Response to Anonymous Referee #1

We thank Referee #1 for carefully reviewing our manuscript and providing critical and valuable comments. Please find below responses to each point raised by the Referee.

Comment: p. 4. L. 1. *Monthly precipitation (totals or means?) were derived from presumably daily rain gauge data. It is interesting to look at the number of days per month with precipitation, as the statistical sample of precipitation amounts involves a small (hence greater sampling fluctuations and less well defined mean estimates) in regions with few wet days. To get larger samples, one may use seasonally (3 months) or annually aggregated statistics. Precipitation may be regarded as having two types of statistical distributions: for dry and for wet days. The dry-day statistics is trivial (zero), whereas the wet-day distribution is often described with the gamma distribution (of exponential for a simple approximation). The classification of the data into 'dry' and 'wet' makes sense because different physical conditions are present when it rains and when it doesn't.*

Response: We thank the Referee for this excellent suggestion. Indeed, we initially considered this exact construct to evaluate the predictability of the frequency of precipitation events or wet/dry days, but omitted due to extra manuscript length. However, we have determined that it could be added with minimal extension to the manuscript and are pleased to do so as suggested.

First, for clarification, to this point we have used monthly and seasonal total precipitation, not daily averages, even though the original gauge data is at the daily scale, as correctly presumed by the Referee. (It should be noted, however, that for this study daily data was only readily available from the six stations maintained by SPCC).

We have framed this new piece as complementary to the seasonal total prediction approach as opposed to an entirely unique undertaking. For this auxiliary analysis, we identify the number of wet days as our predictand. As in the original analysis, we use principal component spatial correlation mapping, composite mapping, and global wavelet analysis in an attempt to identify potential predictors of number of wet days.

Interestingly, approximately 85% of the variance experienced in the number of wet days for all stations was captured by the first principal component (PC) of the data. Spatial correlation of the first PC with global SST revealed high correlations within the region of the Pacific typically associated with ENSO, suggesting that the ENSO phenomenon not only controls the seasonal volume of precipitation that reaches the region, but also the number of days during which it falls. No additional regions or climate variables (e.g. sea level pressure, geopotential height, etc.) were identified using this method. Further, composite mapping and global wavelet analysis yielded no additional potential predictors for incorporation into the prediction model. Therefore, the wet-day prediction model uses only the OND Niño 3.4 season-ahead ENSO index as a direct predictor to produce a deterministic prediction of number of wet days in any given JFM season.

New text is added throughout the manuscript in reference to this auxiliary analysis. Specifically, the following will be included in Section 7 of the revised manuscript (now retitled as Additional Prediction Modifications, with three subsections: Extended Lead Time; Spatial Disaggregation of Regional Predictions; and Prediction of Wet/Dry Days):

> "Although predictions of JFM seasonal precipitation totals may be useful for a variety of stakeholders throughout the region, some may prefer additional detailed information such as the frequency of precipitation events expected across a given rainy season. The number of wet or dry days and the intensity of precipitation events can have widespread and serious agronomic/phenologic (Robertson et al., 2008) and infiltration/runoff implications (Mandal and Nandi, 2017). Such information may also be informative to condition stochastic weather simulators for a wide range of hydrologic or agricultural models (Robertson et al., 2006). To evaluate seasonal statistics of wet/dry day frequency for southern Peru, six of the 29 stations having daily data are analyzed. Analogous to the seasonal total precipitation prediction modeling approach, spatial correlation mapping, composite mapping, and global wavelet analysis are all utilized to identify potential predictors describing the expected number of wets days across the JFM season.
>
> Interestingly, approximately 85% of the variance in the number of wet days for all six stations was captured by the first principal component of the data. High correlations are observed between this first principal

component and SST within the region typically associated with ENSO. No additional regions or climate variables (e.g. sea level pressure, geopotential height, etc.) were identified using this method. Further, composite mapping and global wavelet analysis yielded no additional potential predictors for incorporation into the prediction model. Therefore, the wet-day prediction model uses only the OND Niño 3.4 season-ahead ENSO index as a direct predictor to produce a deterministic prediction of number of wet days in any given JFM season. Using the same cross-validation method described previously, the number of wet days per season is predicted for each station.

In addition to correlation coefficients between the predicted and observed number of wet days, the average prediction error for above-average and below-average years is reported for each station. Station-specific statistics are listed in Table 4.

Table 4: Correlation values and average absolute errors for predictions of wet days at each station.

Station (with average number of wet days)	Correlation value between prediction and observation	Average absolute error in years with above average number of wet days	Average absolute error in years with below average number of wet days
1 (25 days)	-0.50	10 days	9 days
2 (36 days)	-0.53	11 days	9 days
3 (51 days)	-0.48	11 days	10 days
4 (54 days)	-0.39	12 days	12 days
5 (54 days)	-0.53	8 days	9 days
6 (33 days)	-0.59	10 days	9 days

Correlations between predictions and observations range from -0.39 to -0.59, with the model performing slightly better in predicting wet days in drier years. In general, however, the simple linear model displays an average absolute error ranging between 8 and 12 days.

To consider overall model performance, a hit miss metric quantifies skill in the two previously introduced categories of years – years with above average number of wet days and years with below average number of wet days (Table 9).

Table 9: Hit miss metric for model predictions of years with above and below average numbers of wet days.

		Predicted conditions	
		W	D
Observed conditions	W	**105**	41
	D	43	**103**

Above average number of wet days (W) and below average number of wet days (D)

Overall, the model correctly predicts whether a given season will have an above or below average number of wet days over incorrectly predicting, with an accuracy of ~72%. The model, however, has a notable bias towards over-predicting near normal conditions (Fig. 13).

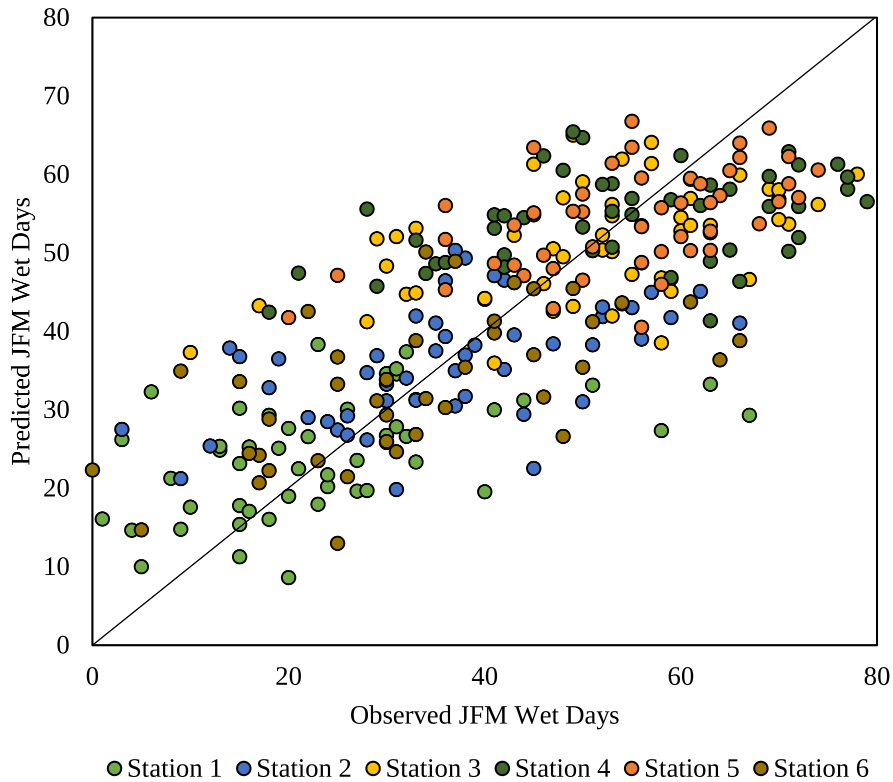


Figure 13: Observed number of wet days compared to predictions."

In addition, we propose adding the following paragraph to Section 8 (Discussion) of the manuscript:

> "The high correlation observed between number of wet days and SST in the equatorial Pacific suggests that the ENSO phenomenon not only controls the regional seasonal volume of precipitation, but also the frequency of wet days. While the prediction model of wet days achieves notable skill, the model in general displays a tendency to under-predict the number of wet days (especially in seasons in which more wet days were observed than dry). More benefit may be gained in using this model at locations with more wet days (such as stations 3 and 4) as opposed to drier stations. Additional prediction skill may be achieved by incorporating local variables such as antecedent soil moisture conditions or low level winds into station-specific models, as is the case with the disaggregation of regional precipitation predictions."

In addition to precipitation event frequency, the Referee also comments on precipitation distribution for wet days. Indeed, this is legitimate; however, we have opted not to include this additional analysis here as we are presently less focused on understanding daily precipitation statistics or fitting stochastic weather generators. That said, it does lay the groundwork for others that may be focused on such applications.

Comment: p. 4. L. 6-11. *Please specify if it is version 1 of the reanalysis. Also, the time period covered and the area selected are important. It is important to have sufficient information so that the analysis can be replicated by others independently. Some of this is discussed further down, but it may be easier for the reader if this is provided in a methods section before the results.*

Response: We acknowledge that we did not initially make this clear and have thus updated the manuscript to explicitly state that version 1 of the reanalysis data is used in this study. Additionally, we have clearly noted the period covered by this dataset (1948 to present). To facilitate introducing this information earlier, as suggested, the geographic areas selected and listed in Table 1 of the paper are now referenced in Section 2 (Data Descrpition).

Comment: p. 5. L. 8. *How much of the variance do the subsequent modes capture, and presumably the second order suggests a bi-pole type pattern? There is no need to show this, but perhaps worth describing its character. It is interesting that the leading PC so closely reproduces the station (not area?) mean precipitation. What does that suggest? That the precipitation is dominated by large-scale climatic phenomena (at least aggregated over 3 months) and that other modes are essentially regional perturbations from the large-scale precipitation? I think it may be worth commenting these aspects, but perhaps later in the discussion.*

Response: The Referee highlights a good point, and we agree that it should be further clarified and discussed. The first mode clearly explains the majority of the variance in data (50%), and the second mode captures an additional ~20% of variance; however, the third drops to ~5%. Only these three modes are investigated in this study, for a cumulative total of 75% of variance captured (Fig. 1). The manuscript has been revised to state the variance explained by each mode considered. Indeed, as suggested by the Referee, the second PC suggests a dipole pattern; this description has also been added to the revised manuscript.

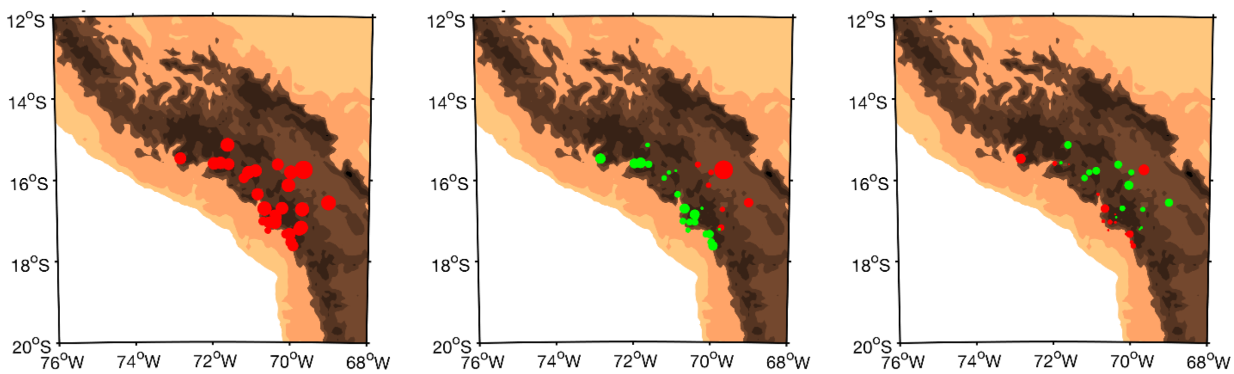


Figure 1: From left to right, spatial pattern produced by the first, second, and third modes of the PCA performed on regional precipitation, explaining ~50%, ~20%, and ~5% of the variance, respectively.

As referenced in the manuscript, Eklundh and Pilesjö (1990) postulated that high correlations between the first EOF of gridded precipitation and area averaged precipitation may suggest the presence of a large-scale climatic phenomena acting homogenously on regional precipitation. Additional studies that support this notion include Ogallo (1980), Mallants and Feyen (1990), Bisetegne et al. (1986). While we use a station average precipitation time series (and not area averaged, as noted by the Referee), the high correlation coefficient between this time series and the first PC of the original set of data may still be interpreted as a widespread homogenous influence on regional precipitation by a large-scale climatic phenomenon. With a correlation between the first principal component of regional JFM precipitation and JFM Niño 3.4 of -0.52, it is likely that this PC describes the modulation stemming from ENSO. As the Referee mentions, the subsequent PCs likely describe regional and local perturbations.

The additional studies mentioned in this response are now referenced in the manuscript.

Additionally, we will add text to Section 8 (Discussion) interpreting the character of each of the PCs considered.

Comment: p. 6. L. 10. *Perhaps the higher modes of the PCA shows the orographic effects.*

Response: The Referee is right that the orographic effects may be evident in various spatial patterns (EOFs), and particularly likely in the higher order modes given that they are more likely associated with regional and local influences. Although this characteristic is not fully explored here, we have added a sentence to the manuscript in Section 3 (Southern Peru Rainy Season and Large-scale Climate Influences) acknowledging that this may indeed be the case:

> "While the first PC likely illustrates ENSO's influence on regional precipitation, it is possible that higher order modes may describe other climatic and topographic forcings such as large-scale climatic phenomena or observed orographic effects."

Comment: p. 8. *Fig. 6: the scatter suggests that more than one factor affects the precipitation, but there is also a discernible anti-correlation between Nino3.4 and the precipitation. An ordinary linear regression can quantify the relationship (and associate a p-value), as can the correlation coefficient. This can be repeated with a subset of the data where the three outliers are excluded to estimate how exceptional they were.*

Response: The Referee is right in assessing that Nino3.4 is highly influential but also not the only relevant signal in descripting precipitation variability. The correlation between JFM precipitation and JFM Niño 3.4 (i.e., concurrent conditions) is -0.57 (p-value = 0.000013). Due to the autoregressive nature of SST in general, Niño 3.4 maintains a relatively high correlation with JFM precipitation for the prior season as well. This has been added to the text and Fig. 6. If the three outlier years (1973, 1990, and 2014) are removed, as suggested by the Referee, this produces a stronger correlation coefficient of -0.66 (p-value = 0.000009), supporting the two-fold notion of ENSO's influence on seasonal precipitation as well as the presence of additional climatic factors that modulate the region's precipitation. This evaluation has also been added to the text immediately following to estimate the importance/influence of these three highly anomalous years, and further underscores the importance of creating a model conditioned on several potential predictors rather than just an ENSO index.

Comment: p. 11. L. 11-16. *Subtracting 9 driest season during El Niño years from the 9 wettest from La Niña years is bound to produce an ENSO signal by design of the analysis. This paragraph seems to be repeated on p. 12. L. 1-5.*

Response: The Referee highlights a valid point. The example composite map, as framed in the manuscript, produces an ENSO signal because only El Niño years and La Niña years are selected for compositing. Thus, this example only marginally supports the points emphasized in this section. Thus, we have removed this figure and text and substituted instead with analysis demonstrating the presence of ENSO through compositing simply the driest and wettest years, regardless of ENSO phase and strength. Accordingly, the manuscript has been revised as follows, including a new Figure 8:

> "Composite maps illustrate climate conditions for a single period or subset of periods, and may be especially useful for understanding forcing mechanisms in anomalous periods. For example, OND SST for the nine subsequent driest JFM seasons on record for southern Peru subtracted from OND SST for the nine subsequent wettest JFM seasons on record for southern Peru produce large positive anomalies in the equatorial Pacific Ocean. This composite map (Fig. 8) further indicates the potential importance of ENSO in explaining JFM precipitation variability in the study region.

