REPLIES TO REFEREE COMMENTS

Reply #1 to Anonymous Referee 1

We thank Referee 1 for reviewing our manuscript and providing constructive, actionable feedback. Below we provide our responses to each point raised.

Comment: P1, L8-16: The abstract should clearly include concrete results. The paper is far more interesting than what the abstract suggests. For example, a mention of the way the models are used in sequential mode, or the skill achieved, can be mentioned there.

Reply: This is an excellent comment, and we have added the following text to the abstract of the working manuscript (P1, L16-27):

"Skillful results (forecasts outperforming climatology) are produced for short lead-times (September 1st; RPSS = 0.31, categorical hit skill score = 61%), with years of Above-Normal (high) and Below-Normal (low) streamflow predicted 82% and 64% of the time, respectively. At longer lead-times, climatological skill exceeds forecast skill, largely due to fewer observations of precipitation. Coupling the September 1st statistical forecast model with a Niño 3.4 region sea surface temperature phase and strength statistical model, however, allows for equally skillful categorical streamflow forecasts to be produced from a May 1st lead, triggered for 60% of the years in the period 1950-2015. Forecasts may not need to be strictly deterministic to be useful for water rights holders; early (May) categorical indication of expected conditions are reinforced with a revised deterministic forecast (September) as more observations of local variables (e.g. precipitation) become available. The reservoir allocation model is skillful at the September 1st lead (categorical hit skill score = 53%); this skill improves to 79% when the model predicts the observed allocation category with at least 80% certainty. This result has broader implications, suggesting that in water rights managed basins, allocation efficiency might improve through the integration of forecasts as part of a reservoir decision framework. The methods applied here advance the understanding of the mechanisms and timing responsible for moisture transport to the Elqui Valley, and provide a unique application of streamflow forecasting in the prediction of per-water right allocations. Both have the potential to inform water right holder decisions."

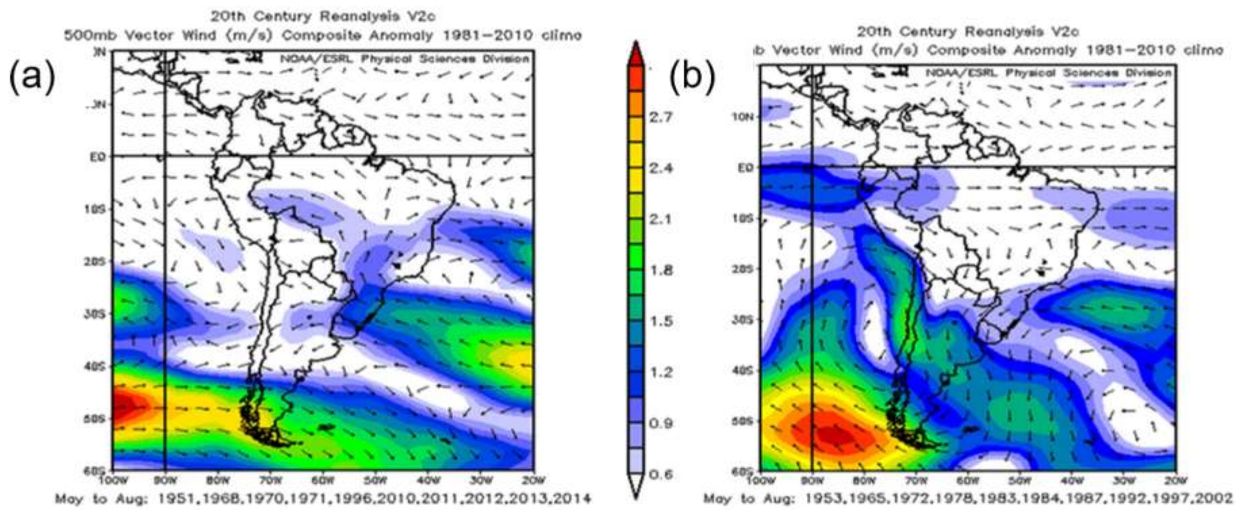
Comment: P7, Section 2.1: Is the data quality-controlled? Maybe add a sentence or two about that, so the reader knows if the data can be trusted.

Reply: Observations of streamflow and snow water equivalent are obtained from the Direccion General de Aguas (DGA), a department of the Ministry of Public Works of the Chilean Government. Collection, validation and quality control of hydrologic measurements are part of DGA's core functions; thus, we treat the data as fully vetted and having met DGA's quality control standards. The referee's comment is valid, and warrants an addition to the manuscript. We have added the following (P7 L15-18):

“One of DGA’s primary functions as the regulator of surface water resources for the Chilean Government is to collect, validate, and perform quality control of hydrologic measurements. Open source data obtained through DGA is considered as having met DGA quality standards.”

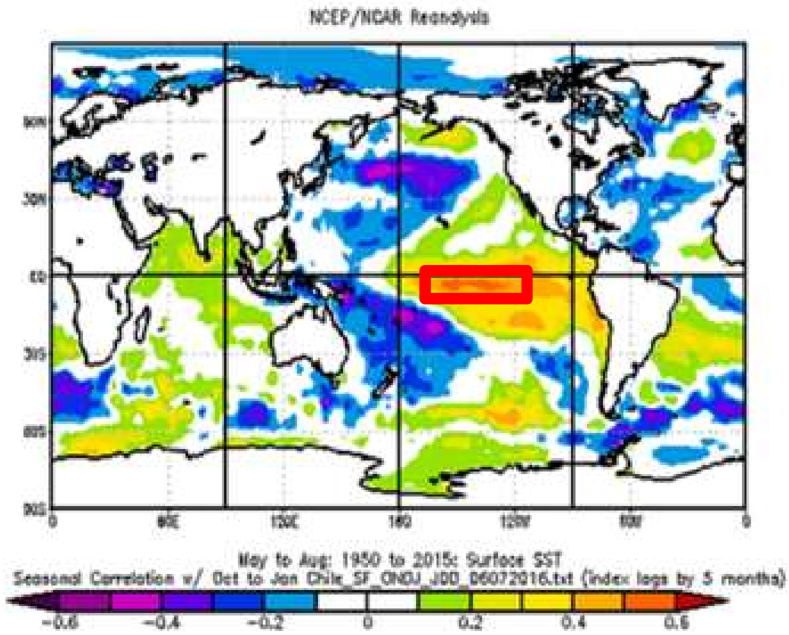
Comment: P7, L17, L21 (and other places): vector winds? This is the first time I see that name. What the authors mean by that? To use both u and v? Why do not just say “winds”?

Results: We are concerned with both the magnitude (colors) and direction (arrows are the resultant of u and v) of vector winds at 500mb (Fig. 4. (a) and (b), *excerpt below*). Both are critical in terms of determining the efficiency of moisture transport to the Elqui Valley. If we ignore the direction component, “winds” or “wind speed” should be used. Additionally, “vector winds” is the name commonly utilized by NOAA and other climate agencies.



Comment: P8L8: why to do a spatial average? I do not fully understand that sentence.

Reply: Gridded potential predictors are identified through spatial composite and/or correlation mapping (e.g. sea surface temperatures (SSTs). To extract the signal(s) from within the gridded data set and avoid noise present at the grid scale, principal component analysis (PCA) is commonly applied to the gridded data. Correlating the first principal component (PC), which is the strongest signal, with the spatially averaged data identifies whether the signal is spatially homogenous. Alternatively, if the first PC does not correlate well with the spatial average, the heterogeneity of the dataset is important, and thus using the spatial average may not be the best approach. For example, the spatial average of SSTs (Fig. 4 (c)), which is identified as a potentially significant as predictor of streamflow for the Elqui River (roughly consistent with the Niño 3.4 region), correlates highly (>0.9) with the first PC of the gridded SST data. Having identified SSTs as spatially homogenous, and consistent with the Niño 3.4 region, we correlate and ultimately select the Niño 3.4 Index as a potential predictor of streamflow as it is well-known, well understood, and well-studied. We do this as opposed to selecting a marginally different (e.g. sub-region of the Niño 3.4 region), but much less understood and perhaps less defensible area. Furthermore, using the spatial average rather than selecting a sub-regional area may be a more conservative approach as it does not guarantee that the strongest possible relationship is identified. In addition, using an index avoids grid cell selection bias (cherry-picking), which could result in an insufficient number of grid cells to be statistically significant, or produce vastly different regions of high correlation (spurious correlations.) The following papers support the claim of teleconnections between precipitation and SST in north-central Chile (Aceituno 1988; Falvey and Garreaud 2007; Garreaud et al. 2009; Montecinos and Aceituno 2003).



Comment: P9L1: are the authors talking about CFSR? They are talking about NCEP-NCAR reanalysis but then they cite Saha et al 2013. Is there a confusion here?

Reply: We appreciate the reviewer catching this improper citation. Clearly, the citation should be (Kalnay et al. 1996) as opposed to Saha et al 2013. We also add (Huang, van den Dool, and Georgarakos 1996) to specifically reference CPC's soil moisture data. The working manuscript has been updated with the appropriate citations.

Comment: P11L21: why a forecast is not issued in that case? Explain in the text.

Reply: The statistical phase and strength model (Stat-P&S) at the May lead does not provide a categorical streamflow forecast for Niño 3.4 Index = (+0.5°C, +0.75°C) or (-0.5°C, -0.75°C) as the range is considered transitional (not weak or moderate as identified by NOAA). Both the magnitude and persistence of SST observations in this range do not allow for production of skillful forecasts. The May 1st forecast lead uses January-April Niño 3.4 Index values to categorically forecast October-January streamflow, which requires prediction through the Spring Barrier (Duan and Wei 2013). Typically, SSTs within the transitional range are not stable and actively moving to either a neutral or strengthened phase. Until these changes occur, at some date beyond May 1st (typically beyond the Spring Barrier), a categorical or deterministic forecast is typically not skillful. Deferring to the September 1st statistical principal component regression model (Stat-PCR) is warranted when SSTs are in the transitional range.

The question is valid, and our original manuscript does not address the reasons for which the transitional range within the Niño 3.4 Index is not used by the Phase and Strength model at the May lead. To provide clarity in our approach we have added the following to the working manuscript (P11 L21-24):

"For these ranges, neither the magnitude (not weak or moderate as defined by NOAA) nor persistence of SST observations allow for production of skillful categorical streamflow forecasts. For years where SSTs fall within these ranges at forecast leads prior to the Spring Barrier, strength and phase are subject to rapid transition, and categorical forecasts are typically not skillful."

Comment: P11Section2.2: I suggest to change the title of the subsection, as it seems to be about a proper dynamical prediction model, and it is really about using dynamical model output in a statistical model.

Reply: Regarding dynamical model prediction, we initially considered raw dynamical climate model outputs of precipitation and SSTs to predict streamflow (since clearly streamflow is not an output of dynamical climate models), but the results were poor. We thus proceeded with statistical post-processing as a means of correcting dynamical model outputs (Gheti 2008). The reviewer's point is valid as the sub-section title may be interpreted as dynamically modeled streamflow, including a physically-based hydrology model. To avoid confusion and as a means of accurately describing the forecast approach we have changed the title of 2.2 to "Hybrid dynamical-statistical streamflow prediction model" to capture the fact that predictors come from the dynamical model, but the prediction model formulation is still statistical in nature.

Comment: P12L8: authors should be a bit more explicit about when local variables have predictive strength. Conditions? Dates? Proportion of total cases? More information is needed.

Reply: Local variables and their predictive strength are discussed in 2.1, and shown in Figure 5 (a) and (c) and in Table 1. The same variables are used, when appropriate, for the statistical model using corrected (quantile mapping) GCM outputs for precipitation and SSTs (Stat-Dyn), with forecasts issued January 1st , May 1st and June 1st. For these leads, local variables are not useful, and therefore only GCM predictions of precipitation and SSTs are used (Table 2. *Excerpt below*). This is not a surprising result considering local variables are skillful in the prediction of October-January streamflow only during months of peak precipitation (May-August) as shown in the manuscript in Figure 5 (a) and (c).

Still, we recognize readers may benefit from additional explanation and have added the following for clarity of local variable inclusion in the working manuscript (P12 L10-13):

"The Stat-Dyn model is meant to provide streamflow forecasts at extended leads, beyond what is possible with global and local observed data used to inform the Stat-PCR model. Local variables (e.g. precipitation, snow water equivalent and soil moisture) hold the most predictive strength during the season of peak precipitation (May-August) and thus are only considered for the Stat-Dyn model for leads at prior to June 1st (Fig. 5 (a.) and (c.)."

Forecast		**Retained Predictors**		
Statistical Approach (Stat-PCR)	Sep 1st	Aug SM	JA Prcp	Aug 3.4
	Aug 1st	Jul SM	JJ Prcp	Jul 3.4
	Jul 1st	Jun SM	MJ Prcp	Jun 3.4
Dynamical Approach (Stat-Dyn)	Jun 1st	JJA 1.2	JJA Prcp	-
	May 1st	JJA 3.4	JJA Prcp	-
	Jan 1st	JJA 3.4		-

Comment: P14L1-2: please check the syntax of the sentence.

Reply: We agree the structure of the sentence can be improved to better illustrate the point. We have changed the sentence in the working manuscript to:

“Allocation, as issued annually by JVRE, and storage outcomes are hindcast in a cross-validated mode for the period of record (1950 – 2015) by coupling the streamflow prediction models to a simple reservoir balance model.”

Comment: P14Section2.4: I suggest to remind the reader that all these results are obtained using cross-validation (a lot of studies out there do not even bother to cross-validate!)

Reply: We thank the referee for the comment, and have included language which reminds the reader the forecast outputs are cross-validated.

Comment: P15L9: why Pearson coefficient?

Reply: Pearson’s correlation coefficient is commonly used to assess both the general parametric association between forecast and observed values, and phase error. While it doesn’t account for forecast bias and is sensitive to outliers, it is selected because it is well known and well understood. In addition, we utilize RPSS and categorical skill score metrics which describe additional performance and features of the forecasts.

Comment: P19L20: approach or model? Which one?

Reply: We appreciate the referee noticing and highlighting this error. For consistency, we use “model”.

Comment: P19L20-21: I do not understand the sentence. When the other 40% occur?

Reply: 40% refers to a fraction of the number of years in the record (1950-2015) not predicted by the Stat-P&S model at the May lead using January-April Niño 3.4 Index because the index values fall within the transitional ranges (+0.5°C, +0.75°C) or (-0.5°C, -0.75°C). The transitional ranges do not provide skillful categorical forecasts for the May 1st lead. For this reason we do not forecast these years until the Stat-PCR model is skillful for the September lead. Our coupled statistical prediction model defers prediction for these years to September.

Comment: P20Step2a and Step2b: what is the real difference here?

Reply: The difference between Step 2a and 2b relates to whether the Stat-P&S model issues a May forecast. If January-April Niño 3.4 region SSTs meet the Stat-P&S criteria, a May 1st categorical forecast is issued (Step 2a). Otherwise, the Stat-PCR model is used to produce a September 1st forecast (Step 2b). The novelty of coupling the Stat-P&S and Stat-PCR models is the Stat-P&S model provides an initial, categorical indication (May 1st lead) of October-January streamflow for 60% of years between 1950-2015. From the perspective of a water rights holder, a skillful categorical forecast at a May 1st lead may provide relevant information to inform

October-January decision making (e.g. cropping decisions by water right holding farmers). The initial forecast is reinforced by the Stat-PCR model, which provides a skillful deterministic forecast, but only for a September 1st lead. The key is that the agreement between the May 1st categorical forecast produced by the Stat-P&S model (when issued) and the September 1st deterministic Stat-PCR model is very high. In applied terms, a water right holder seeking to make forecast informed decisions has information which outperforms climatology at leads up to 4 months prior to the issuance of the actual allocation value.

Comment: P25L25: 92% is extremely high. Can you please confirm there is not a typo there?

Reply: We agree, 92% is a very high 'hit score'. However, this is a calculation of how often the forecast category aligns with the observed category, and is not a correlation. The hit score referenced here is for two categories, divided at 0.75 L s^{-1} as opposed to three categories as discussed at length in the paper. This case provides less overall information (probability of the allocation above or below the threshold) and thus we are not overly surprised that the score increases dramatically. In fact, we select this case specifically to compare with the three-category allocation model, to illustrate how categorical skill is a product of the bounds selected by the stakeholder.

