 30 minutes to the forecast, and presence/absence of 14Z SMB ceiling adds/subtracts 21 minutes to the forecast.

(3) 15Z

Below is the equation of the SJSU 15Z Scaled Model, with the predictors in bold typeface:

$$\begin{aligned}
 \text{UTC_SBY} = & 19.05 + 1.13 * (\text{UTC_Sunrise}) \\
 & + 0.97 * (\text{1400_SFO_Zi}) \\
 & + 0.70 * (\text{1500_SQL_U}) \\
 & - 2.90 * (\text{1500_SFO_RR}) \\
 & + \begin{cases} -0.25 & \text{if } \text{1500_SMB_Cig} = \text{"no"}, \\ 0.25 & \text{if } \text{1500_SMB_Cig} = \text{"yes"} \end{cases}
 \end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
UTC_Sunrise is the SFO sunrise time (in UTC),
1400_SFO_Zi is the 14Z SFO inversion height (m),
1500_SQL_U is the 15Z SQL U wind component (m/s),
1500_SFO_RR is the 15Z SFO Radiometer Ratio (RR), and
1500_SMB_Cig is the presence/absence of ceiling at
SMB.

(17)

For 15Z, (17) reveals that later times of sunrise, higher inversion heights, greater wind speeds, and cloud ceilings at SMB all result in later SBY times, and higher values of RR result in earlier SBY times. During the predictor selection process for 15Z, the 14Z SFO inversion height had a slightly larger F-ratio than the 15Z SFO inversion height. This was probably because the 14Z Z_i is the first value of inversion base height after the climatological sunrise time of 13.33Z. The RR is the fraction of incident sunlight that reaches the surface, and is proportional to the liquid water content of the stratus layer, so higher values of RR mean there is less liquid water to evaporate, less solar radiation is heating up the marine layer, and the burnoff time is likely to be earlier. Figure 29 shows the PAM structure functions for the SJSU 15Z predictors.

Figure 29: PAM structure functions for SJSU 15Z predictors.

The structure functions for sunrise time and Z_i resemble those from earlier forecast times, but the structure functions for the 15Z SFO RR and 15Z SQL U wind speed have new shapes: the RR function has one knot, and the U function has two knots. The structure function for

RR has a convex shape, and it shows that the forecast is most sensitive to RR when it varies between 0 and 0.27, and less sensitive when it varies between 0.27 and 0.84. No additional time is added to the forecast when RR exceeds 0.84. It is interesting to compare the RR structure function with the graph in Figure 30, which shows a relationship between cloud depth, RR, and liquid water content. In Figure 30, the contours of liquid water content are further apart for larger values of RR, which means that the change of liquid water content is more sensitive to changes in RR when RR is small. This is consistent with the structure function of RR.

Figure 30: Cloud depth, RR, and liquid water content (Zwack and Tardif, 1998).

The structure function for the U wind in Figure 29 has three distinct "steps". The first step shows that the U wind adds no time to the forecast when the speed is less than -1.3 m/s. A negative U wind means that the wind has an easterly component, which prevents cool advection from the ocean and hastens the stratus burnoff. Time is quickly added to the forecast when the U wind speed increases from -1.3 m/s to -0.9 m/s, and the time added to the forecast is constant as the U wind varies from -0.9 m/s to 3 m/s. So when the wind gains a westerly component, cool advection is returning and impeding the stratus burnoff. Additional time is quickly added to the forecast as the U wind increases from 3 m/s to 3.6 m/s, and no additional time is added to the forecast when the U wind is greater than 3.6 m/s. The structure function is adding time to the forecast because more cool advection occurs at larger values of U.

Figure 31 shows a windrose analysis of historical 15Z winds at SQL. The most frequent direction is WSW. Figures 26, 28, and 31 show that from 13Z to 15Z, the climatological wind direction rotates towards the south, and higher wind speeds become more common. This is

probably why the 15Z U wind structure function has two levels of positive U wind speed.

Figure 31: Windrose of Historical 15Z MIT/LL Anemometer Data at SQL.

(4) 16Z

Below is the equation of the SJSU 16Z Scaled Model,
with the predictors in bold typeface:

$$\begin{aligned}
\text{UTC_SBY} = & 19.88 + 1.72 * (\text{UTC_Sunrise}) \\
& + 0.60 * (1600_SQL_Zi) \\
& + 1.01 * (1400_SFO_dU/dt) \\
& - 2.06 * (1600_SFO_RR) \\
& - 1.67 * (1600_SQL_RR) \\
& + \{ -0.26 \text{ if } 1600_SMB_Cig = \\
& \qquad \qquad \qquad \text{"no"}, \\
& \qquad \qquad \qquad 0.26 \text{ if } 1600_SMB_Cig = \\
& \qquad \qquad \qquad \text{"yes"} \}
\end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
 UTC_Sunrise is the SFO sunrise time (in UTC),
 1600_SQL_Zi is the 16Z SQL inversion height (m),
 1400_SFO_dU/dt is the change in SFO U wind speed from
 13Z to 14Z (m/s),
 1600_SFO_RR is the 16Z SFO Radiometer Ratio,
 1600_SQL_RR is the 16Z SQL Radiometer Ratio, and
 1600_SMB_Cig is the presence/absence of ceiling at
 SMB.

(18)

For 16Z, (18) indicates that later times of sunrise,
 higher inversion heights, increases in U wind speed, and
 cloud ceilings at SMB all result in later SBY times, and
 higher values of RR result in earlier SBY times. These are
 all similar to the 15Z model.

Figure 32 shows the PAM structure functions for the SJSU 16Z predictors. The sunrise time structure function has a less steep sensitive area, and the forecast is sensitive to all sunrise times later than 13.63Z, which corresponds to late August through all October. The Z_i structure function is similar to previous ones, but this function has a tighter sensitive forecast range, from 538 m to 645 m. The climatological wind at SFO at both 13Z and 14Z is from the WSW (Figure 33), and the coastal mountains are higher in that direction from SFO (Figures 34, 35). The structure functions might show that when the SFO U wind increases enough between 13Z and 14Z, the marine layer is flowing over the mountains to the WSW of SFO and delaying the SBY time. The Z_i needs to be higher on average to allow the cool air to keep passing over these higher mountains. So at 16Z, a check of the 16Z SQL Z_i determines if the cool marine air will keep flowing over these mountains and delay the stratus burnoff or if this air will be "cut off". Both structure functions for 16Z RR have the same convex shape as the 15Z RR function, and the 14Z dU/dt structure function resembles the 15Z U wind function. This indicates that the radiation and wind characteristics affect the 16Z forecast in a similar way to the 15Z forecast.

Figure 32: PAM structure functions for SJSU 16Z predictors.

Figure 33: Windrose of Historical 13Z (top) and 14Z (bottom) MIT/LL Anemometer Data at SFO.

From Pos: 544717.7, 4164050.3 To Pos: 554355.9, 4164050.3

Figure 34: Elevation profile toward the west of SFO.

