

21

22 **Abstract**

23 After more than a decade of moderate seasonal deviations from the expected climate, it is easy to
24 forget that California is actually prone to instabilities in precipitation patterns that occur on various
25 scales. Using modern satellite and reanalysis data we reassess certain aspects of the precipitation
26 climate in California from the past three decades. California has a well-pronounced rain season that
27 peaks in December-February. However, the 95% confidence interval around the climatological
28 precipitation during these months imply that deviations on the order of 60% of the expected amounts
29 are very likely during the most important period of the rain season. While these positive and negative
30 anomalies alternate almost every year and tend to cancel each other, severe multi-year declines of
31 precipitation in California seem to appear on decadal scales. The 1986-1994 decline of precipitation was
32 similar to the current one that started in 2011, and is apparent in the reanalysis data. In terms of
33 accumulated deficits of precipitation, that episode was no less severe than the current one. While El
34 Niño (the warm phase of the El Niño Southern Oscillation, ENSO) is frequently cited as the natural
35 forcing expected to bring a relief, our assessment is that ENSO has been driving at best only 6% of
36 precipitation variability in California in the past three decades. It means El Niño needs to be stronger and
37 longer, in order to have a higher likelihood of a positive impact, and the current one does not match
38 these criteria. Using fractional risk analysis of precipitation populations during normal and dry periods,
39 we show that the likelihood of losing the most intensive precipitation events drastically increases during
40 the multi-year drying events. Since storms delivering up to 50% of precipitation in California are driven
41 by atmospheric rivers making landfall, thus the importance of their suppression and blockage by
42 persistent ridges of atmospheric pressure in the northeast Pacific.

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53 **Introduction**

54 California is perceived as a premier habitation, and, apart from its tech sector, is also a top
55 agriculture state, all attributable to its ideal climate. Dollar figures on the agricultural output
56 from California are placing the state at the top amongst agricultural states, leaving Texas
57 ranked only fourth by cash receipts [CDFA, 2012]. With \$42.6 billion agricultural output at stake
58 [CDFA, 2012], the attention to the lack of precipitation in California is understandable.

59

60 Positive and negative precipitation anomalies here alternate every year, tend to cancel each
61 other in consecutive years, and perhaps result in a perceived harmony in the short-term
62 memories. However, there exist numerous studies using historical records from rain gauges and
63 reconstructed tree ring records (Dettinger et al., 1998; Haston and Michaelson, 1997) that
64 present evidences of strong intrinsic variability of precipitation, and persistent droughts, in the
65 past decades and centuries in California. Pioneering in their nature, these studies also laid the
66 foundation of the present day understanding of the precipitation climate in California.

67

68 Comprehensive studies of droughts and drought indexes are also available. Keyantash and
69 Dracup (2002) put together an exhaustive comparative summary of drought indexes. These are
70 complex entities, encompassing more than just precipitation: they also include variables like
71 soil moisture, evaporation, river runoff, lakes levels, etc. While complex in their computation
72 techniques, the drought indices are easy to understand and use by resource analysts, as well as

73 by the general public. They are an excellent tool to evaluate severity of a drought, and relate
74 past episodes and different locations to a common denominator most suitable for agricultural
75 applications.

76

77 By no means do we attempt to make a drought assessment, which is out of scope here, using
78 precipitation deficits. In this study we simplify the sources of data and terms in which we
79 quantify the variability in general, and the deficits in particular, of precipitation in California, so
80 that they can be understood and used by a wider readership.

81

82 In this effort, we explore the usability of the most recent satellite and reanalysis data as
83 estimators of the likeliest precipitation amounts. We quantify the nominal precipitation season
84 in California, as well as the range of likeliest deviations, observed in the most recent decades.
85 The numbers we issue can be easily converted into absolute amounts of expected fresh water
86 input, around which realistic expectations and contingencies can be built for the state of
87 California on average. As an example, we show the accumulated precipitation deficit in the two
88 consecutive California rain seasons starting in August 2012. These are the optimistic amounts
89 California needs on average to recover, and ideally gradually, rather than in the form of
90 persistent torrential rains, which would shift the issue from drought to different problems like
91 mudslides and flushing the excess precipitation down the rivers. More realistic estimates,
92 however, should consider that the current decline of precipitation in California actually started
93 in the rain season of 2011-2012.

94

95 The impact of ENSO on precipitation in general has been extensively studied (Becker et al.,
96 2009; Dettinger et al., 1998). We reevaluate the impact of ENSO on the precipitation in
97 California using most recent satellite and reanalysis data. With only 6% impact on variability of
98 precipitation in California on average, the chances of El Niño having positive influence increase
99 only if it is stronger and longer.

100

101 A substantial source of precipitation is delivered to California by atmospheric rivers (Dettinger
102 et al. 2011). Relatively few storms contribute the bulk of California’s precipitation each year,
103 and it is the land falling atmospheric rivers that are normally causing most of the largest of
104 these storms. In a long-term average, atmospheric-river storms contribute 20–50% of the
105 state’s precipitation totals. However, they can be weakened or even blocked by large ridges of
106 atmospheric pressure forming in the northeast Pacific. We demonstrate the high probability of
107 losing the most intensive precipitation events during multi-year dry episodes, which implies on
108 the persistency and dominating role of the blocking ridges. This indeed can be clearly seen in
109 the yearly averages of the anomalies of winds and precipitation from MERRA.