Comment: P14, eqs 3 and 4: how are these equations obtained?

Reply: The purpose of the reservoir allocation model is to compare allocation and storage outcomes from the forecast and climatology informed reservoir operations against observations (which constitute a perfect forecast); this provides a means of evaluating the streamflow forecast in an applied context. Thus, equations 3 and 4 are simply a modified version of the reservoir balance. To include the annual, end-of-year storage target used by reservoir operators in the Elqui (100 million cubic meters), we adjust allocation for period $i+1$ by the storage deficit or surplus at the end-of-year i. For example, if the forecast informed allocation, $A_{i_{ONDJ}}$, results in an end-of-year storage $S_{i_{Feb}} \leq 100M\ m^3$, $A_{i+1_{ONDJ}}$ is penalized by the difference $100 - S_{i_{Feb}}$. In contrast, if $S_{i_{Feb}} \geq 100M\ m^3$, $A_{i+1_{ONDJ}}$ is boosted by the absolute value of the difference of $100 - S_{i_{Feb}}$. It is important to note that the equations are applied uniformly to the forecast, climatology, and observations, so a fair assessment of performance can be achieved.

Comment: P16L22-24: confusing sentence… too many commas?

Reply: We thank the referee for this comment, and agree that the sentence is confusing. We have replaced it the working manuscript with the following:

"As forecast lead increases, both Hit Score and RPSS decrease, while Extreme Miss Score increases. These results occur because less information regarding the MJJA rainy season is available, which is consistent with decreased correlations between ONDJ streamflow and predictors (Fig. 5.)"

Minor Comments: (all accepted and corrected in the manuscript)
P1L20: "institutions"

P4, L13, L16: something is wrong with the way the references are being written. E.g., it should be Aceituno, 1988.

P10: define N.

P15L10: …as opposed to *a specific quantity*….

P11L28: I think the authors mean "North American Multi-Model Ensemble".

P16L2: references in capital

P17L11: maybe change "affirming" to "confirming"?

References:

Aceituno, Patricio
1988 On the Functioning of the Southern Oscillation in the South American Sector. Part I: Surface Climate. Monthly Weather Review 116(3): 505–524.

Duan, Wansuo, and Chao Wei
2013 The "spring Predictability Barrier" for ENSO Predictions and Its Possible Mechanism: Results from a Fully Coupled Model. Internation Journal of Climatology 33: 1280–1292.

Falvey, Mark, and René Garreaud
2007 Wintertime Precipitation Episodes in Central Chile: Associated Meteorological Conditions and Orographic Influences. Journal of Hydrometeorology 8(2): 171–193.

Garreaud, René D., Mathias Vuille, Rosa Compagnucci, and José Marengo
2009 Present-Day South American Climate. Palaeogeography, Palaeoclimatology, Palaeoecology 281(3–4). Long-Term Multi-Proxy Climate Reconstructions and Dynamics in South America (LOTRED-SA): State of the Art and Perspectives: 180–195.

Gheti, Rares
2008 Statistical Post-Processing of Dynamical Surface Air Temperature Seasonal Predictions Using the Leading Ocean-Forced Spatial Patterns. http://digitool.library.mcgill.ca/R/?func=dbin-jump-full&object_id=18670&local_base=GEN01-MCG02, accessed March 30, 2017.

Huang, Jin, Huug M. van den Dool, and Konstantine P. Georgarakos
1996 Analysis of Model-Calculated Soil Moisture over the United States (1931–1993) and Applications to Long-Range Temperature Forecasts. Journal of Climate 9(6): 1350–1362.

Kalnay, E., M. Kanamitsu, R. Kistler, et al.
1996 The NCEP/NCAR 40-Year Reanalysis Project. Bulletin of the American Meteorological Society 77(3): 437–471.

Montecinos, Aldo, and Patricio Aceituno
2003 Seasonality of the ENSO-Related Rainfall Variability in Central Chile and Associated Circulation Anomalies. Journal of Climate 16(2): 281–296.

Reply #2 to Anonymous Referee 1

We thank Referee 1 for reviewing our responses and once again providing valuable feedback. Below we provide our responses to each point raised.

Comment: P8L8 – on the spatial average. (Add text to manuscript)

Reply: To further clarify the purpose for and process by which spatial data is averaged we have added the following to the working manuscript (P8, L8 – P9, L5):

"The first principal component (PC) from the gridded variable region, representing the dominant signal in the gridded field, correlated with the spatial average of the gridded variable region can identify if the signal is spatially homogenous (representative) across the region. If the first PC does not correlate well with the spatial average, the heterogeneity of the dataset is likely important, and adopting the spatial average as a predictor may be ineffective. For example, the spatial average of SSTs (Fig. 4 (c.)), a potentially significant predictor of streamflow for the Elqui River, correlates highly (>0.9) with the first PC of the gridded SST data. This region of SSTs is closely aligned with the quintessential ENSO pattern in the equatorial Pacific Ocean, and is evident when correlating the entire ONDJ streamflow record with SST anomalies in the preceding MJJA, which suggests ENSO, in general, plays some role in explaining streamflow variability within the Elqui Valley (Fig. 4(c.)) Having identified SSTs as spatially homogenous, and consistent with the Niño 3.4 region, we select the Niño 3.4 Index as a potential predictor of streamflow, in lieu of the SST region initially identified (Fig. 4c), as it is well-known, well understood, and well-studied."

Comment: P19L20-21 –on the 40%. (Add text to manuscript)

Reply: To further clarify the Stat-P&S model criteria we have added the following to the working manuscript (P20, L21-25):

"These ranges are transitional and do not provide skillful categorical forecasts for the May 1st lead. For this reason, the coupled statistical prediction model defers prediction for these years to September 1st, when the Stat-PCR model is skillful." The Stat-PCR approach provides deterministic forecasts of ONDJ streamflow, it is only skillful at a September 1st forecast lead, which may limit water rights holders ability to benefit from longer lead times."

Comment: It is better to call them "wind vectors" rather than "vector winds", but not asking the authors to make any change about that.

Reply: To avoid any confusion, we provide reference to both vector winds and wind vectors in the manuscript. The term "vector winds" is common amongst the climate community, thus we have opted to retain it as well. (P7, L20):

"…vector (also referred to as wind vectors) and meridional winds…."

Reply to Anonymous Referee 2

We thank Referee 2 for carefully reviewing our manuscript and providing thoughtful feedback. Below we provide our responses to each point raised. We cite several instances where changes are made to the working manuscript, which will be submitted to HESS (if accepted to move forward) consistent with the review timeline.

Comment: The manuscript is limited to the study case, and as such it is not likely to help readers "gain broader insights in hydrological processes, modelling concepts, and/or improvements of existing modelling tools and methods."

Reply: We agree that the streamflow forecast component represents a location-specific contribution, however we believe this forecast coupled with the human managed allocation system is collectively novel and broadly relevant. While we address the unique set of circumstances posed by the Elqui Valley, Chile, the implications of the framework apply to basins where water rights represent a mechanism to promote equity and efficiency in the use of limited water resources.

The comment is valid, and accordingly we have made this point clearer in the discussion and conclusions. We address this in the working manuscript by describing how water rights driven basins might increase allocation efficiency by implementing forecasts as opposed to climatology based information as part of their decision framework.

Additional novelty lies in the coupling of the Stat-P&S and Stat-PCR forecast models, which provides a May 1st categorical prediction followed by a deterministic prediction on September 1st. The high level of agreement between the models suggests that while determinism is lost extending the lead from September 1st to May 1st, accurate categorical predictions are possible. We are not aware of work which has produced similar forecast skill at a May 1st lead in North Central Chile. This result also holds the potential for broader applications. Coupled forecasts need not be strictly deterministic, and using early categorical forecasts to provide an indication of expected conditions, and reinforcing the prediction with a revised deterministic forecast as more observations of local variables (e.g. precipitation) become available may be useful for a water rights holder.

Our discussion and conclusions section does address this point, but is lacking in terms of linking to a broader application. We address this in the working manuscript by bolstering the existing discussion.

Comment: The manuscript contains no clear hypothesis against which the research can be assessed.

Reply: This is a valid comment and is addressed in the working manuscript both in the introduction, discussion and conclusions by reframing the purpose of the research, namely to test if:
"…skillful streamflow forecasts can be coupled with reservoir allocation decision models to improve allocation efficiency as compared to climatology based decisions."
Additional discussion pertaining to the outcome of the research, as it pertains to addressing the hypothesis, is included in the discussion and conclusions.

Comment: Separating Section 2 into distinct 'data' and 'modelling approach' sections may make the modelling approaches more clear to the reader.

Reply: We are compelled to combine both the data and the modelling approaches in a common section as the data are not shared by each model. The Stat-PCR models are informed by observations of precipitation, soil moisture and sea surface temperatures, while the Stat-P&S model makes use of Niño 1.2 and 3.4 Index values, and the Stat-Dyn uses dynamical model outputs of both precipitation and sea surface temperatures. Rather than consistently refer to a data section when describing the modelling approach, we feel the logical approach is to introduce the data as it corresponds to the appropriate model and lead.
Still, we acknowledge the validity of this comment, noting that data and methods are presented separately in many peer reviewed papers. If the Referee feels strongly about separating the sections, we are happy to do so.

Comment: The Referee notes a lack of description of the reasons for which the modelling approaches are selected. Specifically, the Stat-P&S model, which uses Niño 1.2 and 3.4 Index values seems inappropriate, and leads are not well described.

Reply: We recognize the presentation of forecast leads for each model are not clearly described in the manuscript. To address this concern, we add additional language to the description of each model to clarify the leads considered, and provide supplemental text in the results section further reinforcing the leads and corresponding model skill. Additional information and detail are provided below (and added to the working manuscript.)
There are three distinct streamflow modelling approaches used in this research, aimed at balancing model skill and lead time. All are classified as statistical.

1) The Principal Component Analysis (Stat-PCR) model is meant to provide a deterministic prediction of streamflow using the most skillful and defensible predictors possible for increasing leads. Use of PCR is common in research focused on season-ahead streamflow prediction, and applying the leave-one-out cross-validated methodology adds additional credibility of the approach. Leads extend monthly from June 1st to September 1st. As described in the manuscript, observed data before June does not add to model skill.

2) The use of quantile mapping to correct dynamical model outputs of precipitation and sea surface temperatures (Stat-Dyn) is implemented in the same manner as the Stat-PCR. The main purpose of the Stat-Dyn approach is to increase the lead time of the streamflow predictions beyond what is possible with the Stat-PCR model. For example, the January 1st dynamical model outputs for May-August precipitation and sea surface temperatures are used to produce statistical streamflow predictions with a January 1st lead. Leads extend monthly from January 1st to June 1st.

3) The Phase and Strength model (Stat-P&S) makes use of the persistence of sea surface temperatures by using the Niño 1.2 and 3.4 indices, as opposed to other predictors which are shorter-lived or only become apparent at later leads (e.g. precipitation, soil moisture, pressure). The Stat-P&S approach is only use to provide a categorical prediction of streamflow, and ultimately proves more skillful at a May 1st lead than the Stat-PCR approach. May 1st is the only lead-time fir Stat-P&S.

The coupling of the Stat-P&S and Stat-PCR approach provides a skillful categorical streamflow prediction at May 1st (Stat-P&S), which is solidified by a September 1st deterministic prediction (Stat-PCR). The strength of the coupled model is the high degree of agreement between the two components. For all but two of the 39 years predicted by the Stat-P&S model, the Stat-PCR model provides a deterministic prediction which falls within the same category as the Stat-P&S model.

Comment: The Referee suggests producing predictions of rainfall and subsequently coupling with a physically-based runoff model as a more obvious approach to predicting streamflow.

Reply: This is a valid comment. However, while the method of precipitation runoff routing is well documented, and certainly applicable to the study area, it is perhaps unnecessary considering the correlation between May-August precipitation and October-January streamflow (Pearson's Correlation Coefficient = 0.80) suggests a strong, direct link exists. As such, predicting precipitation to inform a hydrology model is unlikely to add additional (appreciable) skill, while perhaps introducing additional uncertainty. This is further compounded by the relative lack of spatially diverse observational data and the complex topography of the upper basin. Previous research has also found a strong link between precipitation and streamflow within North Central and Central Chile (Waylen and Caviedes 1990; Verbist et al. 2010). Further, a concurrent study (performed by others) utilized the Water Evaluation and Planning (WEAP) model to address the contribution of rainfall runoff to streamflow in the Elqui basin, and found similar skill in predicting October-January streamflow.

Comment: The (Giorgi 1990) reference should be updated.

In the working manuscript, we substitute (Giorgi 1990) for (Fowler and Ekström 2009; Rauscher et al. 2010; Kendon et al. 2014) which each cite the use of general circulation models or regional climate models in seasonal and sub-seasonal precipitation forecasting at or below 20 kilometer resolution, as opposed to 600 kilometers.

Comment: Given that October-January streamflow is heavily influenced by concurrent season snow-melt, snow cover and snow depth should provide predictive strength.

The link between snow-melt and streamflow in the basins of North Central Chile is well documented (Souvignet et al. 2008; Vicuña, Garreaud, and McPhee 2011; Ribeiro et al. 2015). However, snow depth, snow cover, snow water equivalent (SWE) are not well sampled in the Elqui both spatially and temporally. The Dirección General de Aguas (DGA), the body charged with hydrologic and meteorological monitoring for Chile, provides SWE for a single location (La Laguna) for the period 1976-2005, which includes significant data gaps. The correlation between May-August SWE and October-January streamflow (Pearson's Correlation Coefficient = 0.67) is not as strong as the correlation between May-August precipitation and October-January streamflow (see above), and arguably provides the same information to the model. As such, we retain precipitation observations as a predictor in the Stat-PCR model. We agree with the Referee that snow observations would seemingly be an obvious predictor of streamflow, and have explored this thoroughly, however in this case, for the reasons mentioned above, it explains less of the overall variance in streamflow as compared with precipitation. We discuss this explicitly in the manuscript and have further highlighted this point in the working version.

Comment: The allocation model description is unclear. Specifically, the end of year (February) target volume seems too high, and the requirement to carry storage shortfall to the next year implies the reservoir has does not replenish. Is this realistic?

While we agree, for a variety of reasons, that a static target volume is generally a suboptimal operational policy, the target volume (50% of maximum storage) is the operating rule enacted by Puclaro's operators as a response to critically low reservoir levels (< 20 MCM) observed during the recent extended hydrologic drought (2009-2014). It was not the purpose of this research to address the performance of existing reservoir operating policies. Rather, we evaluate the performance of the October-January streamflow and climatological forecasts, translated to per-water right allocation values using the reservoir allocation model, against perfect foresight as a means of assessing the value of the forecast. A concurrent project is aimed at optimizing Puclaro's operational policies.

The purpose of carrying the storage shortfall or surplus from February and using it as a constraint or benefit for the subsequent October-January per-water right allocation value is that it recognizes the storage target as non-binding (can be violated by over or under allocation in the previous year), but consequential, in the allocation model. As such, the reasonable place to impose the effect is in terms of the following year's allocation. Effectively, it represents a mechanism for the reservoir operator to compensate for over or under allocation in the previous year. In addition, reservoir replenishment from snow melt typically does not occur until December, which is three months after the allocation issuance date of September 1st, and such is the reason why a forecast is produced. The use of the deficit or surplus becomes a hedge against the uncertainty of the forecast. Ultimately, we believe the carryover of deficit or surplus is an appropriate way to include the operational goal of the reservoir operators.

Comment: The summary and discussion are uninformative. As such, they should be split into distinct "Discussion" and "Conclusions" sections and significant effort applied to drawing more scientific conclusions from the research.