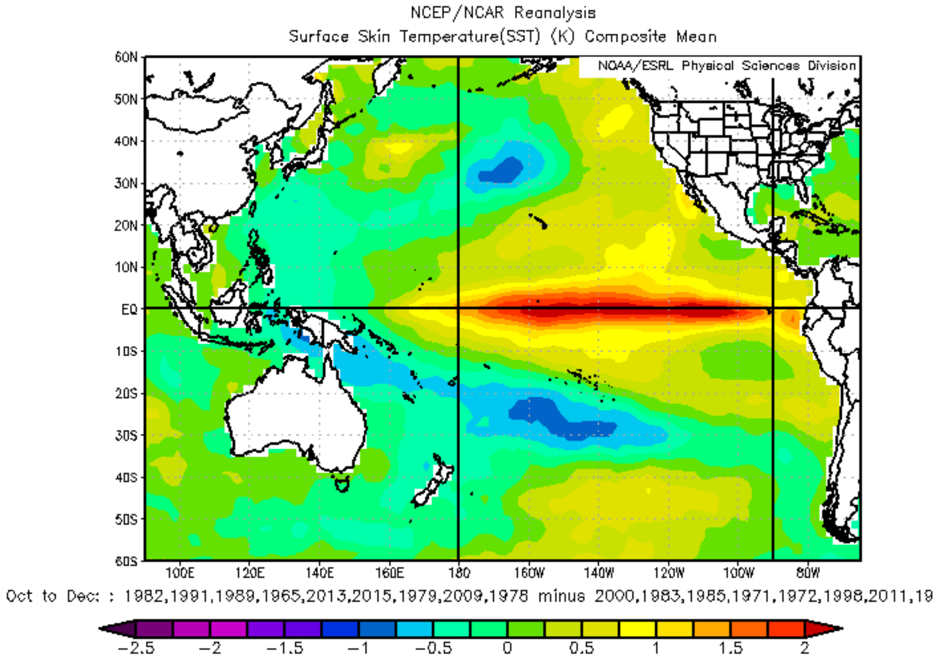


Figure 8: Composite SST OND conditions of nine subsequent driest JFM seasons (1983, 1992, 1990, 1966, 2014, 2016, 1980, 2010, and 1979) and subtracted SST OND conditions of nine subsequent wettest JFM seasons (2001, 1984, 1986, 1972, 1973, 1999, 2012, 1974, and 1997).”

Additionally, any unintended repetition with regard to composite mapping has been removed from the manuscript.

Comment: p. 13. L. 10-14. *It is evident that the PCA applied to area means according to Table 1, but this should also be stated more clearly in the main text. Also, the text should explain how different units are handled - was the PCA applied to standardized indices?*

Response: Thanks for pointing out the need for better clarity. The text has been revised to include reference to the fact that PCA is applied to area mean values of the selected potential predictors. Also, all predictor values are standardized in the PCA process so as not to cause any unintended preference. The text has been appropriately revised.

Comment: p. 14. L. 16-17. *It is not clear how hindcasts were generated from residuals from cross-validation. Please elaborate.*

Response: We agree that this may not have come across clearly in the original manuscript. Hindcasts for precipitation prediction are performed using principal component regression in a drop-one cross-validated mode. This includes – for each year of the hindcast – dropping the predictor data (Z) from the year being hindcasted, forming new PCs (and EOFs) conditioned on the remaining years, and fit to observations using multiple regression, providing an intercept coefficient, regression coefficients, and error term. The predictor data (Z) from the year dropped are then projected onto the EOFs to provide PCs for the dropped year. Finally, these PCs are multiplied by the appropriate regression coefficients and added to the intercept coefficient to provide a deterministic precipitation prediction for the dropped year. This is repeated for each year.

To create ensemble hindcasts, error terms from all years are assembled and a distribution is fit (using a kernel density estimator; the distribution is approximately Gaussian). For each hindcast year, 1000 random draws from the distribution are added to the deterministic precipitation prediction to form an ensemble.

The manuscript has been revised accordingly to clarify this process.

Comment: p. 19. L. 6-8. *From a sample of test results, one will expect some to score high from pure chance. If there are 100 stations, one would expect 5 to score above the 95% confidence level by chance - this is how the confidence interval is defined.*

Response: The Referee makes a valid point. The manuscript text has been modified appropriately to reflect this, as follows:

> "None of the stations experience statistically significant decreases in correlation as a result of disaggregation. For two of the stations, correlation values between station-level predictions and station-level observations increase (statistically significant at the 95% confidence interval) as compared with correlation values between regional-level predictions and station-level observations. (However, it should be noted that there is a 5% probability that this happens by chance.) The remaining stations exhibit no statistically significant change in correlation as a result of station-level scaling."

Minor Comments (all accepted and corrected in the manuscript)

p. 4. L. 2. *'multi-regression' should perhaps be <u>'multiple regression'</u> or 'multivariate regression'*

p. 5. L. 1. *EOFs often refer to principal components analysis (PCA) of gridded data, weighted by the gridbox area. PCA is mathematically the same thing, but a term used more generally than EOFs. However, this is a matter of taste.*

p. 5. L. 8. *Unless the precipitation has been gridded to onto a regular mesh, the term 'area average' should be replaced with 'station average'.*

p. 19 L. 12. *Split discussions and conclusions into two sections. The conclusions should be brief and repeat the main findings.*

References

Bisetegne, D., Ogallo, L., and Ininda, J.: Rainfall characteristics in Ethiopia, Technical Conference on Meteorological Research in Eastern and Southern Africa, Nairobi, Kenya, 1986.

Mallants, D., and Feyen, J.: Defining Homogenous Precipitation Regions by Means of Principal Component Analysis, Journal of Applied Meteorology, 29, 892-901, 1990.

Mandal, A., and Nandi, A.: Hydrological Modeling to Estimate Runoff and Infiltration in Southeastern Appalachian Debris Flow Complex., 3rd North American Symposium on Landslides, Roanoke, Virginia, USA, 2017.

Ogallo, L.: Regional classification of East African rainfall stations into homogeneous groups using the method of principal component analysis, as in Ikeda, S. et a1. (eds), Statistical Climatology. Developments in Atmospheric Sciences, 13. 225-266, Elsevier, Amsterdam, 1980.

Robertson, A., Kirshner, S., Smyth, P., Charles, S., and Bates, B.: Subseasonal-to-inderdecadal variability of the Australian monsoon over North Queensland, Quarterly Journal of the Royal Meteorological Society, 132, 519-542, 2006.

Robertson, A., Moron, V., and Swarinoto, Y.: Seasonal predictability of daily rainfall statistics over Indramayu district, Indonesia, International Journal of Climatology, 29, 1449-1462, 2008.

Response to Referee #2

We thank Dr. Harrigan for carefully reviewing our manuscript and providing critical and valuable comments. Please find below responses to each point raised.

Comment: *Throughout the text, including the title, the term 'drought' is used with many statements making the connection to a "hydrologic extreme" (*p. 1. L. 17.*) and for example "the city's water supplies were reduced" (*p. 2. L. 13-14.*) etc. It took me until the last line of the introduction (excluding the abstract) to realize it was prediction of meteorological drought (precipitation) rather than hydrological drought that was being pursued. Clearly improving prediction of meteorological drought is still valid, but precipitation deficit does not necessarily propagate to a soil moisture, streamflow, and/or groundwater drought, which are more societally relevant. Often there are more complex processes at play, including temperature/evapotranspiration feedbacks. See Van Loon (2015) for more detail. This should be acknowledged and please be more explicit about the focus on meteorological drought throughout. I think if you are more explicit within the abstract and main text I would not be pedantic about asking to change the title, as it is a good title.*

Response: We apologize for not being clearer in our manuscript. Our goal is to create a predictive model to prognosticate meteorological drought conditions, and not necessarily consequential hydrologic drought. While these two topics are intrinsically related, we fully agree they are not interchangeable. The text of the manuscript has been changed such that meteorological drought is more explicitly stated as the focus of the research, with references to the tangential potential of hydrologic drought given meteorological drought conditions.

Comment: *The introduction does not do the paper justice as it fails to clearly establish core research aims/objectives/questions. The fundamental finding of the paper is that the newly created PCR model was found to be more skillful than a climatological forecast AND a simpler Niño 3.4 index-based model forecast, especially for dryer conditions – Is this not the foundation of your research question(s)? If so, needs to be in the Introduction.*

Response: We appreciate the opportunity to clarify our objectives in the Introduction, and propose adding the following paragraph to the manuscript:

> "In this paper, we develop a season-ahead principal component regression (PCR) model to predict seasonal precipitation totals. This PCR model draws on a pool of large-scale climate variables that influence southern Peru precipitation through ocean-atmosphere teleconnections. The model is evaluated against climatology and simpler Niño index-based models to understand if the inclusion of several predictors leads to more skillful prediction, particularly for dry years in this drought-sensitive region."

Comment: *Even though drought prediction remains largely unexplored in Peru, there is no background nor reference to the international literature on general seasonal forecasting methods in the introduction section, nor previous work done internationally on statistical forecasting. For example, what is the justification for selecting a statistical forecasting approach over others (i.e. lack of climate/hydrological modelling, limited hydrological data...)?*

Response: Statistical forecasts have been developed and evaluated for many applications globally, although more effort is still focused on the application of dynamical model predictions. There are numerous advantages for selecting statistical models for season-ahead precipitation prediction over other methods involving global atmospheric general circulation models, most notably reviewed by Xu (1999). These include GCMs inability to represent sub-grid features and dynamics, vertical level mismatches between GCMs ability and hydrology needs (atmospheric vs surface), and discrepancies in the importance placed on variables used in dynamical models. Essentially, dynamical models are exceptional tools for macroscale climate modeling, but struggle in scales similar to that of our project area. Additionally, the complex topography of the region complicates the use of GCMs for regional predictions. Although we are focused on meteorological drought and not necessarily hydrologic drought, the interconnectedness of these two types of drought necessitates a methodology that can be justified if meteorological predictions were to be used for hydrologic application. For this case, the merits of statistical modeling outweigh those of dynamical modeling.

We have revised the manuscript to include these advantages and reference Xu's review. Although the full application of statistical forecast models is clearly too wide to synthesize, as we hope the Referee agrees, we have attempted to justify why the selection of a statistical modeling approach is valid in this case.

Comment: *Methods and Results are scattered over several sections. Reforming methods into a 'Section 4 Methods' and 'Section 5 Results' together with the use of sub-headings would help. I especially found it frustrating to have Sect. 7 after the results section. Surely this should not be hard to have the results divided by sub-heading for 'Sect. 5.1 Season-ahead' and 'Sect. 5.2 Extended Lead Time and Spatial Disaggregation of Regional predictions', or something similar.*

Response: We agree with this recommended restructuring. Our original intention was for Section 7 to serve as a supplement to the focus of the manuscript, however we fully acknowledge that integrating the topics of extended lead-time, spatial disaggregation, and prediction of wet/dry days (as recommended by Referee #1) throughout the manuscript is warranted and improves the flow. Changes to the manuscript include moving the technical details of these additional applications into the Introduction, Methods and Results (newly named sections as suggested) as appropriate. The authors are appreciative of the Referee's suggestion.

Comment: *The 'Summary and Discussion' section does an excellent job of outlining the practical implications of the work. However, it does not discuss results in light of the international forecasting literature. Is the degree of increased skill on par with other areas/forecasting approaches?*

Response: The Referee raises an interesting point. The skill achieved in this study surpasses that of existing approaches – namely dynamical models and simple Nino-based index models – as we hope has been illustrated and presented clearly. The challenge of course is putting this in the context of progress made elsewhere, and whether the improvements presented here represent a moderate or sizeable step forward. To be honest, comparing across climatologically diverse case studies is nontrivial. We can argue with some assurance that we have demonstrated improvement in comparison with other (existing) model structures for the same set of circumstances (i.e. same set of observations), however this may not hold true for a similar experiment in another location. Model performance is very site specific in our experience, including the "best" modeling approach.

We may argue that statistical approaches "typically" outperform dynamical models in predicting local precipitation, but this is not universal, and there are certainly a number of caveats. To this end, we have added a paragraph that discusses this idea and thank the Referee for highlighting this point:

> "In this case, the statistical approach explored has produced results that are arguably more skillful than existing methods of precipitation prediction for this region of Peru. Therefore, one may be tempted to draw the conclusion that a statistical approach of this sort can be applied in a similar fashion at any other location of interest and produce equally skillful results. A conclusion along these lines would be temerarious. Although model frameworks are transferable to other locations, there are no guarantees that one approach will still be superior to another. Furthermore, there is no guarantee that observed increases in skill in one location will translate to expected equivalent increase in skill in another location."

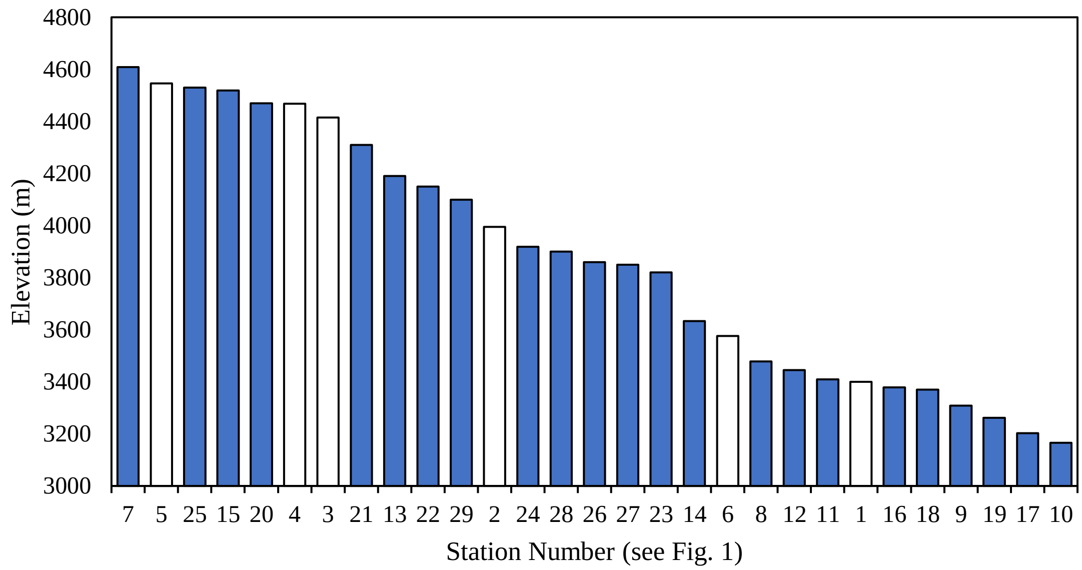
Comment: p. 3. Fig. 1: *Do white circles not represent SPCC stations, and blue the SENAMHI?*

Response: We thank the Referee for noticing this error. Indeed, the six white circles represent SPCC stations, and the blue circles represent SENAMHI stations. The caption of Fig. 1 has been revised accordingly.

Comment: p. 3. L. 5. *The elevation range in Peru is substantial. It would therefore be beneficial for an international audience to provide the mean or median and the range of elevation for the 29 precipitation stations.*

Response: The topography of the region is noteworthy. Section 2 of the manuscript has been revised as follows to provide this context:

> "The topography of the region is noteworthy. While the 29 stations considered in the study cover an elevation range from 3,100 m to 4,600 m (Fig. 2, mean elevation 3870 m), this portion of southern Peru ranges from sea level at the Pacific Ocean to over 6,000 m in the high Andes.



> **Figure 2: Elevations of all 29 stations included in the study. Bars are numbered and colored in accordance with Fig. 1, with white bars representing SPCC stations and blue bars representing SENAMHI stations."**

The station numbers referenced in Fig. 2 have been added to Fig. 1 to easily identify any station's location within the region and quantify its elevation. Figure numbers throughout the remainder of the manuscript have been revised accordingly.

Comment: p. 4. L. 3. *What is the average correlation and is the method used Pearson?*

Response: The average Pearson's correlation coefficient for the missing points is 0.92, implying that this interpolated data is reasonably representative of actual conditions not captured by the data. We have also clarified in the text that we are using Pearson correlation throughout.

Comment: p. 4. L. 21. *Agree a focus on JFM is justifiable. To help convince the reader that forecasting the wettest season is relevant to water resources/drought perhaps worth mentioning that it is during the wet season that reservoir/aquifer stores are replenished for use during dryer summer months. Being able to skillfully forecast anomalously low precipitation for the wet season is indeed valuable.*

Response: The following passage has been added to the manuscript to reflect the relevance of seasonal precipitation to regional hydrology and water resources management:

> "JFM precipitation represents, on average, more than two-thirds of annual precipitation for the region, with some locations receiving up to 85% of annual precipitation during the three-month period. This precipitation

> is crucial to the region's economic activities and environmental stability. During the rainy season, for example, surface reservoirs and underground aquifers are replenished for multi-sectoral water resource use during the dry conditions that characterize the rest of the year. These rains also directly impact the phenology of many wild plants and agricultural operations, and are intrinsically tied to the function of quebradas, or seasonal creeks, that drain the region. As mentioned, severe and wide-reaching economic, environmental, and societal consequences can be realized in an abnormally dry rainy season. Thus, JFM is identified as the season of interest for this study."

