

1 Low stratus as a driver of electrical demand 2 variability independent of temperature in 3 the greater Los Angeles region

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10 11 **Abstract**

12 The relationship between low cloud in the in the greater Los Angeles region (Southern California
13 Edison service area) and discrepancies from the electrical demand expected for each day based solely on
14 observed temperatures is examined using historical meteorological station temperature observations,
15 GOES satellite cloud albedos, and daily peak electrical demand as recorded by the California
16 Independent System Operator (CalISO). Electrical demand from the Western Electricity Coordinating
17 Council (WECC) was obtained as well, but not used due to errors in the recorded times in the data set
18 and disagreement between CalISO and WECC in reported loads for 2005. The historical meteorological
19 data exhibit problems as well, including blocks of time when uncorrected shifts in the time of
20 observation cause daily maximum temperatures to be mis-registered, as indicated by disagreements
21 with nearby stations reporting hourly observations. A daily peak electrical demand model was formed
22 by a regression between daily minimum and maximum temperature, weekend/holiday status, and
23 observed electrical load. Observed departures from the load calculated by this model were analyzed to
24 determine their relationship to cloud cover. Days with more electrical demand than anticipated (based
25 upon the temperature) were associated with a weak or absent marine layer, while days with less
26 electrical demand showed a stronger than usual cloud cover in the region. The relationship between

27 cloud cover and load discrepancies could be further explored with more spatially complete temperature
28 measurements, which might uncover whether the discrepancies are due to lack of temperature
29 measurements in the critical region at the mean inland edge of the marine layer, or to additional solar
30 heating of structures.

31 **1. Introduction**

32 The electrical demand for a day is strongly influenced by the day's peak temperature, especially
33 in relatively warm regions where annual electrical load is dominated by summer air conditioning, such
34 as California. Temperatures from the two previous days also have some effect (Garcia-Cerrutti et al.
35 2011). Beyond temperature, other meteorological conditions may affect energy demand as well, such as
36 humidity, wind speed, and solar insolation (e.g., Robinson 1997; Mirasgedis et al. 2006). However non-
37 temperature meteorological factors are small by comparison to temperature, and may be hard to
38 uncover given the pronounced serial auto-correlation in meteorological time series (Mirasgedis et al.
39 2006).

40 Although energy utilities consider their demand forecast methods proprietary and so are not
41 generally available for study, the California Energy Commission (CEC) evaluates energy demand using a
42 weighted average of the current day and two previous days' temperature, along with information on the
43 day of the week (weekends generally have lower electricity demand for a given temperature) and civic
44 holidays (Garcia-Cerrutti et al. 2011). We adopt this methodology to estimate electrical demand in the
45 greater Los Angeles region (specifically, the Southern California Edison service area) during the summer
46 of 2010 on the basis of temperatures observed on that day, and compare estimated to actual peak
47 electrical demand recorded on that day. Using observed temperatures in our electrical demand estimate
48 excludes as a source of load forecast errors any errors in forecasting daily minimum/maximum
49 temperature, which are not of interest here, although of course they are an operational concern. Our

50 purpose is to examine discrepancies between the actual electrical demand and that anticipated on the
51 basis of temperature, day-of-week, and holiday status, and determine if those discrepancies are
52 associated with varying cloud cover in the region. In other words, we construct a surrogate electrical
53 demand “hindcast” (similar to a forecast, but based on historical observations) using daily temperature
54 and then investigate the errors in the hindcast to determine if there are systematic influences by other
55 meteorological factors, such as cloud cover, which explain why the anticipated demand was not
56 realized.

57 This study brings together meteorological data with electrical load data to investigate how they
58 are related. Section 2 outlines the sources of our data. We found notable problems with the data from
59 both sources that make this analysis challenging. Results from the data analysis are shown in section 3
60 and discussed in section 4. Summary comments along with suggestions for future work are given in
61 section 5.

62 **2. Data**

63 **2.1 Meteorological data**

64 **2.1.1 Station temperature data**

65 The California Energy Commission (CEC) bases the utility-wide average temperature used for
66 forecasting electrical demand on a limited number of stations that have a high quality, long term record.
67 The station locations are shown in Figure 1, and the weighting applied to each station when computing
68 the average temperature for the Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San
69 Diego Gas & Electric (SDG&E) utilities are shown in Table 1.

70 Station temperature data was obtained from the Global Surface Summary of Day (GSOD, version
71 7; <ftp://ftp.ncdc.noaa.gov/pub/data/g sod/>) archive, and includes daily minimum (Tmin) and maximum

72 (Tmax) temperature. For two stations (KSEE and KNKX) with substantially incomplete records in GSOD
73 this was augmented with data from the daily Global Historical Climatology Network (GHCN;
74 <http://www.ncdc.noaa.gov/oa/climate/ghcn-daily/>). Data gaps in individual station records were filled
75 by linear regressions based upon historical relationships with the nearest stations with valid data. After
76 this procedure the utility-averaged, weighted Tmax time series was typically left with ~20 unfilled gaps
77 over the data period with an average length of ~1.5 days (0.04% of the data).

78 One problem with the station temperature observations is that some stations report a daily
79 reading (as opposed to hourly), and the time of observation has shifted over the years at some stations.
80 At one time many stations that report once-daily temperature took the observation in the late
81 afternoon. In this event, the day's maximum temperature is likely to be reported for the day of
82 observation. More modern practice is to take a single observation in the morning. This means that the
83 maximum temperature reported belongs to the previous day.

84 Although some meteorological station records are supposed to be corrected for this effect,
85 evidence often suggests otherwise. This can be determined using reference meteorological stations that
86 report hourly data, in which case there is no ambiguity about the day that the measurement applies to.
87 For example, Figure 2 shows the lag (in days) between annual time series of daily Tmax at KBUR (the
88 Burbank airport) from the GSOD once-daily data set, and daily Tmax derived from 4 nearby hourly-
89 reporting reference stations (shown in the 4 panels). In all 4 hourly reference stations a clear pattern
90 emerges that the hourly and GSOD data agree on the reported day between 1975 and 1992, and again
91 after 2005 (i.e., the correlation between the two time series peaks at a lag of 0 days), but disagree
92 between 1993 and 2002. During the latter period there is a one-day lag between the two time series,
93 which suggests that during this period the GSOD data set may be using a morning reporting time
94 without being corrected. In this work, which is meant to be exploratory and not comprehensive, we only
95 use data from 2010, and checked that the lagged correlations suggest that the reported times are

96 correct in the stations we use, but an incorrectly reported day in the temperature data could be a
97 significant issue during some time periods.

98 The size of the red dots in Figure 2 are proportional to the correlation value (in the one-year
99 window) between the GSOD Tmax time series and the Tmax time series derived from the hourly
100 reference station. The top left panel is particularly interesting because it shows the GSOD and hourly
101 data for the same station, KBUR. Correlation values are not uniformly close to 1.0, as might be expected.
102 To see whether this is a quirk of KBUR or a more general problem, Figure 3 shows time series of hourly
103 temperature (red line) and daily Tmax (horizontal blue lines) for KSAN (San Diego Lindbergh Field) for
104 the period 7 April 2006 to 20 April 2006. Although many days show the same maximum temperature in
105 the two records, there are also some sizable differences. On 14 April 2006, the hourly temperature
106 readings never exceeded 18°C, while the daily maximum temperature reported for this day in the GSOD
107 data set exceeds 31°C, a difference of 13°C.

108 Lacking complete metadata on the instruments we can only speculate why such a discrepancy
109 might occur. An instrumental problem is always possible. On the other hand, the sudden drop in daily
110 maximum temperature from April 13 to 14 suggests that a strong marine layer may have formed on the
111 14th, which is not unusual at this location. Such marine layers can have sharp transitions between clear
112 and cloudy conditions, so perhaps the discrepancy reflects a different location for a daily maximum
113 recording thermometer and an hourly reading temperature instrument. Or, perhaps a maximum
114 recording thermometer is used for the GSOD data and it was not reset correctly, and so is reporting the
115 previous day's late afternoon high temperature as the value for the 14th. The one thing we can say with
116 certainty is that the various temperature records are not self-consistent, even for a single reported
117 location.

118 **2.1.2 Cloud data**

119 Cloud data in the form of albedo estimated using the visible wavelength sensor on the GOES
120 satellite (<http://www.goes.noaa.gov/>) was provided by S. Iacobellis of the Scripps Institution of
121 Oceanography (Iacobellis and Cayan 2013). The data were processed as documented at
122 http://www.star.nesdis.noaa.gov/smcd/spb/fwu/homepage/GOES_Imager.php, including corrections
123 for degradation of the sensor (post-launch calibration), and has been interpolated to a fixed 1 km grid (S.
124 Iacobellis, *pers. comm.*). Data for the period we analyze here (summer 2010) was obtained by GOES11.

125 **2.2 Electrical load data**

126 Electrical load data were obtained from two sources: 1) Hourly load data from the Western
127 Electricity Coordinating Council (WECC) as archived by the California Energy Commission over the period
128 2005-2010 (described in detail in section 2.2.2). These data are not publically available. 2) Hourly load
129 data from the California Independent System Operator (CAISO), which operates California's electrical
130 power grid, via its Oasis web site, both the newer (<http://oasis.caiso.com>) and older
131 (<http://oasishis.caiso.com/>) versions (section 2.2.3). These data are freely available.