We agree with the Referee's comment to break the "Summary and Discussion" section into and "Discussion" and "Conclusions" sections, and have done this in the working manuscript. The Discussion section now more thoroughly describes where models are both successful and limited in terms of prediction, and how the limitations (e.g. tradeoff between lead and skill) of the models we construct align with previous research. The Conclusions section establishes the broader insights gained from the research, including the potential for improved water right allocation efficiency achieved by coupling hydroclimate streamflow prediction with a reservoir allocation framework which may benefit both reservoir operators and water rights holders. In addition, the Conclusion presents the coupled Stat-P&S and Stat-PCR models as achieving both increase in forecast lead while maintaining skill, by adjusting the type of forecast provided (categorical to deterministic). The broader insight gained here is that by sacrificing forecast precision, the lead can be skillfully extended. We hypothesize this information to be of potential value to water rights holders who must make decisions (e.g. cropping) prior to the annual setting of the per-water right allocation value.

Comment: The manuscript should be shortened. In depth descriptions of well understood methods and metrics may be removed.

We recognize that the interdisciplinary nature of this manuscript may draw readers who have limited methodological knowledge of hydroclimate prediction and reservoir allocation forecasts. Therefore, we provide explicit detail of both methods and metrics used to construct and evaluate models, respectively. The comment is reasonable, and in the working manuscript we have removed all but necessary discussion of principal component analysis, multiple linear regression, cross-validation, and metrics.

LIST OF RELEVANT CHANGES MADE TO MANUSCRIPT

Most of the relevant changes to the manuscript are addressed explicitly in responses to Referees. We list a summary of the areas of the paper most substantially revised.

1. The abstract was bolstered significantly. It now contains quantitative results and broader implications for the research.

   "Skillful results (forecasts outperforming climatology) are produced for short lead-times (September 1st; RPSS = 0.31, categorical hit skill score = 61%), with years of Above-Normal (high) and Below-Normal (low) streamflow predicted 82% and 64% of the time, respectively. At longer lead-times, climatological skill exceeds forecast skill, largely due to fewer observations of precipitation. Coupling the September 1st statistical forecast model with a Niño 3.4 region sea surface temperature phase and strength statistical model, however, allows for equally skillful categorical streamflow forecasts to be produced from a May 1st lead, triggered for 60% of the years in the period 1950-2015. Forecasts may not need to be strictly deterministic to be useful for water rights holders; early (May) categorical indication of expected conditions are reinforced with a revised deterministic forecast (September) as more observations of local variables (e.g. precipitation) become available. The reservoir allocation model is skillful at the September 1st lead (categorical hit skill score = 53%); this skill improves to 79% when the model predicts the observed allocation category with at least 80% certainty. This result has broader implications, suggesting that in water rights managed basins, allocation efficiency might improve through the integration of forecasts as part of a reservoir decision framework. The methods applied here advance the understanding of the mechanisms and timing responsible for moisture transport to the Elqui Valley, and provide a unique application of streamflow forecasting in the prediction of per-water right allocations. Both have the potential to inform water right holder decisions."

2. Referee #2 identified the need to clearly state the research hypotheses. We address this in the Introduction with the following:

"Recognizing that variable precipitation effects streamflow and subsequently water right allocation values, this research tests two hypotheses as a means of addressing the unique climate conditions of the Elqui Valley, which may be applied more broadly to water rights managed basins with limited water resources:

1) Skillful season-ahead streamflow forecasts can be produced for existing water right allocation decision points.
2) Skillful streamflow forecasts coupled with reservoir allocation decision tools can improve allocation efficiency."

3. The reasons for which spatial averaging (e.g. sea surface temperature) was done was unclear. We address this in the manuscript with the following:

   The first principal component (PC) from the gridded variable region, representing the dominant signal in the gridded field, correlated with the spatial average of the gridded variable region can identify if the signal is spatially homogenous (representative) across the region. If the first PC does not correlate well with the spatial average, the heterogeneity of the dataset is likely important, and adopting the spatial average as a predictor may be insufficient. For example, the spatial average of SSTs (Fig. 4 (c.)), a potentially significant predictor of streamflow for the Elqui River, correlates highly (>0.9) with the first PC of the gridded SST data. This region of SSTs is closely aligned with the quintessential ENSO pattern in the equatorial Pacific Ocean, and is evident when correlating the entire ONDJ streamflow record with SST anomalies in the preceding MJJA, which suggests ENSO, in general, plays some role in explaining streamflow variability within the Elqui Valley (Fig. 4(c.)) Having identified SSTs across this region as spatially homogenous, and consistent with the Niño 3.4 region, we select the Niño 3.4 Index as a potential predictor of streamflow, in lieu of the SST region initially identified (Fig. 4(c.)), as it is well-known, well understood, and well-studied.

4. Referee #2 identified excessive explanation of methods (e.g. principal component analysis, Ranked Probability Skill Score, etc…) To address this, we remove equations 1, 2, 5, 6 and 7 and corresponding explanations. We retain more basic language which shorten the manuscript.

5. Referee #2 indicated use of snow depth or snow water equivalent as influential as a predictor of streamflow. We address this comment in the manuscript with the following:

   "Snow water equivalent (SWE) is not retained as a predictor as its May-August correlation with October-January streamflow (Pearson's Correlation Coefficient = 0.68) is not as strong as the correlation between precipitation and streamflow for the same lead, and arguably provides the same information to the model. As such, observations of precipitation are retained for the Stat-PCR model

6. The Summary and Discussion were lacking both in depth of analysis and in liking the forecast and allocation framework to broader applications. We address this in the manuscript by constructing both Discussion and Conclusion sections which retain elements of the first submission, and include new language which addresses the broader insights and usefulness of the framework. A sample of additional content is provided below.

(Discussion): "While the approaches in this research are predominantly a demonstration of concept, the model framework is consistent with the current operations of Puclaro Reservoir. However, it is not optimized to hedge against expected future (multi-year) conditions. While the model may be informative over the long-term, resulting in allocation and storage values better matched with observations than climatology-based allocations, it performs poorly in certain years, most notably during the 2009 – 2015 hydrologic and meteorological drought (Fig. 9(a.)) While poor model performance during this period is undoubtedly due in part to the limited reservoir operating rules, the Stat-PCR approach tends to under predict extremes, especially when they occur consecutively. Further forecast model development will focus on improving predictive skill of extreme events, particularly dry periods, making use of non-parametric methods and additional multi-model approaches, and dynamic rule structures and simulation techniques. Even so, adoption of the approaches presented here by water managers and rights holders bodes well for improved economic efficiency and benefits across the Elqui Valley."

(Conclusions): "The broader insight gained is in the coupling of the Stat-P&S and Stat-PCR models to produce initial (May 1st) and updated (September 1st) forecasts which may be valuable to both reservoir managers and water rights holders. From a reservoir management perspective, properly setting the per right water allocation (September 1st) is critically important to satisfy rights holders and maintain adequate reservoir storage for the uncertain future. The Stat-PCR component of the coupled model provides skill superior to climatology, and likely better informs allocation decisions. Reservoir managers, however, are also expected to provide a non-binding May 1st allocation forecast, allowing rights holders, specifically farmers with crop choice flexibility and/or water right leasing potential, to supplement through the water market as necessary. The Stat-P&S categorical forecast with a May 1st lead can inform these longer planning actions. The strong categorical consistency between the May 1st Stat-P&S and September 1st Stat-PCR forecasts may also serve to reinforce confidence in the forecast outcomes; the two models only differ in prediction categories twice in the 66 years evaluated. The conclusion here is that coupled forecasts need not be strictly deterministic, and using early categorical forecasts to provide an indication of expected conditions, and reinforcing the prediction with a revised deterministic forecast as more observations of local variables (e.g.

precipitation) become available may be useful for water rights holders. In addition, linking the streamflow forecast with the human managed allocation system is broadly relevant as a mechanism to promote efficiency in the use of limited water resources. The framework presented here addresses the unique set of circumstances in water rights managed basins, and represents an advancement in linking season-ahead streamflow forecasts to water resources systems."

~~A Framework for Advancing Streamflow and Water Allocation Forecasts in the~~ Evaluation of model-based seasonal streamflow and water allocation forecasts~~ing~~ for the Elqui Valley, Chile

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Abstract.

In many semi-arid regions, agriculture, energy, municipal, and environmental demands often stress available water supplies. Such is the case in the Elqui River valley of northern Chile, which draws on a limited capacity reservoir and annually variable snowmelt. With infrastructure investments often deferred or delayed, water managers are forced to address demand-based allocation strategies, particularly challenging in dry years. This is often realized through a reduction in the volume associated with each water right, applied across all water rights holders. Skillful season-ahead streamflow forecasts have the potential to inform managers with an indication of likely future conditions upon which to set the annual water right volume and thereby guide reservoir allocations. This work evaluates season-ahead statistical prediction models of October-January (austral growing season) streamflow at multiple lead times associated with manager and user decision points, and links predictions with a simple reservoir allocation tool. Skillful results (forecasts outperforming climatology) are produced for short lead-times (September 1^{st}; RPSS = 0.31,~~), where~~ categorical hit skill score =~~is~~ 61%), with years of Above-Normal (~~wet~~high) and Below-Normal (~~dry~~low) streamflow ~~years achieving~~predicted 82% and 64% ~~skill~~of the time, respectively. At longer lead-times, climatological skill exceeds forecast skill, largely due to ~~less~~fewer observations of precipitation~~ in the statistical model (August 1^{st} RPSS = 0.02 and July 1^{st} RPSS = -0.39)~~. Coupling the September 1^{st} statistical forecast model with a Niño 3.4 region sea surface temperature phase and strength statistical model, however, allows for equally skillful categorical streamflow forecasts to be produced ~~for~~from a May 1^{st} lead, triggered for 60% of the years in the period 1950-2015. ~~The key insight here arises from the coupling of statistical models which we conclude~~Forecasts may ~~need~~ not need to be strictly deterministic to be useful for water rights holders;~~,~~ ~~such that~~ early (May) categorical indication of expected conditions are~~,~~ reinforced with a revised deterministic forecast (September) as more observations of local variables (e.g. precipitation) become available. The reservoir allocation model is skillful at the September 1^{st} lead (categorical hit skill score = 53%); this skill improves to 79% when ~~, and using a probabilistic modelling approach, forecast-based allocations are categorically skillful (79%) when~~ the model predicts the observed allocation category with at least 80% certainty. This result has broader implications, ~~and~~ suggestings that in water rights ~~driven~~managed basins, allocation efficiency might improve through the ~~implementation~~integration of forecasts ~~as opposed to climatology based information~~ as part of a reservoir ~~manager~~ decision framework. The methods applied here advance the understanding of the mechanisms and timing responsible for moisture transport to the Elqui Valley, and provide

a unique application of streamflow forecasting in the prediction of per-water right allocations. Both have the potential to inform water right holder decisions.

1 Introduction.

The sustainability of many water systems is challenged by current climate variability, and may come under additional stress with changes in future climate and user demands. Concerns over increasing water scarcity have prompted progressive governments, institutions, water resource managers, and end-users to adopt a wide variety of conservation policies, typically targeting supply augmentation or demand reduction at the basin or jurisdictional boundary scale (Tanaka et al., 2006). These decisions, which are ideally informed by a variety of models, are inherently uncertain across time-scales, and produce numerous risks stemming from human activity and hydroclimatic variability/change (Narula and Lall, 2009). Advanced hydroclimatic information is often attractive to progressive water managers to support management and planning of water systems (Barsugli et al., 2012). At the seasonal scale, a skillful streamflow forecast may allow more efficient water allocation and predictable tradeoffs between flows for energy, irrigation, municipalities, environmental services, etc. Such forecasts often provide the ability to prepare for anticipated conditions, not simply react to existing conditions, potentially reducing climate-related risks and offering opportunities (Helmuth et al., 2007). This may be especially informative in years with extreme conditions (floods, droughts.) Further motiviation stems from evidence that addressing climate variability as part of water development is key for stabilizing and improving country economies (Brown and Lall, 2006).

While improvements in seasonal climate forecast skill and advocacy for integration into risk reduction strategies are well documented (Barnston et al., 1994; Block, 2011; Block et al., 2009; Dee et al., 2011; Hansen et al., 2004; Mason and Stephenson, 2008), demonstrated use of forecasts in current water allocation and policy strategies is limited (Barnston et al., 1994; Christensen et al., 2004; Hamlet et al., 2002; Sankarasubramanian et al., 2009; Stakhiv, 1998). This is partially attributable to the wide-spread use of static operational policies, which may be based on average streamflow or the drought of record, and established with minimal to no accounting of uncertainty, thus limiting water system flexibility (You and Cai, 2008). Effectively translating emerging climate information into hydrology to support adaptable water resources decision-making, and ultimately policy, warrants further study.

The water system in the semi-arid Elqui Valley in north-central Chile's IVth Region (Fig. 1) is contending with increasing levels of water stress and demand, coupled with insufficient investment in infrastructure, taxing its ability to sufficiently meet multiple water uses and maintain environmental quality. The Valley footprint is relatively small (< 10,000 square kilometers), but boasts elevation changes ranging from sea level in the west to nearly 5,000 meters in the east along the Andes, in the span of less than 150 kilometers. The Atacama Desert lies just to the north. The Valley is fed from a retreating glacier to serve its

600,000 inhabitants, and is very narrow, with vineyards and plantations covering the floor and increasingly moving up the Valley sides; forty three percent of the region's surface land area is devoted to agricultural activities (Cepeda and Lopez-Cortes, 2004). Agricultural exports, particularly grapes, fruits, and avocados, dominate the Valley's economy (Young et al., 2009), and are maintained by an extensive irrigation channel system latticing the Valley, which diverts water from the main Elqui River. The Puclaro reservoir is the dominant storage facility in the Valley, with a holding capacity of 200 million cubic meters (Fig. 1.) The reservoir provides irrigation for about 21,000 hectares of the Elqui Valley, as well as small-scale hydropower (5.6 MW capacity) and being a popular tourist destination, particularly for sailing and windsurfing (Cepeda and Lopez-Cortes, 2004).

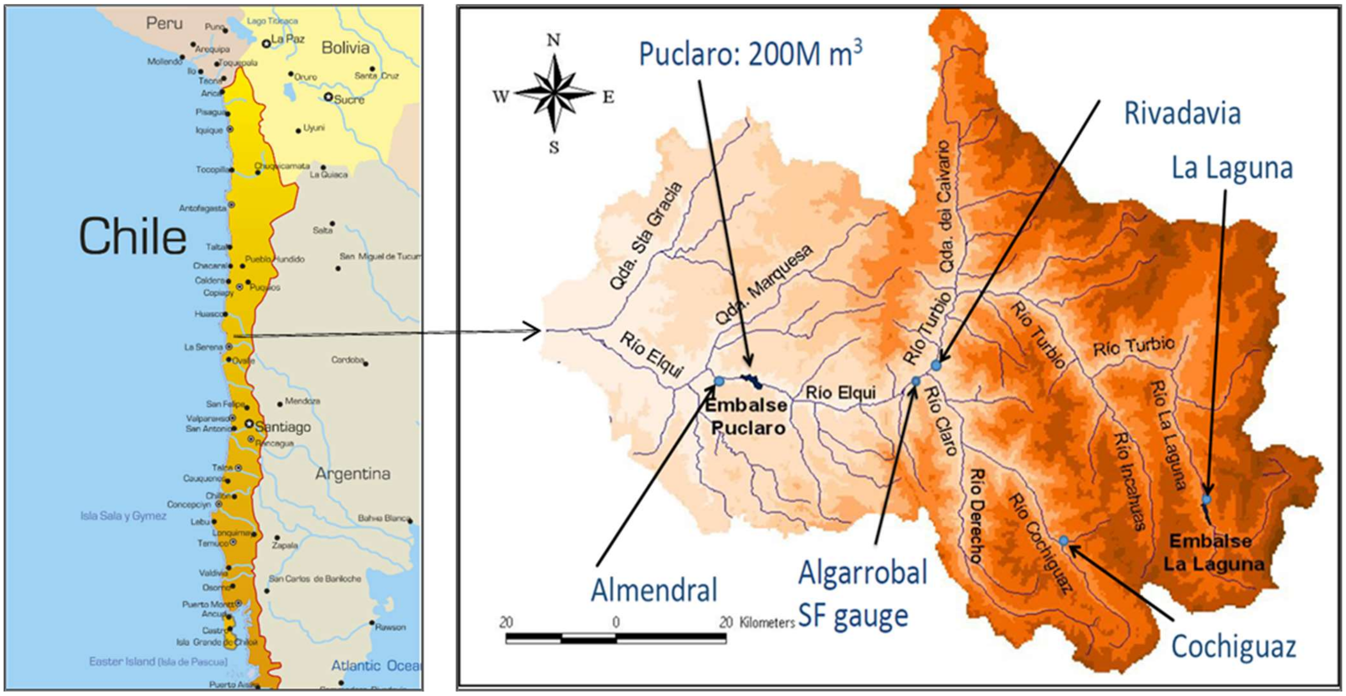

Figure 1: Location of Elqui River Valley, Chile

Chile uses a market-oriented approach to water allocation, guided by its Water Code of 1981 (G Donoso, 2006). The intent is to allow for optimal allocation and efficiency through a politically neutral mechanism via permanent trades or leasing (Olmstead, 2010; Wheeler et al., 2013). Rights are granted through the national water authority (Dirección General de Aguas, hereafter DGA), while supervision, reservoir management, and issuance of annual per right allocation is left to the privately-held, local water authority, Junta de Vigilancia del Rio Elqui (JVRE.) Water rights along the Elqui River are fully allocated, with 25,000 total rights valued at 1 liter per second each. In years with above normal precipitation and snowpack, this value can be attained, however near normal and below normal precipitation years typically require a reduction in per right allocation, on the order of 0.5 liters per second. Prolonged periods of drought (2009-2015) have resulted in allocations as low as 0.2 liters per second (JVRE, *personal communication*.) All water rights are of equal standing; no prioritization or junior/senior status exists. Thus, right holders above Puclaro are guaranteed equal per right allocations as their counterparts downstream; under the current framework, surplus supply cannot be allocated to users downstream of the reservoir once the annual per right allocation has been officially issued, to guarantee equality. Approximately 92% of water rights are held by farmers, with half of those held by a small minority engaged in large-scale viticulture. Municipalities and the mining industry share the balance of water rights. Meeting targets for renewable energy through hydropower, ecosystem services, specifically minimum instream flows, and reservoir storage are also important competing non-consumptive or non-water right holding priorities.