Figure 35: Elevation profile toward the WSW of SFO.

(5) 17Z

Below is the equation of the SJSU 17Z Scaled Model,
with the predictors in bold typeface:

$$\begin{aligned} \text{UTC_SBY} = & 21.39 & - & 1.43 * (\mathbf{1700_SFO_RR}) \\ & & - & 2.58 * (\mathbf{1700_SQL_RR}) \\ & & + & 1.26 * (\mathbf{1700_SFO_|\vec{V}|}) \end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
1700_SFO_RR is the 17Z SFO Radiometer Ratio,
1700_SQL_RR is the 17Z SQL Radiometer Ratio, and
1700_SFO_ $|\vec{V}|$ is the 17Z SFO wind speed (m/s).

(19)

For 17Z, (19) indicates that faster wind speeds result in later SBY times, and higher values of RR result in earlier SBY times. This behavior is similar to the earlier models. There are only three predictors in this model because the number of historical cases where SBY occurred at 17Z or later is less than for the earlier forecast times. A reduced sample size makes it harder for a predictor to pass the F-ratio criterion because the degrees of freedom are reduced. Note that the sunrise time and Z_1 did not make the "cut" for 17Z. This may indicate that for cases where stratus still persists at 17Z, the sun is high

enough so that the incident solar radiation at 17Z plays a greater role in dissipating stratus than the solar energy absorbed by the marine layer between sunrise and 17Z. Z_i may not be significant at 17Z because from Figure 17 in part A, the most frequent burnoff time is around 10AM PDT (17Z). Note also that the climatological SBY time for 1996-2000 is 17.9Z. As discussed in A.5.d, the trend of Z_i can detect synoptic and mesoscale phenomena on the order of hours. If stratus burnoff were imminent within the 17Z hour, then Z_i would not be a useful predictor at that time.

Figure 36 shows the PAM structure functions for the SJSU 17Z predictors. The 17Z RR functions have the same convex shape as before. Note that the 17Z SFO radiometer is reporting ratios over 1, which means that the instrument is probably out of adjustment over the historical period. However, the structure function doesn't subtract any additional time from the forecast when $RR > 1$. The wind speed structure function is almost linear, and resembles the 14Z SQL wind speed structure function. Figure 37 shows that the 17Z SFO climatological wind direction is WSW, and higher wind speeds are common.

Figure 36: PAM structure functions for SJSU 17Z predictors.

Figure 37: Windrose of Historical 17Z MIT/LL Anemometer Data at SFO.

(6) 18Z

Below is the equation of the SJSU 18Z Scaled Model,
with the predictors in bold typeface:

$$\begin{aligned}
 \text{UTC_SBY} = & 19.48 & - & 1.00 * (\mathbf{1800_SQL_RR}) \\
 & & + & 1.74 * (\mathbf{1800_SQL_V}) \\
 & & + & 1.20 * (\mathbf{1400_SFO_Zi})
 \end{aligned}$$

where UTC_SBY is the forecasted time of SBY (in UTC),
1800_SQL_RR is the 18Z SQL Radiometer Ratio,
1800_SQL_V is the 18Z SQL V wind component, and
1400_SFO_Zi is the 14Z SFO inversion height (m/s).

(20)

As was seen in the 17Z model, only three predictors are selected for 18Z because there are not many historical cases. For 18Z, (20) shows that higher Z_i results in later SBY times, and higher values of RR result in earlier SBY times, which is similar to earlier models. Sunrise time was not selected as an 18Z predictor, and probably for the same reason that was hypothesized for the 17Z model. For cases where stratus still persists at 18Z, the 18Z SFO Z_i tends to be higher on average than at earlier times (Figure 38), which probably explains why the earlier Z_i is more relevant. The 14Z Z_i was probably most important because it is the first Z_i after the climatological sunrise time. The 14Z effect of the V wind on forecast time is more complicated, and one needs to examine its structure function.

Figure 39 shows the 18Z structure functions, which exhibit different behaviors than before: the forecast is sensitive to a larger range of Z_i , the RR function is not convex, and the wind function is concave. This suggests that on days where stratus still remains in the approach zone after 18Z, different dynamics affect the dissipation.

Figure 38: Average SFO Z_i values ± 1 error bar.

The 18Z SQL V wind structure function adds no time to the forecast for strong northerly winds ($V < -4.5$ m/s). As the V wind increases from -4.5 m/s to $+1.4$ m/s, time is slowly added to the forecast, and time is added more quickly as V surpasses $+1.4$ m/s. Figure 40 shows why the structure function does this. The climatological 18Z SQL wind direction is from the north (negative V), which brings warm, dry inland air to the approach zone. Time is added to the forecast as V increases because the wind typically changes from a northerly wind to a westerly wind, and the resulting cold advection will delay the stratus burnoff. The windrose shows that higher wind speeds are associated

with the west winds, which advect the cool marine layer towards the approach zone.

Figure 39: PAM structure functions for SJSU 18Z predictors.

Figure 40: Windrose of Historical 18Z MIT/LL Anemometer Data at SQL.

d. Model Performance by Forecast Hour

Figures 41 through 45 compare the performance of the SJSU Scaled models to every MIT/LL model at every forecast hour. The SJSU Scaled models were compared to the MIT/LL models in a pairwise fashion, where the models are compared using the sample of stratus days where both models gave a forecast. This allows an accurate gauge of one model's performance versus another.

The figures show that the SJSU Scaled models' errors are equivalent to or less than the MIT/LL models' errors except for the Consensus and Regional models at 15Z and 18Z (Figs. 42 and 45, ovals). This suggests that the predictors used in the SJSU models at 15Z and 18Z probably do not represent the most important dissipation factors at those times. This is supported by the unusual behavior of the 18Z SJSU structure functions. It could mean that the F-ratio threshold of 9 was too high for these forecast times, and more SJSU predictors were needed to produce better forecasts, or it might mean that larger-scale dynamics are more significant at 15Z and 18Z, which might explain why the Consensus and Regional models had less error for these forecasts.

2001 Model Performance, along with Number of Cases for each Model

Figure 41: RMSE (top) and MAE (bottom) for the SJSU-Scaled model vs. the Consensus model.

2001 Model Performance, along with Number of Cases for each Model

Figure 42: RMSE (top) and MAE (bottom) for the SJSU-Scaled model vs. the COBEL model.

Figure 43: RMSE (top) and MAE (bottom) for the SJSU-Scaled model vs. the Local model.

2001 Model Performance, along with Number of Cases for each Model

Figure 44: RMSE (top) and MAE (bottom) for the SJSU-Scaled model vs. the Regional model.

2001 Model Performance, along with Number of Cases for each Model

Figure 45: RMSE (top) and MAE (bottom) for the SJSU-Scaled model vs. the Satellite model.