110

111 **Data and methods used**

112 The satellite observations we use are data from the joint NASA and Japan Aerospace
113 Exploration Agency (JAXA) mission, Tropical Rainfall Measuring Mission (TRMM). In particular,

114 we use the version 7 of 3B43, TRMM and Other Data Precipitation Product (Huffman, 2007)
115 which is aggregated to monthly intervals. The latter product is output from TRMM Multi-
116 Satellite Precipitation Analysis (TMPA; computed at monthly intervals), which combines the
117 estimates generated by the TRMM and several other satellites. Furthermore, Version 7 of this
118 product shifted to using the rain gauge analysis from the Global Precipitation Climatology
119 Center (GPCC) throughout, rather than employing the one from the Climate Analysis and
120 Monitoring System (CAMS). The 3B43 observations of rainfall are at $1/4 \times 1/4$ degree grid boxes
121 for each month. They are available from January 1998, till October 2014.

122

123 The reanalysis data are from the Modern-Era Retrospective Analysis for Research and
124 Application (MERRA). MERRA data are derived from the Goddard Earth Observing System
125 version 5 (GEOS-5) data assimilation system. It is a combination of a NASA general circulation
126 model (Rieneker et al., 2007), and the grid point statistical interpolation analysis developed in
127 collaboration with the National Centers for Environmental Prediction. We use the monthly
128 time-averaged surface fluxes diagnostics (short name MATMNXFLX) for the total surface
129 precipitation flux, and the monthly assimilated state (short name MAIMCPASM) for the winds.
130 The surface diagnostic is produced on a $2/3 \times 1/2$ (longitude x latitude) degree grid, while the
131 assimilated state is given at 1.25×1.25 deg. There are numerous references describing in details
132 the MERRA data and the underlying incremental analysis update assimilation system (Bloom et
133 al., 1996; Bosilovich et al., 2011). The MERRA data are available from January 1979, until
134 present.

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136

137 For definiteness, we use standard shape files to extract data over California only. Where
138 appropriate, Student's t-test of 95% confidence level is applied, and thus only the results that
139 are statistically significant at 95% confidence level are presented. For example for anomalies,
140 the hypothesis is that the local monthly precipitation does not deviate from the multi-decadal
141 climatology for that month. Only when this hypothesis is rejected at 95% confidence, the
142 deviations are used as confident anomalies. Paraphrased, we show only the anomalies that
143 deviate with high degree of confidence from the naturally occurring variability in the past
144 decades (35 years for MERRA, and 17 years for TRMM). Thus it should be understood that every
145 time we use words "confident" and "confidently", test of significance was applied.

146

147 As an ENSO indicator we use the Multivariate ENSO Index (MEI) provided by Wolter and Timlin
148 (1993; 1998).

149

150 Our risk analysis of losing high intensity precipitation events is an approach very similar to what
151 is known as fraction of attributable risk. The latter is frequently applied in studies of increased
152 frequency (risk) of certain anomalies, (Knutson et al., 2014). In our case, it is calculated as a
153 difference between frequencies of occurrence of the most intensive precipitation in the
154 exposed and normal populations, relative to the frequency of occurrence in the normal

155 population: $R=(F_e-F_n)/F_n$. For the sake of simplicity, the exposed population is drawn from the
156 precipitation series during the decline of precipitation, whereas the rest are considered normal
157 population. The threshold value for the most intensive precipitation is set to that of the 95
158 percentile of the monthly precipitation anomalies (deviations from the average climate) in the
159 normal population. Similarly, the risk analysis is applied to the weakest 5 percentile of
160 precipitation. The frequencies of occurrence are normalized such that the sum of all
161 frequencies in a histogram is equal to 1.

162 **Results**

163 MERRA is a result of many years of refining of assimilations techniques. It is based in particular
164 on incremental analysis update, where the difference between general circulation model
165 forecast and optimally fused ground and satellite observations is forcing a second, corrective
166 run of the circulation model, (Bosilovich et al., 2011; Rienecker et al., 2011). The combined
167 satellite retrieval, TMPA (Huffman et al., 2010), similarly is in a state of quality and maturity
168 that allows users in many countries to apply it as a true observation when radar or rain gauge
169 measurements are not available.

170

171 Thus, the expected precipitation climate over California in the most recent decades estimates
172 consistently from reanalysis and satellite data, Figure 1, and is in agreement with the California
173 climate reported in the past (Caldwell et al., 2009). If by March-April California does not receive
174 its regular amounts, it will very likely miss the target until the next water season. Even though
175 the seasonal precipitation pattern is well pronounced in Figure 1, strong variability is

176 manifested by the length of the bars in the plot. The bars represent the two-side 95%
177 confidence interval for the climate of the month, as an average of all grid cells in California,
178 from the TRMM data. Similar are the confidence intervals from MERRA, not shown for the sake
179 of clarity. Within the peak of the rain season, December-February, dry or wet anomalies on the
180 order of 1 mm/day, which is about 30% of expected amounts, are very likely to happen in any
181 one year.