The decision framework driving water allocation and market activity in the Valley is complex and involves many actors. For the water year October to September, the local water authority initially projects the annual per right allocation in the preceding May and officially sets it in September. Water rights holders (users) thus have two decision points, May and September, to evaluate their allocation and weigh the need to supplement through market activity (trade or lease.) This setting serves as an impetus for developing a framework to advance streamflow and water allocation forecasts at those decision points to better guide decision-making across the Valley.

1.1 Elqui Hydro-climate Characteristics.

The Elqui Valley is one of the most sensitive areas to water variability in all of South America, given its dryland ecosystem nature, susceptible to even small changes in the water cycle (Santibañez et al. 1992; N Kalthoff et al. 2006). The climate of the region is affected by three major factors that lead to its semi-arid nature: the southeast Pacific anticyclone, the cold Humboldt current along the Pacific coast, and the eastern longitudinal barrier created by the Andes mountains (Kalthoff et al., 2002). The majority of precipitation is frontal in nature, falling in the austral winter (May-August, MJJA) as rain in the Valley and snow in the mountains; this leaves the remaining months extremely dry (Fig. 2;(Aceituno, 1988). Annual rainfall totals approach 90mm on average and express a high degree of variability (Young et al., 2009). The El Niño Southern Oscillation (ENSO) is well known to have a role in this variability, with positive precipitation anomalies during El Niño events, and below normal precipitation mostly associated with La Niña conditions (Fig. 3; (Aceituno, 1988; Falvey and Garreaud, 2007; Garreaud et al., 2009; Montecinos and Aceituno, 2003). For Vicuña, a city located in approximately the center of the Valley, between 1950-2000, El Niño years produced average annual precipitation of 134mm, compared with 68 mm during La Niña years – a stark difference (Young et al., 2009).

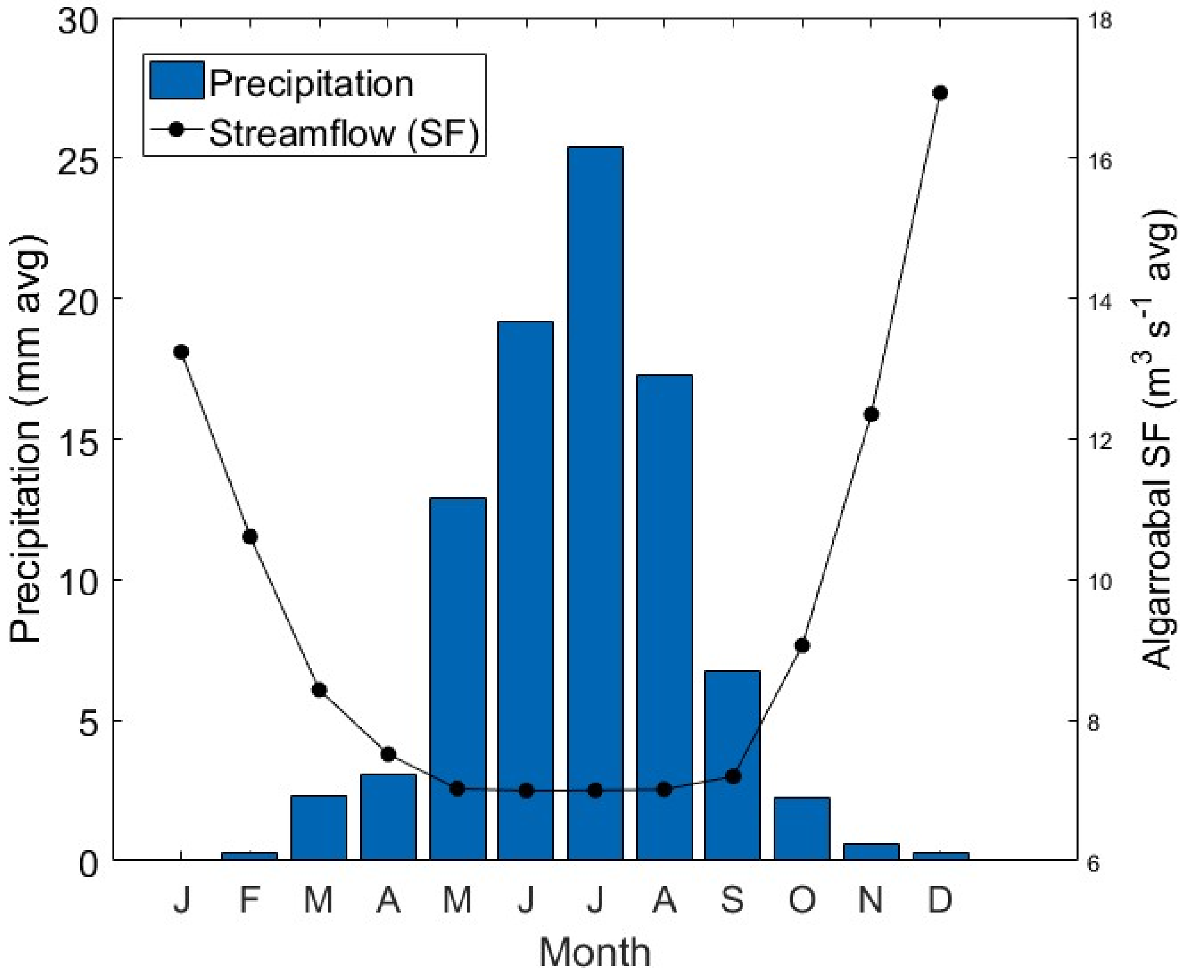

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Figure 2: Annual cycle of average precipitation and streamflow (1950-2015)

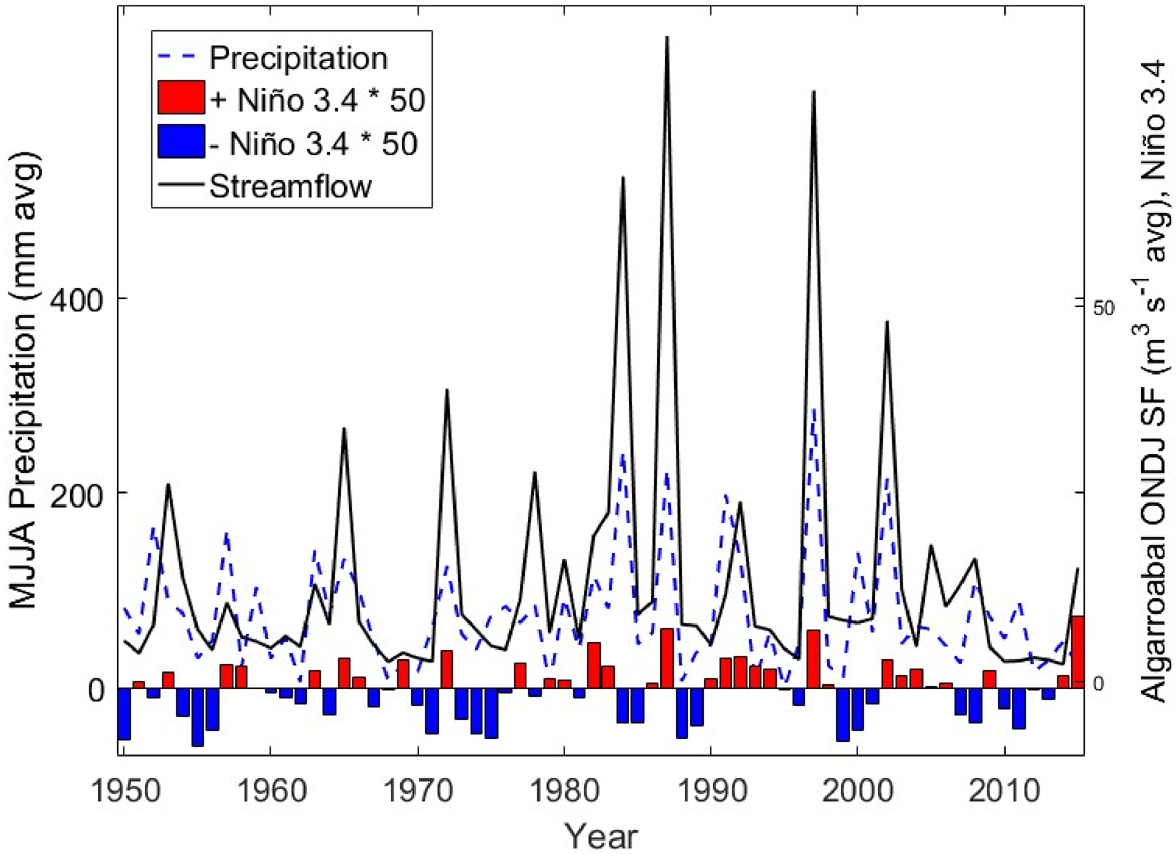

Figure 3: Total annual precipitation (dashed), streamflow (solid) & May-August Niño 3.4 sea-surface temperature anomalies (bars)

The Elqui River is predominantly fed through snowmelt over the October - January (ONDJ) season, dictating the agricultural calendar. Historical rates of average streamflow over this season, however, indicate enormous interannual variability, ranging from 2.2 - 89 cubic meters per second at the Algarrobal station (Fig. 3; Santibañez et al. 1992), commonly considered as a surrogate for inflow to the Puclaro Reservoir (Fig. 1.) Recognizing ~~the~~that ~~effect~~ variable precipitation effects ~~has on~~ streamflow and subsequently water right allocation values, this research tests two hypotheses as a means of addressing the unique climate conditions of the Elqui Valley, which may be applied more broadly to water rights ~~driven~~managed basins with limited water resources:

3) Skillful season~~-~~-ahead streamflow ~~seasonal~~ forecasts ~~of streamflow~~ can be produced ~~consistent with~~for existing water right allocation decision points.

4) Skillful streamflow forecasts ~~can be~~ coupled with reservoir allocation decision tools ~~to~~can improve allocation efficiency ~~as compared to climatology based decisions~~.

~~Thus, a skillful streamflow forecast characterizing the ONDJ season has utility for providing advanced information to guide decisions in the Valley, particularly for dry conditions.~~

2 Modelling Framework and Performance Metrics.

Historically, water managers in the Elqui Valley have subjectively considered simple analog prediction models for ONDJ streamflow at Algarrobal, conditioned on the multivariate ENSO index (MEI), for allocation decisions and reservoir operations, with limited success (JVRE, *personal communication*.) Previous efforts to evaluate hydro-climate forecast skill for the Elqui River have considered leads consistent with the current water rights forecast structure; a preliminary May allocation forecast and September allocation issuance (Robertson et al., 2014; Verbist et al., 2010). Roberston et al. (2014) report a significant increase in forecast skill, comparing September to May, but suggest further investigation to more fully understand forecast skill with increasing lead time.

This recommendation is addressed by building a modeling framework to evaluate potential improvement in predicting ONDJ streamflow at multiple lead times, starting with a 1-month lead (September 1^{st}) and increasing at monthly intervals (i.e. August 1^{st}, July 1^{st}, etc.) to May 1^{st}, when the first water allocation forecast is preliminarily issued. Both statistical and dynamical prediction approaches are explored. Subsequently, the ability to effectively predict water rights allocations is investigated by coupling streamflow predictions with a reservoir allocation model.

2.1 Statistical Streamflow Prediction Models

Statistical forecast methods rely on identification of spatiotemporal patterns in historical data (Chambers et al., 1971). Observations of streamflow at Algarrobal (monthly, 1948-present), valley-wide precipitation stations (daily, 1950-present), and snow-water equivalent (daily, 1950-2009) are each readily available through the Chilean DGA. One of DGA's primary functions as the regulator of surface water resources for the Chilean Government is to collect, validate, and perform quality control of hydrologic measurements. Open source data obtained through DGA is considered as having met DGA quality standards. A suite of potential predictor variables are evaluated which have been shown to influence either streamflow or precipitation, including sea surface temperatures (SST), specifically in the Niño 1.2 and Niño 3.4 regions, sea level pressure (SLP), geopotential height, vector (also referred to as wind vectors) and meridional winds, local soil moisture, and the Multivariate ENSO Index (MEI), which combines several equatorial Pacific atmospheric and oceanic anomalies (Montecinos and Aceituno, 2003; Wolter and Timlin, 1993). These variables can illustrate the mechanisms controlling moisture transport to the basin, and subsequent inter-annual variability in streamflow. For example, in the ten lowest ONDJ streamflow years (dry), vector winds follow a weak, dissociated pattern in the preceding season, which indicates that moisture transport from the Pacific Ocean is inefficient (Fig. 4(a.) In the ten highest ONDJ streamflow years (wet), vector winds are anomalously strong, and follow a coherent clockwise pattern off the coast of Chile, which suggests more efficient moisture transport is possible from the Pacific Ocean to the Elqui Valley (Fig. 4(b.)