Comment: p. 5. L. 2. *Referring to both EOF and PCA throughout. Stick with one to avoid confusion.*

Response: We apologize for the confusion and acknowledge that indeed EOF and PCA refer to the same process. Our intent in using both terms is to distinguish between the spatial patterns (EOF) and temporal trends (PCs) that come out of this process and provide complimentary information. Thus, we have opted to use both EOF and PC (and PCA as a descriptor of the process), and have also added a sentence to make this explicitly clear:

> "To evaluate the spatial and temporal patterns of regional precipitation, a principal component analysis (PCA) is performed on JFM seasonal precipitation totals (von Storch and Zwiers, 2001) based on data from the 29 stations. In PCA, a dataset is decomposed into orthogonal, uncorrelated modes representing distinctive signals, or variance, present in the dataset. PCA yields information describing both spatial patterns (empirical orthogonal functions, EOFs) and temporal trends (principal components, PCs) of variance experienced in the dataset…"

Comment: p. 5&6. Fig. 3&4. *It was not clear to me why PCA was used for the observed JFM precipitation totals? What purpose does it serve if the main target for the PCR model is for areal averaged precipitation totals anyway? Also, it is not stated what the physical interpretation of PC2 and PC3 are in this context (i.e*. p. 9. L. 26. *and* p. 10. L. 9.*). As it stands Fig. 3 does not really add anything. It is too difficult to see any difference the size of the red dots. Perhaps adding a scale and/or some gradual colour scale would help? Could you include what elevation threshold the topographic shading represents?*

Response: PCA was performed on JFM precipitation using all stations individually to understand how the first PC (explaining the most variance of all signals across the stations) compares with the station average across the region. The idea is to simply justify if the station average is a good representation of individual stations. In general, station averaged precipitation total correlates well with station-level data, however the variance experienced at each station is clearly not identical, as expected. We have clarified this in the text by adding:

> "… Additionally, the first principal component (PC) of the precipitation time series captures 51% of the variance in the data, and correlates well with station-averaged JFM seasonal precipitation observations (r = 0.99; Fig. 4). This exceptional level of correlation between the averaged observations and its first PC (as well as high levels of correlation between this first PC time series and individual station data) suggest that the station-averaged time series is an appropriate representation of regional precipitation."

Although the dominant signal present in this dataset correlates highly with the station-averaged time series, we do not mean to imply that higher modes of variance do not have an impact on regional precipitation. Referee #1 made a similar comment inquiring about the nature of PC2 and PC3. As per our response to Referee #1:

> The Referee highlights a good point, and we agree that it should be further clarified and discussed. The first mode clearly explains the majority of the variance in data (50%), and the second mode captures an additional ~20% of variance; however, the third drops to ~5%. Only these three modes are investigated in this study, for a cumulative total of 75% of variance captured. The manuscript has been revised to state the variance explained by each mode considered. Indeed, as suggested by the Referee, the second EOF suggests a dipole pattern; this description has also been added to the revised manuscript.

> As referenced in the manuscript, Eklundh and Pilesjö (1990) postulated that high correlations between the first EOF of gridded precipitation and area averaged precipitation may suggest the presence of a large-scale climatic phenomena acting homogenously on regional precipitation. Additional studies that support this notion include Ogallo (1980), Mallants and Feyen (1990), Bisetegne et al. (1986). While we use a station average precipitation time series (and not area averaged, as noted by the Referee), the high correlation coefficient between this time series and the first PC of the original set of data may still be interpreted as a widespread homogenous influence on regional precipitation by a large-scale climatic phenomenon. With a correlation between the first principal component of regional JFM precipitation and JFM Niño 3.4 of -0.52, it is likely that this PC describes the modulation stemming from ENSO. As the Referee mentions, the subsequent PCs likely describe regional and local perturbations.

The studies mentioned in this response are now referenced in the manuscript. In addition to this response to Referee #1, the following passage has been added:

> "While the first EOF likely illustrates ENSO's influence on regional precipitation, it is possible that higher order modes may describe other climatic and topographic forcings such as interconnected large-scale climatic phenomena or observed orographic effects. For example, the second EOF exhibits a dipole pattern, which may be related to the rain shadow phenomenon that causes the northeastern portion of the region to be wet and southwestern to be dry."

Finally, we removed Fig. 3 entirely and instead described the information more explicitly in text:

> "… Even with significant changes in elevation across the region, the sign of the first EOF spatial pattern of all stations is negative (and at similar magnitudes) generally implying spatial homogeneity (Eklundh and Pilesjö, 1990) of JFM seasonal precipitation within this relatively small region. Additionally, the first principal component (PC) of the precipitation time series captures 51% of the variance in the data, and correlates well with station-averaged JFM seasonal precipitation observations (r = 0.99; Fig. 4)."

Figure numbers throughout the remainder of the manuscript have been revised accordingly.

Comment: p. 6. L. 12-13. *Am I correct in thinking none of the precipitation stations used here are within the rain shadow?*

Response: Technically, the Atacama Desert is the manifestation of the Andean rain shadow. While no precipitation stations used in this study are located there (although some are located at its edge), this portion of the Andes is unique in the sense that the mountain range is at its widest. Instead of an abrupt switch between wet and dry conditions as might be expected by some other notable rain shadows in the world, the Altiplano (and the majority of the stations used in this study) exists in a transitionary zone of sorts and exhibits a wet to dry gradient from northeast to southwest.

Comment: p. 7. Fig. 5: *Add units of SST anomalies (i.e. ℃)? You could improve plot by adding two horizontal lines to represent El Niño/La Niña thresholds (i.e., ± 0.5°C). Also, define that you are using Pearson's correlation coefficient in the first instance (in the text) and define symbol as r. Then use r in every instance throughout the paper for clarity. I note this is done in some places and not in others (e.g.* p. 9. L. 30.*).*

Response: We appreciate the suggestion to include thresholds in Fig. 5; they have been added to the figure and are referred to in the text and figure caption as follows:

> "… Strong El Niño (warm SST) conditions in the Niño 3.4 region are typically associated with drought in southern Peru, whereas La Niña (cool SST) conditions often align with wetter-than-average conditions (Fig. 5, El Niño and La Niña thresholds of 0.5°C and -0.5°C, respectively, included for context).

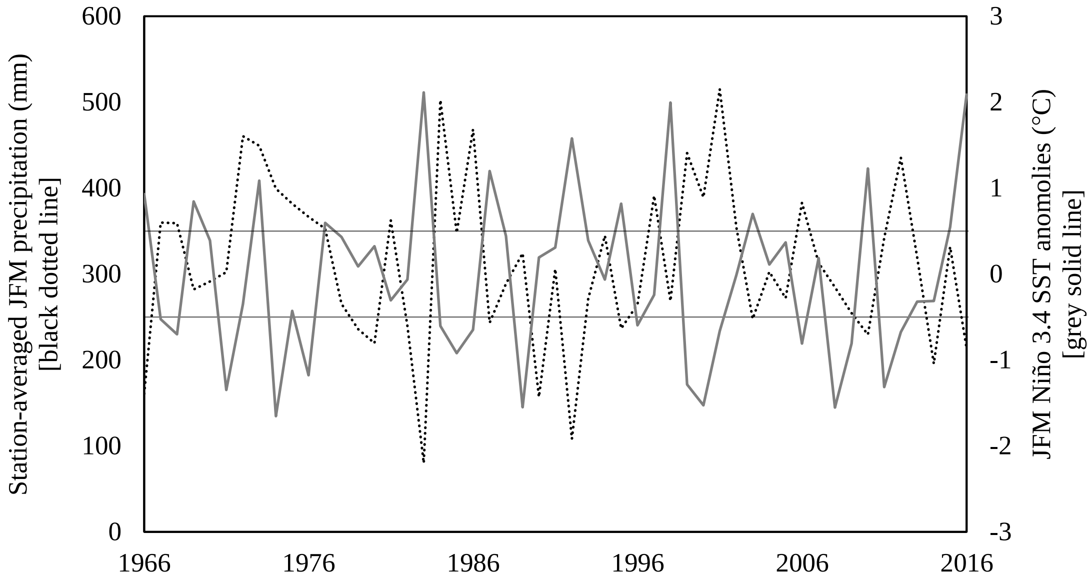


Figure 5: Station-averaged JFM precipitation and concurrent JFM Niño 3.4 SST anomalies (r=-0.57). El Niño and La Niña thresholds marked with black solid line. During the period of record, 13 JFMs exceeded the El Niño threshold (0.5°C) and 18 years the La Niña threshold (-0.5°C).”

We have also revised the manuscript to define our use of the Pearson correlation coefficient at its first instance and replaced subsequent references to correlation with the symbol r where appropriate.

Comment: p. 10. Fig. 7: *Why use the first PC of regional JFM precipitation instead of just the area-averaged JFM precipitation total? I do note these are very similar and map would look the same.*

Response: We agree with the Referee that these two maps do look quite similar, and there may be motivation for simply presenting the station-average for simplicity; however, we have opted to present PC1 of the regional precipitation to highlight the dominant signal modulating precipitation. Again, this may look similar to the station-average, but it does not necessarily need to. Further, by evaluating PC1, we can identify distinct regions of SST, etc. that may lead us to better understand the controlling factors or phenomena (e.g. ENSO) that may be less obvious or evident using station-average. Then, this can be repeated for additional PCs to understand other (orthogonal) signals. Fig. 7 serves simply as an example of this type of analysis for predictor identification.

Comment: p. 12. L. 3. *“the JFM precipitation series”… but which one? First PC or observed totals?*

Response: The global wavelet analysis was performed on the JFM observed totals. We appreciate the clarification and have amended the manuscript to explicitly state this.

Comment: p. 13. Table 1. & L. 1-4. *The use of the asterisks is a little confusing. When I first looked at table 1 I presumed the asterisks was for statistically significant correlations. But are these instead those that are NOT correlated with JFM precipitation? Although you say that all are significant with at least one of the first three PCs. I can see here how perhaps the use of the first three PCs is useful but the reader is left with a bit of a jump to understand this without understanding what PC2 and PC3 represent. Could adding three additional columns to the right hand side of Table 1 for PC1, PC2, and PC3 help with this, then have the asterisks marking any value with statistically significant correlations. This allows the reader to see that perhaps one climate variable is correlated with all four precipitation series, or just e.g. PC3?*

Response: We apologize for the confusion and have revised Table 1 as well as the associated text.

"In total, 11 potential predictors are identified for prediction of station-averaged JFM precipitation based on previous literature and inference from spatial correlation maps, composite maps, and global wavelet analysis (Table 1). These potential predictors include both established climate indices and relevant regions of SST, SLP, and GH (as well as gradients of these variables).

All potential predictors included display a statistically significant correlation with at least one of the first three PCs of the station-averaged precipitation time series. In addition, five potential predictors are also statistically significant correlated with the station-averaged times series of precipitation, and marked with asterisks in Table 1.

Table 1: The suite of potential predictors for JFM precipitation; correlations are based on JFM total precipitation and spatial averages across the regions noted, with statistically significant correlations marked with an asterisk.

Name	Large-scale climate variable	Timeframe	Region		Corr. w/ JFM precip.	Most Correlated PC (Corr)
Niño 3.4	SST	OND	5° N-5° S	170° W-120° W	-0.53*	PC1 (-0.52)
PDO	SST	OND	all areas north of 20° N		-0.19	PC2 (-0.35)
NP	SLP	D	65° N-35° N	160° E-140° W	-0.18	PC3 (0.28)
WHWP	SST	OND	28° N-8° N	110° W-40° W	-0.16	PC3 (-0.32)
	SST	OND	0° -5° S	160° W-140° W	-0.54*	PC1 (-0.54)
	SLP	D	35° N-20° N	150° W-135° W	0.15	PC2 (-0.36)
	SST gradient	OND	0° -15° S	15° W-35° W	0.30*	PC2 (-0.29)
			(25° S-40° S)	(15° W-35° W)		PC3 (0.28)
	SST gradient	OND	50° N-40° N	150° W-135° W	0.38*	PC3 (-0.37)
			(35° N-30° N)	(180° -165° W)		PC2 (0.27)
	GH 200 hPa	D	10° S-15° S	70° W-65° W	-0.35*	PC1 (-0.31)

Comment: p. 14. L. 18-19. *Not clear how the ensemble in Fig. 10 was created. More detail needed here. Also, how many ensemble members etc.?*

Response: We agree that this may not have come across clearly in the original manuscript. Referee #1 made a similar comment in their review of the manuscript. As per our response to Referee #1:

Hindcasts for precipitation prediction are performed using principal component regression in a drop-one cross-validated mode. This includes – for each year of the hindcast – dropping the predictor data (Z) from the year being hindcasted, forming new PCs (and EOFs) conditioned on the remaining years, and fit to observations using multiple regression, providing an intercept coefficient, regression coefficients, and error term. The predictor data (Z) from the year dropped are then projected onto the EOFs to provide PCs for the dropped year. Finally, these PCs are multiplied by the appropriate regression coefficients and added to the intercept coefficient to provide a deterministic precipitation prediction for the dropped year. This is repeated for each year.

To create ensemble hindcasts, error terms from all years are assembled and a distribution is fit (using a kernel density estimator; the distribution is approximately Gaussian). For each hindcast year, 1,000 random draws from the distribution are added to the deterministic precipitation prediction to form an ensemble.

The manuscript has been revised accordingly to clarify this process.

Comment: p. 15. L. 6. *A few issues with this sentence. Suggest changing to something like: "An RPSS value less than zero signifies no forecast skill over the reference climatology forecast (i.e. it is ….), a value equal to zero for when the forecast is only as skillful as climatology, and values greater than zero represents a skillful forecast. A value of one represents a perfect forecast".*

Response: We appreciate the Referee's suggestion to restructure this sentence. The text of this passage now reads:

> "An RPSS value less than zero signifies no forecast skill over the reference climatology forecast (i.e. the information provided by the developed forecast model is statistically less accurate than that provided by climatology), a value equal to zero for when the forecast is only as skillful as climatology, and values greater than zero represents a skillful forecast. A value of one represents a perfect forecast".

Comment: p. 15. L. 9-14. *Need more details about the use of 3x3 contingency tables, you might find the Svensson (2016) paper (and references therein) useful for this and as an example of statistical seasonal forecasting more generally. Also, more definition of what is meant by "extremely dry conditions". I know this is mentioned in the results, but it should be here that the methods details are given.*

Response: The authors thank the Referee for the reference, which has been added along with the following paragraph to clarify this point:

> "… Results are presented in a three-by-three matrix, or contingency table, that illustrates the performance of the model for each category. Contingency tables are an alternative method of assessing the precision of model predictions that relies on categorical probabilities as opposed to simpler methods such as correlation (Svensson, 2016). Of particular interest in this study is the hit rate statistic, or the percentage of time the model accurately predicts (categorically) the actual observed condition. In addition, because prediction of regional drought is of particular interest, the likelihood of extremely dry conditions is also considered. For this case, extremely dry conditions are defined as station-averaged JFM precipitation totaling less than 250 mm, which occurs approximately 25% of the time, or approximately in 13 years across the time series."

Comment: p. 15. L. 16-18. Which combinations of the 11 predictors in Table 1 made it into the final PCR model? I know PCA was used, but can weight be given to original 11 predictor variables? For example, can I tell how important, if at all, Niño 3.4 is to the final model?

Response: The Referee raises a good point that we did not explicitly address in the manuscript. While we used the Generalized Cross-Validation (GCV) skill score considering all 11 potential predictors to determine the optimal number of PCs to retain as predictors (i.e., 4), we did not present results on how the inclusion or exclusion of subsets of the 11 variables changed overall skill performance. We have now partially addressed this in the revised manuscript by evaluating the difference in model skill for a second model construct, one in which Niño 3.4 and SST from 160° W-140° W 0° -5° S are dropped from the pool of potential predictors. While this is not exhaustive, these two predictors are the most highly correlated with JFM precipitation (and intrinsically are highly correlated with one another), and the differences in skill can give indication of the value in retaining this particular predictor – even though a PCA structure is used. The following text has been added to the Discussion section:

> "The intent of this research was to explore the importance of including additional climate information in a predictive model that incorporates ENSO-based indices. To determine the importance of a model that does not include information regarding SST in the equatorial Pacific, a second hindcast model is developed using only 9 of the 11 original potential predictors. Niño 3.4 and SST from 160° W-140° W 0° -5° S are dropped in the modified model construct. Using the same cross-validated PCR methodology (as well as GCV to

determine the optimal number of potential predictor PCs to incorporate, i.e., 3), we produce hindcasts for the period of record (Fig. 13).

