

IDENTIFICATION OF CALIFORNIA CLIMATE DIVISION RAIN YEAR PRECIPITATION ANOMALY PATTERNS
(1895-96 TO 2013-14 SEASONS) WITH BAYESIAN ANALYSES OF OCCURRENCE PROBABILITIES RELATIVE
TO EL NINO, NEUTRAL, OR LA NINA EPISODES

Charles J. Fisk *
Naval Base Ventura County - Point Mugu, CA

1. INTRODUCTION

The state of California, nearly 800 miles long and 250 miles wide, is divided into seven National Climatic Data Center Climate Divisions. Based on areal-averaging techniques, month-to-month precipitation statistics have been compiled, division by division, since 1895 (and just recently, utilizing new and improved techniques, a recalculation completed of the entire division-by-division precipitation statistics, by year). With such huge distances between the northern to southern borders, and the great topographical variation, it would seem inevitable that the character of rain year (July-June) relative precipitation anomalies may not be consistent, division-to-division, from one year to the next. The degree and nature of these contrasts, and possible significant associations with phenomena such as the various ENSO phases ("El Nino", "Neutral", or "La Nina") should make for interesting study.

To this end, the existence and relative frequencies of California Climate Division rain year anomaly variation patterns (or "modes") is investigated using K-Means Clustering Analysis integrated with the V-Fold Cross Validation Algorithm. Period of record is 1895-96 thru 2013-14, some 119 seasons.

As applied to K-Means, the V-Fold Cross Validation Algorithm is an automated, iterative training sample type procedure that tends to optimize the number of resolved K clusters, depending on the choice of statistical distance metric and a specified percent distance improvement cutoff threshold, the latter measured by comparing, between successive $n=K$ and $n=K+1$ cluster candidates, the percentage reduction in average training sample statistical distances from their respective cluster centroids.

The present study performs the cluster analysis on the 119 seasons' (normalized) data utilizing the Squared Euclidean distance metric combined with the (default) 5-percent distance improvement threshold. Then, with the "optimal" number of clusters determined, and through referencing of two lists from the NOAA Climate Prediction Center online site which identify past ENSO episode phases back through 1895-96, a Bayesian statistical analysis is performed that addresses the following questions: given an impending ENSO phase type, what are the conditional ("posterior") probabilities that each of the inter-divisional anomaly patterns will be realized for a given July-June rain season. Results are described and interpreted, with the Bayesian probabilities compared among episode types.

* *Corresponding author address:* Charles J. Fisk, Naval Base Ventura County, Point Mugu, CA. 93042: e-mail: charles.fisk@navy.mil

2. THE K-MEANS AND V-FOLD CROSS VALIDATION METHODOLOGIES

The original K-means methodology was introduced by Hartigan (1975), and the basic methodology consists of assigning observations to a designated number of K clusters such that the multivariate means across the clusters are as different as possible. The differences can be measured in terms of Euclidean, Squared Euclidean, City-Block, and Chebychev statistical distances (Nisbet, et. al., 2009).

Applied to K-Means, the V-fold cross-validation scheme involves dividing the overall data sample into V "folds", or randomly selected subsamples. K-means analyses are then successively applied to the observations belonging to the V-1 folds (training sample), and the results of the analyses are applied to the sample V that was not used in estimating the parameters (the testing sample) to assess the predictive validity or the average distances of the training sample arrays from their cluster center centroids. The procedure is repeated for cluster sizes $K+1$, $K+2$, ..., etc., until the incremental improvement in the average distances is less than some threshold, at which time the "optimal" cluster size is considered attained (Nisbet, et. al., 2009).

The STATISTICA Data Miner Clustering module was utilized to employ this technique. Preliminary to the analyses, the Climate Division data were normalized, an internal automatic software feature, to reduce them to a common scale (between 0.0 and 1.0) and lessen the influence of outliers. Cluster results would be presented in pre-normalized data form.