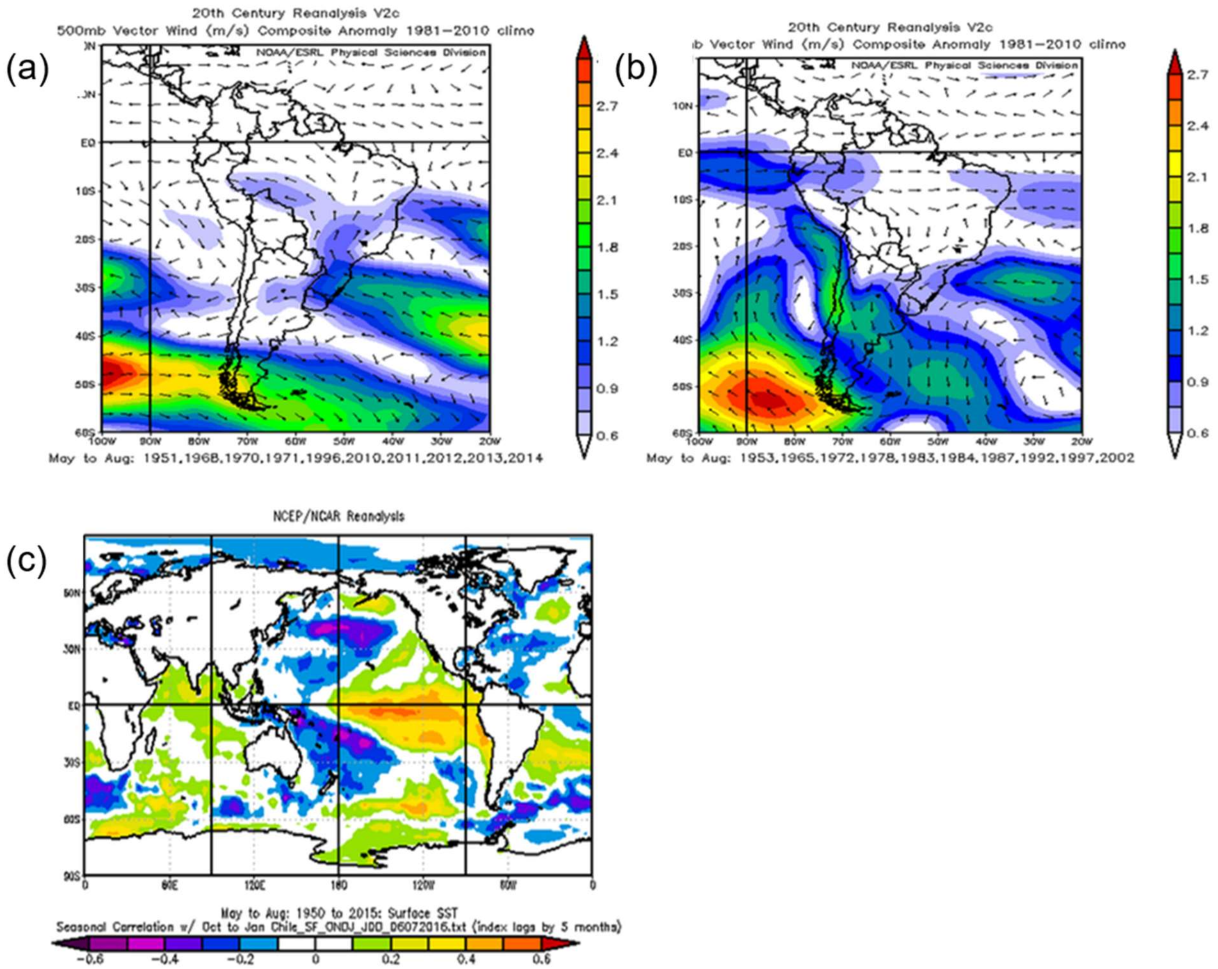

Figure 4: (a) Composite May-August (MJJA) vector wind anomaly preceding ten lowest October-January (ONDJ) streamflow years, (b) same as (a) for ten highest ONDJ streamflow years, (c) correlation of MJJA sea-surface temperature anomaly with ONDJ streamflow (1950-2015)

To identify potential predictors, each variable is correlated with ONDJ streamflow at lead times consistent with those discussed above (Fig. 5; not all variables shown.) Regions (gridded data sets) with statistically significant correlations in locations that have the potential to affect moisture transport (Table 1) are spatially averaged and retained for further evaluation. The first principal component (PC) from the gridded variable region, representing the dominant signal in the gridded field, correlated with the spatial average of the gridded variable region can identify if the signal is spatially homogenous (representative) across the region. If the first PC does not correlate well with the spatial average, the heterogeneity of the dataset is likely important, and adopting the spatial average as a predictor may be ~~ineffective~~insufficient. For example, the spatial average of SSTs (Fig. 4 (c.)), a potentially significant predictor of streamflow for the Elqui River, correlates highly (>0.9) with the first PC of the gridded SST data. This region of SSTs is closely aligned with the quintessential ENSO pattern in the equatorial Pacific Ocean, and is evident when correlating the entire ONDJ streamflow record with SST anomalies in the preceding MJJA, which suggests ENSO, in general, plays some role in explaining streamflow variability within the Elqui Valley (Fig. 4(c.)) Having identified SSTs across this region as spatially homogenous, and consistent with the Niño 3.4 region, we select the Niño 3.4 Index as a potential predictor of streamflow, in lieu of the SST region initially identified (Fig. 4c), as it is well-known, well understood, and well-studied. SST, SLP, geopotential height, meridional and vector winds are obtained at a 2.5 x 2.5 degree grid resolution from the National Oceanic and Atmospheric Administration's Climate Diagnostics Center (NOAA-CDC), which are based upon the National Center for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data, available from 1949 to the present (Kalnay et al., 1996). Soil moisture data is obtained from NOAA's Climate Prediction Center's (CPC) global monthly soil moisture dataset, at 0.5 x 0.5 degree grid resolution, which is available from 1948 to the present (Huang et al., 1996; Kalnay et al., 1996; Saha et al., 2013). MEI data is available from NOAA's Earth System Research Laboratory (ESRL) bimonthly as the first unrotated principal component of six spatially filtered variables in the tropical Pacific (Wolter and Timlin, 1993, 1998).

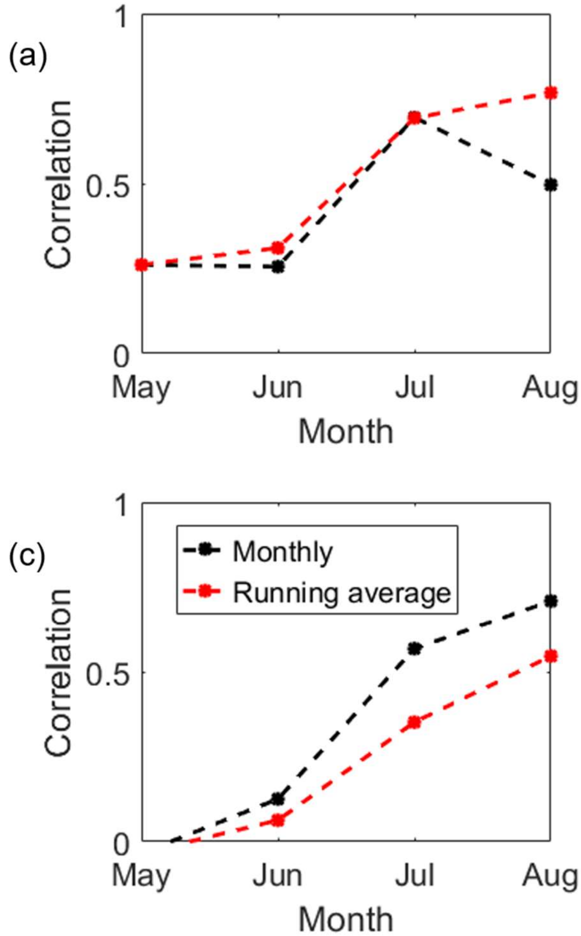

Figure 5: Temporal correlations of October-January streamflow and potential predictors: (a) precipitation, (b) Niño 3.4 sea surface temperatures, (c) soil moisture

Table 1: List of potential predictors (bold predictors retained for statistical model)

Potential Predictors	Location	MJJA Pearson's correlation with ONDJ Streamflow
	Local	
Precipitation	18 Stations (Valley Wide)	+0.80
Soil Moisture	29°- 30° S, 70°-71° W	+0.55
Snow-water equivalent	1 Station (La Laguna)	+0.68
	Global	
Geopotential Height (800 mb)	45°- 60° S, 100°-120° W	+0.43
Meridional Wind	0°-5° S, 160°- 180° W	+0.37
Multivariate ENSO Index	Tropical Pacific Anomaly	+0.35
Sea Level Pressure	60°- 70° S, 100°-120° W	+0.22
Sea Surface Temperatures (Niño 1.2)	0°-10° S, 80°- 90° W	+0.40
Sea Surface Temperatures (Niño 3.4)	5°N-5° S, 120°-180° W	+0.49
Vector Wind	20°- 60° S, 120°-180° W	+0.47

Principal component regression (PCR) (Lins, 1985) is commonly applied in forecasting to decompose space-time fields, which reduces both dimensionality and multicollinearity of a set of variables. PCR is a two-step process, the first of which identifies modes of dataset variability iteratively, by identifying the direction which maximizes the variance explained in the data. ~~The resultant principal component (PC) is the sum of least squares distance between the factor direction and the predictor data. The second factor is applied in the direction which maximizes dispersion in the dimension of next greatest variability to form the second PC, and so forth. All PCs are orthogonal.~~ The result is a set of principal components (PC)~~s~~ representing the variance in the predictors, with PCs ordered by the amount of variance explained. PCs with eigenvalues greater than one are retained, following Kaiser's rule; (Zwick and Velicer, 1986). The second step of PCR is multiple linear regression, using the PCs retained as predictors. ~~as shown by Eq. (1):~~

$$\cancel{\hat{y}_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n,\ for\ t = 1\ to\ N} \qquad \cancel{(1)}$$

$$\cancel{\varepsilon_t = \hat{y}_t - y_t} \qquad \cancel{(2)}$$

~~where $\hat{y}_t$ is the predicted value of ONDJ streamflow in year t, x_n, . . ., x_n are the PCs retained as predictor variables, ε_t is an error coefficient calculated as the difference of predicted and observed values of streamflow, as shown by Eq. (2), β_0, . . ., β_n are the fitted regression coefficients, and N is the number of years predicted.~~ A leave-one-out cross validated hindcast is undertaken to produce a deterministic prediction of expected streamflow for each year (1950-2015) (Block and Rajagopalan, 2007). A prediction distribution is generated using prediction errors ~~(ε_t)~~ from the hindcast fit to a normal distribution with a mean of zero, and added to the deterministic hindcast prediction. In this work, the median and upper 80th percentile hindcasted flows from the ranked outputs are analyzed. The 80th percentile streamflow time series is used as a conservative estimate of streamflow to simulate potential risk aversion on the part of a reservoir manager. Hereafter the statistical principal component regression approach is referred to as Stat-PCR.

As previously mentioned, ENSO influences Elqui River streamflow variability. The strength of an El Niño or La Niña event relates to the degree of SST deviations from the long-term mean; using the Niño 3.4 Index, NOAA has established weak (+/- 0.25° C), moderate (+/- 0.75° C), and strong (+/- 1.0° C) categorical thresholds as a means of describing ENSO phase and strength (2016). Recent research has illustrated a potential relationship between streamflow and ENSO phase and strength (Zimmerman et al., 2016). In a separate statistical approach, a streamflow prediction model based on ENSO phase and strength (Stat-P&S) is developed to provide categorical predictions of ONDJ streamflow. The Stat-P&S approach utilizes Niño 3.4 Index values, prior to the ONDJ season of interest, to provide a categorical streamflow prediction. To qualify for prediction using Stat-P&S, at least one month during a selected Niño 3.4 Index window must be at least moderate in strength for a given phase, ≥ +0.75°C (El Niño) or ≤ -0.75°C (La Niña.) Years satisfying this criterion are categorically predicted as Above Normal (A; highest 33% of long-term streamflow observations) or Below Normal (B; lowest 33% of long-term streamflow observations) ONDJ streamflow, respectively. Window selection determines hindcast date, and may fall prior to or during a phenomenon known as the Spring Barrier, when SSTs in equatorial Pacific generally reset, losing predictive strength (Webster and Hoyos, 2010). However, the effects of moderate and strong ENSO events have some tendency to persist (Balmaseda et al., 1995). When values from the Niño 3.4 Index fail to exceed +/- 0.5°C, ONDJ streamflow is predicted to fall into the Normal (N; middle 33% of long-term streamflow observations) category. For years where the Niño 3.4 Index values are (+0.5°C, +0.75°C) or (-0.5°C, -0.75°C), the Stat-P&S model does not issue a forecast. For these ranges, neither the magnitude (not weak or moderate as defined by NOAA) nor persistence of SST observations allow for production of skillful categorical streamflow forecasts. For years ~~where~~in which SSTs fall within these ranges at forecast leads prior to the Spring Barrier, strength and phase are subject to rapid transition, and categorical forecasts are typically not skillful.

2.2 Dynamical Climate Model Informed Statistical Streamflow Prediction Model.

General Circulation Models (GCM) and Regional Climate Models (RCM) are physically-based, three dimensional representations of gridded atmospheric, oceanic and land surface processes, with typical spatial resolutions ~~of 250 - 600 km~~at or below 20 kilometer resolution ~~(~~(Fowler and Ekström, 2009; Kendon et al., 2014)~~(Giorgi, 1990)~~. GCMs have proven skillful in prediction of large scale physical processes, such as SSTs and pressure systems, however, their relatively coarse resolution often limits predictive ability for smaller scale weather and climate phenomena, including precipitation (Bosilovich et al., 2008). Furthermore, outputs from each GCM are unique, and based on individualized parameterization schemes, initial conditions, data assimilation processes, etc. Considering the National American Multi-Model Ensemble (NMME; (2012) suite of models, (Verbist et al., 2010) demonstrate skillful prediction of North Central Chile precipitation based on equatorial Pacific

SSTs in the ENSO region using NOAA's National Centers for Environmental Protection's (NCEP) Climate Forecast System Version 2 GCM, available 1982 – present (CFSv2; (Kalnay et al., 1996). Considering both the findings of Verbist et al. (2010), and a strong Pearson's correlation coefficient between observed ONDJ streamflow and MJJA precipitation in the Elqui Valley (0.80), both precipitation and SSTs outputs from CFSv2 are retained for further evaluation. Specifically, the mean value of the 40-member ensemble of outputs for gridded precipitation (29˚- 30˚S, 70˚-71˚W) and the Niño 1.2 and 3.4 indices at leads between January 1st and May 1st are obtained and independently corrected using a statistical quantile mapping approach based on the cumulative distribution functions of both predicted and observed data (Maraun, 2013). For each lead, predicted values are replaced with values from the observed distribution, based on matching probabilities (Fig. 6; not all variables shown.) The same PCR framework as in the Stat-PCR approach is applied using GCM corrected precipitation and SSTs to predict ONDJ streamflow, referred to as the Stat-Dyn model. The Stat-Dyn model is meant to provide streamflow forecasts at extended leads, beyond what is possible with global and local observed data used to inform the Stat-PCR model. Local variables (e.g. precipitation, snow water equivalent and soil moisture) hold the most predictive strength as observations during the season of peak precipitation (May-August) and thus are only considered for the Stat-Dyn model for leads ~~at~~ prior to June 1st (Fig. 5 (a.) and (c.).