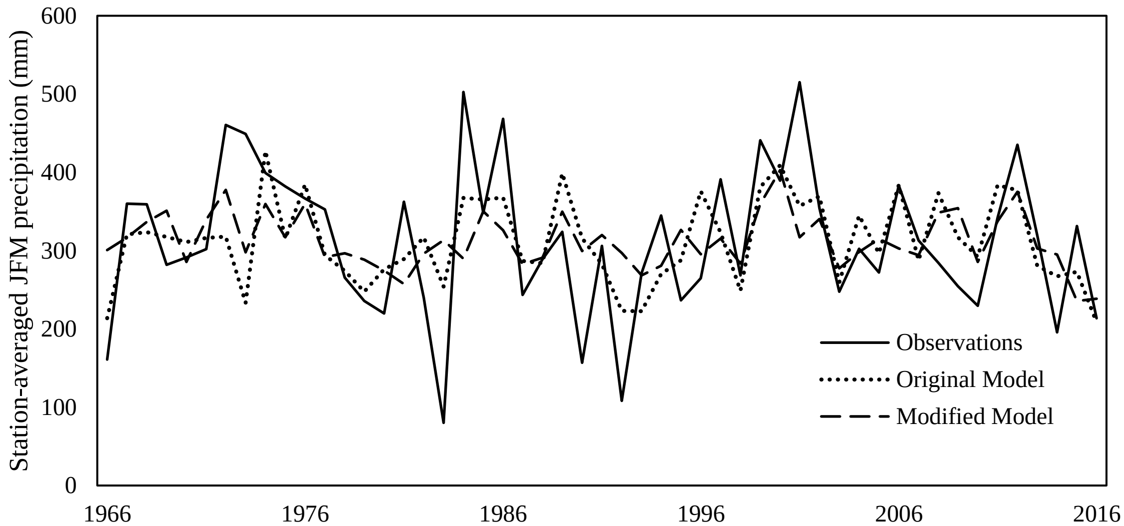


Figure 13: Observed conditions for the period of record, as well as hindcasts produced using the original model (11 potential predictors, 4 PCs) and the modified model (9 potential predictors, 3 PCs).

When comparing the results of the modified model to the original model, the importance of including ENSO in a model construct for precipitation prediction in southern Peru is highlighted. For example, the correlation coefficient between predicted conditions and observations for the modified model drops from r = 0.58 to r = 0.37 (still statistically significant, but skill reduced by roughly one-third). In addition, RPSS drops to only 0.05% from the original 16%, indicating that the information provided by the modified model is just barely more useful that that provided via climatology. In considering the hit-miss metric, the diminished skill of the modified model is also visible (Table 4).

Table 4: Hit-miss matrix for the modified model with three equal categories: above normal (A), near normal (N), and below normal (B) precipitation.

		Predicted conditions		
		A	N	B
Observed conditions	A	**6**	10	1
	N	0	**15**	2
	B	1	14	**1**

Above normal (A), near normal (N), below normal (B)

The modified model displays an evident bias towards predicting near normal conditions (more than 75% of the time). While the hit score of this model is reduced to 43%, more striking is the fact that the modified model produces an instance in which above normal conditions are prognosticated, but instead below normal conditions are experienced, arguably a more devastating forecast error in this region than the opposite situation (predicted below normal, experienced above normal). These metrics only reflect the critical importance of considering ENSO in regional precipitation prediction."

Comment: p. 16. L. 5-7. *The main message I get from Table 2 is that Near normal and Below normal precipitation is good, but it is the above normal that drags the hit rate to 51%.*

Response: This interpretation is accurate. Because of this, we explored the additional hit-miss matrix to evaluate above normal/near normal and extreme below normal precipitation predictions. Text has been added to the manuscript to explicitly state this interpretation.

Comment: p. 17. Sect. 7. *I like the idea of extended lead time analysis, but the technical details should be first outlined in the proposed 'Methods' section and results presented under a sub-heading within the 'Results' section.*

Response: As recommended by a previous comment, we have redistributed the technical details of the auxiliary applications to the 'Methods' section under appropriate subheadings. The results of these analyses are presented similarly in the 'Results' section.

Comment: p. 18. Fig. 12: *I'm missing how you are going from regional level to station level here. The extended lead time is good, but the spatial disaggregation is the weakest part of the analysis at present.*

Response: In an effort to more explicitly explain the spatial disaggregation portion of the study, the following text has been added to the manuscript:

> "… Using the regional-level categorical prediction probabilities for each year (above normal, near normal, and below normal; Fig. 12), ensemble predictions for each station are generated based on that station's own climatology. For example, the categorical probabilities at the regional-level for 2016 are predicted as 2% above normal, 7% near normal, and 91% below normal. For each station, JFM precipitation observations from all other years (excluding 2016) are randomly selected 1,000 times from that station's JFM precipitation distribution conditioned on the regional probabilities. Thus, the ensemble of predictions for that station for 2016 will have approximately 91% of its members from the below normal category, 7% near normal, and 2% above normal.
>
> The purpose of spatially disaggregating in this fashion is to maintain the statistical integrity of the regional-level prediction while reflecting appropriate magnitudes of precipitation experienced at different locations (Maraun, 2013). Station-level predictions are evaluated using the same metrics previously described."

Comment: p. 19. L. 6-9. *What statistical test is used to determine if the difference between regional and station correlation values is statistically significant or not?*

Response: Because the regional and station values are related, a dependent t-test for paired samples was used. The purpose of this statistical test is to search for significant changes or differences between two dependent variables. The goal of disaggregation was to produce a scaled precipitation forecast for local stations that maintained the statistical integrity of the regional prediction. Thus, a dependent t-test result of no statistically significant change is desired. We have clarified this in the revised manuscript.

Comment: p. 19. Sect. 8. *There is no discussion of the key limitations of the forecasting method/model (e.g. poor for above average precipitation). It would be good here to offer some suggested avenues for further research to overcome such methodological limitations.*

Response: We agree with this Referee comment. We will include a paragraph in the discussion section of the revised manuscript that explicitly discusses limitations, including poor performance in predicting above average precipitation conditions, the regional versus local nature of predictions and associated skill, real-time data requirements and trade-offs with longer prediction lead time, etc. In addition, we will outline potential avenues for further research such as alternative modeling approaches and integration with hydrology and other sectoral/decision-making models.

Comment: *I like the final paragraph on* p. 20 *as it highlights well the practical importance of seasonal forecasting using climate information in a region where none is currently available.*

Response: We truly do hope that the work undertaken by our group will be of practical use to stakeholders in the region. To clarify, though, it was not our intention to frame this study as the Prometheus of seasonal forecasting for the people of southern Peru. Certain national and local entities (both public and private) currently do employ forecasting techniques to predict regional precipitation to varying extents. For example, SENAMHI uses Niño index-based forecasts and SPCC has explored and developed predictive models that employ artificial neural networks. Instead, the purpose of this study is to expand on the region's existing capacity to predict precipitation. The manuscript has been edited to reflect this sentiment in a more appropriate and explicit manner.

Minor Comments (all accepted and corrected in the manuscript)

p. 1. L. 28. Change "vary drastically" to e.g. "vary considerably"

p. 2. L. 19. Change "wreaked havoc" to e.g. "was particularly severe"

p. 2. L. 26. Change "The dire" to e.g. "The societally challenging"

p. 4. Fig. 2. Add "…using data from 29 precipitation stations in Sect. 2" to caption.

p. 5. L. 7. The Eklundh and Pilesjö (1990) reference is for Ethiopia. Should reference go after "homogeneity" instead?

p. 6. L. 11. Add a comma in (Garreaud, 1999)

p. 8. L. 5-8. Very short paragraph, better added to the previous one

p. 9. L. 3. Change "hydrometeorologic" to "hydrometeorological"?

p. 9. L. 21. Change "previously identified" with "identified in Sect. 3"

p. 10&11. Fig. 7&8. Worth adding a dot/circle to mark study region on the maps for an international audience?

p. 11. L. 1-5. Delete section as repeated from p. 10.

p. 13. Table 1. Add space between 'Time frame'

p. 18. L. 9. Add full stop after "…etc.)"

p. 1. L. 19. Add "regional" and "totals" in front of and after "January-March precipitation", respectively.

References

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Regression-based season-ahead drought prediction for southern Peru conditioned on large-scale climate variables

Eric Mortensen[1], Shu Wu[2], Michael Notaro[2], Stephen Vavrus[2], Rob Montgomery[3], José De Piérola[4], Carlos Sánchez[4], Paul Block[1]

[1]Department of Civil and Environmental Engineering, University of Wisconsin–Madison, Madison, 53706, USA
[2]Nelson Institute Center for Climatic Research, University of Wisconsin–Madison, Madison, 53706, USA
[3]Montgomery Associates Resource Solutions LLC, Cottage Grove, 53527, USA
[4]Southern Peru Copper Corporation, Santiago de Surco, Lima 33, Peru

Correspondence to: Paul Block (paul.block@wisc.edu)

Abstract.

Located at a complex topographic, climatic, and hydrologic crossroads, southern Peru is a semi-arid region that exhibits high spatiotemporal variability in precipitation. The economic viability of the region hinges on this water, yet southern Peru is prone to water scarcity caused by seasonal meteorological drought. ~~D~~Meteorological droughts in this region here are often triggered during El Niño episodes; however, other large-scale climate mechanisms also play a noteworthy role in controlling the region's hydrologic cycle. An extensive season-ahead ~~drought~~ precipitation prediction model is developed to help bolster existing capacity of stakeholders to plan for and mitigate ~~the~~ deleterious impacts of drought ~~of this hydrologic extreme~~. In addition to existing climate indices, large-scale climatic variables, such as sea surface temperature, are investigated to identify potential drought predictors. A principal component regression framework is applied to eleven potential predictors to produce an ensemble forecast of regional January-March precipitation totals. Model hindcasts of 51 years, compared to climatology and another model conditioned solely on an El Niño-Southern Oscillation index, achieve notable skill and perform better for several metrics, including ranked probability skill score and a hit-miss statistic. Extending the lead time of and spatially disaggregating precipitation predictions to the local level as well as forecasting the number of wet/dry days per rainy season may further assist regional stakeholders and policymakers in preparing for ~~and responding to~~ drought.

1 Introduction.

Southern Peru is a semi-arid region just north of the Atacama Desert, located at a complex topographic, climatic, and hydrologic crossroads. With elevations ranging from sea level to over 6,000 meters, the area is a patchwork of snow-capped Andean mountains, highlands and plateaus, and large expanses of coastal desert. Due to its proximity to the Amazon rainforest, the Atacama Desert, and the Pacific Ocean, the climate patterns that govern the region's precipitation vary ~~drastically~~considerably, both seasonally and annually. Although a notable portion of this region drains to Lake Titicaca, which is itself a part of a larger endorheic basin, the majority of the region's water flows into the Pacific Ocean through networks of small rivers and quebradas, or seasonal creeks. While the topographic, climatic, and hydrologic factors of the region produce spatiotemporal variability in the distribution of water resources (Tapley and Waylen, 1990), southern Peru can generally be characterized as water scarce (Alegría, 2006; Kuroiwa, 2007; Ugarte, 2012; Chinchay Alza, 2015).

Nonetheless, southern Peru displays a high economic dependence on activities driven directly by water availability, specifically agriculture and mining (Higa Eda and Chen, 2010). The region is home to some of the nation's richest olive and grapevine fields, as well as several large-scale copper mining operations. Both of these industries are heavily dependent on water consumption. Additionally, several large urban areas such as Arequipa, Juliaca, and Tacna (Fig. 1) necessarily require large quantities of water to thrive as economic and cultural centers.

Although not equivalent, meteorological drought in this region often directly translates into hydrologic drought. Droughts, like the one that struck in early 2016, have a critical impact on the success and survival of the region. During that year, agricultural outputs of southern Peru were reduced by up to 75% (ANA, 2016), necessitating the creation of an emergency contingency fund for impacted farmers by Peru's national water authority (in Spanish, Autoridad Nacional del Agua, or ANA). ~~The~~ ANA also declared states of emergency for two cities, Tacna and Arequipa. Consequentially, the cities~~y~~'~~s~~ water supplies were reduced by more than one-fourth. The mining operations of the region were also negatively impacted, with ANA ordering mining companies such as Southern Peru Copper Corporation (SPCC), to reduce their water consumption and, transitively, copper production, resulting in lost economic potential and reduced fiscal resources for the region as a whole.

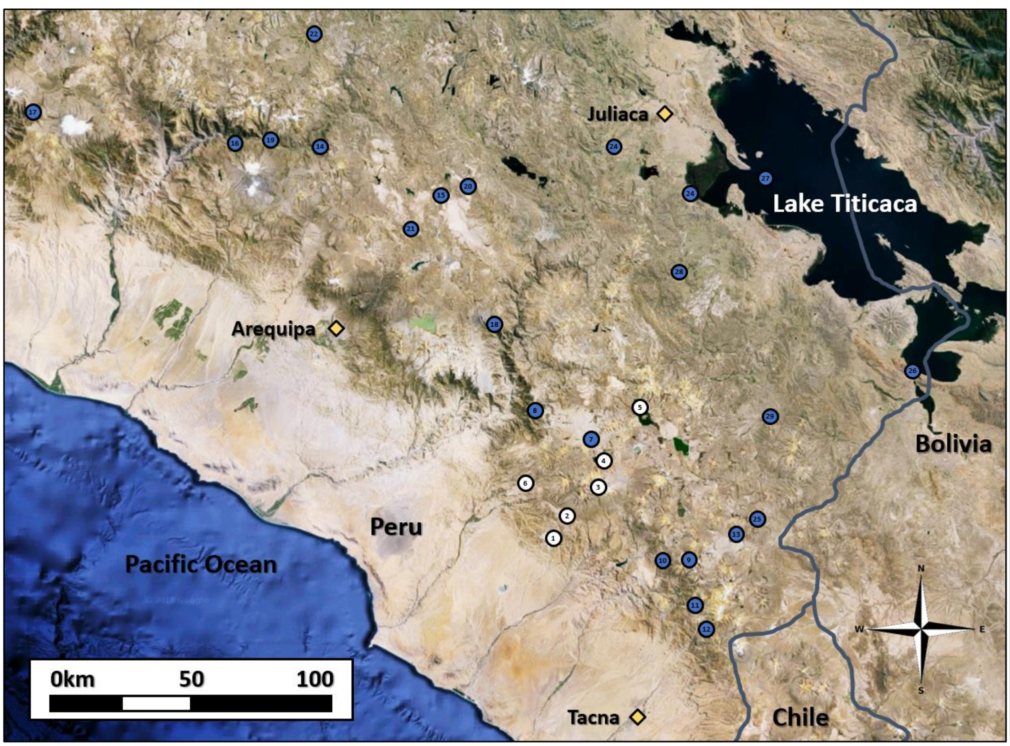
The severity of this most recent bout of drought, unfortunately, is not unprecedented; other droughts in the past have also caused serious economic and social consequences. The drought event of early 1983 ~~wreaked havoc~~was particularly severe across southern Peru (Caviedes, 1985). Before this event, hazard preparedness essentially did not exist in Peru. The drought, which coincided with deadly flooding in the northern part of the country, was met with slow and uncoordinated official disaster relief. Even after Peru developed their national hazard preparedness program following this event, the region continued to be vulnerable to drought. In 1998, an estimated $200 million in direct losses occurred over the southern Andes of Peru due to drought (Lavado-Casimiro et al., 2013).