182

183 The time series of the monthly precipitation anomalies, Figure 2, aid in understanding the large
184 confidence intervals in Figure 1. Confidently large wet and dry anomalies are most common in
185 the rainy season, in the winter. The anomalies estimates from MERRA and TRMM are so
186 consistent, that they appear as overlapping lines for the time period of the TRMM mission. We
187 also note the lack of any artificial trends in the MERRA anomalies of precipitation in California in
188 Figure 2. This is a manifestation that neither the MERRA precipitation climate, nor the
189 anomalies (for California) are impacted by the onset of AMSU data from *NOAA-15* (November
190 1998) and *NOAA-16* (January 2001) satellites. The impact of AMSU on the MERRA assimilation
191 system has been discussed by Robertson et al. (2011).

192

193 While Figure 2 demonstrates the magnitude of precipitation variability in California, it cannot
194 reveal long-term accumulations of deficits and excesses. The combination of the strength and
195 duration of the successive precipitation anomalies accumulates over months and years,
196 resulting in long-term deficits and surpluses.

197

198 We demonstrate accumulated anomalies by computing cumulative sum of the time series of
199 the anomalies in Figure 2, and present the result in Figure 3. Now it becomes clear that, as a
200 state-wide average, California received cumulative surpluses during most of the past three
201 decades. There was a sharp accumulation of precipitation that started in 1982, in a recovery to
202 a previous dry period, and that lasted for about five years, until 1986.

203

204 Starting in 1986, the climate in California shifted to a pattern of persistent deficits that
205 gradually deepened to levels not seen in the past 35 years (Figure 3). In the winter of 1994-
206 1995 the precipitation started to rebound, with a particularly strong recovery in the winter of
207 the strong 1997-1998 El Niño. The current decline of precipitation, an episode that Figure 3
208 implies started in 2011, shows up as very similar to the 1986-1994 episode.

209

210 For the overlapping period of 1998-2011, TRMM and MERRA compare closely (Figure 3). Both
211 reveal that these 13 years were characterized with mild precipitation-deficit seasons that were
212 alternated and comfortably balanced by precipitation-surplus seasons that were relatively
213 stronger and longer. MERRA and TRMM practically overlap in reflecting the decline of
214 precipitation in the most recent dry episode. We'll turn to this period to assess the rate at
215 which precipitation deficit accumulated, using both MERRA and TRMM.

216

217 The climatologically expected accumulations of precipitation from TRMM and MERRA, averaged
 218 over California only, are presented in Figure 4. Even though the expected means are computed
 219 over 35 years of MERRA, and 17 years of TRMM data, both data sets give very close estimates
 220 of expected accumulation of precipitation over a year, Table 1. Both TRMM and MERRA are
 221 very consistent in estimating the accumulated 2-year deficit of precipitation at about -330 mm.

222

223 Table 1. Expected and received 1-year accumulations, and the resulting 2-year accumulated
 224 deficit, (mm)

	TRMM	MERRA
Expected	518	487
2012-2013	382	360
2013-2014	325	284
Deficit	-329	-330

228

229

230 For comparison, in Figure 4 we also plot the accumulated surplus of precipitation in the 2004-
 231 2005 water season coincident with moderately strong but prolonged El Niño. TRMM shows a
 232 more optimistic estimate of the surplus, Table 2, than MERRA. However, even this more
 233 favorable estimate shows that an “above average” El Niño may not help to completely offset
 234 declined precipitation similar to the most recent episode, and resolve the deficit in one year.
 235 Technically, to eliminate the deficit by the end of the 2014-2015 rain season (that is, August
 236 2015), California should receive the expected for the season and the accumulated deficit, to a
 237 total of 847 mm. Our early estimates (not shown), using less accurate real-time TRMM and
 238 GEOS-5 forecast, reveal California received about 350 mm, from August 2014 till late March
 239 2015. This means that the state must receive almost yearly amounts for the remaining months

240 of the current rain season, April-July, 2015. Since these are the months when the precipitation
241 is seasonally declining (Figure 1), the chances of full recovery in this season are slim.

242

243 Table 2. Expected and received accumulations, and accumulated surplus (all in mm) during
244 2004-2005 El Nino

	TRMM	MERRA
Expected	518	487
2004-2005	745	645
Surplus	+227	+158

245

246

247 The two onsets of substantial recoveries from precipitation deficits, in 1982 and in 1998(Figure
248 3) coincide with the two strongest El Niños on the record for the duration of MERRA data. The
249 coincidence of the two strongest El Niños with the onset of the two multi-year periods of
250 favorable precipitation, while circumstantial given the short record considered here, should not
251 be completely dismissed. The impact of ENSO on precipitation has been extensively studied
252 (Becker et al., 2009; Dettinger et al., 1998).