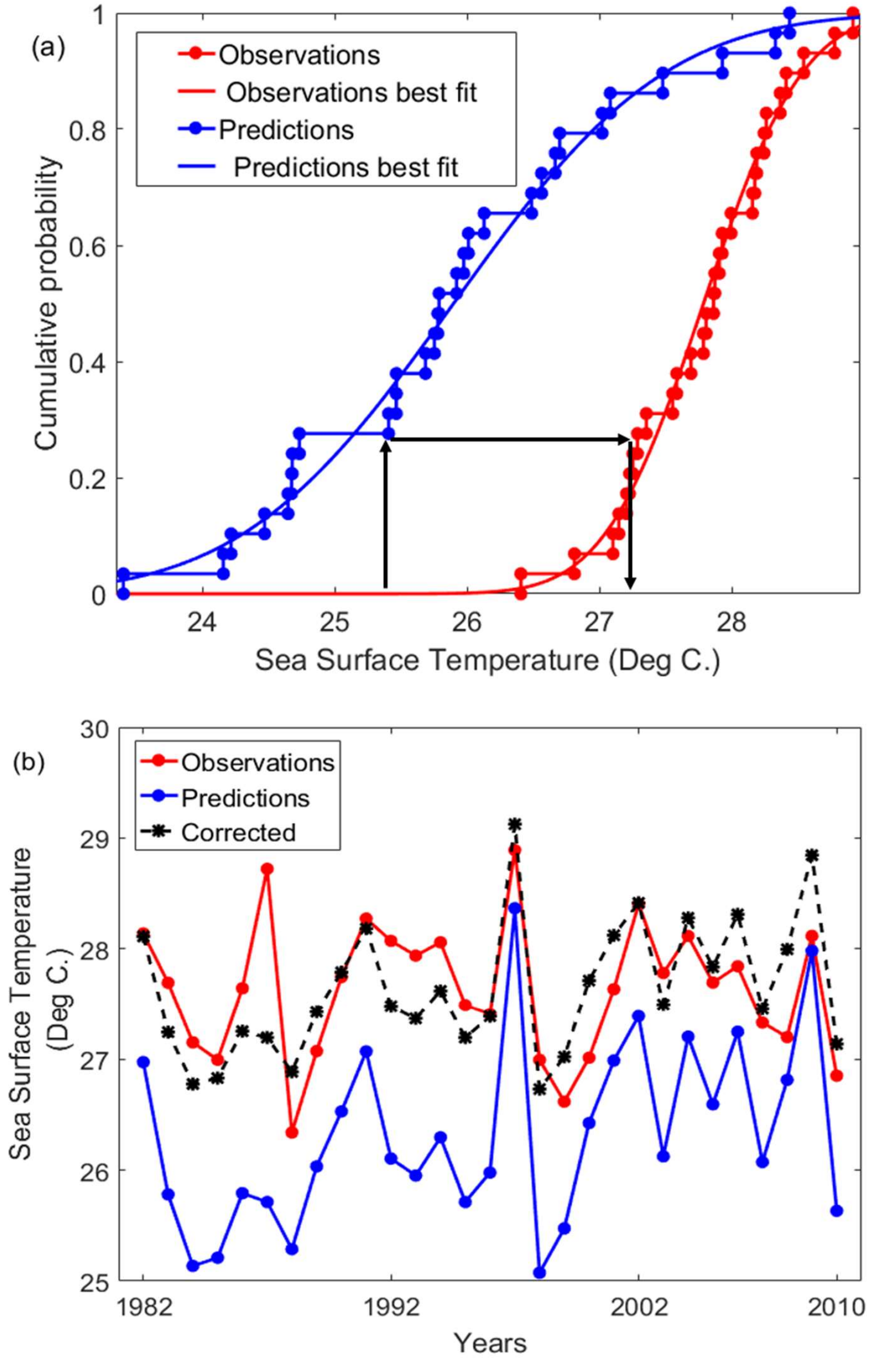

Figure 6: (a) Quantile mapping of predicted and observed NOAA NCEP CFSv2 Niño 3.4 sea surface temperature (SST) data, (b) observed, predicted and statistically corrected NOAA NCEP CFSv2 Niño 3.4 SST data

2.3 Allocation Forecast Model.

Allocation, as issued annually by JVRE, and storage outcomes are hindcast in a cross-validated mode for the period of record (1950 - 2015) by coupling the streamflow prediction models to a simple reservoir balance model. As previously mentioned, if allocations are reduced to less than the defined maximum of 1 liter per second, all rights are reduced equivalently across rights holders, per Chile's Water Code. The Puclaro operating rules adopted here focus on the end of water year (February 1st) target reservoir volume, set at 100 million cubic meters (50% capacity), which is consistent with current management practices for Puclaro Reservoir. To account for annual deviation from the end of water year storage target, allocation for ONDJ in year $i+1$ is adjusted by the difference between end of water year storage and the target in year i. Allocations may be larger if end of year storage exceeds target storage, or smaller if there is a shortfall in end of year storage, as shown by Eq. (1~~3~~), where

$$A_{i+1,ONDJ_{prediction}} = \frac{Q_{i+1_{prediction}}}{\frac{WR_u}{WR_D}+1} - \left(100Mm^3 - S_{i,Fe\ \ adjusted}\right) \tag{$1\cancel{3}$}$$

$A_{i+1,ONDJ_{prediction}}$ is the predicted allocation for ONDJ in year $i+1$. $Q_{i+1_{prediction}}$ is the prediction of inflow in year $i+1$, with streamflow predictions for the non-ONDJ months constructed by regressing median ONDJ streamflow predictions onto February – September streamflow observations to produce predicted February – September streamflow. WR_u and WR_D are the number of water rights upstream and downstream of Puclaro, respectively, and $S_{i,Feb_{adjusted}}$ is the previous end of water year adjusted storage volume, as shown by Eq. (2~~4~~), where

$$S_{i,Feb_{adjusted}} = S_{i,Sep_{prediction}} - (A_{i,ONDJ_{prediction}} - A_{i,ONDJ_{observation}}) \tag{$2\cancel{4}$}$$

$S_{i,Sep_{prediction}}$ is the predicted storage at the time of ONDJ allocation issuance in year i, and $A_{i,ONDJ_{prediction}}$ and $A_{i,ONDJ_{observation}}$ are the forecast-based and observed allocation values in year i. This adjusted volume (predictions – observations) accounts for storage deficit or surplus resulting from forecast-based allocations (forecasts ~~will not be perfect, i.e. not~~never perfectly match observations), and allows for adjustment of allocation in the following year~~ to either replenish the reservoir or provide additional allocation, respectively~~. Effectively, this accounts for the error in forecast-based allocations. The ~~purpose of carrying the ~~February storage shortfall or surplus ~~from February and~~is ~~using it as a constraint or benefit for~~applied to the subsequent October-January per-water right allocation value, ~~is that it recognizes~~as the storage target ~~as~~is non-binding (can be violated by over or under allocation in the previous year), but consequential, in the allocation model. ~~As such, the reasonable place to impose the effect is in terms of the following year's allocation. Effectively, it represents~~This functions as a mechanism ~~for the reservoir operator~~ to compensate for over or under allocation in the previous year. ~~In addition, reservoir replenishment from snow melt typically does not occur until December, which is three months after the allocation issuance date of September 1st, and such is the reason why a forecast is produced. The use of the deficit or surplus becomes a hedge against the uncertainty of the forecast. Ultimately, the carryover of deficit or surplus is one way to include the operational goal of the reservoir operators.~~

Annual per water right allocations based on forecasts of September 1st reservoir volume, probabilistic inflow predictions, and end-of-water-year target reservoir volumes, are reported as a probability of falling into three allocation categories: "Moderate" (≥ 0.5 Liters per second), "Severe" (0.5 Liters per second – 0.25 Liters per second), and "Extreme" (<0.25 Liters per second.) The selected categories are consistent with those used by the U.S. Drought Monitor to describe similar ranges of industrial, social and environmental impacts expected due to reduced access to water resources (Svoboda et al., 2002). Numerical thresholds assigned to the categorical boundaries align approximately with tercile values from the cumulative distribution of allocations derived from observed inflow and storage data, using the same reservoir operating rules as forecast-based allocations. Further, the breaks in categories closely follow decisions made by JVRE: a water right value of 0.5 liters per second is not uncommon and approximately represents the lower bound in normal years (Hearne and Easter, 1995); during the most recent severe drought (2009-2014) water right values of 0.2 liters per second were common (D. Betancourt, *personal communication.*)

2.4 Performance Metrics.

The performance of each cross-validated modeling approach is assessed deterministically (Pearson's correlation coefficient) and with a variety of categorical metrics to assess model skill in the prediction of specific categories, as opposed to a specific quantity or pattern (Regonda et al., 2006; Souza Filho and Lall, 2003). Two sets of categories are evaluated, as previously defined. The first is for streamflow hindcast prediction, with Above- (A), Near- (N), and Below-Normal (B) categories (ranges) based on a climatological distribution of observed ONDJ streamflow, each containing 33% of observations. The second is for per water right allocation hindcast prediction, applying the Moderate, Severe, and Extreme categories, as previous defined and contingent on reservoir storage and forecast inflow. Categorical outputs are illustrated with contingency tables, comparing predicted versus observed categorical occurrences. Perfect model skill occurs when the cross-validated predicted conditions match or 'hit' observed conditions~~.~~, which describes the categorical performance of the entire forecast in comparison to observations. ~~Equation (5) illustrates the 'Hit Score' summary metric, as applied by (Barnston, 1992), which describes the categorical performance of the entire forecast in comparison to observations, where~~

$$\cancel{Hit\ Score = \frac{\sum(Hits_A, Hits_N, Hits_B)}{n} \times 100\% \qquad (5)}$$

~~$\sum(Hits_A, Hits_N, Hits_B)$ is the sum of the count of years predicted correctly in each category, while n is the total number of years in the record.~~ Individual categorical Hit Scores describe under which flow conditions the model is most skillfull, and is the count of years predicted correctly in a category divided by the number of years observed in the same category. A 'Miss' results when the predicted value does not fall within the observed category. An 'Extreme Miss' constitutes a categorical prediction missing an observation by two categories (model predicts Above-normal while Below-normal is observed or vice-versa.) The 'Extreme Miss Score' ~~, as shown by Eq. (6),~~ is the fraction of the sum of ~~misses~~ times Above-normal is predicted but Below-normal is observed ~~($miss_{A|B}$)~~ plus the sum of ~~misses~~ times Below-normal is predicted but Above-normal is observed ~~($miss_{B|A}$)~~ and the total number of hindcast years. ~~, n,~~

$$\cancel{Extreme\ Miss\ Score = \frac{\sum miss_{A|B} + \sum miss_{B|A}}{n} \times 100\%} \qquad \text{~~(6)~~}$$

Ranked Probability Skill Score (RPSS) is a categorical measure of an ensemble prediction of each modeling approach compared to a reference forecast, in this case climatology (Saunders and Fletcher, 2004). ~~To calculate RPSS, the Ranked Probability Score (RPS), as shown by Eq. (7) must first be calculated for each simulation.~~

$$\cancel{RPS = \frac{1}{N-1}\sum_{n=1}^{N}\left[\sum_{c=1}^{n} p_c - \sum_{c=1}^{n} o_c\right]^2} \qquad \text{~~(7)~~}$$

~~The RPS is a measure of square differences in the cumulative probability of a multi-categorical hindcast ensemble, where N is the number of hindcast categories, p_c is the probability of the predicted value in category c, and o_c is a binary indicator with a value of one if the observation falls in category c, or a value of zero otherwise. The RPS ranges from 0 to 1, increasing for predictions farther from the observed outcome.~~

The RPSS ~~utilizes RPS, and~~ ranges from -∞ to 1; values between 0-1 indicate greater skill than simply using climatology (i.e. basing prediction on long-term averages), while RPSS values less than zero indicate predictions are inferior to climatology. An RPSS value is generated for each of year of the hindcast using Eq. (3~~8~~); the median RPSS value is reported.

$$RPSS = \frac{\overline{RPS} - \overline{RPS}_{reference}}{0 - \overline{RPS}_{reference}} = 1 - \frac{\overline{RPS}}{\overline{RPS}_{reference}} \qquad (3\cancel{8})$$

3 Model Performance.

3.1 Statistical and Dynamical Streamflow Prediction Models.

For each cross-validated streamflow modelling hindcast assessment (Stat-PCR: 1950 – 2015; Stat-Dyn: 1982 – present), a unique set of predictors and principal components are selected and evaluated with the categorical performance metrics (Pearson's correlation coefficient, 'Hit Score', 'Extreme Miss Score', and RPSS; Table 2.) As forecast lead increases, both Hit Score and RPSS decrease, while Extreme Miss Score increases. ~~These results occur because~~This is not surprising, as less ~~information regarding the~~ MJJA rainy season observations are~~is~~ available with increasing lead, which is consistent with decreased correlations between ONDJ streamflow and predictors (Fig. 5.)

Table 2: Stat-PCR and Stat-Dyn forecast model performance metrics

Forecast		Retained Predictors			PC1	PC2	Pearson's Correlation Coefficient	Hit Score	Extreme Miss Score	RPSS
Statistical Approach (Stat-PCR)	Sep 1st	Aug SM	JA Prcp	Aug 3.4	89%	-	0.88	53%	11%	0.31
	Aug 1st	Jul SM	JJ Prcp	Jul 3.4	63%	24%	0.63	50%	12%	0.02
	Jul 1st	Jun SM	MJ Prcp	Jun 3.4	44%	38%	0.49	31%	24%	*-0.39*
Dynamical Approach (Stat-Dyn)	Jun 1st	JJA 1.2	JJA Prcp	-	65%	35%	0.45	26%	50%	*-0.32*
	May 1st	JJA 3.4	JJA Prcp	-	58%	42%	0.41	21%	53%	*-0.41*
	Jan 1st	JJA 3.4		-	-	-	0.38	20%	57%	*-0.76*

For the Stat-PCR set of models, the predictors for each lead-time follow a similar pattern, utilizing soil moisture and SST from the month prior, and precipitation for the two months prior to the forecast date (e.g. September 1st forecast uses August soil moisture and SST, and July-August precipitation.) Snow water equivalent (SWE) is not retained as a predictor as its May-August correlation with October-January streamflow (Pearson's Correlation Coefficient = 0.68)~~, which~~ is not as strong as the correlation between precipitation and streamflow for the same lead, and arguably provides the same information to the model. As such, observations of precipitation are retained for the Stat-PCR model. The September 1st lead is promising, however for longer leads this relationship does not necessarily hold. An August 1st lead is approximately equivalent to using climatology, and by July 1st it is worse. For the Stat-Dyn modeling approach, using the mean of CFSv2 ensemble forecasts for MJJA precipitation, Niño 3.4 and 1.2 SSTs at Jun 1st, May 1st and January 1st lead times, produces low Hit, high Extreme Miss and negative RPSS scores (Table 2), confirming the challenges of predicting through the Spring Barrier.

The first principal component of the Stat-PCR September 1st forecast is highly correlated with SST in the Niño 3.4 region (0.88), which confirms that streamflow and therefore precipitation in the Elqui Valley are at least partially characterized by anomalous changes in SSTs. From a categorical perspective, the statistical model is most skillful in predicting Above-Normal streamflow years (Hit Score: 82%; Table 3); categorical outcomes for Near- and Below-Normal streamflow years were less successful (Hit Scores: 36% and 64%, respectively.) The large disparity between Above-, Near-, and Below-Normal categorical outcomes may be explained by evaluating cross-validated, global spatial correlation maps (1° x 1°) of ONDJ streamflow with the MJJA MEI, following Zimmerman et. al (2016.) The spatial correlation plots (1950 – 2015; Fig. 7) illustrate that years with positive MEI generally correspond with El Niño events and Above-Normal streamflow conditions, while years with negative MEI generally correspond with La Niña events and Below-Normal conditions. This produces a strong positive correlation (0.65) between streamflow and SST in the Niño 3.4 region during years with positive MEI, and a moderate positive correlation (0.29) during years with negative MEI in the equatorial Pacific Ocean, but slightly outside the common ENSO index regions. Correlation mapping between all years and streamflow produces a moderate correlation (0.35) in the common ENSO region, suggesting that El Niño years likely dominate this relationship. However, ENSO is non-linear, and the amount of moisture transported to the basin during El Niño or La Niña years will vary dependent upon strength (Meehl et al., 2001), and other factors, as previously discussed and illustrated in Fig. 4.