Since the percent improvement threshold default setting (5 percent) can be changed, potentially resulting in a different "best" cluster size, an alternative graphical tool is available that can provide a different selection option. This tool, the Scree Plot, traces the actual (usually decreasing) mean training sample statistical distances over a range of increasing K's. Inflection points on the Scree Plot can be interpreted as "natural" cutoff points, the "best" cluster size corresponding to the inflection point's Kth position on the graph. The percent improvement cutoff K may differ (the iterations having stopped at $K+1$), so, alternatively, if one opts to choose the inflection point as the "right" K and it is different than the percent improvement threshold K, the program can be rerun, "forcing" the "optimal" cluster size and accompanying analysis and information to correspond to that at K, and K only. If one is interested in a more exhaustive analysis, the forcing could be done at a Scree K-value that exhibits essentially zero change in mean training sample statistical distance from the preceding K-1 level. At even higher K levels, of course,

the statistical distance curve might trend back upward, reflecting over-fitting.

In this study, the 5 percent default distance improvement cutoff threshold was utilized along the Squared Euclidean distance metric (default: Euclidean), together with Scree Plot inspection.

3. BAYESIAN ANALYSIS

From *Wikipedia*, Bayesian inference is a method of which Bayes' rule is used to update the probability estimate for a hypothesis as additional evidence is acquired. In the context of this study, the initial hypothesis would be a probabilistic belief, or "Prior Probability", that a given anomaly pattern (cluster) would occur unconditionally (historical percent frequency of the pattern), updated by a processing of evidence that relates the occurrence of the pattern to ENSO phase. The latter could be referred to as "accounting for evidence" and the result, or "impact", multiplied by the "Prior Probability" would produce a "Posterior Probability" that incorporates this new conditional information (the ENSO phase) into a revised probabilistic belief that the given pattern will occur. A desirable outcome would be a marked contrast in magnitudes between the Posterior and Prior probabilities which would indicate that knowledge about the conditional variable "matters". The actual Bayesian expression will appear in a later section in which a case example is demonstrated on the California Climate Division precipitation data.

4. THE DATA

The raw data were downloaded via an NCDC online link which had the newly modified complete history for the July 1895 to June 2014 period of interest. Figure 1 is a map of the California Climate Divisions. Their full titles, in numeric ordering are, 1.) "North Coast Drainage, 2.) "Sacramento Drainage", 3.) "Northeast Interior Basins", 4.) "Central Coast Drainage", 5.) "San Joaquin Drainage", 6.) "South Coast Drainage", and 7.) "Southeast Desert Basin". In the results' discussions below, the titles appear in shortened fashion, with the "Drainage" and "Basin" portions omitted.

Also, Figure 2 is a bar chart of the 119-year mean July-June precipitation figures, by division, and Figure 3 a similar type bar chart of the standard deviation statistics, by division. From Figure 2, there is a wide range of mean statistics, from nearly 50" in the North Coast division, to only 6" in the Southeast Desert. The standard deviation statistics in Figure 3 range from ~13" for the North Coast, to 2" in the Southeast Desert.

With such a wide division-to-division range in overall mean precipitation and variability across the State, it makes sense from an interpretation standpoint to express the individual cluster results, division-by-division, in terms of relative or standardized deviations from the overall averages in Figure 2, based on the overall standard deviation statistics depicted in Figure 3.

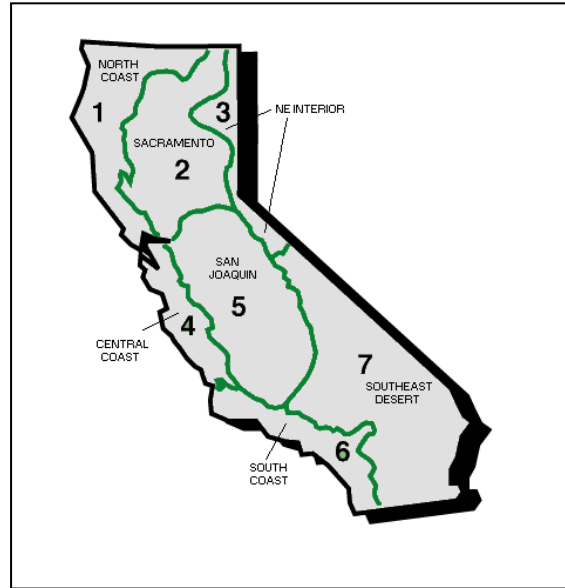


Figure 1 – Map of California Climate Divisions – from NCDC.