D. Conclusions and Suggestions for Future Studies

A nonlinear statistical regression analysis of historical data from SFO, SQL, and SMB resulted in several SJSU models that were used to forecast the dissipation of 2001 summer stratus in the SFO approach zone. These SJSU models have the best overall performance when they are compared to the 2001 operational MIT/LL models. This indicates that the SJSU methodology of forward-stepwise F-ratio predictor selection along with PAM nonlinear scaling of predictors can be successfully applied to stratus forecasting. The SJSU models contained predictors related to factors in the conceptual stratus dissipation model of MIT/LL, so the good performance of the SJSU models validates this conceptual model.

When the SJSU models are compared pair-wise to the MIT/LL models for each forecast hour, the Consensus and Regional models have smaller errors at 15Z and 18Z. This suggests that larger-scale dynamics may have more influence on the dissipation of stratus at these times. It might also mean that the SJSU F-ratio threshold of 9 was too

stringent, and more local predictors were needed in the 15Z and 18Z SJSU models to reduce the error further.

A future study could investigate this issue by applying this study's model-building methodology to the entire MIT/LL combined set of predictors that were used for their Local, Regional, and Satellite models. The resulting models would have predictors that would represent the most influential meteorological processes in stratus dissipation at SFO for every forecast hour, and one could conclude if local and larger-scale factors were important at each hour.

A future study could also consider some additional predictors. For example, the thickness of the stratus layer was a potential predictor for this study, but it was never selected for any model. The thickness had two measures: (Z_i - lowest SFO ceiling) and (Z_i - lowest SFO cloud). The Z_i was considered to be the top of the stratus layer, and the lowest SFO ceiling or cloud layer was considered to be the bottom of the stratus layer; however, the theoretical bottom is the Lifting Condensation Level

(LCL). The height of the LCL can be estimated from the surface temperature (T) and dewpoint (T_d):

$$LCL(m) = 125[T(^{\circ}C) - T_d(^{\circ}C)] \quad (21)$$

This LCL could be used as another measure of a cloud "bottom" and incorporated into the potential predictor set.

Since advection is a major factor in dissipation, one could use the MIT/LL 5-minute wind data to produce a vector-averaged wind speed and direction over an hour. This value would represent the net amount of air transport over the previous hour, and might prove to be a useful predictor.

The MIT/LL wind, sodar, and radiometer data were all used in almost every SJSU model, so it's very important that these stations are well-maintained and updated so that they continue to provide useful wind, inversion and radiation data. The radiometer ratio exceeded 1 many times over the historical period and during 2001, so this instrument may need to be calibrated or the algorithms used to interpret the data may need to be modified. The

inversion height reported by MIT/LL's algorithm was inappropriate at times. Sometimes the inversion base was placed below the lowest cloud ceiling or changed dramatically during the morning (Figure 46), which suggests that the algorithm had trouble finding the "true" inversion. The MIT/LL algorithm should be modified so that the inversion height is always above the lowest clouds, and remains stable.

The sectors used in the Satellite model were selected to be geographically homogenous. Given the large errors of the Satellite model, these arbitrary sectors may not be the most appropriate grouping of the data. A future study could use statistics to find natural "groupings" of the satellite data, which may prove to be better predictors.

Figure 46: SFO Z_i (red) and SFO ceiling (green) for June 13, 1998.

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APPENDIX A: Listing of the candidate predictors

Times	Label	Description
12Z	OAKZi	MIT/LL Oakland Inversion Height
12Z	OAKZiQuality	MIT/LL quality number of OAKZi
12Z	SQZiQuality	MIT/LL quality number of SQZi
12Z	SFZiQuality	MIT/LL quality number of SFZi
12Z-18Z	Sunrise	SFO Sunrise Time
12Z-18Z	SQZi	SQL Inversion Height
12Z-18Z	SFZi	SFO Inversion Height
12Z-18Z	AvgZi	Average of SQZi and SFZi
12Z-18Z	SFCig	SFO Ceiling
14Z-18Z	SQCig	SQL Ceiling
12Z-18Z	SMCig	SMB Ceiling
12Z-18Z	SFCld	SFO Lowest Cloud
14Z-18Z	SQCld	SQL Lowest Cloud
12Z-18Z	SMCld	SMB Lowest Cloud
12Z-18Z	SFth1	Cloud Thickness (SFZi - SFCig)
12Z-18Z	SFth2	Cloud Thickness (SFZi - SFCld)
14Z-18Z	SQth1	Cloud Thickness (SQZi - SQCig)
14Z-18Z	SQth2	Cloud Thickness (SQZi - SQCld)
12Z-18Z	SMth1	Cloud Thickness (SQZi - SMCig)
12Z-18Z	SMth2	Cloud Thickness (SQZi - SMCld)
12Z-18Z	SFWd	SFO Wind Direction
12Z-18Z	SFWv	SFO Wind Speed
12Z-18Z	SFWW	SFO U Wind
12Z-18Z	SFWS	SFO V Wind
14Z-18Z	SQWd	SQL Wind Direction
14Z-18Z	SQWv	SQL Wind Speed
14Z-18Z	SQWW	SQL U Wind
14Z-18Z	SQWS	SQL V Wind
12Z-18Z	SFLLWd	MIT/LL SFO Wind Direction
12Z-18Z	SFLLWv	MIT/LL SFO Wind Speed
12Z-18Z	SFLLWW	MIT/LL SFO U Wind
12Z-18Z	SFLLWS	MIT/LL SFO V Wind
12Z-18Z	SQLLWd	MIT/LL SQL Wind Direction
12Z-18Z	SQLLWv	MIT/LL SQL Wind Speed
12Z-18Z	SQLLWW	MIT/LL SQL U Wind
12Z-18Z	SQLLWS	MIT/LL SQL V Wind
12Z-18Z	SMWd	SMB Wind Direction
12Z-18Z	SMWv	SMB Wind Speed
12Z-18Z	SMWW	SMB U Wind
12Z-18Z	SMWS	SMB V Wind
12Z-18Z	SFRR	MIT/LL SFO Radiometer Ratio
12Z-18Z	SQRR	MIT/LL SQL Radiometer Ratio
12Z-18Z	SFORNO	Pressure Gradient SFO-RNO
12Z-18Z	SFORBL	Pressure Gradient SFO-RBL

APPENDIX B: SJSU Model Building Statistics

Development of 13z SJSU Local Model

1. Unscaled

Response: SBY_13z
Summary of Fit

RSquare	0.219178
RSquare Adj	0.204445
Root Mean Square Error	1.290142
Mean of Response	17.92115
Observations	217

Parameter Estimates

Term	Estimate
Intercept	5.0609748
13SFCig[0-1]	-0.441844
Sunrise	0.8589912
13SFZi	0.0018868
13SQL_u	0.1682727

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
13SFCig	1	1	25.198035	15.1388	0.0001
Sunrise	1	1	34.472716	20.7110	<.0001
13SFZi	1	1	16.408500	9.8581	0.0019
13SQL_u	1	1	20.561178	12.3530	0.0005