We develop a statistically-based season-ahead principal component regression (PCR) model that predicts seasonal precipitation totals to address this existing gap. The PCR model draws on a far-reaching pool of large-scale climate variables that influence southern Peru precipitation through ocean-atmosphere teleconnections. The model is evaluated against climatology and simpler Niño index-based models to understand if the inclusion of several predictors leads to more skillful prediction, particularly for dry years in this drought-sensitive region. In addition, several ancillary applications of this model are explored, including lead time extension, spatial disaggregation, and wet/dry day frequency prediction, in an attempt to

~~produce~~provide further detailed information which may be more relevant to certain stakeholders. We address this gap in southern Peru by developing and evaluating a statistical precipitation prediction model for the region

2 Data Description.

Monthly precipitation data are available for 29 stations distributed across the region over a period of 51 years (1966-2016; Fig. 1). Six of the 29 stations are owned and operated by SPCC, with the remaining stations belonging to Peru's national meteorological service (in Spanish, Servicio Nacional de Meteorologia e Hidrologia del Peru, or SENAMHI). ~~SPCC acquired SENAMHI data for this study.~~



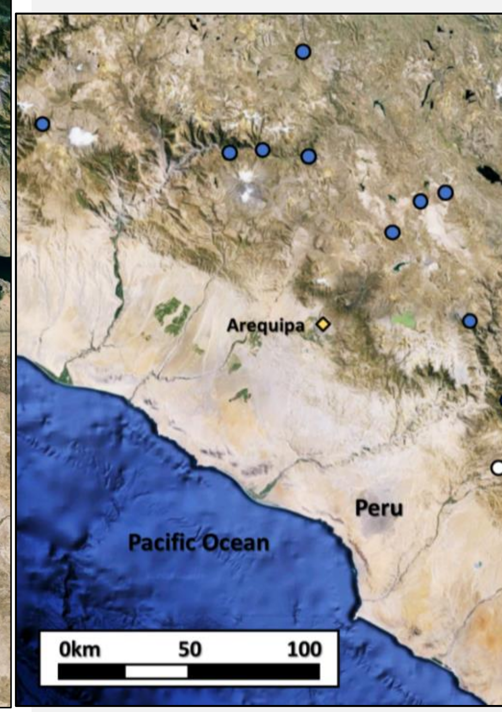


Figure 1: ~~Blue~~ White circles represent locations of SPCC stations; ~~white~~ blue circles represent SENAMHI stations. Three major urban centers are labeled ~~(map generated using Google Earth imagery and station information from SPCC).~~and stations are numbered from 1-29 (map generated using Google Earth imagery and station information from SPCC).

The 29 stations provide spatial coverage for an area of 65,000 km^2 and are located in a variety of environments, including the edge of the Atacama Desert, the islands of Lake Titicaca, the dry grassy plains of the Altiplano, and the mountainous terrain of the Central Andes. The topography of the region is noteworthy. While the 29 stations considered in the study cover an elevation range from 3,100 m to 4,600 m (Fig. 2, mean elevation 3870 m), this portion of southern Peru ranges from sea level at the Pacific Ocean to over 6,000 m in the high Andes.

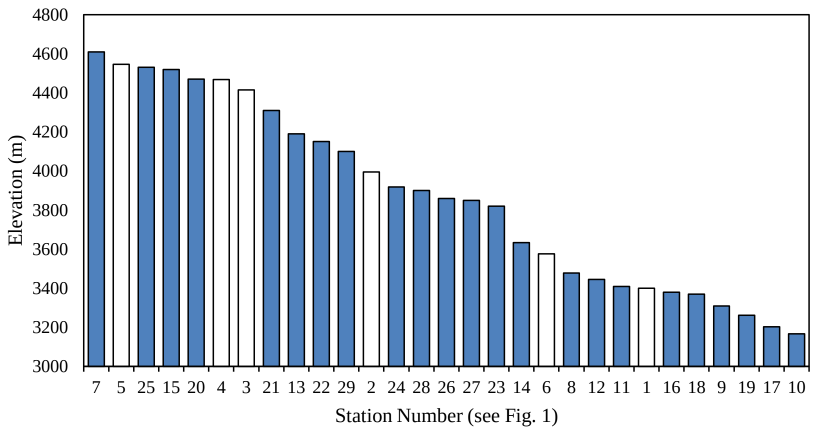


Figure 2: Elevations of all 29 stations included in the study. Bars are numbered and colored in accordance with Fig. 1, with white bars representing SPCC stations and blue bars representing SENAMHI stations.

Cross-correlations between all of the stations were calculated based on available monthly precipitation totals (average Pearson's correlation coefficient, r=0.92). For any missing station data (<1% of total data), the ten most highly correlated stations were identified, and ~~multi-regression~~multiple regression based on monthly statistics was used to interpolate a probable missing value. In most cases, high correlation coefficients between estimated missing points and observed data suggest that this simple methodology is effective in filling the data.

Potential large-scale climate predictors, including sea surface temperature (SST), sea level pressure (SLP), and geopotential height (GH), were retrieved from the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory Physical Sciences Division (ESRL-PSD). The data are based on National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) reanalysis data, version 1 (Kalnay et al., 1996) and are available as monthly average on a 2.5° x 2.5° global grid (this dataset is available in full from 1948 to present). The specific regions and periods of the aforementioned climate variables considered in this study are listed in Table 1 of Section~~.~~ 4. In addition, ESRL-PSD monthly/seasonal climate correlation and composite mapping tools are used in this analysis.

In addition to the aforementioned large-scale climate variables, several established teleconnection indices, such as Niño 3.4 (Rayner et al., 2003), Pacific Decadal Oscillation (PDO; Mantua et al., 1997), North Pacific index (NP; Trenberth and Hurrell, 1994), and Western Hemisphere Warm Pool (WHWP; Wang and Enfield, 2001), are ~~also~~ evaluated in this study.

3 Southern Peru Rainy Season and Large-scale Climate Influences.

In the mid-high elevation regions of southern Peru, as in most tropical zones, the annual cycle is dominated by a wet and dry season (Fig. 3~~2~~). For southern Peru, the rainy season occurs from November to April (Kuroiwa, 2007); however, the majority of precipitation in the region occurs during January, February, and March (JFM; 315 mm on average). JFM precipitation represents, on average, more than two-thirds of annual precipitation for the region, with some locations receiving up to 85% of annual precipitation during the three-month period. This precipitation is crucial to the region's economic activities and environmental stability. During the rainy season, for example, surface reservoirs and underground aquifers are replenished for multi-sectoral water resource use during the dry conditions that characterize the rest of the year. These rains also directly impact the phenology of many wild plants and agricultural operations, and are intrinsically tied to the function of ~~quebradas, or~~ seasonal creeks~~,~~ that drain the region. As mentioned, severe and wide-reaching economic, environmental, and societal consequences can be realized in an abnormally dry rainy season. Thus, JFM is identified as the season of interest for this study. ~~JFM precipitation represents, on average, more than two-thirds of annual precipitation for the region, with some locations receiving up to 85% of annual precipitation during this period. Thus, JFM is identified as the season of interest for this study.~~

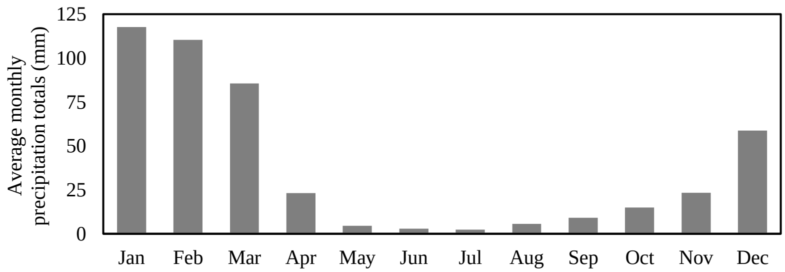


Figure ~~2~~3: Average monthly precipitation (mm) ~~in~~ of 29 stations southern Peru.

To evaluate the spatial and temporal patterns of regional precipitation, a principal component analysis (PCA) is performed on JFM seasonal precipitation totals (von Storch and Zwiers, 2001) based on data from the 29 stations. In PCA, a dataset is decomposed into orthogonal, uncorrelated modes representing distinctive signals, or variance, present in the dataset. PCA yields information describing both spatial patterns (empirical orthogonal functions, EOFs) and temporal trends (principal components, PCs) of variance experienced in the dataset~~To evaluate the spatial and temporal patterns of regional precipitation, a principal component analysis (PCA) is performed on JFM seasonal precipitation totals (von Storch and Zwiers, 2001) based on data from the 29 stations. In PCA, a dataset is decomposed into orthogonal, uncorrelated modes representing distinctive signals, or variance, present in the dataset~~.

Even with significant changes in elevation across the region, the sign of the first EOF spatial pattern of all stations is negative (and at similar magnitudes) generally implying spatial homogeneity (Eklundh and Pilesjö, 1990; Ogallo, 1980; Mallants and Feyen, 1990; Bisetegne et al., 1986) of JFM seasonal precipitation within this relatively small region. Additionally, the first PC of the precipitation time series captures 51% of the temporal variance in the data, and correlates well with station-averaged JFM seasonal precipitation observations ($r = 0.99$; Fig. 4).

Figure 4: Station~~-~~averaged JFM precipitation (mm) and the first PC anomalies for the period of record, 1966-2016, using data from 29 precipitation stations (introduced in Sect. 2).

This exceptional level of correlation between the averaged observations and the first PC (as well as high levels of correlation between this first PC time series and individual station data) suggest that the station-averaged time series is an appropriate representation of regional precipitation. It should be noted that the second mode captures an additional ~20% of variance, with the third dropping to ~5%. These three PCs represent a cumulative 75% of variance experienced in the dataset (it is assumed that the remaining PCs describe only minor or spurious variance). To identify physical mechanisms that modulate precipitation that result in the observed temporal variance, the complex regional climate system must be comprehensively analysed.

During the rainy season, the tropical Southern Hemisphere receives increased amounts of solar radiation that destabilizes the atmospheric boundary layer, inducing deep convection and moist air advection (Vuille et al., 1999; Garreaud, 1999). This directly translates to increased levels of evapotranspiration in the Amazon basin, with moisture transported deep into the atmosphere by a complex network of deep convection systems, including the upper level of the Bolivian High (Lenters and Cook, 1997). In general, the winds associated with this deep convection are easterly and northerly, carrying moisture towards the Andes from the Amazon (Fuenzalida and Rutllant, 1987; Chaffaut et al., 1998; Rao et al., 1996; Vizy and Cook, 2007). The Andes induce an orographic effect in which more precipitation occurs at windward locations and higher elevations of the region (Garreaud, 1999). Meanwhile, the precipitation at the leeward (western) side of the mountain range and lower elevations is markedly reduced; this region of southern Peru exists in the rain shadow of the Andes, a fact especially relevant for the study. Instead of an abrupt switch between wet and dry conditions as might be expected by some other notable rain shadows in the world, ~~though,~~ the Altiplano (and the majority of the stations used in this study) exists in a transitionary zone of sorts and exhibits a gradual wet to dry gradient from northeast to southwest.

Previous studies have identified SST anomalies in the equatorial Pacific ~~Ocean~~ as a substantial factor impacting regional precipitation patterns in southern Peru (Vuille et al., 2000; Garreaud et al. 2003; Espinoza Villar et al. 2009; Lavado-Casimiro et al., 2013; Cid-Serrano et al., 2015). This area of the Pacific is commonly associated with the El Niño-Southern Oscillation (ENSO) phenomenon, and several studies further identify the SST domain of 5° N-5° S, 120° W-170° W, known as Niño 3.4 (Trenberth, 1997), as particularly influential in modulating JFM precipitation. Strong El Niño (warm SST) conditions in the Niño 3.4 region are typically associated with drought in southern Peru, whereas La Niña (cool SST) conditions often align with wetter-than-average conditions (Fig. 5, El Niño and La Niña thresholds of 0.5°C and -0.5°C, respectively, included for context).~~Strong El Niño (warm SST) conditions in the Niño 3.4 region are typically associated with drought in southern Peru, whereas La Niña (cool SST) conditions often align with wetter-than-average conditions (Fig. 5).~~

~~Furthermore, prior studies have determined that droughts in southern Peru are not generally caused by limited moisture availability, but rather limited moisture transport. During El Niño episodes, enhanced upper-level westerly flow from the Pacific Ocean weaken the typical wind patterns of the region, blocking easterly winds laden with moisture that normally falls as precipitation in southern Peru (Garreaud et al., 2003; Takahashi, 2006). During La Niña, easterly flow is enhanced, often resulting in greater precipitation and cloud cover, and lower temperatures in the central Andes (Vuille, 1999).~~

Figure 5: Station-averaged JFM precipitation and concurrent JFM Niño 3.4 SST anomalies (r=-0.57, p-value = 0.000013). El Niño and La Niña thresholds marked with black solid line. During the period of record, 13 JFMs exceeded the El Niño threshold (0.5°C) and 18 JFMs the La Niña threshold (-0.5°C).~~Time series of JFM precipitation and concurrent JFM Niño 3.4 SST anomalies (r=-0.57).~~

Furthermore, prior studies have determined that droughts in southern Peru are not generally caused by limited moisture availability, but rather limited moisture transport. During El Niño episodes, enhanced upper-level westerly flow from the Pacific Ocean weakens the typical wind patterns of the region, blocking easterly winds laden with moisture that normally falls as precipitation in southern Peru (Garreaud et al., 2003; Takahashi, 2006). During La Niña, easterly flow is enhanced, often resulting in greater precipitation and cloud cover, and lower temperatures in the central Andes (Vuille, 1999).

The phase and strength of ENSO does not necessarily ~~translate~~correspond to ~~into~~ a specific outcome for seasonal precipitation, a fact particularly evident in three notable cases (bolded and underlined, Fig. 6). In late 1972, a strong El Niño developed off the coast of South America; however, instead of expected dry conditions, JFM 1973 surprisingly turned out to be one of the wettest rainy seasons on record for the region (Garreaud et al., 2003). In contrast, ENSO index values indicative of neutral to weak La Niña conditions prior to JFM 1990 and 2014 would have typically ~~indicated~~ been interpreted to mean normal to slightly wetter-than-~~usual~~ average conditions, yet these years ~~resulted in~~~~were logged as~~are two of the driest rainy seasons on record.

Figure 6: ~~Scatterplot of JFM precipitation and concurrent Niño 3.4 SST anomalies.~~ Three outlier years in which general relationship between Niño 3.4 and regional precipitation did not hold to be true are bolded and underlined~~.~~. If the three outlier years (1973, 1990, and 2014) are removed, the relationship between precipitation and SST anomalies strengthens (r=-0.66, p-value = 0.000009).

Such deviations from the generally understood relationship between ENSO and regional JFM seasonal precipitation are likely due to other climate phenomena, and support the two-fold notion of ENSO's influence on seasonal precipitation as well as the presence of additional climatic factors that modulate the region's precipitation. R~~; r~~egions and variables of interest highlighted in other studies (and considered in this study) as mechanisms potentially ~~controlling~~modulating precipitation in southern Peru include ~~the~~ Tropical Atlantic SST, several SST regions of the Pacific, and the Bolivian High.

~~Such deviations from the generally understood relationship between ENSO and regional JFM seasonal precipitation are likely due to other climate phenomena; regions and variables of interest highlighted in other studies as mechanisms potentially controlling precipitation in southern Peru include the Tropical Atlantic SST, several SST regions of the Pacific, and the Bolivian High.~~

ultimately originates over the trade wind regions of the ~~t~~Tropical Atlantic (Vuille et al., 2000), the primary source of moisture to the Amazon. In particular, SST anomalies in the North Tropical Atlantic regulate dry season precipitation anomalies in the western Amazon (Marengo et al., 2008; Zeng et al., 2008; Yoon and Zeng, 2010; Fernandes et al., 2011). When the North Tropical Atlantic is anomalously warm, the Intertropical Convergence Zone shifts northward, causing net water vapor divergence, anomalous subsidence, and reduced precipitation in western/southern Amazon (Marengo, 1992; Marengo et al., 2008; Yoon and Zeng, 2010), and southern Andes (Lavado-Casimiro et al., 2012). ~~This study considers climatic variables from the Tropical Atlantic Ocean.~~

In the Pacific Ocean, locations outside of the traditional ENSO region also appear to impact precipitation in this region of South America. Although the subtropical Pacific is immediately adjacent to the region of interest, it typically contributes little moisture to southern Peru because low-level zonal flow and associated moisture from the sea is blocked by steep regional terrain and large-scale subsidence (Rutllant and Ulriksen, 1979). The Pacific Ocean, however, still plays a significant role in controlling the regional hydrologic cycle due to these zonal winds. The Pacific Decadal Oscillation (PDO) has also been identified as modulating precipitation ~~variability for~~throughout much of South America (Enfield, 1996; Kayano and Andreoli, 2007). This multi-decadal, low frequency oscillation of North Pacific SST impacts several regional climate systems and has been widely accepted by the hydrometeorological community as being distinct from ENSO (Deser and Blackmon, 1995; Mantua and Hare, 2002; Wang et al., 2008). Additionally, the Western Hemisphere Warm Pool (WHWP), a region of abnormally warm SST off the coast of Central America with lobes in the Caribbean and Pacific Ocean, may likewise influence regional precipitation as a result to the warming cycle’s impact on rainy season precipitation in equatorial Central and South America via tradewind modulation (Wang and Enfield, 2003; Wang and Enfield, 2006). Finally, the North Pacific (NP) index, which describes SST and SLP variability in the North Pacific, has a direct connection with changes to Tropical Pacific SST and circulation patterns (Trenberth and Hurrell, 1994). PDO, WHWP, and NP indices are all considered in this study.