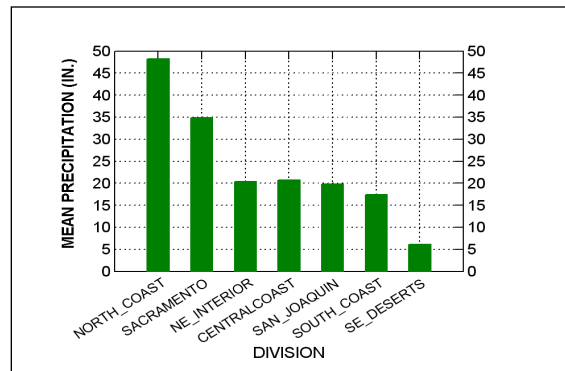


Figure 2 – Mean Seasonal (July-June) Precipitation (In.) for NCDC California Climate Divisions (1895-96 thru 2013-14 Period of Record)

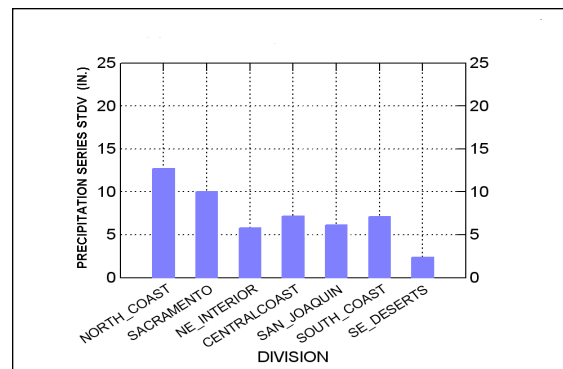


Figure 3 – Seasonal (July-June) Precipitation Series' Standard Deviations (In.) - NCDC California Climate Divisions (1895-96 thru 2013-14 Period of Record)

5. RESULTS

The K-Means/V-Fold algorithm produced six clusters, ranging in individual percent frequency from 23.5% to 11.8% for a pair of patterns.

5.1. – Scree Plot

Figure 4 is a Scree Plot of the iterative results. An inflection point is visible at K=6, matching the “Best” K determined by the 5% default improvement threshold setting - a reinforcing outcome. The curve is also essentially flat from K=6 to K=7, further reinforcement that there are essentially six inter-divisional anomaly modes in existence for California July-June total precipitation.

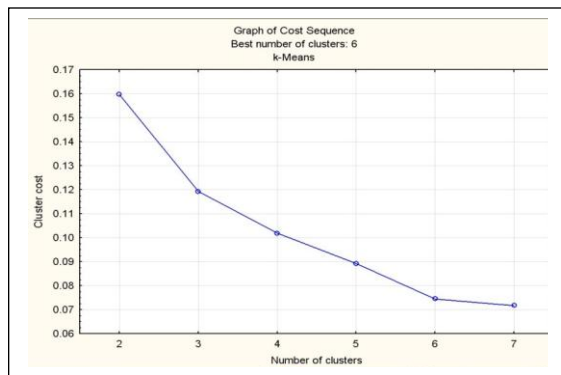


Figure 4 – Scree Plot of K-Means/V-Fold Cross Validation Algorithm Analysis of California Climate Divisions' Seasonal (July-June Total) Precipitation Anomalies.

5.2. – Standardized Mean Anomaly Charts for the Individual Patterns.

Figures 5 thru 10 present the division-by-division standardized mean anomalies for each of the six patterns, in descending order of importance.

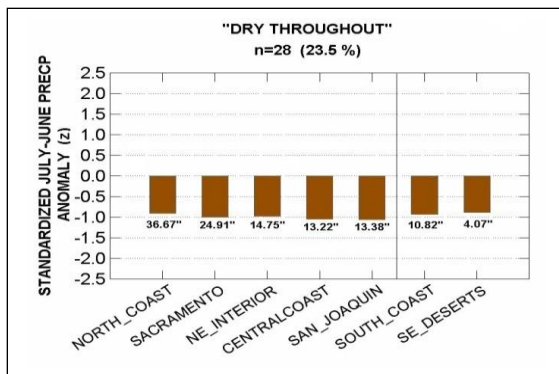


Figure 5 – Standardized Mean Division-by-Division Anomalies for the “Dry-Throughout” Pattern (Mode #3).