253

254 In the next section we re-evaluate the portion of California precipitation variability that is
255 driven by ENSO. We built anomalies using 3-month sliding average at every grid cell, and for the
256 climate base period use all data available from MERRA (1979-2014), and TRMM (1998-Sep
257 2014). Thus built anomalies at every grid cell are then regressed with the ENSO index. The
258 result is actually the Pearson correlation coefficient between precipitation anomalies and ENSO

259 index at every grid cell. The correlation coefficient is tested for 95% confidence, and only the
260 grid cells that pass the test are shown in Figure 5. Precipitation over most of California is
261 confidently influenced by ENSO. The positive correlation means that the precipitation is very
262 likely enhanced during the El Niño, the warm phase of ENSO, and suppressed during the La
263 Nina, the cold phase. We estimate the portion of precipitation variability that is driven by ENSO,
264 by taking the square of the correlation coefficient at every grid cell in Figure 5, and then
265 computing the area average over California only. TRMM and MERRA are again consistent,
266 estimating that only 5-6% of precipitation variability in California is driven by ENSO, Table 3.
267 This leaves lots of chances for El Niño, and in particular the weak events, to have no favorable
268 effect on the precipitation in California.

269

270 Table 3. Precipitation variability in California contributed by ENSO, in percents

	TRMM	MERRA
contribution (%)	6	5

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272

273 We now assess the risks of receiving anomalously weak precipitation, and risks of losing
274 intensive precipitation events, during the extensive periods of declined precipitation over
275 California, in the MERRA and TRMM record. Let's call the subset time series of these
276 precipitation anomalies "exposed population". The risks are expressed in terms of increased
277 frequency of anomalously weak precipitation, and decreased frequency of intense
278 precipitation, during periods of declining precipitation (exposed population), all relative to

279 “normal” periods (normal population). Taking advantage from the longer MERRA record, we
280 define as normal population the MERRA subset from 1/1979 to 6/1986, and from 8/1994 to
281 6/2011. Whereas the two abnormal periods with declining precipitation are defined as from
282 7/1986 to 7/1994, and from 7/2011 to 7/2014. We will regard the two periods of declining
283 precipitation separately to assess their relative severity. Also, we will validate the risks of
284 anomalous precipitation for the most recent dry period estimated from both, MERRA and
285 TRMM data. The TRMM normal precipitation population is from 1/1998 to 6/2011, and the
286 period of declined precipitation is the same as the second one for MERRA, from 7/2011 to
287 7/2014.

288

289 The histograms of monthly precipitation anomalies over California only are shown in Figure 6.
290 The dramatic decline of the frequency of intense precipitation events (positive anomalies)
291 revealed by TRMM for the recent dry period stands out immediately. This loss is apparent in
292 MERRA histograms as well, even though to a lesser extent. Both TRMM and MERRA histograms
293 manifest increase in the frequency of occurrence of anomalously weak precipitation (or longer
294 periods of no precipitation) during the dry periods. MERRA implies that this process was even
295 more severe in the 1986-1994 dry episode.

296

297 The normalized frequencies F_e , F_n in the risk analysis $R=(F_e-F_n)/F_n$ are computed by integrating
298 the histograms from Figure 6. The threshold values used in the integration are the 5 and 95
299 percentile of precipitation anomalies in the normal population. The threshold values are shown

300 as vertical dotted lines in Figure 6. The frequencies F_e are computed from the histograms of
 301 the exposed populations, while F_n are computed from the histograms of the normal
 302 populations.

303

304 TRMM and MERRA yield somewhat different estimates of risks in their overlapping period of
 305 2011-2014, Table 4. TRMM data indicate that the risk of losing high intensity precipitation
 306 dominated, whereas MERRA implies that the risk of more frequent weak precipitation doubled,
 307 during this period of declining precipitation. This is perhaps normal to expect, given the coarser
 308 MERRA grid resolution that should smooth the most intensive precipitation, but would
 309 otherwise come up even on average when closing global mass and energy budgets (Bosilovich
 310 et al., 2011). Indeed on area-average scale, precipitation anomalies from TRMM and MERRA are
 311 shown here to be in excellent agreement, Figures 2-3. Taking MERRA only, the current decline
 312 of precipitation is characterized by higher risk of disappearing of intensive precipitation, which
 313 is replaced by much likelier weak precipitation.

314

315 Table 4. Risks of anomalous deviations, using TRMM and MERRA data, (%)

	MERRA		TRMM
	1986-1994	2011-2014	2011-2014
Loss of intense precipitation	55	63	87
Gain of weak precipitation	62	100	61

318

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320

321 The increased risk of disappearance of intense precipitation reflects the suppression of
322 atmospheric rivers that are normally causing most of the largest of these storms (Dettinger et
323 al. 2011). The driving force behind that is the persistent ridge of high atmospheric pressure in
324 the northeast Pacific Ocean. The strength of the resulting anomalous geopotential heights, as
325 well as their attribution to anthropogenic forcing, has been analyzed in detail (Herring et al.,
326 2014). Figure 7 demonstrates that MERRA very clearly reflects this anomaly. Instead of
327 geopotential heights, though, we show the vector field of wind anomalies at 850 mb, averaged
328 over the entire 2013. The MERRA precipitation anomalies for the same time period are
329 overplotted as shades. Since this is an yearly average, apparently the winds anomalies
330 respond with very persistent anticyclonic pattern in the northeast Pacific. The wind anomalies
331 are easterly at the south edge of the vortex, i.e. working against the atmospheric rivers.
332 Precipitation anomalies are collocated, extending as a dry river from the north California into
333 the east Pacific.