Whole-Model Test
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	99.05011	24.7625	14.8772
Error	212	352.86679	1.6645	Prob>F
C Total	216	451.91690		<.0001

2. Scaled

Response: SBY_13z
Summary of Fit

RSquare	0.26918
RSquare Adj	0.255391
Root Mean Square Error	1.248149
Mean of Response	17.92115
Observations	217

Parameter Estimates

Term	Estimate
Intercept	16.998022
13SFCig[0-1]	-0.373567
Sunrise	1.0600933
13SFZi	1.2385145
13SQL_u	1.2557987

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
13SFCig	1	1	17.511621	11.2407	0.0009
Sunrise	1	1	37.090851	23.8086	<.0001
13SFZi	1	1	23.545703	15.1140	0.0001
13SQL_u	1	1	23.251905	14.9254	0.0001

Whole-Model Test
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	121.64706	30.4118	19.5213
Error	212	330.26984	1.5579	Prob>F
C Total	216	451.91690		<.0001

Development of 14z SJSU Local Model

1. Unscaled

Response: SBY_14z
Summary of Fit

RSquare	0.341746
RSquare Adj	0.325124
Root Mean Square Error	1.177528
Mean of Response	17.82453
Observations	204

Parameter Estimates

Term	Estimate
Intercept	2.908493
Sunrise	0.9435569
14SFZi	0.0024111
14SMCig[0-1]	-0.397661
14SFCig[0-1]	-0.515231
14SQL_ V	0.267537

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
Sunrise	1	1	35.804831	25.8225	<.0001
14SFZi	1	1	22.451726	16.1922	<.0001
14SMCig	1	1	23.381482	16.8628	<.0001
14SFCig	1	1	26.176008	18.8782	<.0001
14SQL_ V	1	1	15.638323	11.2784	0.0009

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	142.53390	28.5068	20.5592
Error	198	274.54148	1.3866	Prob>F
C Total	203	417.07539		<.0001

2. Scaled

Response: SBY_14z
Summary of Fit

RSquare	0.346091
RSquare Adj	0.329578
Root Mean Square Error	1.173636
Mean of Response	17.82453
Observations	204

Parameter Estimates

Term	Estimate
Intercept	16.439288
Sunrise	1.2391083
14SFZi	1.3293095
14SMCigY[0-1]	-0.354416
14SFCigY[0-1]	-0.50375
14SQL_ V	1.1759965

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
Sunrise	1	1	35.149586	25.5184	<.0001
14SFZi	1	1	24.273578	17.6225	<.0001
14SMCig	1	1	18.366877	13.3342	0.0003
14SFCig	1	1	25.054878	18.1897	<.0001
14SQL_ V	1	1	13.675046	9.9280	0.0019

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	144.34592	28.8692	20.9589
Error	198	272.72946	1.3774	Prob>F
C Total	203	417.07539		<.0001

Development of 15z SJSU Local Model

1. Unscaled

Response: SBY_15z
Summary of Fit

RSquare	0.430922
RSquare Adj	0.417688
Root Mean Square Error	1.0116
Mean of Response	17.873
Observations	221

Parameter Estimates

Term	Estimate
Intercept	8.2259145
Sunrise	0.7344852
15SFRR	-2.525241
14SFZi	0.0014693
15SQL_u	0.1107222
15SMCig [0-1]	-0.288788

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
Sunrise	1	1	20.386829	19.9220	< .0001
15SFRR	1	1	66.008963	64.5038	< .0001
14SFZi	1	1	9.363055	9.1496	0.0028
15SQL_u	1	1	15.240157	14.8926	0.0002
15SMCig	1	1	11.050460	10.7985	0.0012

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	166.60323	33.3206	32.5609
Error	215	220.01692	1.0233	Prob>F
C Total	220	386.62015		<.0001

2. Scaled

Response: SBY_15z
Summary of Fit

RSquare	0.476851
RSquare Adj	0.464685
Root Mean Square Error	0.96992
Mean of Response	17.873
Observations	221

Parameter Estimates

Term	Estimate
Intercept	19.050928
15SMCig [0-1]	-0.253577
15SQL_u	0.7009086
15SFRR	-2.903835
Sunrise	1.1314151
14SFZi	0.9694669

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
15SMCig	1	1	8.423439	8.9540	0.0031
15SQL_u	1	1	11.474909	12.1977	0.0006
15SFRR	1	1	58.721460	62.4202	< .0001
Sunrise	1	1	25.633954	27.2486	< .0001
14SFZi	1	1	14.436229	15.3455	0.0001

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	5	184.36021	36.8720	39.1946
Error	215	202.25994	0.9407	Prob>F
C Total	220	386.62015		< .0001

Development of 16z SJSU Local Model

1. Unscaled

Response: SBY_16z
Summary of Fit

RSquare	0.480758
RSquare Adj	0.464862
Root Mean Square Error	0.945576
Mean of Response	18.02325
Observations	203

Parameter Estimates

Term	Estimate
Intercept	13.351969
Sunrise	0.4269641
16SQZi	0.0016118
16SFRR	-1.879709
16SQRR	-1.412868
14SFO_du_dt	0.1486417
16SMCig[0-1]	-0.237322

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
Sunrise	1	1	5.411384	6.0522	0.0148
16SQZi	1	1	10.541104	11.7894	0.0007
16SFRR	1	1	40.970327	45.8222	<.0001
16SQRR	1	1	21.731883	24.3055	<.0001
14SFO_du_dt	1	1	11.419748	12.7721	0.0004
16SMCig	1	1	5.886759	6.5839	0.0110

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	162.25768	27.0429	30.2455
Error	196	175.24642	0.8941	Prob>F
C Total	202	337.50410		<.0001

2. Scaled

Response: SBY_16z
Summary of Fit

RSquare	0.574677
RSquare Adj	0.561657
Root Mean Square Error	0.855797
Mean of Response	18.02325
Observations (or Sum Wgts)	203

Parameter Estimates

Term	Estimate
Intercept	19.878944
16SMCigY[0-1]	-0.261268
Sunrise	1.7201831
16SFRR	-2.057333
16SQRR	-1.66659
16SQZi	0.6017531
14SFO_du_dt	1.0137256

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
16SMCigY	1	1	7.149000	9.7612	0.0021
Sunrise	1	1	16.583472	22.6430	<.0001
16SFRR	1	1	44.710837	61.0479	<.0001
16SQRR	1	1	13.934576	19.0262	<.0001
16SQZi	1	1	6.605969	9.0198	0.0030
14SFO_du_dt	1	1	8.486451	11.5874	0.0008

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	6	193.95584	32.3260	44.1377
Error	196	143.54826	0.7324	Prob>F
C Total	202	337.50410		<.0001

Development of 17z SJSU Local Model

1. Unscaled

Response: SBY_17z
Summary of Fit

RSquare	0.450892
RSquare Adj	0.442222
Root Mean Square Error	0.850742
Mean of Response	18.51663
Observations (or Sum Wgts)	194