132 **2.2.1 Hour beginning versus hour ending load data**

133 The electrical load data are reported using one of two different time standards: hour beginning
134 or hour ending. The meaning of these two standards was determined by comparing reported hour
135 beginning and hour ending values to the CAISO's real-time updating load graph
136 (<http://www.caiso.com/Pages/Today's-Outlook-Details.aspx>), which was assumed to provide a correct
137 reference load versus time relationship. Based on this comparison, hour beginning values are (as the
138 name suggests) the instantaneous demand values at the start of the hour. So, for example, a reported
139 electrical demand value for "hour beginning 07" shows the instantaneous electrical demand that
140 occurred at 7:00 AM.

141 A similar comparison shows that “hour ending” values are arithmetic means over the hour
142 previous to the reported time. So, for example, a value for “hour ending 9” is approximately the average
143 from 8:01 AM to 9:00 AM, i.e., centered at a time of 8:30 AM. The comparison of recorded values to the
144 real-time load graph is not sensitive enough to determine if the exact time averaging interval is 8:00 AM
145 to 8:59 AM, 8:01 AM to 9:00 AM, 8:00 AM to 9:00 AM, or something else. However, for our purposes,
146 this one-minute uncertainty is not relevant, since the meteorological observations are only available
147 with a resolution of 1 hour or longer in any event.

148 Since hour starting data is instantaneous at the start of the indicated hour but hour ending data
149 is the average over the previous hour, time series of the same actual loads but reported in the two
150 different ways will be shifted by half an hour, with the hour ending data lagging the hour starting data.
151 E.g., an 8 AM reported value is centered at 8 AM in the hour starting data but 7:30 AM in the hour
152 ending data.

153 **2.2.2 WECC load data**

154 The WECC data is available with hourly time resolution over the period 2005-2010. Values are
155 spatially aggregated by electrical utility.

156 In California during the summer, electrical load peaks in the late afternoon due to air
157 conditioning and is smallest in the early morning hours (~4 AM). The mean daily cycle found in the WECC
158 data in July for each available year (2005-2010) is shown in Figure 4 for the Los Angeles Department of
159 Water and Power (LADWP). To facilitate comparing different years the data have been normalized so
160 that the difference between the minimum and maximum value is 1.0, which reduces discrepancies
161 between the cycles that arise from changes in population and economic activity over the period. (In
162 particular, the recession of 2008 had a notable effect on electrical demand.)

163 For convenience the horizontal grey line and annotations in Figure 4 show the local time of day
164 at which the average July electrical demand reached 63% of maximum. It is immediately evident that

165 the reported times in the WECC data set cannot be taken at face value, since it is implausible that
166 electrical demand as a function of time of day would shift in nearly exact half- or full-hour increments
167 between different years, as can be seen by the time when each year's curve reaches 63% of maximum
168 (annotated on the figure). More likely is that different standards of reporting have been used in
169 different years, resulting in a varying (and undocumented) time standard used for each year. Some of
170 the factors that could explain this varying time standard include: 1) Switching between hour starting and
171 hour ending reporting, which, as noted above, causes a half hour shift in the time of reported data; 2)
172 Switching between reporting times that include daylight savings time and times ignoring daylight
173 savings, which would cause a 1 hour shift in the time of the reported data; 3) Switching between
174 reporting times based on time at WECC headquarters (located in Salt Lake City UT, which is in the
175 mountain time zone) and time at the local utility (the Pacific time zone, for LADWP data). This would
176 also cause a 1 hour shift in the time of the reported data.

177 Figure 4 suggests that 2010 was reported with a different hour starting/ending standard than
178 the other years, since otherwise there is no plausible way to generate a half-hour shift in the data. Data
179 for year 2005/06 has a one-hour shift relative to data for years 2007-9, which suggests that one of the
180 one-hour shifts noted above are at play, i.e., a change between reporting times that include or exclude
181 daylight savings time, or a change between reporting times on the basis of time at the WECC
182 headquarters versus time at the local utility. Given the absence of metadata recording the process by
183 which the times of the electrical loads were recorded this cannot be determined with certainty,
184 however the large, integer multiple of 30-minutes shifts between groups of consecutive years (2005/6,
185 2007/8/9, and 2010) that themselves have relatively minor variation between them is a clear sign that
186 these problems exist in the reported times. Errors in reported time on sub-year timescales were not
187 examined.

188 **2.2.3 CalISO OASIS load data**

189 The OASIS data is available from before 2002 to present time, with near-real time updating. In
190 this work we do not examine data prior to 2002 since the so-called California electricity crisis affected
191 loads in 2000 and 2001 (e.g., Sweeney 2002).

192 The daily cycle of electrical demand in July over the period 2005-2010 is shown in Figure 5 for
193 Southern California Edison (SCE). As indicated in Figure 1 and Table 1, SCE demand is dominated by
194 temperatures in the greater Los Angeles region (represented by stations in Riverside, Long Beach, and
195 Burbank). The actual service area of SCE covers a large part of both southern and central California,
196 which is why Fresno temperatures contribute to SCE electrical demand (Table 1), but the weighting is
197 only 6%. Accordingly, Figure 5 (SCE) can be compared to Figure 4 (LADWP), at least in a qualitative way.

198 It is clear from Figure 5 that the OASIS data does not suffer from the time reporting problems
199 seen in the WECC data. In addition, the OASIS data is specifically indicated as being reported on an hour
200 ending basis, and that is consistent with the fact that OASIS-reported SCE load reaches 63% of peak load
201 at 10:30 AM (i.e., on the half hour; Figure 5).

202 **2.2.4 Comparing WECC and OASIS data**

203 Comparing Figure 5 to Figure 4, we speculate that WECC year 2010 was reported on an hour
204 ending basis but neglecting daylight savings time (10:30 PDT is 9:30 PST), which would account for a 1-
205 hour shift earlier in the WECC data, while 2005/6 were reported on an hour beginning basis, which
206 would account for a half-hour shift later in the WECC data. Similarly, 2007/8/9 may have been reported
207 on an hour beginning basis with respect to the WECC headquarters time zone (since the reported times
208 appear to be 1.5 hours later than found in OASIS).

209 The problems with the changing time standard in the WECC data can be avoided if the daily
210 maximum load is examined, since that is the same no matter what time standard is used. Since we have
211 data for both WECC and OASIS, we can compare their daily maximum loads to see if they agree. Results
212 are shown in Figure 6, presented as both time series (upper panel) and scatterplots (lower panel).

213 Although there are a few random days when the peak loads disagree (generally with WECC reporting
214 higher loads than OASIS), by and large the WECC and OASIS peak loads are consistent in years 2006-
215 2010 (nearly all the green circles fall on the black one-to-one regression line). However in year 2005 the
216 two data sets notably disagree, as can be seen both in the time series and in the regression, with the
217 WECC data reporting uniformly lower daily peak loads than OASIS (brown circles in lower panel). The
218 fact that the WECC values are much lower than other years in 2005 than 2006, while the OASIS data is
219 about the same in 2005 and 2006 as other years, suggests that it is the WECC data that has the error,
220 barring a reasonable explanation for why electrical demand should have been anomalously low in 2005.
221 The differing slopes of the green and brown lines in the lower panel of Figure 6 suggest that the error is
222 proportional to the total load, i.e., as if there is a missing load in the WECC data that is responding to the
223 same environmental/meteorological conditions as the rest of the electrical system, rather than being a
224 fixed constant load error.

225 Because of these errors in the WECC data, we used the CalISO OASIS load data in this work.

226 **3. Results**

227 **3.1 Load-temperature relationships**

228 Our purpose is to examine discrepancies between the actual electrical load on summer days and
229 the anticipated load based on temperature alone, so we must first develop a credible model for demand
230 as a function of temperature. We do this using regressions, as will now be described.

231 The relationship between utility region-averaged Tmax (using the stations and weights in Table
232 1) and electrical demand is shown in Figure 7 for PG&E, SCE, and SDG&E. Different years are indicated
233 by colors. Red shows results from 2002, the first year in the data set, which has the highest cool-
234 temperature energy use of any of the years in PG&E. In the other utilities 2002 is one of the lowest
235 consuming years at the cooler temperatures, as might be expected given the general increase in

236 population and economic activity over the time period (notwithstanding the recession of 2008/9). The
237 reason for this discrepancy in the 2002 PG&E data is unknown.

238 In all the utilities electrical demand is minimized when daily maximum temperature is just under
239 70°F. Additionally, the increase in electrical demand with temperature is approximately linear for warm
240 daily temperatures, which we take advantage of by exploring regressions between electrical demand
241 and Tmax only during a three-month summer period (15 June to 15 September, taken to be consistent
242 with Garcia-Cerrutti et al. 2011). Since it is anticipating the year's highest peak electrical demands that is
243 of primary interest for avoiding the potential of brownouts or rolling blackouts, it is sensible to restrict
244 our attention to load forecast errors found in the summer.