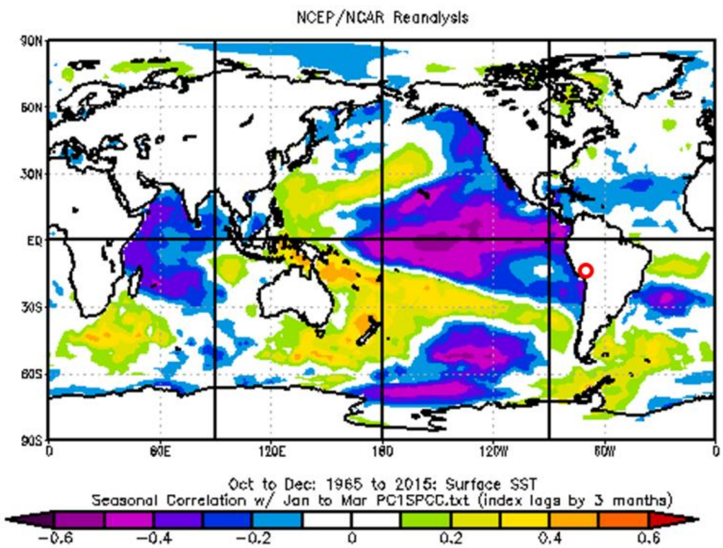
The upper-level Bolivian High, located over the Altiplano during December-April, is related to latent heat release over the Amazon (Silva Dias et al., 1983; Lenters and Cook, 1997). The position and strength of the High has been linked to precipitation anomalies over the Altiplano during the rainy season. Specifically, a weakened, northward shifted Bolivian High is often associated with persistent dryness on the Altiplano (Aceituno and Montecinos, 1993; Lenters and Cook, 1999; Vuille et al., 2000), whereas a strong, southward shifted Bolivian High favors deep convection on the Altiplano and increased moisture availability (Garreaud and Aceituno, 2001; Garreaud et al., 2003). Thus, the position of the Bolivian High impacts zonal winds during the Altiplano’s rainy season; dry (wet) conditions over the Altiplano are associated with anomalous westerly (easterly) flow in the region (Aceituno and Montecinos, 1993; Lenters and Cook, 1999).

While the first EOF of regional precipitation likely illustrates ENSO’s influence on regional precipitation, it is possible that higher order modes may describe other climatic and topographic forcings such as interconnected large-scale climatic phenomena or observed orographic effects. For example, the second EOF exhibits a dipole pattern, which may be related to the rain shadow phenomenon that causes the northeastern portion of the region to be wet and southwestern to be dry.

4 Identification of Seasonal Precipitation Predictors.

Potential predictors of JFM precipitation are identified by analyzing persistent large-scale and local climate variables in the prior season of October–December (OND) based on the suite of variables and indices ~~previously~~ identified in Section~~.~~ 3, and validated through correlation mapping, composite mapping, and global wavelet analysis. The purpose of these three methods is to identify climate variables and indices that partially explain the variance in JFM precipitation and as a result may ~~thus~~ serve as potentially skillful predictors in the development of a season-ahead precipitation prediction model.

~~C~~Spatial correlation maps between the first three PCs of JFM regional precipitation (explaining approximately 75% of the variance) and global OND climatic variables, including SST, SLP, and GH at 200 hPa, illustrate regions of correlation and potentially relevant teleconnections. Only December values are used for SLP and GH given their limited atmospheric persistence. For example, the correlation between OND SST and the first PC of JFM regional precipitation produces a pattern emblematic of the classic ENSO phenomenon (Fig. 7). The area near (but not exactly) Niño 3.4 has the strongest correlation ($r=-0.54$), indicative of a relationship in which, generally, abnormally warm (cool) water in this region corresponds with dry (wet) conditions in southern Peru, supporting previous findings.



~~**Not all regions that display high correlations with the PCs are necessarily physically relevant however. To limit spurious correlations, only regions of statistical significance at the 95% confidence level and justifiable (via relevant, peer-reviewed literature) physical influence on moisture transportation to southern Peru are selected as potential predictors.**~~

~~**Additional areas of interest identified through correlation mapping include an area of SLP off the western coast of Mexico/USA (roughly 35° N-20° N, 150° W-135° W) and an area of geopotential height above southern Bolivia/northern Argentina (not shown). These two areas, in addition to the aforementioned region of SST in the equatorial Pacific, displayed statistical significance at the 95% confidence level to at least one of the three analyzed PCs. We speculate that these two regions of high correlation likely have a physical relation to the WHWP and Bolivian High, respectively.**~~

Not all regions, however, that display relatively high correlations with the PCs are necessarily physically relevant ~~however~~. To limit spurious correlations, only regions of statistical significance at the 95% confidence level and justifiable (via relevant, peer-reviewed literature) physical influence on moisture transportation to southern Peru are selected as potential predictors.

Composite maps illustrate climate conditions for a single period or subset of periods, and may be especially useful for understanding forcing mechanisms in anomalous periods. For example, OND SST for the nine subsequent driest JFM seasons on record for southern Peru subtracted from OND SST for the nine subsequent wettest JFM seasons on record for southern Peru produce large positive anomalies in the equatorial Pacific Ocean. This composite map (Fig. 8) further indicates the potential importance of ENSO in explaining JFM precipitation variability in the study region.

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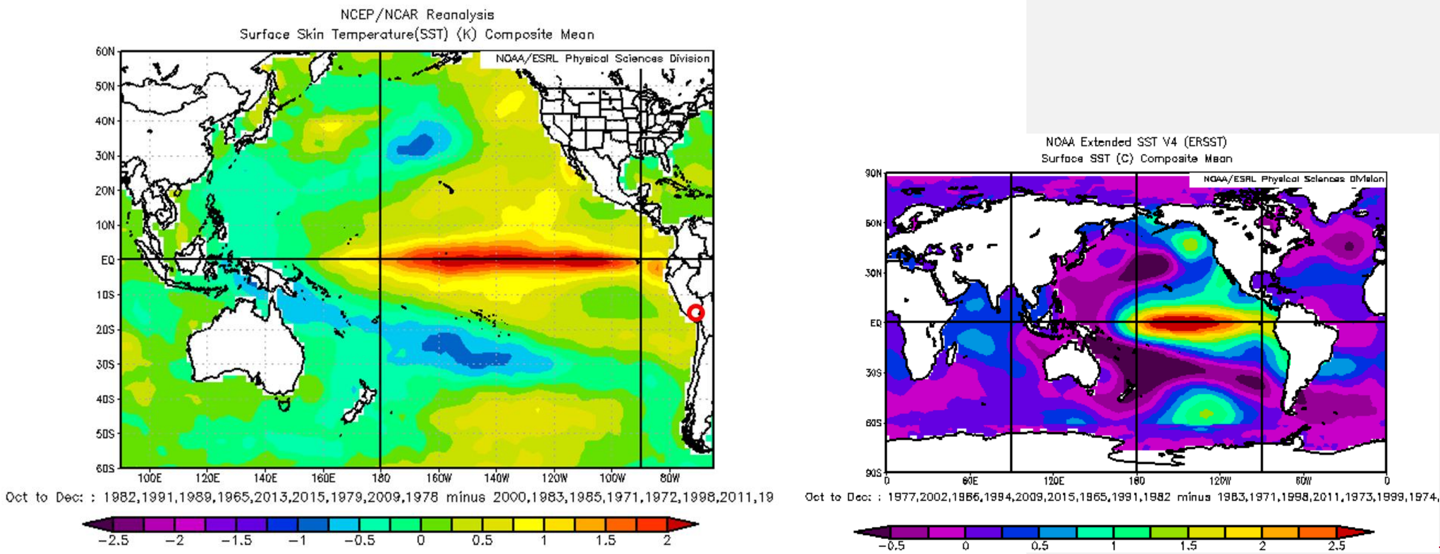

Figure 8: ~~Composite~~ SST ~~OND~~ conditions for~~of~~ ~~nine~~ OND seasons following the nine ~~subsequent~~ driest JFM seasons~~-~~ (1983, 1992, 1990, 1966, 2014, 2016, 1980, 2010, and 1979) ~~and~~ subtracted from SST ~~OND~~ conditions ~~of~~for OND seasons following the nine ~~subsequent~~ wettest JFM seasons (2001, 1984, 1986, 1972, 1973, 1999, 2012, 1974, and 1997)~~Composite SST conditions of dry El Niño years subtracted from wet La Niña years~~. Study region identified with red circle.

Additional composite maps, namely subsets of years with the strongest El Niño and La Niña years or years with wetter-than-average El Niño years and drier-than-average La Niña years, led to identification of ENSO, SST gradients in the North Pacific and Tropical Atlantic Oceans, and the Pacific lobe of the WHWP as potentially skillful predictors of JFM precipitation. Interestingly, for deviations from the typical ENSO-precipitation relationship (i.e., dry- vs. wet-El Niño JFMs and dry- vs. wet-La Niña JFMs), the resulting anomalies in the North Pacific as well as WHWP appear to be similar in size and magnitude. Thus, during the unexpectedly wet 1973 JFM or unexpectedly dry 1990 JFM, for example, these two SST regions may have modulated the effect of other large-scale climate variables, such as equatorial Pacific SST, on regional precipitation.

Finally, wavelet analysis is applied to the observed station-averaged JFM precipitation totals to identify differentrent~~ring~~ frequency signals that may exist in the dataset~~e observed station average precipitation dataset~~. More specifically, wavelet analysis is mainly used to detect the changing of dominant periods with time. Wavelet analysis decomposes a time series into time-frequency space to identify significant modes of variability and illustrate how variability may change with time (Torrence and

Compo, 1998). Using a Morlet 6.00 transform (Morlet et al., 1982) on the station-averaged JFM precipitation time series, signals at a ~3-5-year band, ~12-16-year band, and ~24-year band are identified as statistically significant at the 95% confidence level (Fig. 9).

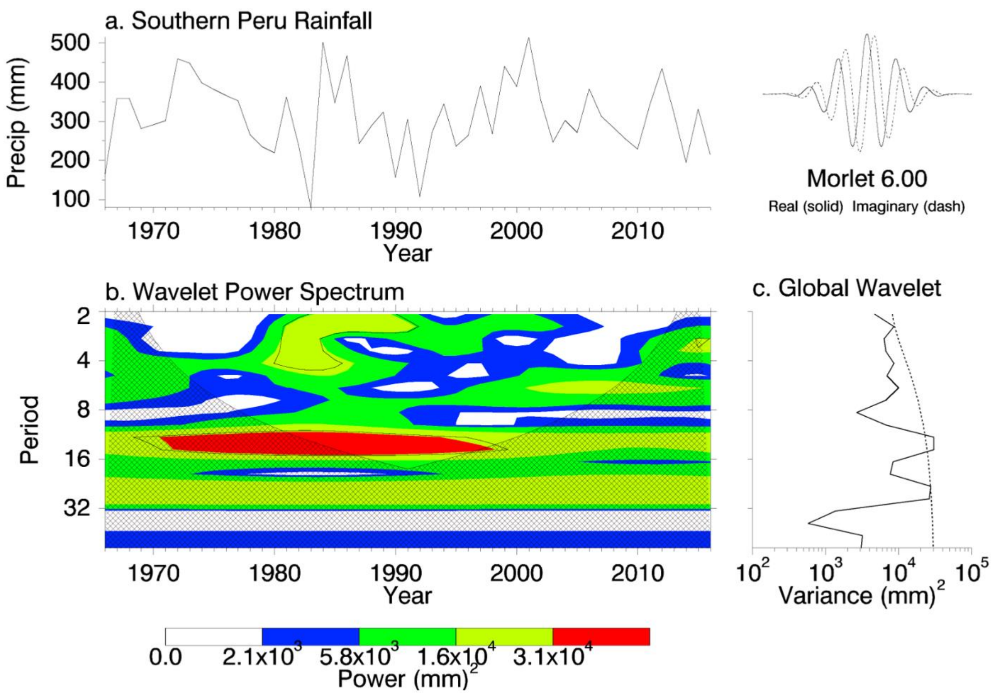

Figure 9: (a) Precipitation time series, (b) statistically significant signals at T = ~3-5, ~12-16, and ~24 years (statistically significant periods at 95% confidence level outlined), (c) global wavelet variance with 95% confidence level delineated by dotted line.

The identified signals at ~3-5 years and ~12-16 years are likely indicative of ENSO and perhaps PDO, respectively. These identified underlying periodicities of the precipitation data further ~~confirm~~ affirm the inclusion of large-scale climate indices with both relatively short and long periods of oscillation. Occasionally, wavelet spectrum analysis can artificially amplify the power of longer periods. To determine whether the ~24-year signal is truly statistically significant, further testing, such as a Fourier power spectrum, may be warranted (Wu and Liu, 2005), but not undertaken here.

In total, 11 potential predictors are identified for prediction of station-averaged JFM precipitation based on previous literature and inference from spatial correlation maps, composite maps, and global wavelet analysis (Table 1). These potential predictors include both established climate indices and relevant regions of SST, SLP, and GH (as well as gradients of these variables). All potential predictors included in the model framework display a statistically significant correlation with at least one of the first three PCs of the station-averaged precipitation time series. In addition, five potential predictors are also statistically significant correlated with the station-averaged times series of precipitation, and marked with asterisks in Table 1.

~~In total, 11 potential predictors are identified for prediction of JFM precipitation based on previous literature and inference from correlation maps, composite maps, and global wavelet analysis (Table 1). These potential predictors include both established climate indices and relevant regions of SST, SLP, and GH (as well as gradients of these variables). Although some predictors listed (marked with asterisks in Table 1) do not display significant levels of correlation with station average JFM precipitation time series, significant correlation is observed with at least one of the first three PCs of the precipitation time series.~~

Table 1: The suite of potential predictors for JFM precipitation; correlations are based on JFM total precipitation and spatial averages across the regions noted, with statistically significant correlations marked with an asterisk.

Name	Large-scale climate variable	Time frame	Spatial region		Corr. w/ JFM precip.	Most Correlated PC (r)
Niño 3.4	SST	OND	5° N-5° S	170° W-120° W	-0.53*	PC1 (-0.52)
PDO	SST	OND	all areas north of 20° N		-0.19	PC2 (-0.35)
NP	SLP	D	65° N-35° N	160° E-140° W	-0.18	PC3 (0.28)
WHWP	SST	OND	28° N-8° N	110° W-40° W	-0.16	PC3 (-0.32)
	SST	OND	0° -5° S	160° W-140° W	-0.54*	PC1 (-0.54)
	SLP	D	35° N-20° N	150° W-135° W	0.15	PC2 (-0.36)
	SST gradient	OND	0° -15° S (25° S-40° S)	15° W-35° W (15° W-35° W)	0.30*	PC2 (-0.29) PC3 (0.28)
	SST gradient	OND	50° N-40° N (35° N-30° N)	150° W-135° W (180° -165° W)	0.38*	PC3 (-0.37) PC2 (0.27)
	GH 200 hPa	D	10° S-15° S	70° W-65° W	-0.35*	PC1 (-0.31)

~~**Table 1: The suite of potential predictors for JFM precipitation; correlations are based on JFM total precipitation and spatial averages across the regions noted.**~~

~~Name~~	~~Large-scale climate variable~~	~~Timeframe~~	~~Region~~	~~Corr. w/ JFM precip.~~

~~Niño 3.4~~	~~SST~~	~~OND~~	~~5° N-5° S~~	~~170° W-120° W~~	~~-0.53~~
~~PDO~~	~~SST~~	~~OND~~	~~all areas north of 20° N~~		~~-0.19*~~
~~NP~~	~~SLP~~	~~D~~	~~65° N-35° N~~	~~160° E-140° W~~	~~-0.18*~~
~~WHWP~~	~~SST~~	~~OND~~	~~28° N-8° N~~	~~110° W-40° W~~	~~-0.16*~~
	~~SST~~	~~OND~~	~~0°-5° S~~	~~160° W-140° W~~	~~-0.54~~
	~~SLP~~	~~D~~	~~35° N-20° N~~	~~150° W-135° W~~	~~0.15*~~
	~~SST gradient~~	~~OND~~	~~0°-15° S~~ ~~(25° S-40° S)~~	~~15° W-35° W~~ ~~(15° W-35° W)~~	~~0.30~~
	~~SST gradient~~	~~OND~~	~~50° N-40° N~~ ~~(35° N-30° N)~~	~~150° W-135° W~~ ~~(180°-165° W)~~	~~0.38~~
	~~GH 200 hPa~~	~~D~~	~~10° S-15° S~~	~~70° W-65° W~~	~~-0.35~~

5 ~~Prediction Model Framework and Evaluation.~~Methods.