Parameter Estimates

Term	Estimate
Intercept	19.948554
17SFO_RR	-1.5579
17SQL_RR	-1.565709
17SFO_ V	0.1615308

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
17SFO_RR	1	1	26.413897	36.4953	<.0001
17SQL_RR	1	1	23.166771	32.0088	<.0001
17SFO_ V	1	1	9.380903	12.9613	0.0004

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	112.91837	37.6395	52.0053
Error	190	137.51472	0.7238	Prob>F
C Total	193	250.43309		<.0001

2. Scaled

Response: SBY_17z

Summary of Fit

RSquare	0.504306
RSquare Adj	0.49648
Root Mean Square Error	0.808306
Mean of Response	18.51663
Observations (or Sum Wgts)	194

Parameter Estimates

Term	Estimate
Intercept	21.391908
17SFO_RR	-1.425269
17SQL_RR	-2.580538
17SFO_ V	1.2649508

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
17SFO_RR	1	1	19.734078	30.2041	<.0001
17SQL_RR	1	1	31.453111	48.1407	<.0001
17SFO_ V	1	1	9.556505	14.6267	0.0002

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	126.29502	42.0983	64.4338
Error	190	124.13807	0.6534	Prob>F
C Total	193	250.43309		<.0001

Development of 18z SJSU Local Model

1. Unscaled

Response: SBY_18z
Summary of Fit

RSquare	0.37252
RSquare Adj	0.355407
Root Mean Square Error	0.813987
Mean of Response	19.20073
Observations	114

Parameter Estimates

Term	Estimate
Intercept	19.863575
18SQL_v	0.1404487
18SQL_RR	-1.315234
14SFO_Zi	0.0012938

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
18SQL_v	1	1	8.155203	12.3084	0.0007
18SQL_RR	1	1	11.881668	17.9326	<.0001
14SFO_Zi	1	1	4.313658	6.5104	0.0121

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	43.26904	14.4230	21.7681
Error	110	72.88323	0.6626	Prob>F
C Total	113	116.15226		<.0001

2. Scaled

Response: SBY_18z

Summary of Fit

RSquare	0.435158
RSquare Adj	0.419754
Root Mean Square Error	0.772291
Mean of Response	19.20073
Observations	114

Parameter Estimates

Term	Estimate
Intercept	19.478564
18SQL_v	1.7362165
18SQL_RR	-1.002727
14SFZi	1.2040891

Effect Test

Source	Nparm	DF	Sum of Squares	F Ratio	Prob>F
18SQL_v	1	1	10.165593	17.0440	<.0001
18SQL_RR	1	1	9.924830	16.6403	<.0001
14SFZi	1	1	6.457499	10.8269	0.0013

Whole-Model Test

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	3	50.54462	16.8482	28.2483
Error	110	65.60764	0.5964	Prob>F
C Total	113	116.15226		<.0001

APPENDIX C: SJSU Model Equations

A. 13Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} = & 5.0609748 + 0.8589912 * \text{UTC_Sunrise} \\ & + 0.0018868 * 1300_SFO_Zi \\ & + 0.1682727 * 1300_SQL_u \\ & + \{-0.441844 \text{ if } 1300_SFO_Cig = \text{"no"}\} \\ & \quad \{0.441844 \text{ if } 1300_SFO_Cig = \text{"yes"}\} \end{aligned}$$

2. Scaled Model:

$$\begin{aligned} \text{UTC_SBY} = & 16.998022 + 1.0600933 * \text{UTC_Sunrise} \\ & + 1.2385145 * 1300_SFO_Zi \\ & + 1.2557987 * 1300_SQL_u \\ & + \{-0.373567 \text{ if } 1300_SFO_Cig = \text{"no"}\} \\ & \quad \{0.373567 \text{ if } 1300_SFO_Cig = \text{"yes"}\} \end{aligned}$$

B. 14Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} = & 2.908493 + 0.9435569 * \text{UTC_Sunrise} \\ & + 0.0024111 * 1400_SFO_Zi \\ & + 0.267537 * 1400_SQL_|V| \\ & + \{-0.515231 \text{ if } 1400_SFO_Cig = \text{"no"}\} \\ & \quad \{0.515231 \text{ if } 1400_SFO_Cig = \text{"yes"}\} \\ & + \{-0.397661 \text{ if } 1400_SMB_Cig = \text{"no"}\} \\ & \quad \{0.397661 \text{ if } 1400_SMB_Cig = \text{"yes"}\} \end{aligned}$$

2. Scaled Model:

$$\begin{aligned} \text{UTC_SBY} = & 16.439288 + 1.2391083 * \text{UTC_Sunrise} \\ & + 1.3293095 * 1400_SFO_Zi \\ & + 1.1759965 * 1400_SQL_|V| \\ & + \{-0.50375 \text{ if } 1400_SFO_Cig = \text{"no"}\} \\ & \quad \{0.50375 \text{ if } 1400_SFO_Cig = \text{"yes"}\} \\ & + \{-0.354416 \text{ if } 1400_SMB_Cig = \text{"no"}\} \\ & \quad \{0.354416 \text{ if } 1400_SMB_Cig = \text{"yes"}\} \end{aligned}$$

C. 15Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} = 8.2259145 & - 2.525241 * 1500_SFO_RRatio \\ & + 0.0014693 * 1400_SFO_Zi \\ & + 0.1107222 * 1500_SQL_u \\ & + 0.7344852 * \text{UTC_Sunrise} \\ & + \{-0.288788 \text{ if } 1500_SMB_Cig = \text{"no"}\} \\ & \quad \{0.288788 \text{ if } 1500_SMB_Cig = \text{"yes"}\} \end{aligned}$$

2. Scaled Model

$$\begin{aligned} \text{UTC_SBY} = 19.050928 & - 2.903835 * 1500_SFO_RRatio \\ & + 0.9694669 * 1400_SFO_Zi \\ & + 0.7009086 * 1500_SQL_u \\ & + 1.1314151 * \text{UTC_Sunrise} \\ & + \{-0.253577 \text{ if } 1500_SMB_Cig = \text{"no"}\} \\ & \quad \{0.253577 \text{ if } 1500_SMB_Cig = \text{"yes"}\} \end{aligned}$$

D. 16Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} = 13.351969 & - 1.879709 * 1600_SFO_RRatio \\ & - 1.412868 * 1600_SQL_RRatio \\ & + 0.0016118 * 1600_SQL_Zi \\ & + 0.1486417 * 1400_SFO_du_dt \\ & + 0.4269641 * \text{UTC_Sunrise} \\ & + \{-0.237322 \text{ if } 1600_SMB_Cig = \text{"no"}\} \\ & \quad \{0.237322 \text{ if } 1600_SMB_Cig = \text{"yes"}\} \end{aligned}$$