245 The results of the regression model predicting observed load from temperature are shown in
246 Figure 8. A generalized least squares fitting routine was used, with a method based on maximizing the
247 restricted log-likelihood. Additionally, because of the strong serial autocorrelation in meteorological
248 data, a first-order autoregressive (AR1) model was used to describe the correlation structure of the data
249 being fitted. The estimated AR1 parameter is 0.44, 0.50, and 0.55 for PG&E, SCE, and SG&E, respectively,
250 values that are large enough to justify taking the serial autocorrelation into account in the regression.
251 The regression uses current day's Tmax rather than a weighted combination of the current and previous
252 two days since a test with the latter formulation did not return a superior fit (as measured by fraction of
253 variance explained) even though it is more complicated. Additionally, Tmin is included along with a flag
254 indicating whether or not the day is a weekend or civic holiday.

255 Because of curvature in the load vs. temperature relationship for SDG&E even in summer (unlike
256 the other two utilities), the CEC perform the fit for three temperature bands for SDG&E (Garcia-Cerrutti
257 et al. 2011). Here we try to reduce the number of parameters somewhat by fitting SDG&E using both
258 Tmax and Tmax², unlike the other two utilities. This increases the fraction of variance explained from
259 0.92 to 0.95, but the strong correlation between the Tmax and Tmax² (> 0.99) must be kept in mind.

260 Values for the regression parameters are given in Table 2 (including a regression for SDG&E that does
261 not include T_{max}^2 , for comparison). Explained variance is lowest for PG&E, and highest for SCE, the
262 utility we examine in more detail below.

263 Although the previous load-temperature regression was done for daily peak load, the
264 regressions can be computed using hourly load as well (i.e., daily T_{min} and T_{max} related to each hour's
265 electrical load). This addresses the question of how well each hour's load can be forecast given
266 meteorological predictions of daily T_{min} and T_{max} . The fraction of explained variance in daily load for
267 the summer of 2010 in SCE as a function of hour-of-day is shown in Figure 9. Daily temperatures are
268 most predictive of loads in the afternoon hours, peaking at 2 PM. So even though T_{min} is more
269 statistically significant and explains a proportionally greater share of the variance than T_{max} in the 5 AM
270 regression (the reverse of the situation in the late afternoon), the T_{min} -dominated early morning
271 regression still does not forecast early morning electrical demand as well as T_{max} forecasts afternoon
272 electrical demand.

273 **3.2 Clouds and load forecast errors in Southern California Edison**

274 Using the regression described in Table 2 to provide an estimate of daily electrical load based on
275 utility-averaged T_{max} in SCE, and actual observed loads from OASIS, Figure 10 shows the difference
276 (actual – predicted load) in SCE during the summer of 2010. The RMS error is ~550 MW. The brown
277 areas show where actual demand exceeded that anticipated based upon temperature, which is
278 potentially a difficult situation for the electrical system to handle, and can in extreme cases lead to
279 brownouts or rolling blackouts if the unanticipated demand is high enough and regionally widespread.
280 Green areas show where actual demand was less than anticipated. The time series of errors does not
281 appear to be white noise, instead exhibiting a modest degree of serial auto-correlation (the actual value
282 is 0.37), which is consistent with a meteorological influence on the load forecast discrepancies.

283 We examine the relationship between load forecast discrepancies and cloud cover by calculating
284 the mean cloud albedo on days when the load forecast discrepancy was in the top tercile (most positive,
285 i.e., the load higher than anticipated based on temperature), the bottom tercile (load lower than
286 anticipated), and taking the difference, top tercile minus bottom tercile. The difference in load
287 discrepancy between the top and bottom terciles is approximately 1180 MW, which represents about
288 5% of the peak SCE load of 24,000 MW seen over the recorded period (Figure 7). This approach shows if
289 the cloud albedo is systematically different on days with positive and negative load forecast error. In the
290 event that cloud albedo (and therefore cloud cover) is unrelated to the load forecast errors, then there
291 will be no systematic difference in albedo between days with positive and negative load forecast errors.
292 We also examined specific humidity (Abatzoglou 2012), but found no significant difference linked to load
293 forecast errors.

294 Results from the tercile analysis of cloud albedos are shown in Figure 11. Since the strength of
295 the marine layer (and therefore degree of cloudiness) is a strong function of time-of-day, with a
296 tendency towards low stratus clouds in the morning that burn off by afternoon, the results are shown at
297 7 AM, 9 AM, 11 AM, and 1 PM local time. The top row shows the mean cloud albedo across all days in
298 summer of 2010 (15 June to 15 September) at the indicated local time. There is a strong tendency for
299 cloud cover to be present along the coastal regions of Los Angeles, Ventura, and Orange counties in the
300 morning hours. The coastal cloud cover persists until at least 9 AM, but in the mean tends to retreat by
301 11 AM and is nearly gone by 1 PM.

302 The second row of Figure 11 shows the difference in cloud albedo (percentage points) between
303 days with the highest and lowest load forecast discrepancies. There is a clear pattern of about -10
304 percentage points difference across areas of Los Angeles and Orange counties that are slightly inland
305 from the coast, extending into the southwestern tip of San Bernardino county, as well as the coastal
306 areas of Ventura county, that peaks between 9 and 11 AM local time. Since the inland edge of the mean

307 cloud cover is very nearly coincident with the center of this negative pattern, we interpret this as a shift
308 in the cloud cover's edge either inland or towards the coast. The sense of the difference is that during
309 the highest load forecast discrepancies (demand higher than anticipated based on temperature), the
310 albedo is lower (less clouds) than during the days when demand is lower than anticipated, when the
311 albedo is higher and clouds extend inland further.

312 The difference in albedo shown in the middle row of Figure 11 is given in percentage points, but
313 to really understand the significance of the difference it is necessary to compare the differences to the
314 mean cloud albedo (top row of Figure 11). The bottom row of Figure 11 shows the percentage change in
315 cloud albedo (with respect to mean climatological conditions over all included days) that is associated
316 with the difference between the top and bottom terciles of load forecast errors. There is up to a 40%
317 difference in albedo associated with the load forecast discrepancies.

318 In sum, these results show that electrical demand tends to be higher than anticipated (based
319 solely on temperature) on days with a weak or missing marine layer along the coast, and vice versa. A
320 point worth re-emphasizing is that the anticipated load already takes into account the actual day's
321 observed temperature. It is not surprising that a day with no clouds is warmer than a day with clouds,
322 and that since temperatures are warmer, electrical demand will be higher on days with a weak or
323 missing marine layer. However the load model already uses the actual observed temperature for the
324 day, so these results show that even when the higher temperatures experienced on days with no marine
325 layer are taken into account, there is still a residual error such that lack of a marine layer leads to higher
326 than anticipated electrical load.

327 The results of the regression and tercile analysis are worth illustrating with a specific case study.
328 Figure 12 shows the forecast and actual loads for all days in the summer of 2010 for SCE. The two red
329 dots show August 17 and 27, which are notable for having almost the exact same Tmax (differing by only
330 0.02°F) and similar Tmin (differing by ~1.7°F). Both were a weekday and not a holiday, and are separated

331 by less than 2 weeks. Despite the similar temperatures and time of year, electrical demand was
332 substantially higher on the 17th (20,700 MW) than on the 27th (18,900 MW), a difference of about 9.5%.
333 Based on the regressions developed in section 3.1 the anticipated difference in electrical load (given the
334 observed temperatures) was only about 0.3 MW (1.7%), so the actual difference was more than five
335 times larger than forecast.

336 The cloud albedo fields for these two days are shown Figure 13. There is a considerable
337 difference between the marine layer in the greater Los Angeles region between the two days, with 17
338 August (the day with high electrical demand) showing substantially less coastal clouds than 27 August
339 (the day with low electrical demand). While any particular example using a pair of similar days does not
340 constitute proof of the relationship suggesting that anomalously high electrical loads in SCE are
341 associated with days lacking a marine layer, it is at least consistent.

342 **4. Discussion**

343 The analysis presented here suggests that electrical demand in the greater Los Angeles basin
344 area is higher than the demand expected based on temperature alone when the marine layer is absent.
345 What are some possible causes of this?

346 One possibility is that the limited number of stations used to estimate the utility-wide Tmax
347 does not fully capture all the important temperature variability that drives demand variations. In the
348 CEC scheme to forecast SCE electrical demand, which we use here, temperature is calculated from four
349 stations (Riverside, Long Beach, Burbank, and Fresno), only one of which (Long Beach) is near the coast
350 (see Table 1 and Figure 1). Our analysis suggests that the load forecast errors are associated with cloud
351 variability on the inland edge of the marine layer (blue areas in the middle row of Figure 11). It is
352 possible that additional temperature information taken specifically from that area could improve the

353 load demand forecasts. The temperature gradient perpendicular to the coast could be estimated with
354 better station coverage, and may be useful in the demand forecast model.