Table 3: September 1st Stat-PCR model categorical streamflow results: observed vs. forecast

		Forecast – September		
		B	N	A
Observed	B	14	3	5
	N	6	8	8
	A	2	2	18

Below-normal (B) Near-Normal (N) Above-Normal (A)

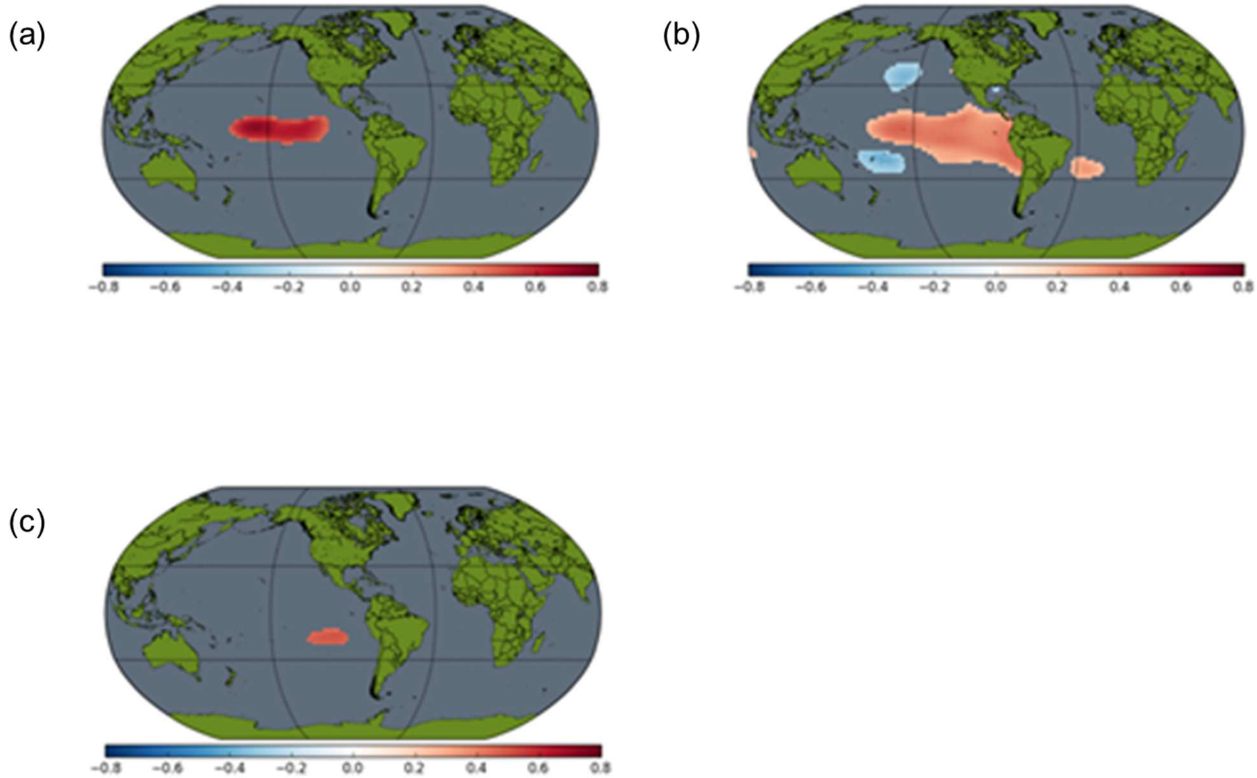

Figure 7: May-August global Multivariate ENSO Index (MEI) correlated with October-January streamflow at Algarrobal for: (a) positive MEI years, (b) all MEI years, (c) negative MEI years

3.2 ENSO Phase and Strength Streamflow Prediction Models.

To evaluate ENSO phase-specific models, the Stat-P&S approach is adopted. While several forecast leads and Niño 3.4 index windows were evaluated, the Stat-P&S model performs best for a May 1st forecast, when SSTs in the Niño 3.4 region are at least moderate in strength for a given phase [≥ +0.75°C (El Niño) or ≤ -0.75°C (La Niña)], or relatively neutral [within +/- 0.5°C departure from the long-term mean], for at least one month during January-April (JFMA; Table 4.) For 1950 – 2015, 60% of years qualify, triggering the May 1st Stat-P&S categorical prediction model. For moderate conditions (positive and negative), this produces categorical Hit Scores of 75% for Above-normal (El Niño) and 58% for Below-normal (La Niña.) For moderate La Niña only conditions, 7 of the 10 lowest ONDJ streamflow years on record are captured. The remaining three years of lowest ONDJ streamflow (1969, 1995, 2010) are predicted as Above-normal by the Stat-P&S model due to JFMA Niño 3.4 SSTs > 1.0°C (strong El Niño conditions.)

Table 4: Stat-P&S model categorical streamflow results: observed vs. forecast

		Forecast – May			
		B	N	A	DNF
Observed	B	7	2	3	27
	N	6	3	6	
	A	3	0	9	

Model does not forecast (DNF)

3.3 Coupled Statistical Prediction Models.

The Stat-P&S and Stat-PCR models each provide skillful forecasts, at different leads. While Stat-P&S performs best for a May 1st forecast lead, particularly for predicting high and low ONDJ streamflow, forecasts are issued only categorically; deterministic predictions from the Stat-PCR and Stat-Dyn models at this lead are relatively weak. That is, the Stat-P&S model relinquishes forecast determinism and in turn increases forecast lead in comparison to the Stat-PCR and Stat-Dyn approaches. The Stat-P&S ~~approach~~ model is also ~~hindered in only being~~ triggered ~~in~~ for only 60% of the period of record. The other 40% of years occur when Niño 3.4 SSTs, for at least one month during JFMA, are (+0.5°C, +0.75°C) or (-0.5°C, -0.75°C.) These ranges are transitional and do not provide skillful categorical forecasts for the May 1st lead. For this reason, the coupled statistical prediction model defers prediction ~~for~~in these years to September 1st, when the Stat-PCR model is ~~skillful~~skilful in producing ~~.” The Stat-PCR approach provides~~ deterministic forecasts of ONDJ streamflow~~, it is only skillful at a September 1st forecast lead, which may limit water rights holders ability to benefit from longer lead times.~~ ~~In contrast, while the Stat-PCR approach provides deterministic forecasts of ONDJ streamflow, it is only skillful at a September 1st forecast lead, which may limit water rights holders ability to benefit from longer lead times~~.

To address the limitations of both the Stat-PCR and Stat-P&S models, a coupled, sequential forecast approach is adopted which utilizes both the Stat-P&S and Stat-PCR models in the following manner:

Step 1. The Stat-P&S model issues a May 1st categorical forecast of ONDJ streamflow when the Niño 3.4 conditions are met. Otherwise no forecast is issued.

Step 2a. If the Stat-P&S model issued a May 1st forecast, the Stat-PCR model re-evaluates this prediction on September 1st forecast, updating ~~the forecast~~ as necessary, and provides a deterministic forecast.

Step 2b. If the Stat-P&S model *did not* issue a May 1st forecast, the Stat-PCR model produces ~~the first~~a deterministic forecast on September 1st.

For performance evaluation, a categorical hit by Stat-P&S model becomes a miss if Stat-PCR model predicts a different (and wrong) category. The Stat-PCR model may also correct a categorical miss by the Stat-P&S model. The May 1st Stat-P&S and September 1st Stat-PCR coupled forecast model revels a large degree of categorical forecast consistency (change between Table 4 and Table 3.) The Stat-PCR model only predicts a different category than the Stat-P&S model in two of the 39 years evaluated, and for these two cases, it changes extreme misses (least desirable outcome) to hits. One such change was for the year 1995, one of the three lowest years of ONDJ streamflow not correctly categorized by the Stat-P&S model (initially predicted Above-normal while Below-normal streamflow observed.) Thus, the coupling of these two Stat models appears to perform superiorly as compared to models individually by skillfully increasing the prediction lead time and allowing for prediction updating, as necessary.

3.4 Allocation Prediction Model

A streamflow prediction-reservoir water balance model system is used to evaluate the performance of water right allocations, as compared with using streamflow observations and streamflow climatology, for a September 1st issuance. Utilizing streamflow observations is synonymous with a perfect forecast. The system is tested in hindcast mode using streamflow median and 80th percentile streamflow prediction scenarios of ONDJ streamflow separately. Both the median and 80th percentile approaches outperform climatology, achieving Hit Scores of 53%, as compared with only a 30% Hit Score using climatology (Table 5.) Additionally, the climatological median fails to predict any years with Extreme reductions (< 0.25 liters per second); the climatology-based approach over-allocates in 55% of years, as opposed to only 27% of years when applying the 80th percentile forecast approach. This is noteworthy from a management perspective, as over-allocation is often considered more problematic than under-allocation from a long-term, drought-focused perspective. The distributions of forecast-based allocations also more closely match observations than climatology, with the median and the 80th percentile forecast scenarios exceeding observation-based allocations by only 0.06 and 0.04 liters per second, respectively, on average (Fig. 8(a.) Over-allocation using climatological streamflow is again evident, as the interquartile range (IQR) of climatological allocations does not align with observations. While the IQR of the forecast-based scenario is larger than the observation-based scenario, it does not systematically over-allocate (Fig. 8(a.) This can also be illustrated by calculating the ratio of each approach (climatology and forecasts) to observed allocations (Fig. 8(b.) In this case, a perfect score would be a consistent value of one, as a climatological or forecast allocation would match each observation-based allocation. The forecast-based allocation ratios produce smaller IQRs and lower median values than climatology-based allocations, implying that the forecasts are better aligned with observations and slightly more conservative.

Table 5: Categorical water right allocation results: observed vs forecast

Median Forecast **Hit Score 53%** **Extreme Miss 5%**		Forecast – Sep		
		Extreme < 0.25 L/s	Severe ≤0.5 L/s	Moderate ≥0.5 L/s
Observed	Extreme	10	11	1
	Severe	5	8	9
	Moderate	2	3	17

80th Percentile Forecast **Hit Score 53%** **Extreme Miss Score 3%**		Forecast – Sep		
		Extreme < 0.25 L/s	Severe ≤0.5 L/s	Moderate ≥0.5 L/s
Observed	Extreme	11	11	0
	Severe	6	9	7
	Moderate	2	5	15

Climatology **Hit Score 30%** **Extreme Miss Score 2%**		Forecast – Sep		
		Extreme < 0.25 L/s	Severe ≤0.5 L/s	Moderate ≥0.5 L/s
Observed	Extreme	0	21	1
	Severe	0	9	13
	Moderate	0	11	11

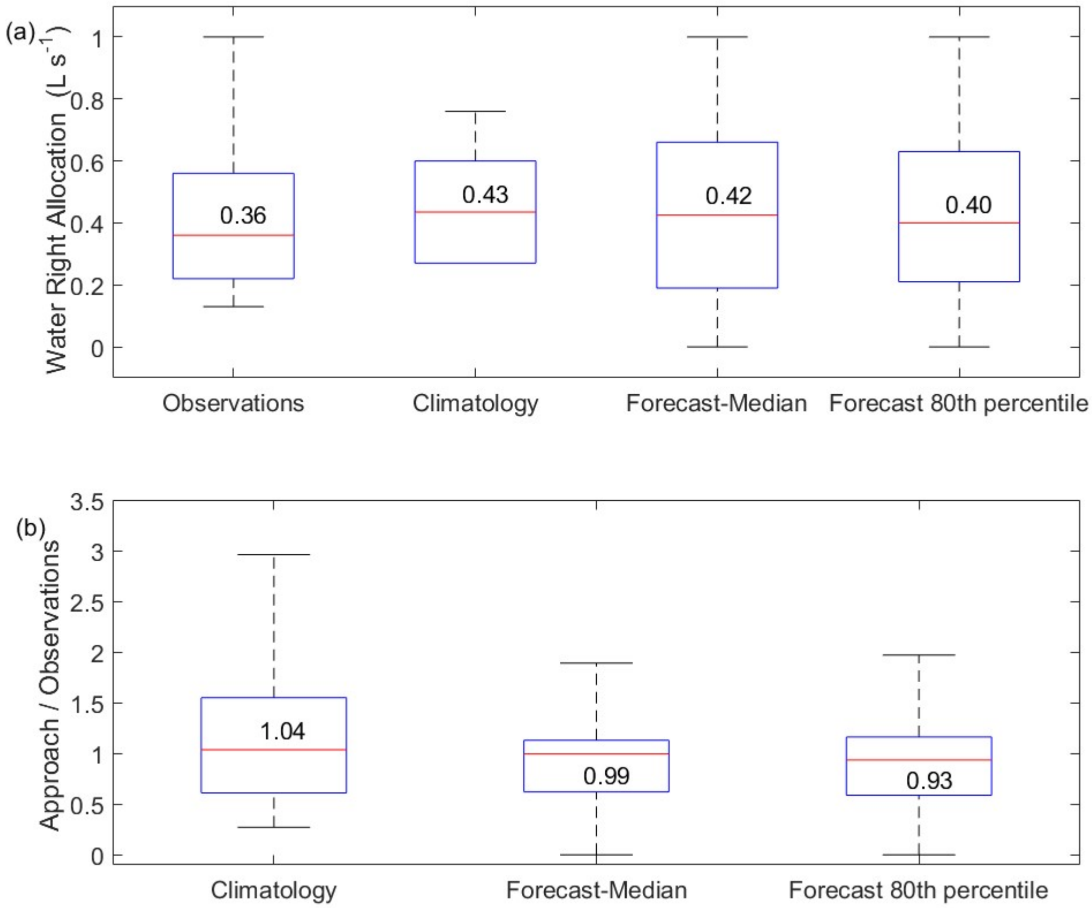

Figure 8: Reservoir model-derived forecast allocations: (a) absolute allocation values, (b) ratio of forecast allocations to observed allocations

The probabilistic modeling approach also allows for an understanding of categorical forecast certainty and strength, that is, the degree to which the model suggest a category (Fig. 9.) In this case, the forecast-based allocations more often indicate a stronger forecast tendency (higher probability) toward one category, whereas the climatology-based allocations often indicate a weaker tendency to shift. While this is not always the case, from a reservoir management perspective, climatology-based allocations provide less actionable information, as the strength of the predicted categories are often not too dissimilar, even in years where correct predictions are made. In contrast, for the 28 years where forecast-based allocations of a category exceed 80% (a strong prediction), the Hit Score is 79%, a high success rate, and further, no extreme misses occur (Moderate category predicted, Extreme category observed), avoiding over-allocation in dry years.

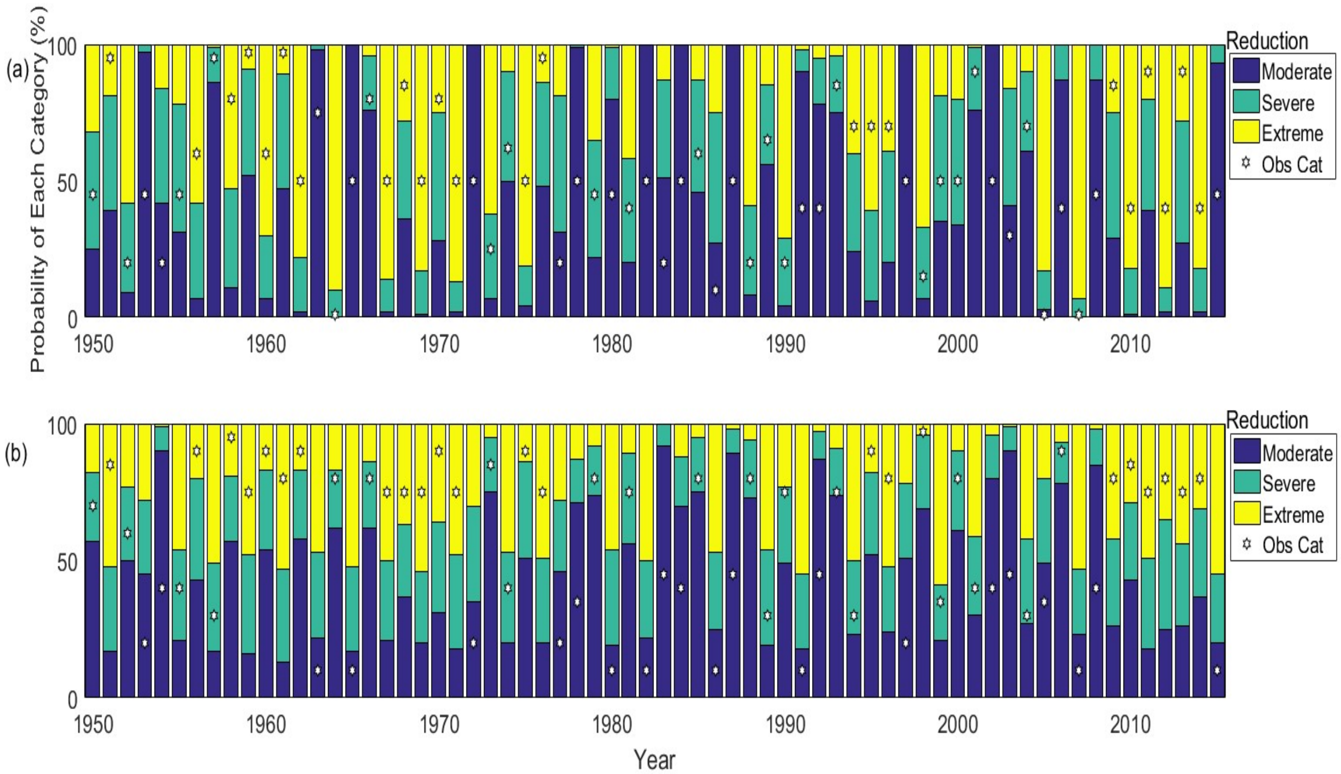

Figure 9: Probabilistic water right allocation forecast using (a) September 1st PCR-Stat model 80th percentile, (b) long-term averages (climatology)

The effect of over- and under-allocation by both forecast- and climatology-based approaches on end of year reservoir storage is also evaluated. Large deviations from the 100 million cubic meter target volume (February 1st) are viewed as problematic to the JVRE and water rights holders (Fig. 10.) The prior analysis demonstrates the propensity for the climatology-based approach to consistently over-allocate, resulting in reservoir volumes consistently below the target. The forecast-based scenarios have a smaller IQR with median values approaching the target value. The climatology-based approach also allocates the full reservoir volume in 33% of years (leaving the reservoir empty), which happens in only 11% of years under the forecast-based scenarios, due to prediction error (Fig. 10.)