Statistical forecasts have been developed and evaluated for many applications globally, although more effort is still focused on the application of dynamical model predictions; however, there are numerous advantages for selecting statistical models for season-ahead precipitation prediction over other methods involving global atmospheric general circulation models (GCMs), most notably reviewed by Xu (1999). These include GCMs' inability to represent sub-grid features and dynamics and~~, vertical level~~ mismatches between GCMs' ~~ability~~strengths and hydrology needs (atmospheric vs surface), ~~and discrepancies in the importance placed on variables used in dynamical models~~both of which statistical models can address.~~ Essentially ,~~ D~~d~~ynamical models are exceptional tools for macroscale climate modeling, but can struggle ~~in~~at the local scale, like~~s~~ ~~similar to~~ that of our project area. Additionally, the complex topography of the region complicates the use of GCMs for regional predictions. ~~Although we are focused on meteorological drought and not necessarily hydrologic drought, the intrinsic interconnectedness of these two types of drought necessitates a methodology that can be justified if meteorological predictions were to be used for hydrologic application.~~ For this case, the merits of statistical model~~sing~~ appear to outweigh those of dynamical mode~~sling~~.

5.1 Principal Component Regression-based Prediction Model.

A ~~principal component analysis (PCA)~~PCA coupled with a multiple-linear regression model construct, otherwise known as ~~principal component regression (~~PCR~~)~~, is used to predict station~~-~~averaged JFM seasonal precipitation for the study region. In this case, the method used to develop the model is advantageous because it accounts for the multi-collinearity present among several of the identified potential predictors (von Storch and Zweirs, 2001) and standardizes all resulting PC values so as not to cause any unintentional preference. After a PCA is performed on the set of area mean values of the identified potential predictors, the PCs are fit to a multiple-linear regression, given as:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + e \tag{1}$$

where y is the observed JFM total precipitation, β_0 is a constant, $\beta_1 \ldots \beta_n$ are coefficients, $x_1 \ldots x_n$ are the PCs, and e is the error term. Coefficients are determined using the ordinary least squares method (Helsel and Hirsch, 2002).

To create a parsimonious model and minimize overfitting, the optimal number of PCs (i.e. predictors) is selected using the generalized cross-validation (GCV) skill score (Walpole et al., 2012; Block and Rajagopalan, 2007), given as:

$$GCV = \frac{\sum_{t=1}^{N} \frac{{e_t}^2}{N}}{(1-\frac{m}{N})^2} \tag{2}$$

where N is the number of data points (JFM seasons in the study), e_t is the prediction error or residual (the difference between model predictions and observations), and m is the number of PCs retained as predictors. GCV scores are computed for each model iteration (models with varying numbers of PCs retained), with the preferred model having the lowest GCV score. Models that overfit may have smaller prediction errors, but are penalized for having a larger number of predictors.

After selecting the optimal number of PCs to incorporate into the model, a drop-one cross validation prediction framework is applied to the 51 years of available data. ~~For any given year, the corresponding recorded values of the potential predictors are dropped, or excluded, from the previously described PCR process (Stone, 1978).~~ The cross-validated predictions~~, in turn, are used for a model assessment through a~~ are assembled into a hindcast for the entire period of interest. ~~.~~This includes – for each year of the hindcast – dropping the predictor data (Z) from the year being hindcasted, forming new PCs (and EOFs) conditioned on the remaining years, and fit to observations using multiple regression, providing an intercept coefficient, regression coefficients, and error term (Stone, 1978). The predictor data (Z) from the year dropped are then projected onto the EOFs to provide PCs for the dropped year. Finally, these PCs are multiplied by the appropriate regression coefficients and added to the intercept coefficient to provide a deterministic precipitation prediction for the dropped year. This is repeated for each year.~~This includes the creation of an ensemble of hindcast values for each historical year based on the residuals of the cross-validated model.~~

~~The residuals of all years form a distribution of potential model prediction errors.~~ To create ensemble hindcasts, error terms from all years are assembled and a distribution is fit (using a kernel density estimator; the distribution is approximately Gaussian). For each hindcast year, 1,000 random draws from the distribution are added to the deterministic precipitation prediction to form an ensemble.

5.2 Extended Lead Time of Predictions.

In the initial version of the model, predictors are drawn from OND, such that predictions may be issued on January 1st for JFM precipitation. This information ~~unfortunately is~~may be too late for certain stakeholders ~~such as~~(e.g. farmers) who have already made critical decisions regarding their operations and short- to mid-term output goals. ~~Extra time to prepare and make decisions may be provided by the shifting of the predictor season chosen for a JFM prediction model.~~ Extending the prediction lead time is explored by evaluating progressively earlier 3-month periods. For example, s~~S~~hifting the predictor season to SON, ~~the~~a JFM precipitation prediction ~~may~~wouls instead be issued on December 1st~~, and so forth~~. The potential predictors for each lead time analyzed are identified in similar fashion to that of the OND predictor season model.

5.3 Spatial Disaggregation of Predictions.

Although seasonal predictions of station-averaged regional precipitation may benefit planning at a larger scale, such as by regional water councils or federal entities, more localized predictions of precipitation may prove to be advantageous for sectoral decision-making (mining, farming, etc.). To address this, spatial disaggregation of predictions from the regional-level to the station-level is evaluated. Using the regional-level categorical prediction probabilities for each year (above normal, near normal, and below normal; Fig. 10), ensemble predictions for each station are generated based on that station's own climatology. For example, the categorical probabilities at the regional-level for 2016 are predicted as 2% above normal, 7% near normal, and 91% below normal. For each station, JFM precipitation observations from all other years (excluding 2016) are randomly selected 1,000 times from that station's JFM precipitation distribution conditioned on the regional probabilities. Thus, the ensemble of predictions for that station for 2016 will have approximately 91% of its members from the below normal category, 7% near normal, and 2% above normal.

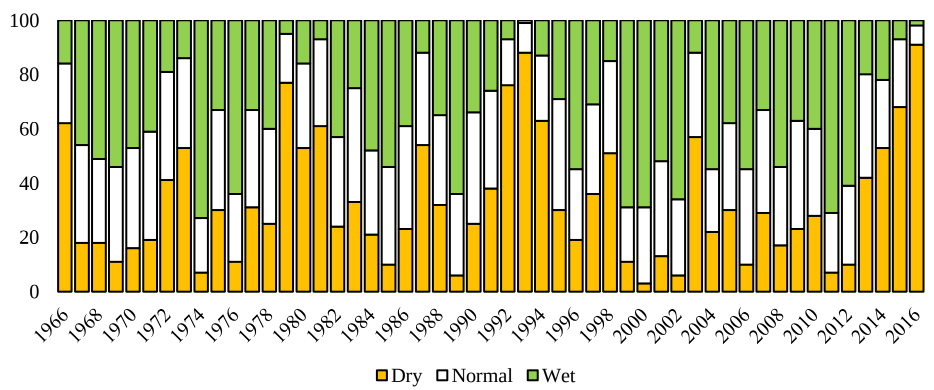

Figure 10: Categorical probabilities for JFM precipitation totals (y-axis) in each year, as predicted by the regional-scale model~~, are used to create representative station-level prediction ensembles~~.

The purpose of spatially disaggregating in this fashion is to maintain the statistical integrity of the regional-level prediction while reflecting appropriate magnitudes of precipitation experienced at ~~different locations~~each station. This methodology ensures that regional- and station-level categorical prediction probabilities match, however absolute precipitation magnitudes across stations may vary significantly (Maraun, 2013). ~~Thus, the main objective of this spatial disaggregation is to create appropriate, local values for each station. One would expect station-level predictions to perform equally, if not better, against regional metrics.~~ Because the regional and station ~~values~~predictions are related, a dependent t-test for paired samples ~~was~~is applied to ~~used. The purpose of this statistical test is to search~~test for significant changes or differences between these two dependent variables. ~~The goal of disaggregation was to produce a scaled precipitation forecast for local stations that maintained the statistical integrity of the regional prediction; a~~ A dependent t-test result of no statistically significant change is desired.

5.4 Wet/dry Day Frequency Analysis.

Although predictions of JFM seasonal precipitation totals may be useful for a variety of stakeholders throughout the region, some may prefer additional detailed information such as the frequency of precipitation events expected across a given rainy season. The number of wet or dry days and the intensity of precipitation events can have widespread and serious agronomic/phenologic (Robertson et al., 2008) and infiltration/runoff (Mandal and Nandi, 2017) implications. Such information may also be informative to condition stochastic weather simulators for a wide range of hydrologic or agricultural models (Robertson et al., 2006). To evaluate seasonal statistics of wet/dry day frequency for southern Peru, six of the 29 stations having readily accessible daily data are analyzed. Analogous to the seasonal total precipitation prediction modeling approach, spatial correlation mapping, composite mapping, and global wavelet analysis are all utilized to identify potential predictors describing the expected number of wets days across the JFM season. ~~This distribution is then applied to the cross-validated predictions via a Monte Carlo method to create an ensemble of potential hindcast values for each year.~~

The cross-validated ensemble ~~forecasts~~ hindcasts and ancillary applications of the model are evaluated deterministically and categorically in this study using three metrics: Pearson's correlation coefficient~~s~~ between observed values and the median of the ensemble forecast; rank probability skill score (RPSS); and a hit-miss statistic presented as contingency tables.

RPSS is based on the ranked probability score (RPS), which measures the categorical accuracy of forecasts (Wilks, 2011). For this study, categories are based on three equal terciles from the observed record (e.g. splitting the ordered observed record into three categories with 17 years in each), and represent above normal (greater than 350 mm), near normal, and below normal (less than 270 mm) total seasonal precipitation. RPS is the cumulative squared difference between categorical probabilities for forecasted and observed conditions, and takes the form:

$$RPS = \frac{1}{K-1}\sum_{m=1}^{K}\left[\left(\sum_{k=1}^{m} f_k\right) - \left(\sum_{k=1}^{m} o_k\right)\right]^2 \quad (3)$$

where K is the number of categories, f_k is the predicted probability for the k^{th} category, and o_k is the observed probability for the k^{th} category (1 if the observation falls in that category and 0 if not). RPS ranges from 0-1, with a perfect forecast scoring 0. RPSS provides the relative improvement of a prediction as compared to a reference prediction – typically climatology (distribution of long-term historical observations), and is given as:

$$RPSS = 1 - \frac{RPS_{forecast}}{RPS_{climatology}} \quad (4)$$

An RPSS value less than zero ~~signifies~~indicates no forecast skill over the reference climatology forecast (i.e. ~~the information provided by~~ the ~~developed~~ forecast model ~~is statistically less accurate than that provided by~~does not outperform climatology). ~~A value equal to zero for when the forecast is only as skillful as climatology.~~ Values greater than zero represent a skillful forecast. A value of one represents a perfect categorical forecast~~RPSS scores less than 0 signify no model skill over climatology (i.e. it is more skillful to simply use the distribution of historical precipitation), whereas scores between 0-1 represent skillful model performance~~.

The hit-miss statistic describes the occurrence of median model predictions falling into the observed category (above normal, near normal, or below normal conditions). Results are presented in a three-by-three matrix, or contingency table, that illustrates the performance of the model for each category. Contingency tables are an alternative method of assessing the precision of model predictions that relies on categorical probabilities as opposed to simpler methods such as correlation (Svensson, 2016). Of particular interest in this study is the hit rate statistic, or the percentage of time the model accurately predicts (categorically) the actual observed condition, as well as the double miss rate statistic, or the percentage of time the model makes a two-category error. Because prediction of regional meteorological drought is of particular interest, the likelihood of extremely dry conditions is also considered. For this case, extremely dry conditions are defined as station-averaged JFM precipitation less than 250 mm, which occurs approximately 25% of the time, or during 13 years across the time series.~~Results are presented in a three-by-three matrix, or contingency table, that illustrate the performance of the model for each category. Of particular interest in this study is the hit rate statistic, or the percentage of time the model accurately predicts (categorically) the actual observed condition. In addition, because this project looks specifically to predict regional drought, an alteration to this statistic that evaluates prediction of extremely dry conditions is also considered.~~

6 Results.

6.1 Principal Component Regression-based Prediction Model.

The best performing model, as determined by GCV, includes the first four PCs ~~-~~explaining 83% of the variance in the original potential predictors. The median of the cross-validated, ensemble predictions of JFM precipitation (Fig. 11~~0~~) correlates with observations at r=0.58.

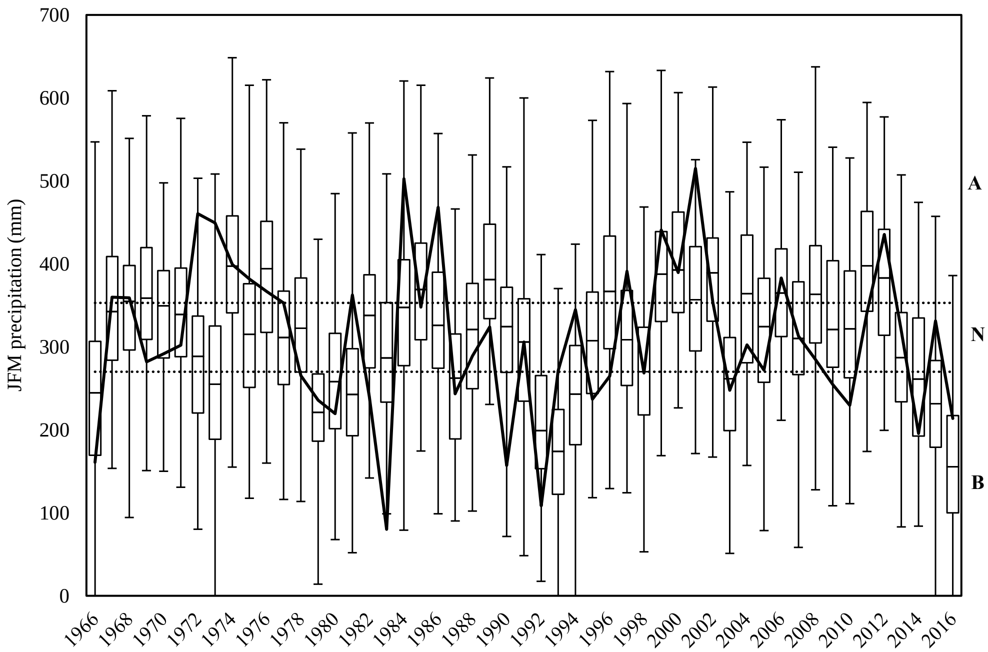

Figure 1~~0~~1: Box plots of cross-validated, ensemble forecasts of JFM precipitation with observed conditions (solid black line) and categorical thresholds (dotted lines, with delineated categories labeled A, N, and B) included.

The median RPSS score for the model is 0.16, indicating marginal, yet noteworthy, improvement over climatology. The model also scores a hit rate of 51%, predicting the correct category in 26 of 51 years (Table 2). With specific regard to below normal conditions, the PCR prediction has a 59% hit rate, with 10 of 17 instances correctly predicted.

Table 2: Hit-miss matrix with three equal categories: above normal (A), near normal (N), and below normal (B) precipitation.