334

335 **Summary**

336 The satellite observations and reanalysis considered here, TRMM and MERRA, are very
337 consistent in depicting the precipitation climate in California. Both estimate properly the well-
338 pronounced water season peaking in December-February. However, these data also reveal the
339 inherently unstable character of precipitation in California. Normally, when precipitation is not

340 in a multi-year declining regime, dry and wet deviations on the order of 30% of the expected
341 climate are very likely in any one year.

342

343 Another decline of precipitation, similar to the one persisting now, occurred in California in
344 1986-1994. A number of research groups conclude that the frequency of the blocking
345 atmospheric patterns driving these episodes has increased since the preindustrial age (Herring
346 et al., 2014). Anthropogenic attributions left aside, every next dry episode is still very likely to
347 be felt stronger. Assuming perfect climate, precipitation amounts in California are finite and
348 constrained at about 500 mm/m² per year. Whereas the population and land use are growing,
349 and thus are likely to exert more significant stresses on water resources demands than climate
350 warming (Hanak and Lund, 2008).

351

352 TRMM and MERRA are in agreement that ENSO is driving on average only about 6% of
353 precipitation variability in California, and, although not strong, this correlation is confidently
354 positive. Thus, stronger El Niños (the warm phase of ENSO), developing before the peak of the
355 precipitation season, like the ones in the winters of 1982-1983 and 1997-1998, are very likely to
356 force more precipitation. That strong El Niños are rare - in the past 35 years, these were the
357 only two of such strength. The current El Niño is weak and most likely will not facilitate any
358 relief in the 2014-2015 water season.

359

360 The episodes of declining precipitation in 1986-1994, and the current one that started in 2011
361 and is still ongoing, are characterized by high risk of losing the most intensive precipitation.
362 TRMM data, being at finer spatial resolution, assess the risks of losing the most intensive 5% of
363 storms to have been at almost 90% for the 2011 episode. Since MERRA data covers both, we
364 can look at how the two episodes compare. MERRA data implies that the loss of the most
365 intensive 5% of storms have been more likely in the current episode. The dramatic difference
366 in the current episode is the doubled likelihood of very weak precipitation (the weakest 5%) as
367 compared to normal periods. In these terms, the current episode, from 2011 till currently at
368 February 2015, is more severe than the 1986-1994 decline of precipitation.

369

370 The majority of intensive storms that reach California are driven by atmospheric rivers, and
371 hence the observed increased risk of losing these storms implies suppression and blocking of
372 the atmospheric rivers. As an example of the persistency and the scale of the blocking
373 atmospheric pressure patterns, we show the 2013 yearly anomalies of MERRA 850 mb winds
374 and precipitation. The yearly average reveals anticyclonic wind anomalies, resulting from
375 anomalously high atmospheric pressure ridge, dominating the northeast Pacific. The
376 precipitation anomalies are confidently aligned with the anticyclonic vortex and are extending
377 west from California into the Pacific, to where atmospheric rivers would normally arrive from.

378

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382 Processing System (PPS) at NASA GSFC, which develop and compute the TMPA as a contribution
383 to TRMM. The data are acquired through the Goddard Earth Sciences Data and Information
384 Services Center (GES DISC).

385

386 MERRA data used in this presentation have been provided by the Global Modeling and
387 Assimilation Office (GMAO) at NASA Goddard Space Flight Center through the NASA GES DISC
388 online archive.

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444 FIGURE CAPTION LIST

445 Figure 1. Precipitation climate in California, from TRMM observations and MERRA reanalysis.
446 The bars reflect the 95% confidence interval of TRMM climatology.

447 Figure 2. Precipitation anomaly from MERRA and TRMM. Area average over California only,
448 using 95% confident anomalies.

449 Figure 3. Cumulative sum of precipitation anomalies from Figure 2.

450 Figure 4. Accumulation of precipitation in California. Expected average accumulation
451 (climatology) from MERRA and TRMM, as compared to El Nino 2004, and the recent dry
452 seasons of 2012-2013, and 2013-2014.

453 Figure 5. Monthly precipitation anomalies from TRMM and MERRA regressed on MEI, at 95%
454 confidence. Red colors indicate enhanced precipitation during El Niño (warm phase), and
455 vice versa during La Niña (cold phase).

456 Figure 6. Histograms of normalized frequencies of monthly precipitation anomalies over
457 California only. Dotted lines indicate the 5 and 95 percentiles threshold values in the
458 histograms of the normal populations.