2. Scaled Model

$$\begin{aligned} \text{UTC_SBY} = 19.8789444 & - 2.0573327 * 1600_SFO_RRatio \\ & - 1.6665905 * 1600_SQL_RRatio \\ & + 0.601753 * 1600_SQL_Zi \\ & + 1.01372557 * 1400_SFO_du_dt \\ & + 1.72018307 * \text{UTC_Sunrise} \\ & + \{-0.261268 \text{ if } 1600_SMB_Cig = \text{"no"}\} \\ & \quad \{0.261268 \text{ if } 1600_SMB_Cig = \text{"yes"}\} \end{aligned}$$

E. 17Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} &= 19.948554 && - 1.5579*1700_SFO_RRatio \\ & && - 1.565709*1700_SQL_RRatio \\ & && + 0.1615308*1700_SFO_|V| \end{aligned}$$

2. Scaled Model

$$\begin{aligned} \text{UTC_SBY} &= 21.391908 && - 1.425269*1700_SFO_RRatio \\ & && - 2.580538*1700_SQL_RRatio \\ & && + 1.2649508*1700_SFO_|V| \end{aligned}$$

F. 18Z

1. Unscaled Model

$$\begin{aligned} \text{UTC_SBY} &= 19.8635747 && - 1.315234*1800_SQL_RRatio \\ & && + 0.14044867*1800_SQL_v \\ & && + 0.00129381*1400_SFO_Zi \end{aligned}$$

2. Scaled Model

$$\begin{aligned} \text{UTC_SBY} &= 19.4785642 && - 1.0027268*1800_SQL_RRatio \\ & && + 1.73621654*1800_SQL_v \\ & && + 1.20408906*1400_SFO_Zi \end{aligned}$$

APPENDIX D: Structure Functions for SJSU Models

A. 13z PAM Predictor Details:

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 13z SBY conditional climatology residuals.

1. UTC_Sunrise

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
13.670	0.000	3.752
13.936	1.000	0.000

MIN: 12.78 scaled to 0.00
MAX: 14.47 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.527	0.000	6.3402
0.684	1.000	0.000

2. 1300_SFO_Zi

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
370.96	0.000	0.002667
745.92	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.335	0.000	2.1549
0.779	1.000	0.000

MIN: 100 scaled to 0.00
MAX: 908 scaled to 1.00

3. 1300_SQL_u

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
2.768	0.000	0.405
5.238	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.604	0.000	3.5927
0.882	1.000	0.000

MIN: -2.59 scaled to 0.00
MAX: 6.28 scaled to 1.00

B. 14z PAM Predictor Details:

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 14z SBY conditional climatology residuals.

1. UTC_Sunrise

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
13.640	0.000	2.567
14.030	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.509	0.000	4.3376
0.740	1.000	0.000

MIN: 12.78 scaled to 0.00
MAX: 14.47 scaled to 1.00

2. 1400_SFO_Zi

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
351	0.000	0.002672
725.311	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.295	0.000	2.2762
0.734	1.000	0.000

MIN: 100 scaled to 0.00

MAX: 852 scaled to 1.00

3. 1400_SQL_|V|

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
1.700	0.000	0.222
6.200	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.135	0.000	1.156
1.000	1.000	0.000

MIN: 1.00 scaled to 0.00
MAX: 6.20 scaled to 1.00

C. 15z PAM Predictor Details

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 15z SBY conditional climatology residuals.

1. 1500_SFO_RRatio

Unscaled structure function parameters:

x	y	slope
0.000	0.000	2.507
0.270	0.677	0.567
0.840	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	3.8612
0.175	0.677	0.8724
0.545	1.000	0.0000

MIN: 0.00 scaled to 0.00
MAX: 1.54 scaled to 1.00

2. 1400_SFO_Zi

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
346	0.744	0.003
714	1.000	0.000

MIN: 100 scaled to 0.00

MAX: 852 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.0000
0.289	0.000	2.3147
0.721	1.000	0.0000

3. 1500_SQL_u

Unscaled structure function parameters:

x	y	slope
0	0.000	0.000
-1.324	0.000	1.015
-0.859	0.472	0.000
3.037	0.472	1.015
3.557	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.221	0.000	10.00
0.268	0.472	0.000
0.663	0.472	10.00
0.716	1.000	0.000

MIN: -3.50 scaled to 0.00
MAX: 13.35 scaled to 1.00

4. UTC_Sunrise

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
13.665	0.000	2.598
14.05	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.524	0.000	4.3898
0.751	1.000	0.000

MIN: 12.78 scaled to 0.00
MAX: 14.47 scaled to 1.00

D. 16z PAM Predictor Details

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 16z SBY conditional climatology residuals.

1. 1600_SFO_RRatio

Unscaled structure function parameters:

x	y	slope
0.130	0.000	2.657
0.400	0.717	0.615
0.860	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	2.9222
0.245	0.717	0.6761
0.664	1.000	0.0000

MIN: 0.13 scaled to 0.00

MAX: 1.23 scaled to 1.00

2. 1600_SQL_RRatio

Unscaled structure function parameters:

x	y	slope
0.116	0.000	3.198
0.349	0.744	0.546
0.817	1.000	0.000

MIN: 0.10 scaled to 0.00
MAX: 1.18 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.015	0.000	3.4536
0.230	0.744	0.5900
0.664	1.000	0.0000

2. 1600_SQL_Zi

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
538	0.000	0.009
644.785	1.000	0.000

MIN: 135 scaled to 0.00
MAX: 820 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.491	0.000	7.679
0.622	1.000	0.000

3. 1400_SFO_du_dt

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
-2.673	0.000	0.951
-2.031	0.610	0.000
1.107	0.610	0.226
2.832	1.000	0.000

MIN: -5.709 scaled to 0.00

MAX: 4.805 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.289	0.000	9.9994
0.350	0.610	0.000
0.648	0.610	2.3793
0.812	1.000	0.000

4. UTC_Sunrise

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
13.634	0.000	1.197
14.47	1.000	0.000

MIN: 12.78 scaled to 0.00

MAX: 14.47 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.506	0.000	2.0226
1.000	1.000	0.000

E. 17z PAM Predictor Details

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 17z SBY conditional climatology residuals.

1. 1700_SFO_RRatio

Unscaled structure function parameters:

x	y	slope
0.120	0.000	1.668
0.479	0.598	0.771
1.000	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	1.8344
0.326	0.598	0.8477
0.800	1.000	0.0000

MIN: 0.12 scaled to 0.00
MAX: 1.12 scaled to 1.00

2. 1700_SQL_RRatio

Unscaled structure function parameters:

x	y	slope
0.130	0.000	3.021
0.340	0.635	0.690
0.870	1.000	0.000

MIN: 0.13 scaled to 0.00

MAX: 1.16 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	3.1114
0.204	0.635	0.7103
0.718	1.000	0.0000

3. 1700_SFO_|V|

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
3.000	0.000	0.141
10.10	1.000	0.000

MIN: 1.40 scaled to 0.00

MAX: 10.10 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.184	0.000	1.2254
1.000	1.000	0.000

F. 18z PAM Predictor Details

Using data from 1996 through 2000, predictor values were scaled from 0 to 1, and then PAMed to 18z SBY conditional climatology residuals.