355 Another possibility is that the additional solar insolation on clear days (weak marine layer)
356 increases the demand above and beyond what would be expected due to the ambient air temperature,
357 perhaps by more efficiently heating structures through windows. This possibility could be ruled out if
358 additional temperature measurements from regions underlying the inland edge of the marine layer
359 showed that temperature alone was enough to anticipate the extra electrical demand, although a more
360 elaborate analysis would be required to demonstrate a connection of load forecast errors to an increase
361 in direct solar heating if the explanation based on temperature was not supported by additional data
362 and analysis. In either event, the most straightforward way to explore this issue further would be to
363 obtain temperature data from additional locations in the relevant parts of Los Angeles, Ventura, and
364 Orange counties, and see if a higher-resolution depiction of daily maximum temperature were enough
365 to account for the errors in the load forecast that we find in this region.

366 The possible role of early morning satellite observations of low stratus cover could also be
367 explored, perhaps providing some limited same-day predictability of the marine layer's effect. The
368 relationship between duration of the marine layer and the effect on load also has not been explored in
369 this work, but could have some influence.

370 **5. Summary**

371 We have analyzed meteorological station temperature data, cloud fields from the GOES
372 satellite, and historical electrical load data to examine the relationship between clouds and electrical
373 load forecast errors in the greater Los Angeles region. The electrical load anticipated for a day is based
374 on that day's observed minimum and maximum temperature and weekend/holiday status. Performing

375 such an analysis is considerably hindered by problems with data quality in both the meteorological and
376 electrical load data.

377 Comparing two sources of electrical load data, from the Western Electricity Coordinating Council
378 (WECC) and from the California Independent System Operator (CalISO) OASIS web site, we found
379 notable inconsistencies and discrepancies between them, particularly in the reported times associated
380 with the WECC data. Implausible shifts in the daily cycle of energy use seen in different calendar years
381 that occur at integer multiples of 30 minutes strongly suggest undocumented changes over the years in
382 the reporting methodology of the times associated with the measured load. Additionally, an overall
383 discrepancy between loads reported for 2005 in the WECC and OASIS data is evident, with no obvious
384 explanation except that the WECC data set is missing about ~8% of California's electrical load in that
385 year.

386 The meteorological data also has some distinctive problems. Based on lag correlations with
387 hourly reporting reference stations , some of the temperature records clearly indicate that changing
388 observation times in the daily temperature time series have not been adjusted for correctly (or at all).
389 Additionally the observations occasionally exhibit substantial differences between daily maximum
390 temperature values recorded in the hourly and daily time series even for the same station, far larger
391 differences than can be accounted for by the hourly stations having a limited sampling rate. Such
392 problems might be caused by physically separated instruments being affected differently by the
393 (sometimes) strong cloud edge associated with the marine layer, but it seems more likely that they
394 could be due to instrument or procedural errors. More investigation using other station records would
395 help to better understand these differences. These problems underscore the importance of monitoring
396 high quality hourly observations from reference stations that can be used to verify the quality of the
397 traditional max/min temperature data from the network of stations that are employed.

398 Using Southern California Edison (SCE) electrical loads in the summer of 2010 as a test case, we
399 constructed a regression between observed daily maximum and minimum temperatures in the utility
400 service area and recorded electrical load (from OASIS) to serve as our “forecast” of electrical demand.
401 This approach using observed historical temperatures is useful because it removes the contribution of
402 weather forecast errors to the load forecast error, allowing us to focus on electrical demand variations
403 that do not arise from unanticipated temperature variations.

404 We find that differences between actual peak load experienced in a day and that expected
405 based on the observed temperatures are associated with changes in the inland penetration of the
406 marine layer. The difference can be up to ~5% of the utility’s peak load, which is smaller than 15%
407 reserve margin utilities are required to maintain, but still might affect operations or reliability in some
408 cases.

409 On days where the marine layer is strong and penetrates farther inland, electrical demand tends
410 to be lower than would be expected given the day’s actual temperatures. On days with a weak or
411 missing marine layer, demand tends to be higher than expected based simply on the day’s
412 temperatures. We speculate that this could be due to the limited number of meteorological stations
413 used to forecast electrical demand for SCE missing the effects of shifts in the inland edge of the marine
414 layer, or possibly due to an extra increment of solar insolation that heats the interiors of structures
415 more during clear days. An expanded analysis that attempted to find and use more meteorological data
416 in the greater Los Angeles area would be able to discriminate between these two possibilities.
417 Additionally, early morning satellite observations of the stratus layer might be useable for a limited,
418 same-day prediction of the layer’s effect on local electrical demand.

419 The present analysis was exploratory and is based only upon 2010 data—other years should be
420 examined to determine to what extent occurs the cloud influence on Load forecast error. Besides the LA
421 Basin region which was the domain considered in the present analysis, another avenue that could be

422 useful would be to explore the PGE and SDGE region to determine if there is a cloud effect there. Also,
423 the particular meteorological characteristics of yearly peak demand days could be examined differently
424 from normal days. For example, perhaps yearly peak demand days are associated with breaks in the
425 marine layer of multiple consecutive days. Finally, this work has considered low stratus effects on
426 electrical load in the Los Angeles area but not other meteorological influences. For example, there are
427 periods during which the monsoonal circulation can affect cloud cover and humidity in the region. Such
428 flows might have different impacts from the cooler air and cloud cover associated with the marine layer,
429 and would be useful to explore in future work.

430 **Acknowledgements**

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432 agreement #500-10-041. Additional support was provided by the California Nevada Applications
433 Program (CNAP) RISA, NOAA award NA11OAR4310150. We thank Tom Gorin and Guido Franco of the
434 California Energy Commission for valuable comments on this work.

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450

Abbreviation	Name	Pacific Gas & Electric weight	Southern California Edison weight	San Diego Gas & Electric weight
KUKI	Ukiah Municipal Airport	0.067		
KSFO	San Francisco International Airport	0.069		
KSJC	San Jose International Airport	0.282		
KSAC	Sacramento Executive Airport	0.169		
KFAT	Fresno Yosemite International Airport	0.413	0.062	
KRIV	March Air Reserve Base (Riverside)		0.371	
KBUR	Bob Hope Airport (Burbank)		0.243	
KLGB	Long Beach Airport		0.324	
KSAN	San Diego Lindbergh Field			0.333
KNKX	Miramar Marine Corps Air Station			0.333
KSEE	Gillespie Field, El Cajon			0.333

451

452 Table 1. Meteorological stations used by the California Energy Commission for forecasting
 453 electrical load for the Pacific Gas & Electric, Southern California Edison, and San Diego Gas and Electric
 454 utilities.

455

Utility	Tmax coeff, (std err), MW/°F	Tmax ² coeff, (std err) , MW/°F ²	Tmin coeff (std err) , MW/°F	Weekend/holiday coeff (std err), MW	Percent of variance explained (R ²)
PG&E	219.5 (22.4)	N/A	71.4 (36.8)	-1141.3 (137.7)	85.6
SCE	209.6 (13.8)	N/A	203.3 (24.2)	-1860.1 (116.4)	95.4
SDG&E	-274.9 (43.4)	1.992 (0.27)	17.1 (4.7)	-206.9 (18.7)	94.5
SDG&E (no T²)	41.5 (3.1)	N/A	30.3 (5.3)	-219.5 (23.6)	91.9

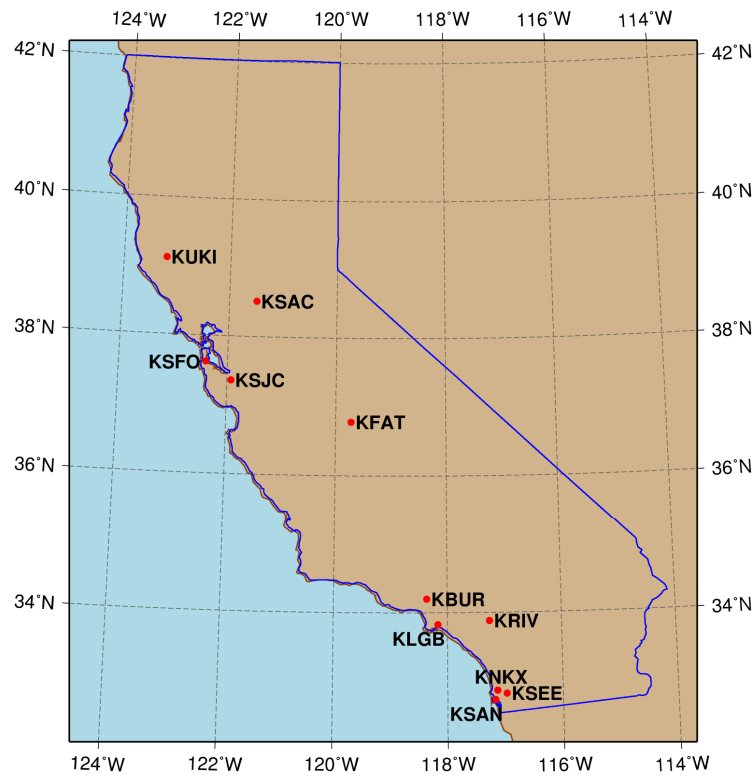
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Table 2. Regression parameters for relating daily maximum load (MW) to daily maximum

458

temperature (°F), minimum temperature (°F), and weekend/holiday status, for the summer of 2010.