459 Figure 7. Anomalies of MERRA winds at 850 hPa (vectors), and precipitation (shades) in 2013.

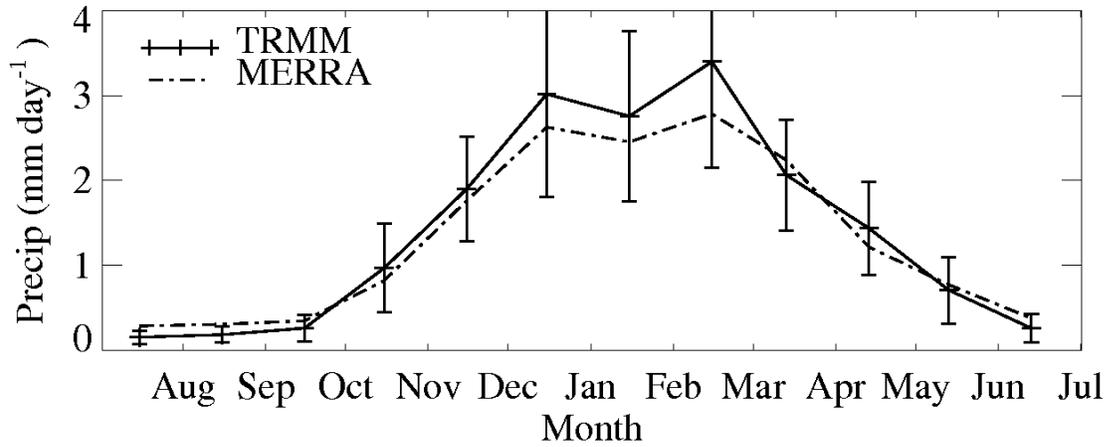
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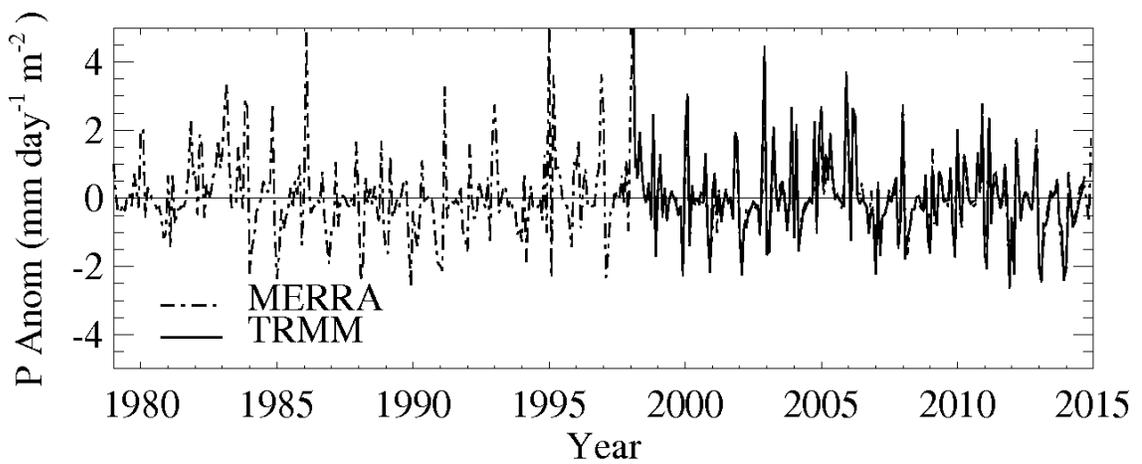


465

466 Figure 1. Precipitation climate in California, from TRMM observations and MERRA reanalysis.
467 The bars reflect the 95% confidence interval of TRMM climatology.

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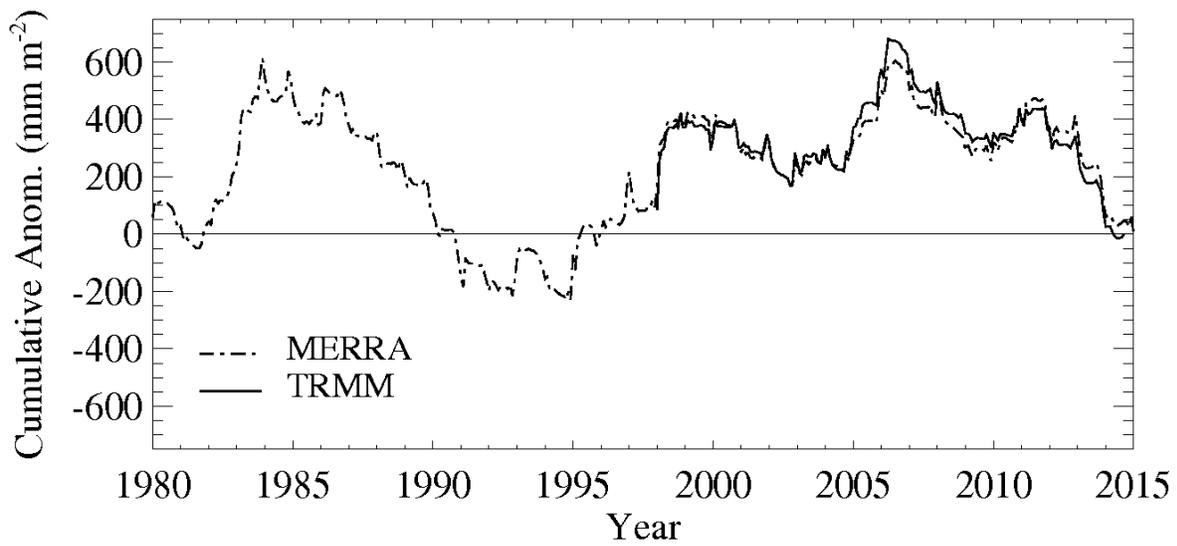
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471 Figure 2. Precipitation anomaly from MERRA and TRMM. Area average over California only,
472 using 95% confident anomalies.