		Predicted conditions		
		A	N	B
Observed conditions	A	**5**	9	3
	N	2	**11**	4
	B	0	7	**10**

Above normal (A), near normal (N), below normal (B)

For the 49% of years in which the model missed the observed category, only three times did the model miss by two categories. In all three cases, below normal conditions are predicted yet above normal precipitation is observed (similar to what occurred in 1973). Overall, though, the model has a strong tendency to predict near normal conditions too often (53% of the time versus an expected 33%). It is apparent that the weakest categorical performance ~~displayed by the model~~ is in predicting above normal conditions, with a hit rate of only 29%.

Since drought prediction is of particular interest in this study, an alternative hit-miss metric that uses only two categories – extreme below normal conditions (eB) and above normal/near normal conditions (A/N) – is also evaluated. Here, extreme dry conditions are defined as the lowest quartile of JFMs on record (specifically, 13 years with less than 250 mm of JFM precipitation). The alternative hit-miss metric has a hit rate of 80% in general and accurately predicts 62% of eB conditions (Table 3), a notable improvement compared with the tercile-based hit-miss metric ~~(Table 3)~~.

Table 3: Hit-miss matrix with only two categories: above normal/near normal (A/N), and extreme below normal (eB) precipitation.

		Predicted conditions	
		A/N	eB
Observed conditions	A/N	**33**	5
	eB	5	**8**

Above normal/near normal (A/N), extreme below normal (eB)

~~Overall~~Overall, model predictions demonstrate moderate skill improvement over predictions conditioned solely on climatology as well as one conditioned on ~~on~~ an ENSO index. While a simple linear regression model using OND Niño 3.4 as a sole predictor for JFM precipitation correlates at r=0.53 (only 0.05 less than the more complex PCR model), the RPSS of this Niño 3.4 model is -0.38, ~~or~~ ~~meaning it is~~or inferior to climatology. Comparing hit-miss metrics, both models perform similarly for tercile-based categories; however, the Niño 3.4 model does not exhibit as much improvement for the two-category assessment (predicting only 23% of eB years correctly). Both models fail to accurately predict 1973 (unexpectedly wet) and 1990 (unexpectedly dry); however, the PCR model does accurately predict JFM 2014 as dry, even though ~~a strong El Niño existed~~neutral/weak La Niña conditions existed prior.

~~7 Extended Lead Time and Spatial Disaggregation of Regional Predictions.~~

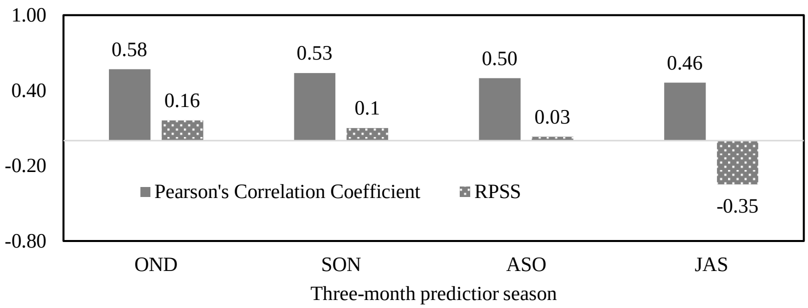

Figure 1~~1~~2: Correlation coefficients between observed and modeled JFM precipitation and ensemble RPSS for various lead times.

Upon using the three-month predictor season of JAS, however, RPSS drops below 0, indicating that predictions produced using JAS climate information (and issued on October 1), would have less skill than those produced using simple climatology.

6.3 Spatial Disaggregation of Predictions.

6.4 Wet/dry Day Frequency Analysis.

Interestingly, the first PC of the data captured approximately 85% of the variance in the number of wet days for all six stations with daily data. High correlations are observed between this first PC and SST within the region typically associated with ENSO. No additional regions or climate variables (e.g. sea level pressure, geopotential height, etc.) ~~were~~are identified using this method. Further, composite mapping and global wavelet analysis yield~~ed~~ no additional potential predictors for incorporation into the prediction model. Thus, the wet/day frequency model uses only the OND Niño 3.4 season-ahead index as a direct predictor ~~to produce a deterministic prediction of number~~ of wet days in any given JFM season. Using the same cross-validation method already described, the number of wet days per season is predicted for each station.

In addition to correlation coefficients between the predicted and observed number of wet days, the average prediction error for above-average and below-average years is reported for each station. Station-specific statistics are listed in Table 4.

Table 4: Correlation values and average absolute errors for predictions of wet days at each station.

Station (~~with~~ average number of wet days)	Correlation value (r) between prediction and observation	Average absolute error in years with above average number of wet days	Average absolute error in years with below average number of wet days
1 (25 days)	-0.50	10 days	9 days
2 (36 days)	-0.53	11 days	9 days
3 (51 days)	-0.48	11 days	10 days
4 (54 days)	-0.39	12 days	12 days
5 (54 days)	-0.53	8 days	9 days
6 (33 days)	-0.59	10 days	9 days

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Correlations between predictions and observations range from r=-0.39 to r=-0.59, with the model performing slightly better in predicting the number of wet days in drier years. In general, however, the simple linear model displays an average absolute error ranging between 8 and 12 days.

To consider overall model performance, a hit miss metric quantifies skill in the two previously introduced categories of years (Table 5) – years with above average number of wet days (W) and years with below average number of wet days (D).

Table 5: Hit miss metric for model predictions of years with above and below average numbers of wet days.

		Predicted conditions	
		W	D
Observed conditions	W	**105**	41
	D	43	**103**

Above average number of wet days (W) and below average number of wet days (D)

Overall, the model correctly predicts whether ~~a given season~~JFM will have an above or below average number of wet days ~~over incorrectly predicting,~~ with an accuracy of ~72%. The model, however, has a notable bias towards over-predicting near normal conditions (Fig. 13).

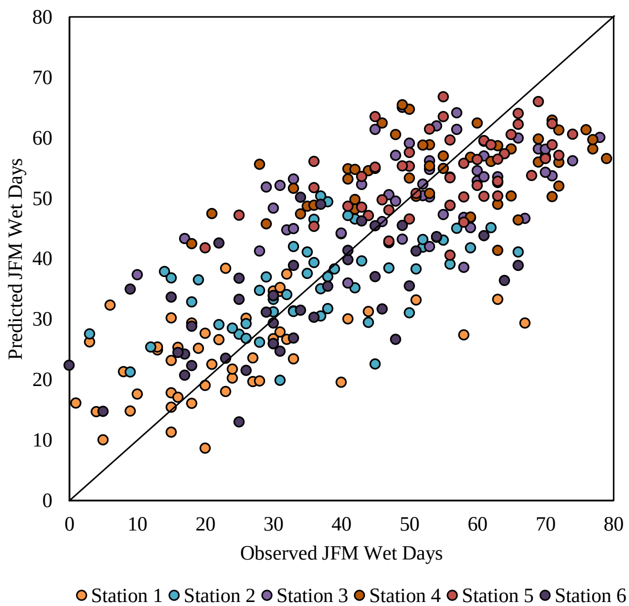

Figure 13: Observed versus predicted number of JFM wet days ~~compared to predictions~~for six stations across 1966-2016.

78 Discussion.

This study quantifies the valuee ~~intent of this research was to explore the importance~~ of including additional climate information beyond ENSO-based indices into a predictionve model ~~that incorporates~~for JFM precipitation in southern Peru ~~ENSO-based indices~~. To ~~determine~~understand the importance ~~of a model that does not include information regarding SST in the~~ equatorial Pacific SSTs, a second hindcast model is developed using only 9 of the 11 original potential predictors, with~~.~~ Niño 3.4 and SST from 160° W-140° W 0° -5° S ~~are~~ dropped ~~in the modified model construct~~. Using the same cross-validated PCR methodology (as well as GCV to determine the optimal number of potential predictor PCs to incorporate, i.e., 3), we produce hindcasts for the period of record (Fig. 14).

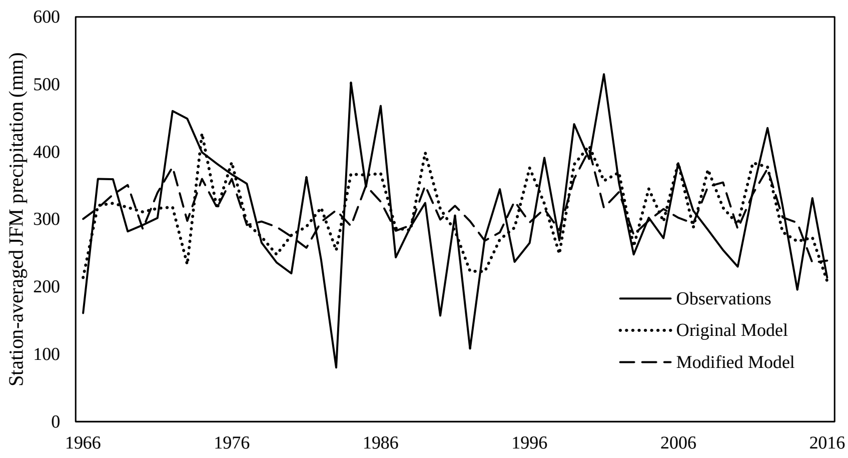

Figure 14: Observed conditions for the period of record, as well as hindcasts produced using the original model (11 potential predictors, 4 PCs) and the modified model (9 potential predictors, 3 PCs).

When comparing the results of the modified model to the original model, the importance of including ENSO in a model construct for precipitation prediction in southern Peru is highlighted. For example, the correlation coefficient between predicted conditions and observations ~~for the modified model~~ drops from r=0.58 to r=0.37 for the for the original and modified models, respectively (~~still statistically significant, but~~ skill reduced by roughly one-third). In addition, RPSS drops to only 0.05% from the original 16%, indicating that the information provided by the modified model is just barely more ~~useful~~skillful thant ~~that provided via~~ climatology. ~~In considering~~ Tthe hit-miss metric also illustrates~~,~~ the diminished skill of the modified model ~~is also visible~~ (Table 6).

Table 6: Hit-miss matrix for the modified model with three equal categories: above normal (A), near normal (N), and below normal (B) precipitation.

		Predicted conditions		
		A	N	B
Observed conditions	A	**6**	10	1
	N	0	**15**	2
	B	1	14	**1**

Above normal (A), near normal (N), below normal (B)

The modified model displays an evident bias towards predicting near normal conditions (more than 75% of the time). While the hit score of this model is reduced to 43%, more striking is the fact that the modified model produces an instance in which above normal conditions are prognosticated, but ~~instead~~ below normal conditions are experienced – ~~arguably~~perhaps a more devastating ~~forecast error~~outcome for this region than ~~the opposite~~a situation ~~(i.e.,~~with ~~predicted~~ below normal predictions~~,~~ but ~~experienced~~ above normal observations). These metrics ~~only~~ reflect the critical importance of ~~considering~~including ENSO in regional precipitation prediction.

Model skill remains relatively constant with increasing predictor lead time, notably predictions produced using ASO predictor information for November 1~~even up to five months~~. This additional lead may prove beneficial to stakeholders in the region. For example, in the 2016 drought, ANA made emergency declarations for the cities of Tacna and Arequipa at the beginning of January based on projected water availability. This allowed minimal time for city officials and local residents to prepare for the impending dry rainy season (even though exceptionally strong El Niño conditions had been predicted several months in advance by multiple entities including the National Weather Service Climate Prediction Center and Peru's Estudio Nacional del Fenómeno "El Niño"). Additionally, farmers in the region – many of whom are subsistent – had already made crucial agricultural decisions well before the beginning of the rainy season.

In addition to extended lead times, spatially disaggregated predictions could prove beneficial to several sectors impacted by spatiotemporal precipitation variability. This investigation produces disaggregated predictions with only minimal significant diminishments in skill, which may require further investigation. The governing large-scale climate mechanisms that deliver precipitation to the region more or less act uniformly across this small area of southern Peru, with relatively distinct signals, while station observations may actually be noisier in comparison.

The high correlation ~~observed~~ between number of wet days and SST in the equatorial Pacific suggests that the ENSO phenomenon not only controls the regional seasonal volume of precipitation, but also the frequency of wet days. While the prediction model of wet days achieves notable skill, the model in general displays a tendency to under-predict the number of wet days (especially in seasons in which more wet days ~~were~~are observed than dry). ~~More benefit may be gained in using this model at locations with more wet days (such as stations 3 and 4) as opposed to drier stations.~~ Additional prediction skill may be achievable~~ed~~ by incorporating local variables such as antecedent soil moisture conditions or low level winds into station-specific models, ~~as is the case with the~~similar to disaggregation of regional precipitation predictions.

There are several limitations of the ~~developed~~ framework, including poor performance in predicting above average precipitation conditions and real-time data requirements. Although the region is highly vulnerable to drought conditions ~~(thus greatly benefiting from accurate season-ahead predictions of drought)~~, the limited ability of the model to predict above normal conditions could translate into missed economic potential for farmers and mining operations. ~~Further work for improving the model's performance in~~ Improving above normal ~~condition~~category prediction could take the form of investigating additional local variables, such as quantifying the orographic impact of the ~~orographic effect of the~~ Andes and investigating other small-scale perturbations to the climate system. In general, though, the prediction framework as developed hinges on readily accessible climate data from the sources used in this study. In some cases, delayed publishing of this data ~~would~~may result in a delayed prediction of JFM precipitation. With some of the ancillary applications, further limitations of the framework include the regional versus local nature of predictions and associated skill and trade-offs with longer prediction lead times.

The potential for enhanced model utility through extended lead times, ~~and~~ spatial disaggregation, and wet/dry day frequency predictions, though, may allow regional stakeholders more time and detailed information to proactively prepare for ~~predicted~~ droughts~~,~~. This, as opposed to reactive measures that have plagued regional drought management in the past. The lynchpin of this proactivity is effective and consistent collaboration among ANA, SENAMHI, and other public and private local, regional, and national entities. Projects such as the Peruvian Drought Observatory have served as a starting point for this collaboration; however, the observatory currently offers minimal climate forecast information, and could benefit from the inclusion of such outputs. As drought continues to deleteriously impact water supply and access in southern Peru, season-ahead predictions may become more instrumental in facilitating proactive and sustainable water management in this semi-arid region of the world.

To enhance planning and management for various sectors in southern Peru, a PCR modeling framework is developed to predict JFM seasonal precipitation across the region~~ at various lead times~~. Eleven oceanic and atmospheric variables that modulate regional precipitation are identified, with the first four PCs selected for incorporation into the season-ahead prediction model. The PCR model proves skillful, with a clear improvement over climatology and a Niño 3.4 index-based model, and most effective at predicting dry conditions, the state of most interest in this semi-arid region. This points to the evident importance of climatic factors other than ENSO in modulating regional precipitation. The explored ancillary applications of the model only further demonstrate the potential posed by the framework to provide an array of likely useful information to regional stakeholers.

Beyond the work performed in this study, additional avenues for further research include alternative modeling approaches and integration with hydrology and other sectoral/decision-making models.

In this case, the statistical approach explored has produced results that are arguably more skillful than existing methods of precipitation prediction for this region of Peru. Therefore, one may be tempted to draw the conclusion that a statistical approach of this sort can be applied in a similar fashion at any other location of interest and produce equally skillful results. A conclusion along these lines would be temerarious. Although model frameworks are transferable to other locations, there are no guarantees that one approach will still be superior to another. Furthermore, there is no guarantee that observed increases in skill in one location will translate to expected equivalent increase in skill in another location

Code Availability.

Should any need arise for the code used in this study, it will be made available upon request by the corresponding author.

Data Availability.

Precipitation data used in this study are either purchased from SENAMHI by SPCC or collected by SPCC. This dataset is not public; however, if needed for additional studies, this dataset may be transferred to appropriate parties. Large-scale climate data come from NOAA and are publicly available for use.

Appendices.

None.

Supplemental Link.

To be included by Copernicus.

Team List.

Eric Mortensen
Shu Wu
Michael Notaro
Stephen Vavrus
Rob Montgomery

José De Piérola
Carlos Sánchez
Paul Block

Author Contribution.

Eric Mortensen and Shu Wu contributed to development and evaluation of the prediction model. Michael Notaro and Stephen Vavrus contributed to diagnosis of large-scale climate processes relevant to the project area. Rob Montgomery, José De Piérola, and Carlos Sánchez contributed to contextual understanding of the project area and provided access to relevant documents, literature, datasets, etc. for project team's use. Paul Block contributed to the hydroclimatological analysis, as well as development and evaluation of prediction model.

Competing Interests.

None.

Disclaimer.

To be added later.

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