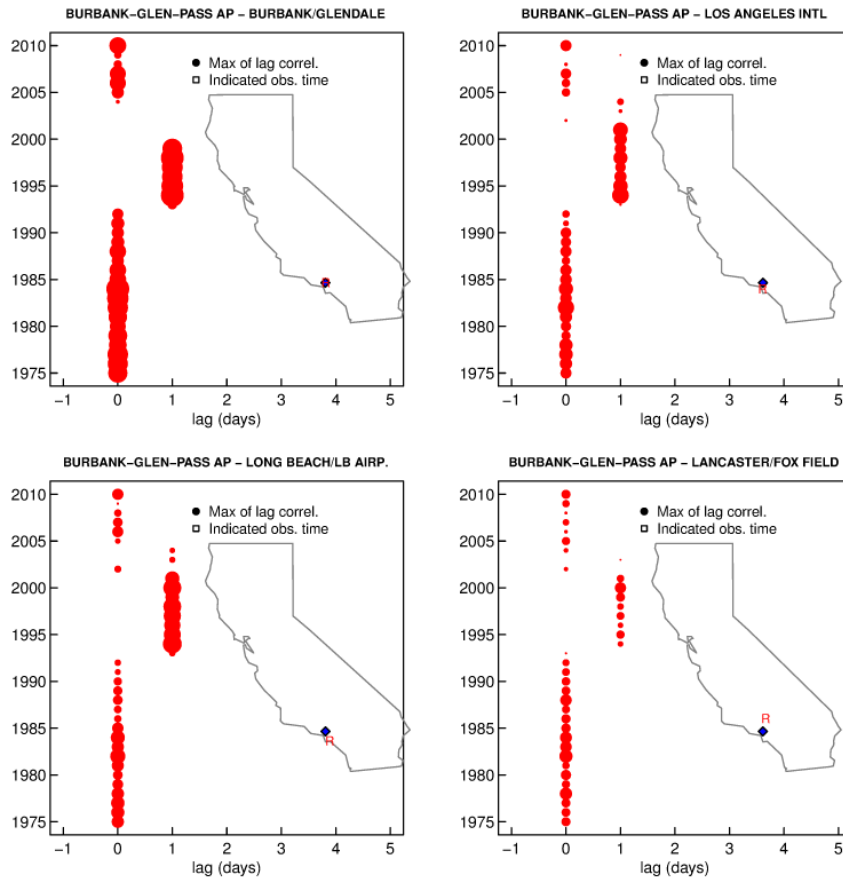
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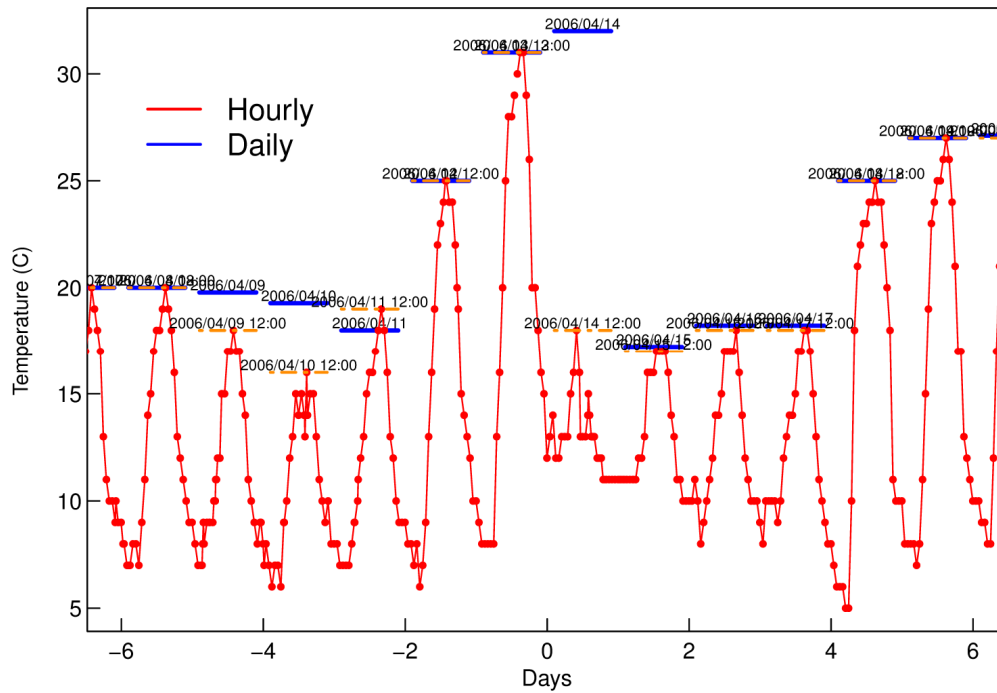
Figure 1. Meteorological stations used for utility load forecasting. See Table 1 for more information. KUKI: Ukiah. KSAC: Sacramento. KSFO: San Francisco. KSJC: San Jose. KFAT: Fresno. KBUR: Burbank. KLGB: Long Beach. KRIV: Riverside. KNKX: Miramar. KSEE: El Cajon. KSAN: San Diego.



/data/obs/station_data/hourly_NOAA_integrated_surf_database/compare_tmax_from_hourly_to_another_sta_v3.R Wed Feb 13 12:16:47 2013

463

464 Figure 2. Red circles show, for calendar years from 1975 to 2010 (vertical axis), the lag (days, on
 465 the horizontal axis) the maximizes the correlation between two time series: a) daily maximum
 466 temperature at KBUR (Burbank airport) derived from global summary of day (GSOD) reports; and b) daily
 467 maximum temperature derived as the highest daily value observed by the indicated hourly-reporting
 468 reference station. Each panel shows a different hourly reference station used for the comparison. Top
 469 left: KBUR (the same station as used in GSOD). Top right: Los Angeles International Airport. Bottom left:
 470 KLGB (Long Beach airport). Bottom right: Lancaster/Fox Field. The inset map shows the location of KBUR
 471 (black diamond) and the reference station being used for the comparison (red "R"). The size of the red
 472 circle is proportional to the correlation between the GSOD and hourly-reporting station's time series.



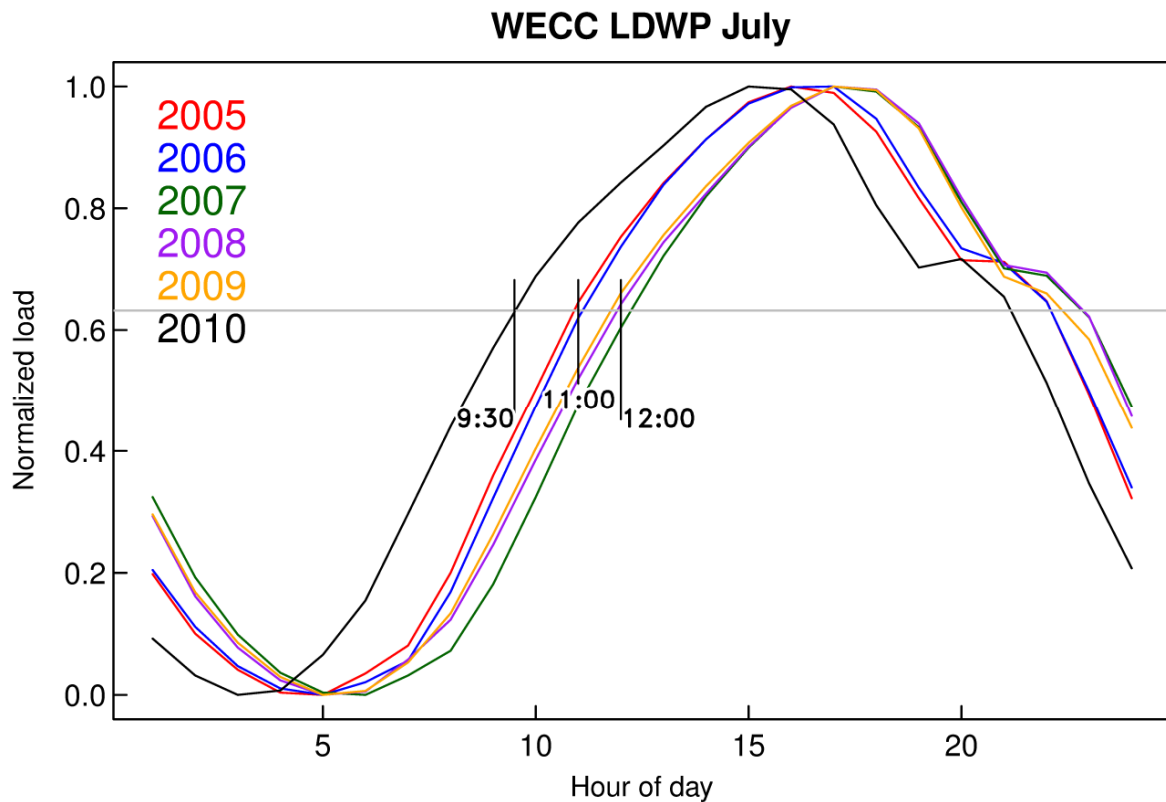
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474

Figure 3. Time series of hourly (red line) temperature and daily maximum temperature (blue horizontal lines with the reporting date indicated) from station KSAN (San Diego Lindbergh Field), as reported in the hourly temperature data set and daily maximum temperature data set, respectively.