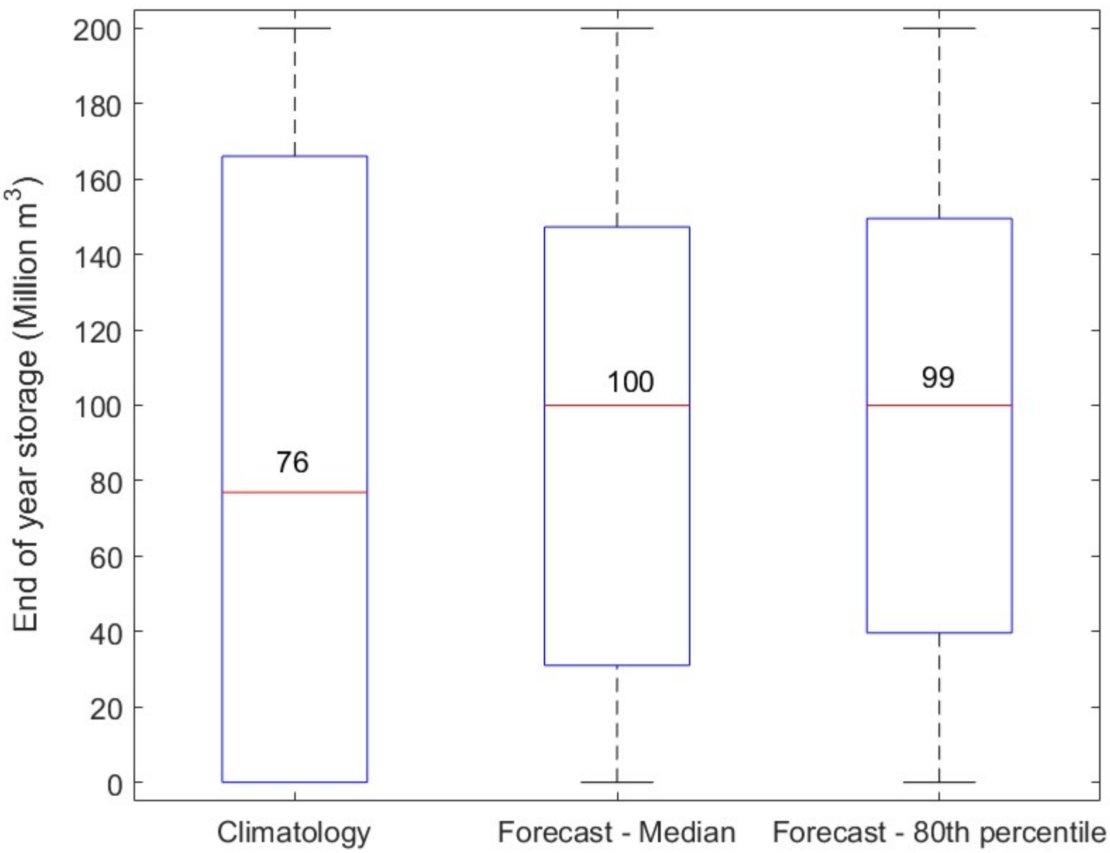

Figure 10: End of year reservoir storage under three allocation approaches; 100 M m^3 is the target

4 ~~Summary and~~ Discussion~~.~~

~~While~~ T~~t~~he frameworks developed here, although ~~are~~ applied specifically to the Elqui Valley~~,~~ in Chile, can provide a broad pathway for ~~water resource~~ managers and ~~water~~ rights holders in water rights ~~driven~~managed basins ~~could~~to benefit from ~~the~~ streamflow forecast-informed ~~and~~ reservoir allocations. ~~While~~Although streamflow ~~the model~~ predictions ~~of streamflow~~ hold modest skill for the Elqui, the coupling of the Stat-P&S and Stat-PCR models, and subsequent coupling of ~~streamflow~~ forecasts ~~to~~with the human managed allocation framework, provide for increases in system efficiency as compared with climatology based forecasts. Specifically, the ~~The~~ Stat-PCR streamflow prediction-reservoir water balance model system produces values closely matched with observations over the historical period, and each forecast (median, 80th percentile) outperforms climatology. Use of the 80th percentile Stat-PCR forecast is intended to represent risk aversion; however, the probabilistic framework allows assessment for any risk preference. Ensemble predictions illustrate the general propensity of a climatology-based allocation to provide limited actionable information in contrast to forecast-based allocations, which exhibit enhanced skill when the model issues strong predictions (>80% categorical likelihood.) However, in years when the Stat-PCR forecast-based allocation model issues a weak prediction (no dominant tendency toward any specific category) other allocation decision frameworks may be worth investigating (e.g. allocation based on existing storage only as a hedge against inflow uncertainty.) The development and implementation of the probabilistic framework by reservoir managers, as a mechanism to convert streamflow forecasts into forecast allocations, may arguably ~~constitute a more appropriate~~necessitate a higher level of communication with water rights holders~~, as opposed to the current forecast structure (inflow to the reservoir)~~. Probabilistic forecasts can provide option value to water rights holders~~,~~ if the strength of the category predicted would alter water rights holders' decisions (e.g. change~~s~~ cropping decisions, ~~drives~~prompt water procurement or sales) acting under the presumption of economic rationality. This hypothesis may also be worth investigating.

Selection of categorical thresholds (three for this case study) is based on equal distribution of observations, and does not necessarily represent the preferences of reservoir managers or rights holders, however these thresholds ~~can be updated~~are easily adjustable. For example, if only two categories are ~~used~~selected as ~~,~~allocations above and below 0.75 L/s, the Hit Score rises to 92%, which could be representative of some productivity threshold (e.g. crop water requirement). The framework is thus sufficiently flexible to allow m~~M~~anagers ~~are thus free~~ to select categories which ~~suit their needs or~~ reflect true differences in the utility of allocations to water rights holders.

While the approaches in this research are mostly a demonstration of concept, the model framework is consistent with the current operations of Puclaro Reservoir, ~~but~~however it is not optimized ~~for or~~to hedge against expected future (multi-year) conditions. While the model may be informative over the long-term, resulting in allocation and storage values better matched ~~to~~with observations than climatology-based allocations, it performs poorly in certain years, most notably during the 2009 – 2015 hydrologic and meteorological drought (Fig. 9(a.)) While poor model performance during this period is undoubtedly due in part to the limited reservoir operating rules, the Stat-PCR approach tends to under predict extremes, especially when they occur consecutively. Further forecast model development will focus on improving predictive skill of extreme events, particularly dry periods, making use of non-parametric methods and additional multi-model approaches, and dynamic rule structures and simulation techniques. Even so, adoption of the approaches presented here by water managers and rights holders bodes well for improved economic efficiency and benefits across the Elqui Valley.

~~The dynamic nature of ocean, atmosphere and terrestrial interactions, which contribute to moisture transport in the Elqui Valley, are undoubtedly complex and challenge hydrologic prediction models at increasing leads.~~ ~~The mixed success of streamflow forecasts currently in use for the Elqui reflect this.~~ ~~The mixed success of streamflow forecasts currently in use for~~

~~the Elqui reflect this. In this work, correlation and composite mapping suggest moisture transport to the Elqui Valley is dependent on the phase, strength and timing of many variables (Fig. 4.) While austral winter precipitation, SST, and soil moisture correlations with ONDJ streamflow at varied leads are encouraging (Fig. 5), the Stat-PCR approach, which makes use of these predictors, is skillful only at a September 1st lead, as indicated by RPSS scores and other forecast validation metrics (Table 2.) The Stat-Dyn approach, using precipitation and SSTs, results in inferior outcomes compared with the Stat-PCR model. The Stat-P&S model, however, provides skillful predictions of ONDJ streamflow at a May 1st lead, albeit categorically and is triggered in only 60% of the period 1950 – 2015.The coupling of the Stat-P&S and Stat-PCR models to produce initial (May 1st) and updated (September 1st) forecasts may be valuable to both reservoir managers and water rights holders. From a reservoir management perspective, properly setting the per right water allocation (September 1st) is critically important to satisfy rights holders and maintain adequate reservoir storage for the uncertain future. The Stat-PCR component of the coupled model provides skill superior to climatology, and is perhaps sufficient to inform these decisions. Reservoir managers, however, are also expected to provide a non-binding May 1st forecast, upon which rights holders, specifically farmers who have crop choice flexibility and/or water right leasing potential, may choose to utilize in preparation for the ONDJ growing season (e.g. determine whether to supplement through the water market.) The Stat-P&S categorical forecast with a May 1st lead can inform these longer planning actions. The strong categorical consistency between the May 1st Stat-P&S and September 1st Stat-PCR forecasts may also serve to reinforce confidence in the forecast outcomes; the two models only differ in prediction categories twice in 66 years.~~

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5 Conclusions.

The focus of this research is to develop an understanding of the mechanisms contributing to austral summer streamflow in the Elqui Valley, investigate model skill at varied forecast leads, and produce forecast-based water-right allocations to inform water resources management decision-making. Like many regions, the dynamic nature of ocean, atmosphere and terrestrial interactions, which contribute to moisture transport in the Elqui Valley, are undoubtedly complex and challenge hydrologic prediction models at increasing leads. The mixed success of streamflow forecasts currently in use for the Elqui reflect this. ~~This work establishes~~Here, a framework is established by which streamflow forecasts can be produced and coupled with human managed allocation systems to promote equity and efficiency in the use of limited water resources.

Correlation and composite mapping suggest moisture transport to the Elqui Valley is dependent on the phase, strength and timing of many variables (Fig. 4.) While austral winter precipitation, SST, and soil moisture correlations with ONDJ streamflow at varied leads are encouraging (Fig. 5), the Stat-PCR approach, which makes use of these predictors, is skillful only at a September 1^{st} lead, as indicated by RPSS scores and other forecast validation metrics (Table 2.) The Stat-Dyn approach, using precipitation and SSTs, results in inferior outcomes compared with the Stat-PCR model. The Stat-P&S model, however, provides skillful predictions of ONDJ streamflow at a May 1^{st} lead, albeit categorically and is triggered in only 60% of the period 1950 – 2015.

The broader insight gained is in the coupling of the Stat-P&S and Stat-PCR models to produce initial (May 1^{st}) and updated (September 1^{st}) forecasts which may be valuable to both reservoir managers and water rights holders. From a reservoir management perspective, properly setting the per right water allocation (September 1^{st}) is critically important to satisfy rights holders and maintain adequate reservoir storage for the uncertain future. The Stat-PCR component of the coupled model provides skill superior to climatology, and ~~is perhaps sufficient to inform these~~likely better informs allocation decisions. Reservoir managers, however, are also expected to provide a non-binding May 1^{st} allocation forecast, ~~upon which~~allowing rights holders, specifically farmers ~~who have~~with crop choice flexibility and/or water right leasing potential, ~~may choose to utilize in preparation for the ONDJ growing season (e.g. determine whether~~ to supplement through the water market as necessary.~~)~~ The Stat-P&S categorical forecast with a May 1^{st} lead can inform these longer planning actions. The strong categorical consistency between the May 1^{st} Stat-P&S and September 1^{st} Stat-PCR forecasts may also serve to reinforce confidence in the forecast outcomes; the two models only differ in prediction categories twice in the 66 years evaluated. The conclusion here is that coupled forecasts need not be strictly deterministic, and using early categorical forecasts to provide an indication of expected conditions, and reinforcing the prediction with a revised deterministic forecast as more observations of local variables (e.g. precipitation) become available may be useful for water rights holders. In addition, linking ~~of~~ the streamflow forecast with the human managed allocation system is broadly relevant as a mechanism ~~which might be used~~ to promote efficiency in the use of limited water resources. ~~The reservoir allocation model is skillful at the September 1st lead (categorical hit skill score = 53%), and using a probabilistic modelling approach, forecast-based allocations are categorically skillful (79%) when the model predicts the observed allocation category with at least 80% certainty. In total, T~~The frameworks presented here addresses the unique set of circumstances ~~posed by the Elqui Valley, Chile~~in water rights managed basins, and ~~but~~ represents an advancement in linking season-ahead ~~season~~streamflow forecasts to water resources systems. ~~The Stat-PCR~~

~~streamflow prediction-reservoir water balance model system produces values closely matched with observations, and each forecast (median, 80th percentile) outperforms climatology. Use of the 80th percentile Stat-PCR forecast is intended to represent risk aversion; however, the probabilistic framework allows assessment for any risk preference. Ensemble predictions illustrate the general propensity of a climatology-based allocation to provide limited actionable information in contrast to forecast-based allocations, which exhibit enhanced skill when the model issues strong predictions (>80% categorical likelihood.) However, in years when the Stat-PCR forecast-based allocation model issues a weak prediction (no dominant tendency toward any specific category) other allocation decision frameworks may be worth investigating (e.g. allocation based on existing storage only as a hedge against inflow uncertainty.)~~

~~Selection of categorical thresholds is based on equal distribution of observations, and does not necessarily represent the preferences of reservoir managers, however these thresholds can be updated. For example, if only two categories are used, allocations above and below 0.75 L/s, the Hit Score rises to 92%. Managers are thus free to select categories which suit their needs or reflect true differences in the utility of allocations to water rights holders.~~

~~The focus of this research is to develop an understanding of the mechanisms contributing to austral summer streamflow in the Elqui Valley, investigate model skill at varied forecast leads, and produce forecast-based water-right allocations to inform water resources management decision-making. While the approaches in this research are mostly a demonstration of concept, the model framework is consistent with the current operations of Puclaro Reservoir, but is not optimized for or hedge against expected future conditions. While the model may be informative over the long-term, resulting in allocation and storage values better matched to observations than climatology-based allocations, it performs poorly in certain years, most notably during the 2009 – 2015 hydrologic and meteorological drought (Fig. 9(a.) While poor model performance during this period is undoubtedly due in part to the limited reservoir operating rules, the Stat-PCR approach tends to under predict extremes, especially when they occur consecutively. Further forecast model development will focus on improving predictive skill of extreme events, particularly dry periods, making use of non-parametric methods and additional multi-model approaches, and dynamic rule structures and simulation techniques. Even so, adoption of the approaches presented here by water managers and rights holders bodes well for improved economic efficiency and benefits across the Elqui Valley.~~

Code Availability.

Should future reproduction of results become necessary, any codes will be made available, by the corresponding author, upon request.

Data Availability.

The data used to produce this research come from open sources, including the Chilean Ministry of Public Works – Dirrecion de Aguas (DGA) and the National Oceanic and Atmospheric Administration. Through use of the International Research Institute's Data Library, all relevant data sets may be obtained.

Appendices.

None.

Supplemental Link.

To be included by Copernicus

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Author Contribution.

Justin Delorit, Edmundo Cristian Gonzalez Ortuya, Paul Block each contributed to the hydroclimatological analysis, developed model code and evaluated simulations.

Competing Interests.

None.

Disclaimer.

To be added later.

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