1. 1800_SQL_RRatio

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.340	0.000	2.545
0.733	1.000	0.000

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.159	0.000	2.7228
0.526	1.000	0.0000

MIN: 0.17 scaled to 0.00
MAX: 1.24 scaled to 1.00

2. 1800_SQL_v

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
-4.461	0.000	0.049
1.400	0.290	0.270
4.029	1.000	0.000

MIN: -5.692 scaled to 0.00

MAX: 4.029 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.127	0.000	0.4811
0.730	0.290	2.6255
1.000	1.000	0.000

3. 1400_SFO_Zi

Unscaled structure function parameters:

x	y	slope
0.000	0.000	0.000
416.3	0.000	0.00187
952	1.000	0.000

MIN: 100 scaled to 0.00

MAX: 952 scaled to 1.00

Scaled structure function parameters:

x	y	slope
0.000	0.000	0.000
0.371	0.000	1.5896
1.000	1.000	0.000

APPENDIX E: 2001 Performance Statistics for all Models

For 2001, There were 85 stratus days with a reported 45 rate or 60 rate.

13z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
13z Cases	74	74	71	61	66	64	N/A
Bias (Hours)	0.222	0.273	0.267	0.414	0.271	0.072	N/A
Std Dev (hours)	1.360	1.324	1.397	1.404	1.518	1.387	N/A
RMSE (hours)	1.378	1.352	1.422	1.464	1.542	1.389	N/A
MAE (hours)	1.026	0.929	1.034	1.041	1.096	1.053	N/A

The 13z SJSU Scaled Model has a lower RMSE and MAE than all other models, and this model also ran for the most cases. In order to have a fair comparison between the models, the model error statistics are next calculated using only the cases where both models gave a forecast. The following tables compare the model performances on an identical sample of stratus days.

13z	SJSU Local (Scaled)	Consensus
Cases	63	63
Bias (Hours)	0.228	0.182
Std Dev (Hours)	1.328	1.416
RMSE (hours)	1.347	1.428
MAE (hours)	0.915	1.031

13z	SJSU Local (Scaled)	COBEL
Cases	55	55
Bias (Hours)	0.222	0.420
Std Dev (Hours)	1.301	1.440
RMSE (hours)	1.320	1.500
MAE (hours)	0.900	1.060

13z	SJSU Local (Scaled)	Local
Cases	62	62
Bias (Hours)	0.235	0.262
Std Dev (Hours)	1.337	1.562
RMSE (hours)	1.357	1.562
MAE (hours)	0.926	1.135

13z	SJSU Local (Scaled)	Regional
Cases	59	59
Bias (Hours)	0.249	-0.034
Std Dev (Hours)	1.266	1.345
RMSE (hours)	1.290	1.345
MAE (hours)	0.866	1.016

13z	SJSU Local (Scaled)	Satellite
Cases	N/A	N/A
Bias (Hours)	N/A	N/A
Std Dev (Hours)	N/A	N/A
RMSE (hours)	N/A	N/A
MAE (hours)	N/A	N/A

For 13z, the SJSU Scaled Local Model has lower RMSE and MAE than all other models.

14z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
14z Cases	82	82	74	63	61	67	40
Bias (Hours)	0.288	0.290	0.322	0.240	0.222	0.218	0.802
Std Dev hours)	1.289	1.249	1.179	1.205	1.074	1.383	0.981
RMSE (hours)	1.321	1.282	1.222	1.229	1.097	1.400	1.267
MAE (hours)	1.051	0.969	0.908	0.910	0.838	1.038	1.016

The 14z SJSU Scaled Model has a higher RMSE than all other models except for the Regional Model, and a higher MAE than all other models except for the Regional and Satellite Models. Note however, that the SJSU Model also ran for the most cases. In order to have a fair comparison between the models, the model error statistics are next calculated using only the cases where both models gave a forecast. The following tables compare the model performances on an identical sample of stratus days.

14z	SJSU Local (Scaled)	Consensus
Cases	74	74
Bias (Hours)	0.200	0.322
Std Dev (Hours)	1.205	1.179
RMSE (hours)	1.222	1.222
MAE (hours)	0.918	0.908

14z	SJSU Local (Scaled)	COBEL
Cases	63	63
Bias (Hours)	0.189	0.240
Std Dev (Hours)	1.138	1.205
RMSE (hours)	1.154	1.229
MAE (hours)	0.869	0.910

14z	SJSU Local (Scaled)	Local
Cases	61	61
Bias (Hours)	0.184	0.223
Std Dev (Hours)	1.078	1.074
RMSE (hours)	1.093	1.097
MAE (hours)	0.834	0.838

14z	SJSU Local (Scaled)	Regional
Cases	67	67
Bias (Hours)	0.253	0.218
Std Dev (Hours)	1.184	1.383
RMSE (hours)	1.211	1.400
MAE (hours)	0.903	1.038

14z	SJSU Local (Scaled)	Satellite
Cases	40	40
Bias (Hours)	0.248	0.802
Std Dev (Hours)	1.104	0.981
RMSE (hours)	1.131	1.267
MAE (hours)	0.909	1.016

For 14z, the SJSU Scaled Local Model has lower RMSE and MAE than all other models except the Consensus model.

15z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
Cases	78	78	72	60	69	65	64
Bias (Hours)	-0.291	0.148	0.346	0.164	0.286	0.016	0.582
Std Dev (Hours)	1.935	1.122	0.983	1.096	1.093	1.009	1.289
RMSE (hours)	1.957	1.132	1.042	1.108	1.130	1.009	1.415
MAE (hours)	1.144	0.852	0.769	0.816	0.836	0.810	0.981

The 15z SJSU Scaled Model has a higher RMSE and MAE than all other models except the Satellite model. Note however that the SJSU model ran for the most cases. In order to have a fair comparison between the models, the model error statistics are next calculated using only the

cases where both models gave a forecast. The following tables compare the model performances on an identical sample of stratus days.

15z	SJSU Local (Scaled)	Consensus
Cases	71	71
Bias (Hours)	0.095	0.341
Std Dev (Hours)	1.089	0.986
RMSE (hours)	1.094	1.046
MAE (hours)	0.805	0.770

15z	SJSU Local (Scaled)	COBEL
Cases	60	60
Bias (Hours)	0.040	0.165
Std Dev (Hours)	1.073	1.096
RMSE (hours)	1.074	1.108
MAE (hours)	0.806	0.816

15z	SJSU Local (Scaled)	Local
Cases	69	69
Bias (Hours)	0.068	0.286
Std Dev (Hours)	1.074	1.093
RMSE (hours)	1.076	1.130
MAE (hours)	0.794	0.836

15z	SJSU Local (Scaled)	Regional
Cases	64	64
Bias (Hours)	0.104	-0.002
Std Dev (Hours)	1.095	1.007
RMSE (hours)	1.100	1.007
MAE (hours)	0.814	0.805

15z	SJSU Local (Scaled)	Satellite
Cases	63	63
Bias (Hours)	0.054	0.585
Std Dev (Hours)	1.016	1.300
RMSE (hours)	1.017	1.426
MAE (hours)	0.759	0.990

When compared on an identical sample of stratus days, the 15z SJSU Scaled Local Model has lower RMSE and MAE than all other 15z models except the Consensus model and Regional model.