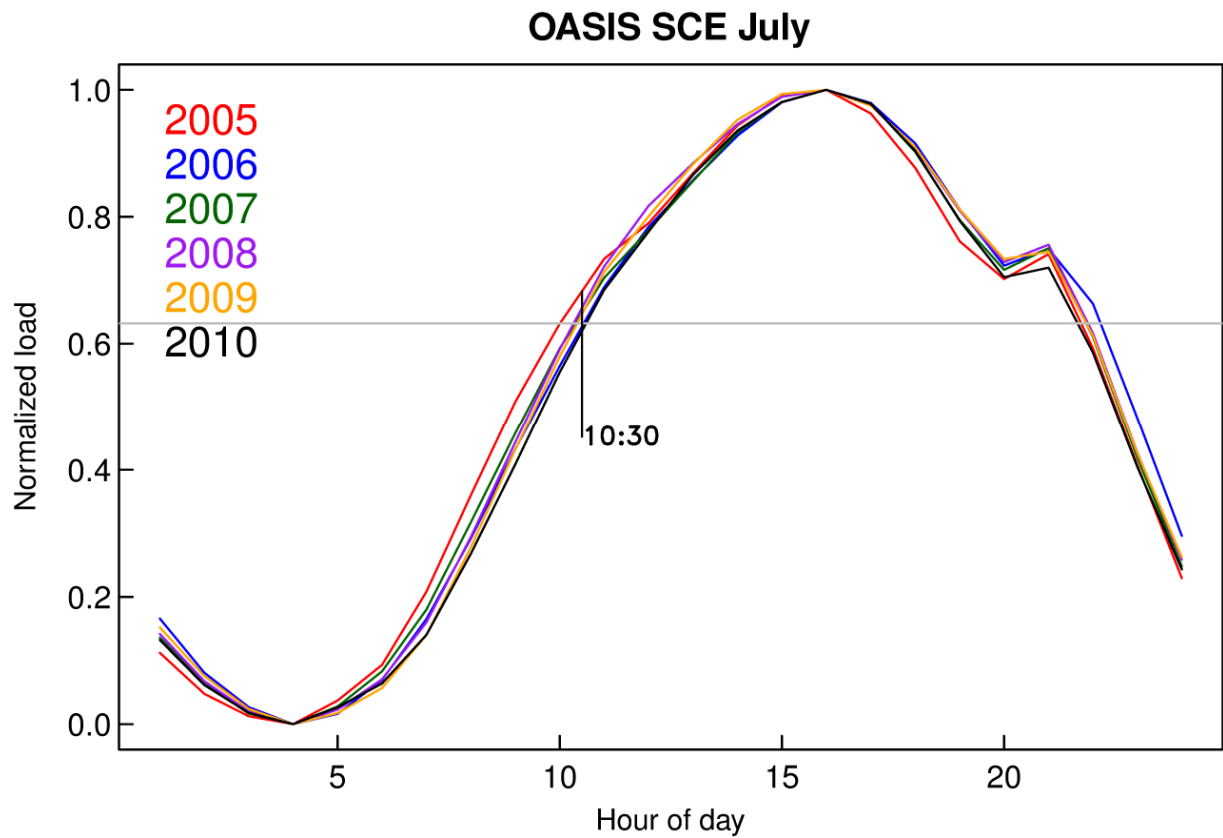
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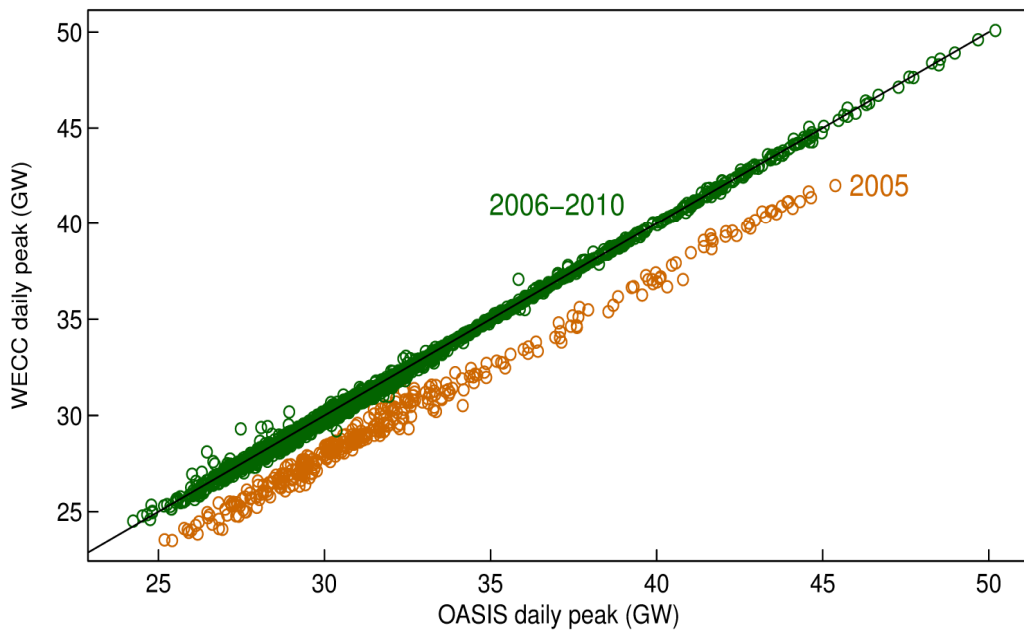
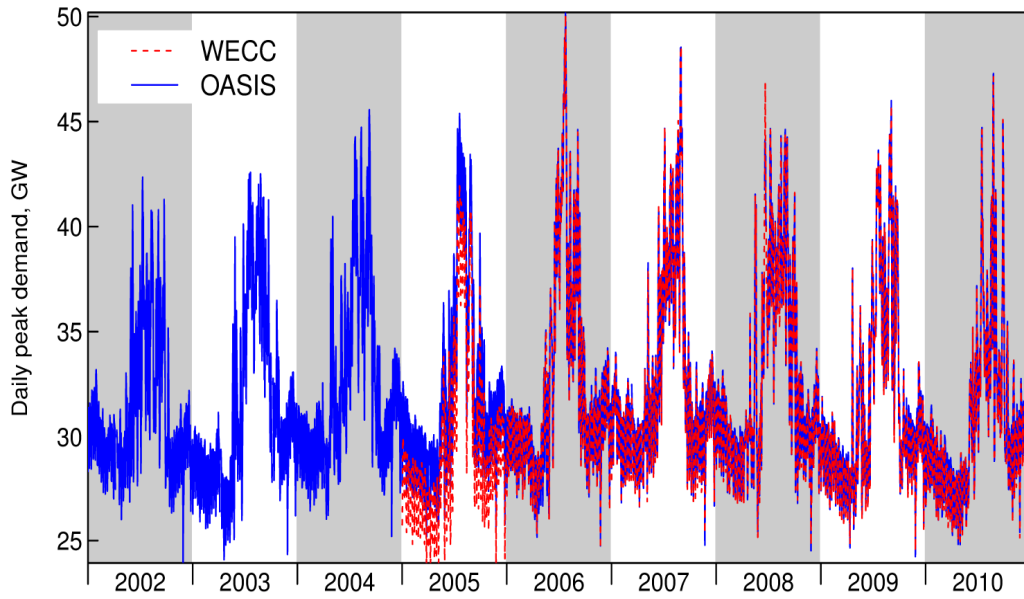
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478 Figure 4. Normalized mean daily cycle of electrical load in the Los Angeles Department of Water
 479 and Power service region for July 2005-2010 (indicated by different colors) in the WECC data set. Also
 480 shown is the time of day at which the normalized load reaches 63% of the maximum (horizontal grey
 481 line with annotations).



482

483 Figure 5. Normalized mean daily cycle of electrical load in the Southern California Edison service
 484 region for July 2005-2010 (indicated by different colors) in the CalISO OASIS data set. Also shown is the
 485 time of day at which the normalized load reaches 63% of the maximum (horizontal grey line with
 486 annotation).