Figure 5 shows the most frequently represented pattern (23.5% incidence), titled “Dry-Throughout”. The standardized division-to-division anomalies are quite uniform, about one standard deviation each below their respective climatologies. The actual cluster means are annotated immediately below the edges of the bars, ranging from 36.67” for the “North Coast” to 4.07” for the “SE Deserts”. These can be compared with the overall averages depicted in Figure 2.

Ranking second is the “Dry North & Central, Near-Normal South” Pattern (21.0% incidence, see Figure 6), exhibiting relatively pronounced mean standardized anomalies (~-0.75) for the northernmost three divisions (“North Coast”, “Sacramento”, and “Northeast Interior”) slightly less negative ones for the middle two (~-0.50) divisions (“Central Coast and San Joaquin”), and near zero ones for the southernmost two (“South Coast” and “SE Deserts”).

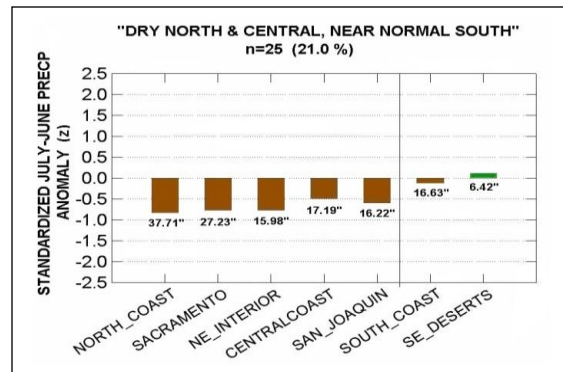


Figure 6 – Standardized Mean Division-by-Division Anomalies for the “Dry North & Central, Near Normal South” Pattern – Mode #4.

Third most frequent is the “Slightly Wet to Slightly Dry Trend” Pattern (18.5% incidence, see Figure 7). This shows a modest north to south “drift” from slightly wet conditions in the North to dry ones in the South.

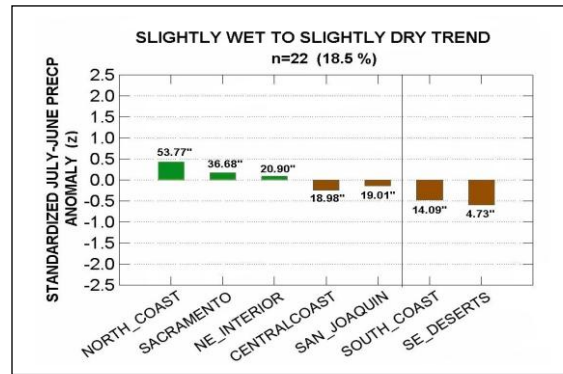


Figure 7 – Standardized Mean Division-by-Division Anomalies for the “Slightly Wet to Slightly Dry Trend” Relative Anomaly Pattern – (Mode # 5).

In fourth place is the “Progressively More Wet Relative Anomalies, N to S” Pattern (13.5 % incidence, see Figure 8). This depicts increasingly wetter character (in the relative sense) from north to south, particularly between the northernmost three divisions and the other four. Mean divisional precipitation for the North Coast (49.83”) is only slightly above overall climatology, while that for the South Coast (23.31”), and SE Deserts (8.15”) are each close to one standard deviation wetter than their overall norms.

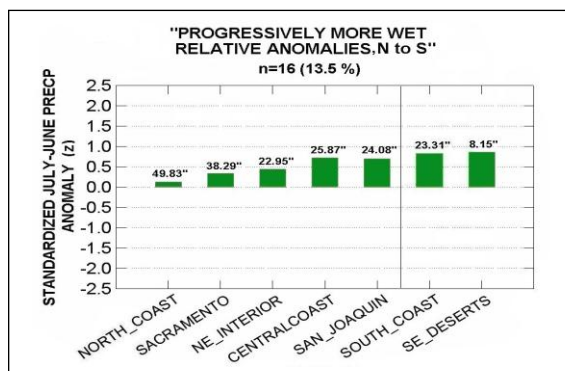


Figure 8 – Standardized Mean Division-by-Division Anomalies for the “Progressively More Wet Relative Anomalies, N to S” Pattern – Mode # 6.