16z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
Cases	71	71	68	54	63	63	57
Bias (Hours)	0.075	0.266	0.377	0.112	0.421	0.184	0.611
Std Dev (Hours)	0.975	0.757	0.775	0.928	0.871	0.978	1.077
RMSE (hours)	0.978	0.802	0.862	0.935	0.967	0.996	1.238
MAE (hours)	0.792	0.663	0.699	0.740	0.770	0.777	0.952

The 16z SJSU Scaled Model has a lower RMSE and MAE than all other models. Only the Consensus model ran for more cases than the SJSU model. In order to have a fair comparison between the models, the model error statistics are next calculated using only the cases where both models gave a forecast. The following tables compare the model performances on an identical sample of stratus days.

16z	SJSU Local (Scaled)	Consensus
Cases	66	66
Bias (Hours)	0.288	0.343
Std Dev (Hours)	0.763	0.760
RMSE (hours)	0.816	0.834
MAE (hours)	0.681	0.675

16z	SJSU Local (Scaled)	COBEL
Cases	54	54
Bias (Hours)	0.307	0.112
Std Dev (Hours)	0.815	0.928
RMSE (hours)	0.870	0.935
MAE (hours)	0.735	0.740

16z	SJSU Local (Scaled)	Local
Cases	61	61
Bias (Hours)	0.308	0.363
Std Dev (Hours)	0.771	0.821
RMSE (hours)	0.830	0.898
MAE (hours)	0.688	0.723

16z	SJSU Local (Scaled)	Regional
Cases	61	61
Bias (Hours)	0.306	0.154
Std Dev (Hours)	0.784	0.981
RMSE (hours)	0.841	0.993
MAE (hours)	0.707	0.767

16z	SJSU Local (Scaled)	Satellite
Cases	56	56
Bias (Hours)	0.238	0.611
Std Dev (Hours)	0.773	1.087
RMSE (hours)	0.808	1.246
MAE (hours)	0.669	0.958

When compared on an identical sample of stratus days, the 16z SJSU Scaled Local Model has a lower RMSE than all other 16z models, and a lower MAE than all other 16z models except the Consensus model.

17z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
Cases	58	58	53	39	51	50	49
Bias (Hours)	0.082	0.080	0.461	0.587	0.406	0.172	0.625
Std Dev (Hours)	0.756	0.619	0.688	0.821	0.696	0.822	1.090
RMSE (hours)	0.760	0.624	0.828	1.009	0.806	0.840	1.256
MAE (hours)	0.569	0.474	0.653	0.751	0.649	0.585	0.915

The 17z SJSU Scaled Model has a lower RMSE and MAE than all other models, and also ran for the most cases. In order to have a fair comparison between the models, the model error statistics are next calculated using only the cases where both models gave a forecast. The following tables compare the pairwise model performances on an identical sample of stratus days.

17z	SJSU Local (Scaled)	Consensus
Cases	53	53
Bias (Hours)	0.073	0.461
Std Dev (Hours)	0.639	0.688
RMSE (hours)	0.644	0.828
MAE (hours)	0.486	0.653

17z	SJSU Local (Scaled)	COBEL
Cases	39	39
Bias (Hours)	0.140	0.587
Std Dev (Hours)	0.642	0.821
RMSE (hours)	0.657	1.009
MAE (hours)	0.507	0.751

17z	SJSU Local (Scaled)	Local
Cases	51	51
Bias (Hours)	0.068	0.406
Std Dev (Hours)	0.651	0.696
RMSE (hours)	0.654	0.806
MAE (hours)	0.497	0.649

17z	SJSU Local (Scaled)	Regional
Cases	50	50
Bias (Hours)	0.053	0.172
Std Dev (Hours)	0.644	0.822
RMSE (hours)	0.646	0.840
MAE (hours)	0.490	0.585

17z	SJSU Local (Scaled)	Satellite
Cases	49	49
Bias (Hours)	0.067	0.625
Std Dev (Hours)	0.648	1.090
RMSE (hours)	0.651	1.256
MAE (hours)	0.493	0.915

When compared on an identical sample of stratus days, the 17z SJSU Scaled Local Model has a lower RMSE and MAE than all other 17z models.

18z	SJSU Local	SJSU Local (Scaled)	Consensus	COBEL	Local	Regional	Satellite
Cases	35	35	31	18	23	27	26
Bias (Hours)	0.223	0.124	0.559	0.102	1.015	0.456	0.742
Std Dev (Hours)	0.865	0.801	0.545	0.833	0.677	0.610	0.753
RMSE (hours)	0.894	0.810	0.780	0.839	1.220	0.762	1.057
MAE (hours)	0.689	0.621	0.677	0.637	1.028	0.619	0.878

The 18z Regional Model has the lowest RMSE and MAE of the models. However, there is a large variation in the number of cases for each model. In order to have a fair comparison between the models, the model error statistics are next calculated using only the cases where both models gave a forecast. The following tables compare the pairwise model performances on an identical sample of stratus days.

18z	SJSU Local (Scaled)	Consensus
Cases	31	31
Bias (Hours)	0.255	0.559
Std Dev (Hours)	0.853	0.545
RMSE (hours)	0.890	0.780
MAE (hours)	0.672	0.677

18z	SJSU Local (Scaled)	COBEL
Cases	18	18
Bias (Hours)	0.077	0.102
Std Dev (Hours)	0.811	0.833
RMSE (hours)	0.814	0.839
MAE (hours)	0.619	0.637

18z	SJSU Local (Scaled)	Local
Cases	23	23
Bias (Hours)	0.414	1.015
Std Dev (Hours)	0.620	0.677
RMSE (hours)	0.746	1.220
MAE (hours)	0.560	1.028

18z	SJSU Local (Scaled)	Regional
Cases	27	27
Bias (Hours)	0.313	0.456
Std Dev (Hours)	0.873	0.610
RMSE (hours)	0.927	0.762
MAE (hours)	0.692	0.619

18z	SJSU Local (Scaled)	Satellite
Cases	26	26
Bias (Hours)	0.164	0.742
Std Dev (Hours)	0.834	0.753
RMSE (hours)	0.850	1.057
MAE (hours)	0.650	0.878

When compared on an identical sample of stratus days, the 18z SJSU Scaled Local Model has a lower RMSE than all models except the Regional and Consensus models, and a lower MAE than all other models except for the Regional model.