487

/home/pierce/projects/cec_heatwaves/load_data_from_CallISO_OASIS/compare_daily_peak_load_OASIS_vs_WECC.R Fri Jan 18 15:35:54 2013

488

Figure 6. Upper: time series of CalISO service area daily peak electrical load from WECC (dashed

489

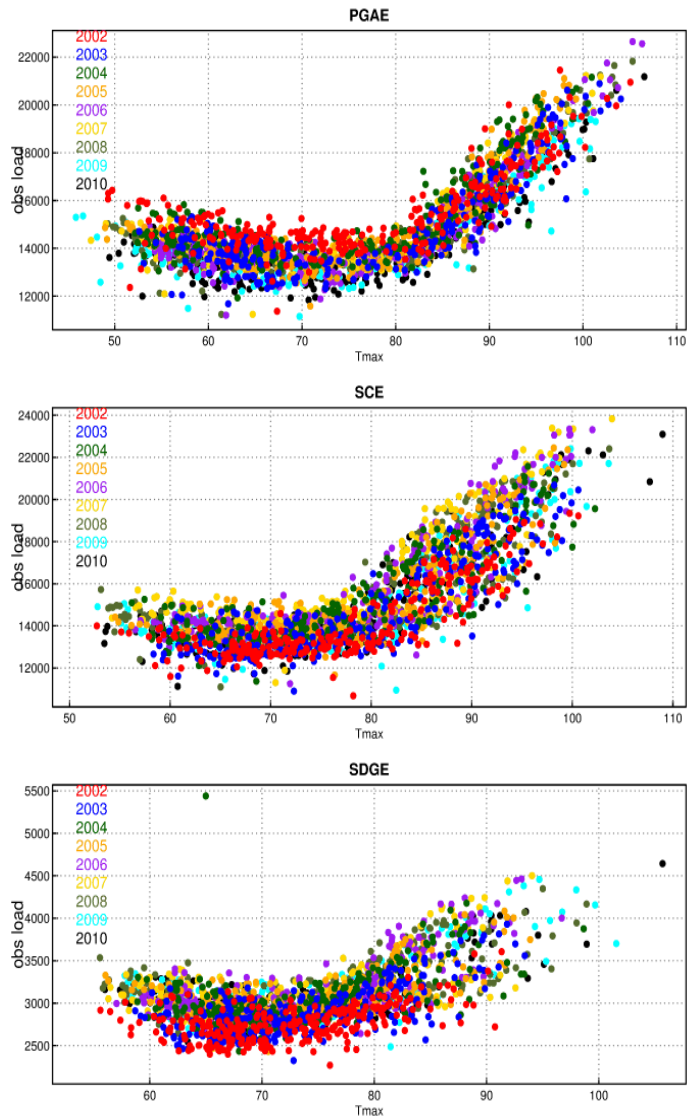
red line) and OASIS (solid blue line). Lower: Regression between OASIS and WECC daily peak values over

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the period 2006-2010 (green circles) and for year 2005 (brown circles). The black line in the lower panel

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shows a one-to-one relationship.



/home/pierce/projects/cec_heatwaves/load_vs_temp_multiyear_v2.R Wed Dec 12 11:37:10 2012

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Figure 7. Relationship between utility-averaged daily maximum temperature (Tmax, horizontal

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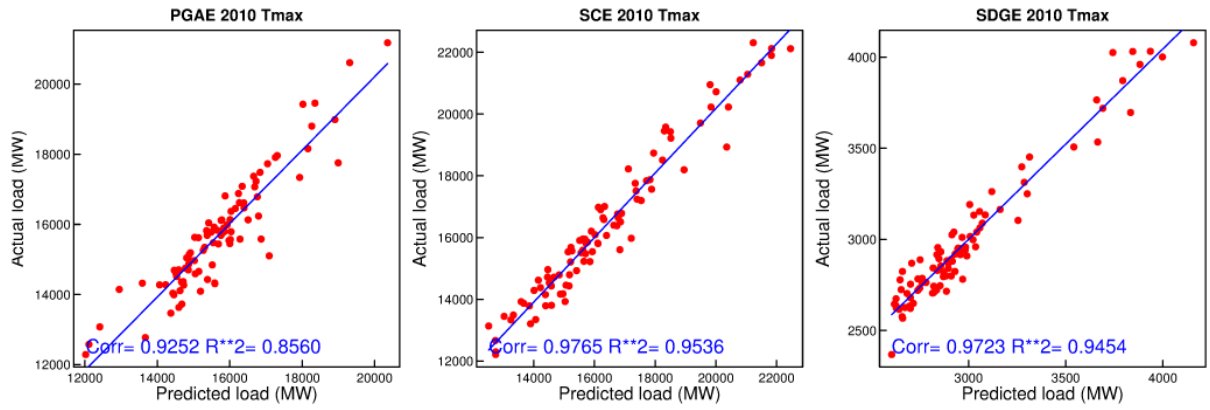
axis, in degrees F) and peak daily load (vertical axis, megawatts) from CalISO OASIS for every day in the

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period 2002-2010 for Pacific Gas & Electric (top), Southern California Edison (middle), and San Diego Gas

496

& Electric (bottom).



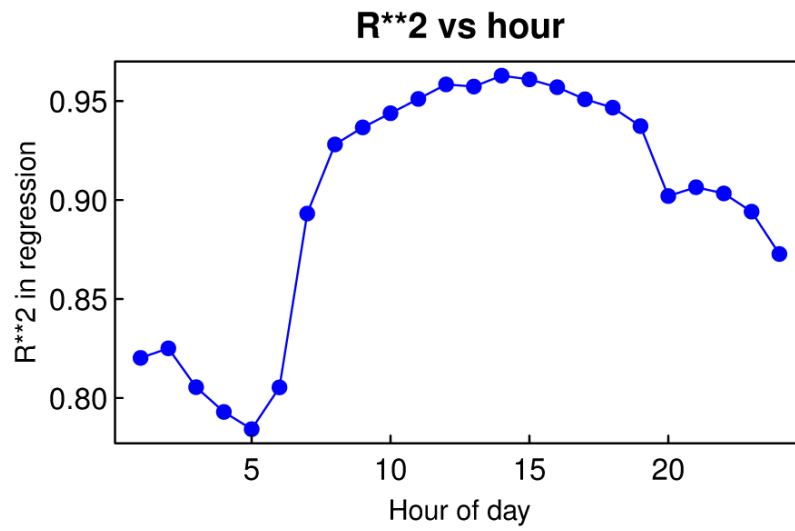
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Figure 8. Regressions between actual electrical demand for summer (15 June to 15 September)

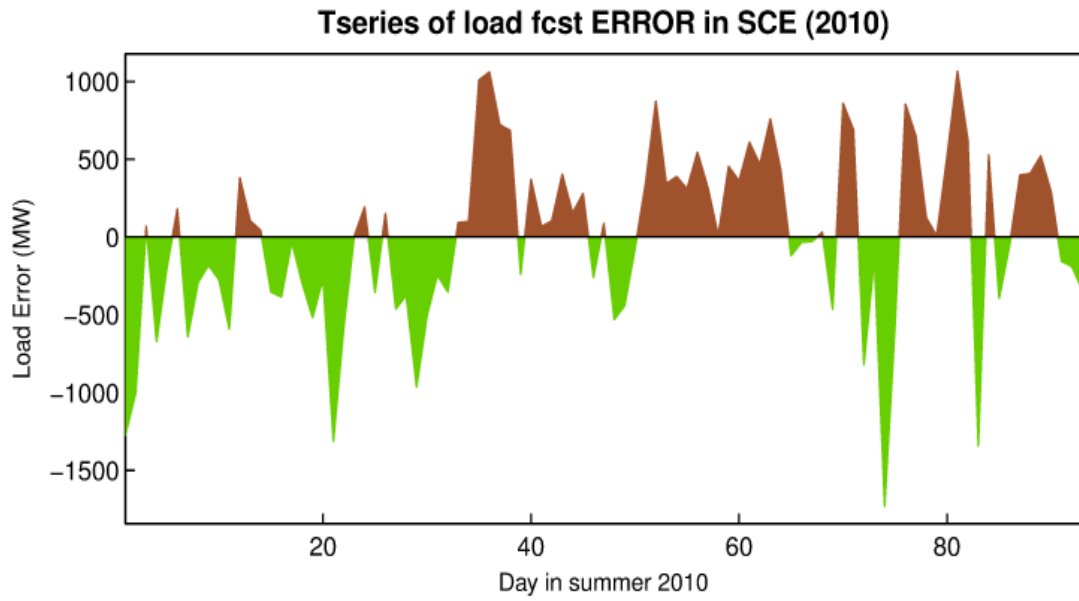
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of 2010 and demand predicted on the basis of Tmax, Tmin, and day-of-week status.