Finally, tied for fifth place are the “Very Wet Throughout” and “Wet North & Central, Dry South” patterns (11.8% incidences each, see Figures 9 and 10, respectively).

Figure 9 exhibits exceptionally “wet” relative anomalies for all divisions, ranging from just under +1.5 standard deviations for the North Coast to nearly +2.0 for the South Coast; Figure 10 shows significantly positive ones for the northernmost five divisions but in a visibly sharp contrast, negative ones for the southernmost two, that for the SE Deserts approaching -0.5.

A few summary remarks can be made about the six patterns. First, Figures 5, 8 and 9, totaling 48.5% of the cases, have the same relative anomaly signs across all divisions; so, to generalize, it appears that in roughly half of the seasons, relative rainfall character across the State is the same (the figure goes up to about 70% if the results of Figure 6 are included, ignoring the slightly positive anomaly of the SE Deserts).

Also, there appears to be dichotomy of sorts in mean anomaly character (either in sign or magnitudes of the same sign) between the northernmost five and the southernmost two divisions, especially noticeable in Figures 6 and 10 (32.8% of the cases) and to a lesser extent in Figures 7 and 8 (another 32%), totaling about 2/3rds of the cases. This is probably due to the more southerly latitude of the South Coast and much of the SE Desert region, and the differing topography (e.g., the EW oriented Transverse ranges, exhibiting an occasional “barrier” effect, along with the more southeasterly oriented coastline, etc.).

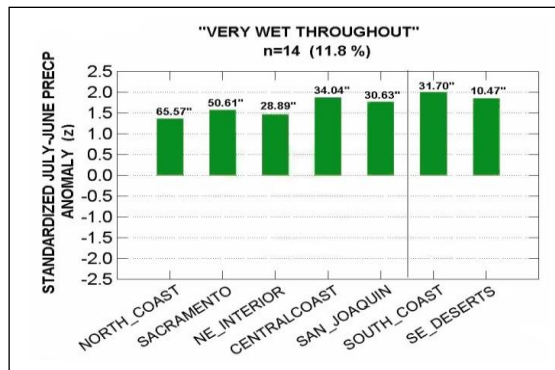


Figure 9 – Standardized Mean Division-by-Division Anomalies for the “Very Wet Throughout” Relative Anomalies” Pattern – Mode # 2.

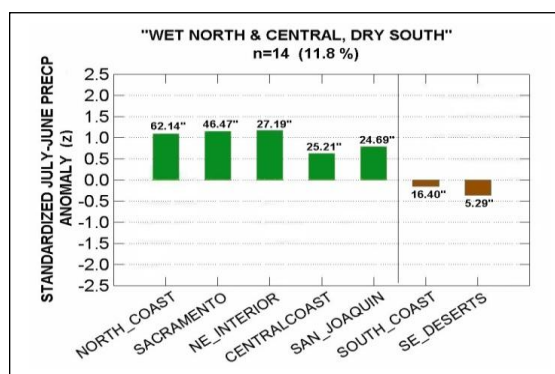


Figure 10 – Standardized Mean Division-by-Division Anomalies for the “Wet North & Central, Dry South” Relative Anomalies Pattern – Mode #1.

5.3. – Pattern Probabilities Conditioned on El Nino, Neutral, or LaNina occurrences – Bayesian Determinations

While the percent frequencies of the above six patterns may be considered as probabilities that they may occur individually for a given July-June rain year, there are other climatic indicators that should provide additional, more refined probabilistic information on occurrence likelihoods. ENSO phase (“El Nino, “Neutral”, or” La Nina”) is one indicator known to influence California rainfall patterns, so the next step is to investigate the possible modifying influences of these three episode types on the “baseline” Prior probabilities above of the six patterns. This would be a conditional probability exercise, and the method of choice, already introduced, would be Bayesian Analysis.