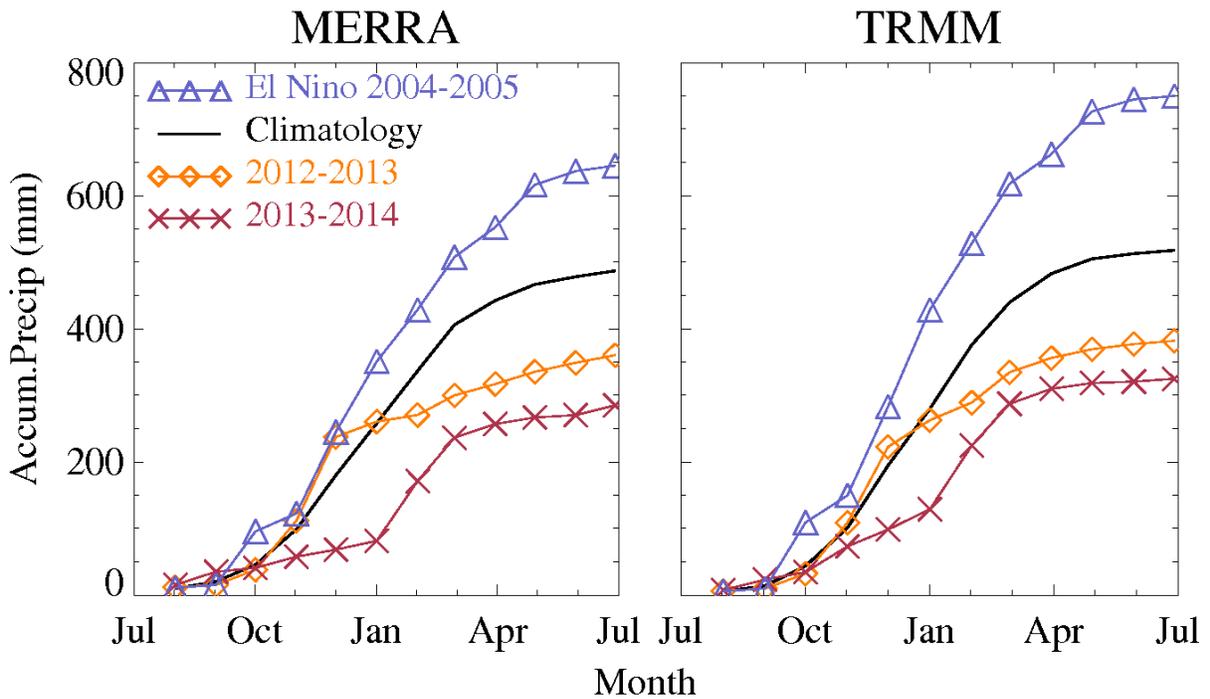
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475 Figure 3. Cumulative sum of precipitation anomalies from Figure 2.

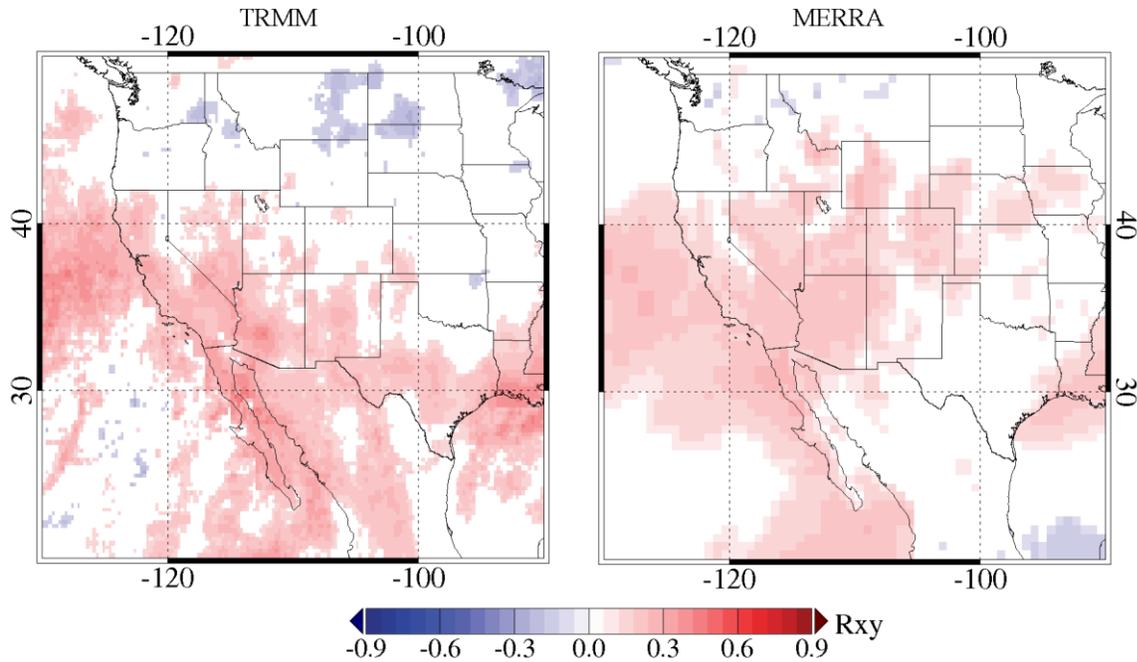
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478 Figure 4. Accumulation of precipitation in California. Expected average accumulation
 479 (climatology) from MERRA and TRMM, as compared to El Nino 2004, and the recent dry
 480 seasons of 2012-2013, and 2013-2014.