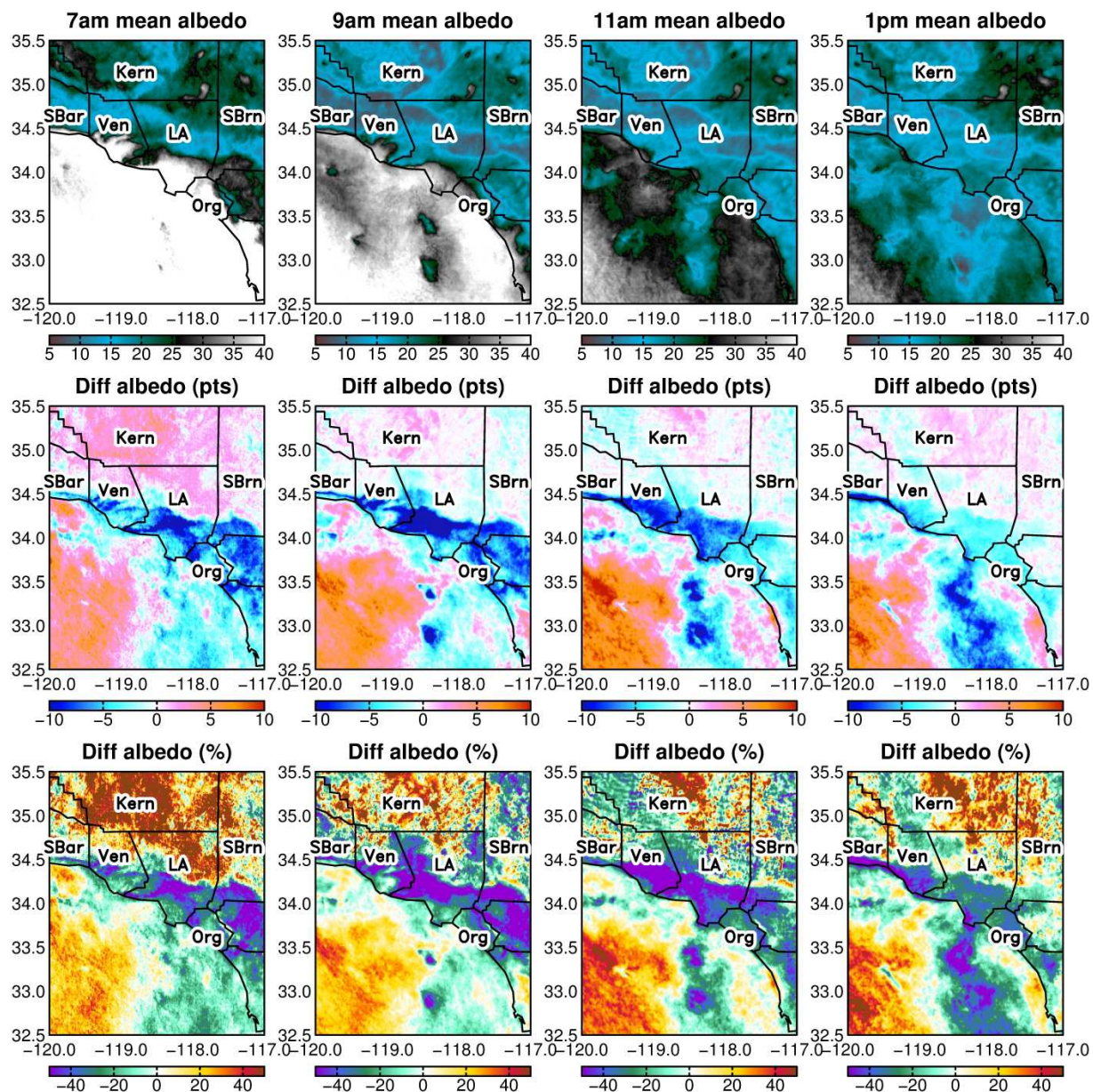
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501 Figure 9. Fraction of variance in the electrical demand vs. temperature relationship explained
 502 when electrical demand is taken by the indicated hour (but still using daily Tmin and Tmax), for SCE over
 503 the summer of 2010.



504

505 Figure 10. Load forecast error, MW (actual daily peak load – peak load predicted based on
 506 temperature and day-of-week) for SCE in the summer (15 June to 15 September) of 2010.



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/home/pierce/projects/cec_heatwaves/analyze_load_fcst_err_vs_clouds_v2b.R Mon Apr 14 17:36:08 2014

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Figure 11. Top row: mean albedo (percent) in the greater Los Angeles basin area during the summer of 2010, from GOES satellite observations, for the indicated local time of day (columns).

509

Outlines and annotations show county boundaries. Middle row: the difference (percentage points) in

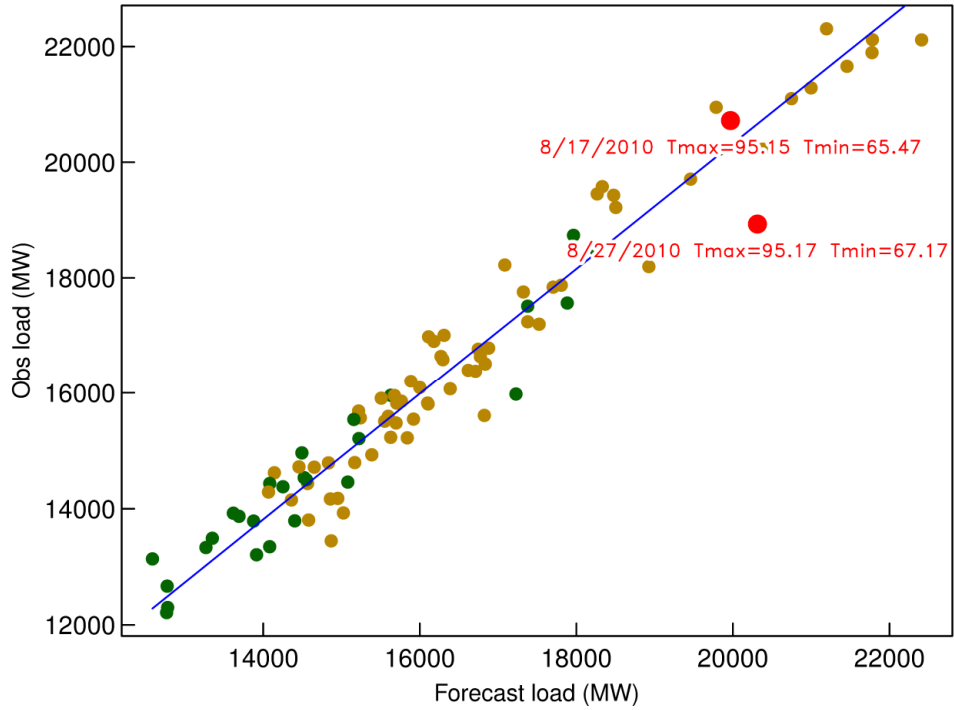
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albedo between days in the top and bottom terciles of load forecast errors. Bottom: same as the middle

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row, but in percent instead of percentage points.

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/home/pierce/projects/cec_heatwaves/load_vs_temp_SCE_v3.R Tue Apr 15 15:29:19 2014

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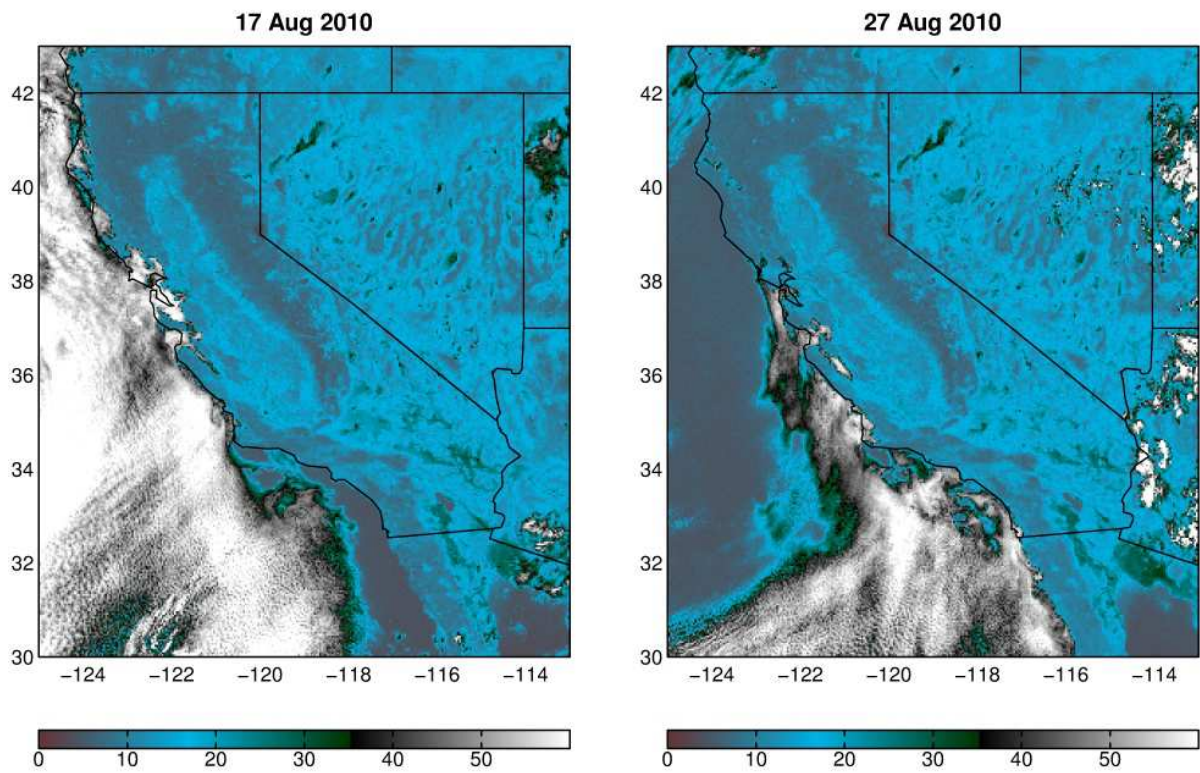
Figure 12. Scatterplot of forecast versus observed load on individual days (dots) in the summer

515

of 2010 for SCE. Green dots show weekends or holidays; gold dots show weekdays. The two red dots

516

show the days examined in more detail in the text and Figure 13.



/home/pierce/projects/cec_heatwaves/plot_example_cloud_fields.R Wed Feb 13 14:47:36 2013

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518

Figure 13. Cloud albedo field on August 17, 2010 (left) and August 27, 2010 (right) at 9 AM local

519 time.