First, the 119 seasons would have to be assigned ENSO episode classification. Identification of ENSO types is a not completely objective process, different researchers having compiled different lists, with likely more uncertainty for those years further back. For the purpose of this research, the lists utilized are those created by the NOAA Climate Prediction Center. The first covers the years 1877-2001, the second

Pattern” will be ultimately be realized, given an impending El Nino. The Posterior Probability in this example is more than double than that of the Prior, indicating that an El Nino episode does “matter”, in this instance, increasing the odds noticeably that the “Very Wet Throughout Pattern” will be expressed for the July-June rain season.

Table 1 lists the Posterior Probability results for all the 18 combinations of 3 ENSO types (columns) and 6 Patterns (rows). Some Posteriors of particular interest are shaded in red.

Pattern #	Name	Posterior P(A B)	Posterior P(A B)	Posterior P(A B)	Prior P(A)
		El Nino	Neutral	La Nina	
1	Wet North & Central, Dry South	5.7%	11.1%	20.0%	11.8%
2	Very Wet Throughout	28.6%	5.6%	3.3%	11.8%
3	Dry Throughout	20.0%	25.9%	23.3%	23.5%
4	Dry North & Central, Near Normal South	20.0%	20.4%	23.3%	21.0%
5	Slightly Wet to Slightly Dry Trend	14.3%	14.8%	30.0%	18.5%
6	Progressively More Wet Relative Anomalies, N to S	11.4%	22.2%	0.0%	13.4%

Table 1 – Posterior Probability Results for all combinations of ENSO Type vs. Pattern

To interpret, for example, the El Nino Posterior Probability column (third from the left), reading down, lists the conditional probabilities that each of the six patterns will be realized, given an El Nino episode. The 28.6% figure, shaded red for the “Very Wet Throughout” Pattern (shown in Figure 9 and having already served as the Bayesian computation example above) is the pattern most likely to happen of the six. As already discussed, this figure is much higher than the “Very Wet Throughout” pattern’s “baseline” 11.8% Prior shown in Column 6. By the same token, if a La Nina is imminent, there is only a 3.3% chance that the “Very Wet Throughout” pattern will be expressed.

The most favored pattern for the La Nina (30.0% Posterior Probability) is the “Slightly Wet to Slightly Dry Trend”, shown in Figure 7; this is markedly higher than the pattern’s Prior (18.5%). Also, La Nina is the most frequent ENSO type associated with the Wet North & Central, Dry South pattern (See Figure 10), its frequency (20.0%) noticeably higher than the pattern’s Prior (11.8%). Finally, there is a zero Posterior Probability associated with La Nina’s and the “Progressively More Wet Relative Anomalies, N to S” pattern (See Figure 8). From these multiple results, it appears that La Nina’s are not generally associated with wet seasons in the South.

So, in conclusion, conditioning the occurrence probabilities of the six patterns on ENSO phases did provide more refined insights on their likelihoods. The range of their Priors was 11.8% to 23.5%, that for the Posteriors 0.0% to 30.0%.

6. SUMMARY

Utilizing the clustering tool K-Means, integrated with the V-fold cross validation algorithm, the existence and character of seasonal (July-June total) precipitation

modes were explored, collectively, for the seven NCDC California climate divisions, accessing the 1895-96 to 2013-14 period of record. Inputs were normalized, areal-averaged total precipitation statistics season-by-season, and division-by-division.

Results resolved, unambiguously, six clusters (also “patterns” or “modes”), characterizing a variety of anomaly configurations across divisions, occasionally on a combined North & Central vs. South basis. Individual pattern frequencies (“Prior probabilities”) ranged from 11.8% to 23.5%. Then, using Bayesian statistical methodology, conditional probability estimates (Posterior probabilities) were made of the occurrence likelihoods of the six patterns, given El Nino, Neutral, or La Nina episodes imminent or already in place. In roughly half of the 18 Posterior Probability calculations, the Posterior magnitudes differed significantly from the Priors (see Table 1), indicative that El Nino type was a useful predictive indicator. These figures ranged from 0.0% to 30.0%.

A combined Clustering/Bayesian analysis of this kind might prove similarly useful in other climatological-related applications.

6. REFERENCES

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