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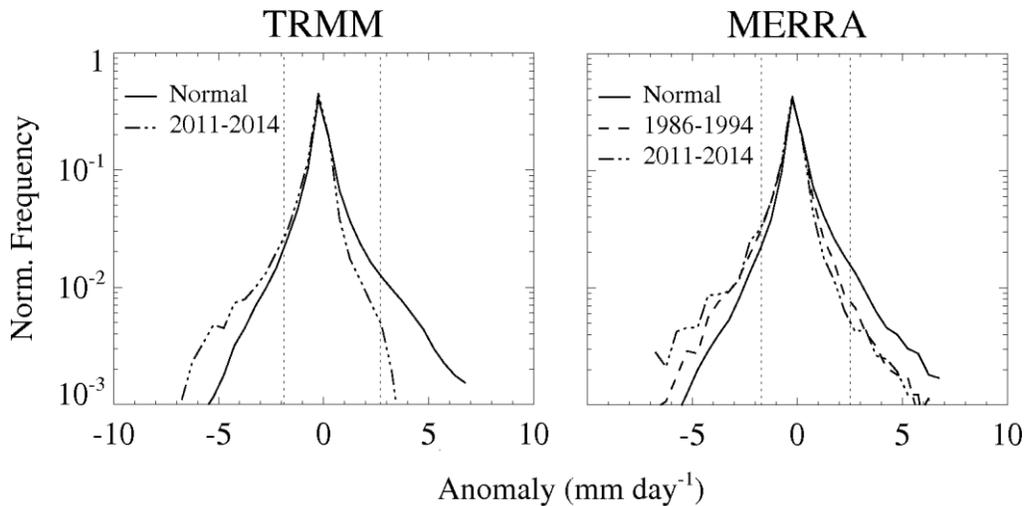


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483 Figure 5. Monthly precipitation anomalies from TRMM and MERRA regressed on MEI, at 95%
 484 confidence. Red colors indicate enhanced precipitation during El Niño (warm phase), and
 485 vice versa during La Niña (cold phase).

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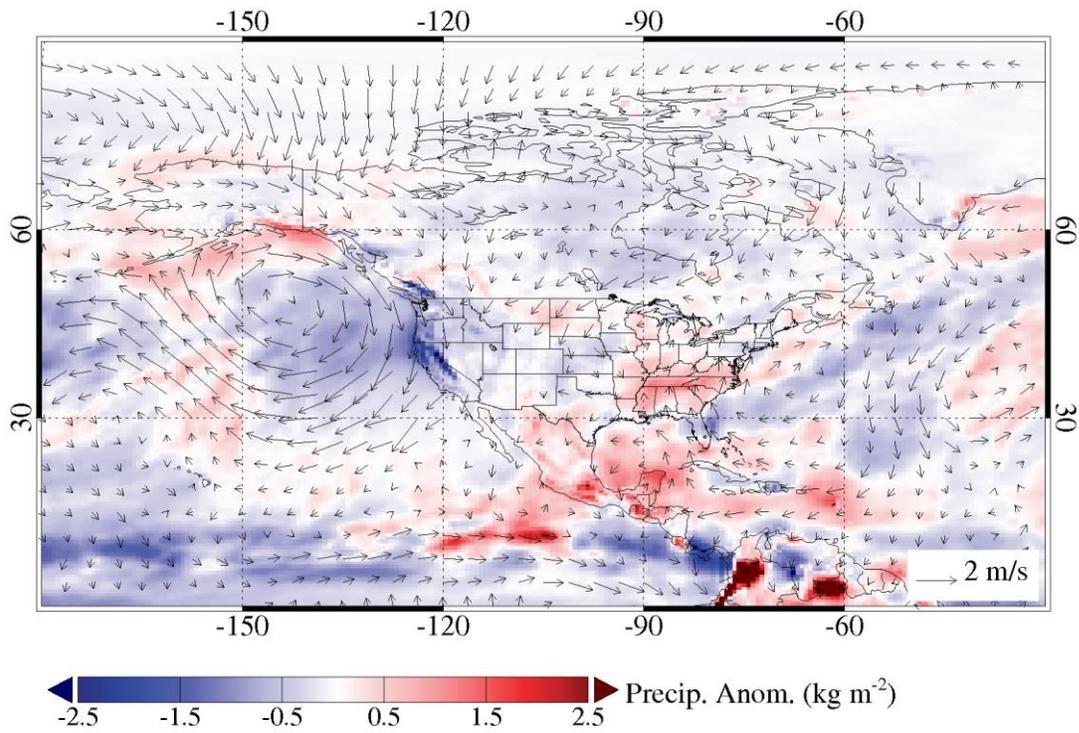
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489 Figure 6. Histograms of normalized frequencies of monthly precipitation anomalies over
 490 California only. Dotted lines indicate the 5 and 95 percentiles threshold values in the histograms
 491 of the normal populations.

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Figure 7. Anomalies of MERRA winds at 850 hPa (vectors), and precipitation (shades) in 2013.