We would like to thank both reviewers for their time and constructive feedbacks. Please find below our clarifications and actions taken. Changes are referenced with line numbers in the revised manuscript. These line numbers are the same for the final and "tracked-changes" versions.

Reviewer 1

Referee Comment: This paper contributes 1) the novel notion of "horizon curve", i.e., a week-by-week assessment of the forecast horizon that is most relevant to release decision during a certain week, and 2) a methodology to derive this curve, with an application to a number of CONUS dams. This methodology is complemented by a random forest analysis to link results with dam characteristics, and with an illustration that integrating horizon curve within a release rule can improve the fit with observations. The idea is creative and very timely, as modelers are working to improve the representation of reservoir release rules within hydrological models. Its strength lies in trying to summarize complex forecast processes, based on disparate and often site-specific information (as authors discuss in the paper), with a single vector mapping the forecast horizon as a function of time of year. Authors are able to substantiate their results with supplemental analysis, and to interpret the results for a range of different situations (this also demonstrates that the methodology works well enough to adapt the results to these different configurations). The paper is also well-written. Overall, this fits well within the remit of HESS both in terms of scope and quality.
Author Response: Thank you for your thoughtful and constructive review.

Referee Comment: Authors correctly identify (line 113-136) that stationarity in operations and forecast availability is a necessary assumption (and / or limitation) here, but they don't actually use the word or relate it to hydrological (non-)stationarity. I would advise authors to move that paragraph to the discussion and relate their assumption to climatic, operational and forecast stationarities: all of them refer to sources of information that reservoir operators may rely on and that may (or do) vary over time.
Author Response: We agree that the term stationarity would help readers better understand this limitation and that the issue should, in part, be related to hydrological non-stationarity (although we suspect the most important driver of non-stationarity in operating rules would be introduction of environmental flow regulations).
Changes to manuscript: We have added some discussion on the idea of non-stationarity **[*LINES 351 – 356]***.

Referee Comment: Discussion and Figure 8: it is unclear what the release rule is and how exactly the horizon curves have been incorporated to it. Improved results from integrating horizon curves within the release rule representation are the exclamation point to this paper (and authors are right to mention in the abstract), so the appropriate details should be given. This should be presented in the methodology (Section 2) as an example of how horizon curves can be implemented in practice. Then results should be described at the end of Section 3 instead of in the discussion. Then lines 21-23: the statement is far too general and assertive. Authors only show that integrating forecast information CAN improve performance, using an unspecified release rule at selected sites.

Author Response: Thank you for highlighting this missing piece of information. The release is computed from the set of optimal piecewise functions (one for each week) that result in the closest fit when generating the horizon curve for each dam. For example, if the best piecewise function for water week X uses a 7-week ahead horizon, then that function will be used to determine the release in re-simulation for week X. We agree that we should expand the method to clarify this for readers.
Changes to manuscript: (1) we have expanded the method section to describe how the release rule is generated as part of the horizon curve derivation ***[LINES 198 – 201]***; (2) move the associated figure into the results section, and (3) change the text in the abstract so that our claim (horizon curve improves simulation performance) reflects the limited nature of the simulation analysis involving eight reservoirs in offline mode ***[LINES 21 – 22]***.

Referee Comment: With this Figure 8 description of how accounting for the horizon curve can improve the representation of reservoir operations, authors may be missing an opportunity by only using the RMSE of release as a performance indicator. This is a general comment that could be better qualified by focusing on very high or very low simulated flows. For instance, they could use goodness-of-fit indicators especially designed to highlight the quality of the fit for high or low flows (see van Werkhoven et al., Advances in Water Resources 32 (2009) 1154–1169). Alternatively, they could define a reservoir's spill as the outflow beyond the maximal quantity of water that can go through hydropower turbine in a day, and look at spill RMSE. Integrating forecast would likely have a significant effect on spills, e.g., in a case like Lake Powell.
Author Response: We had actually looked at some other metrics and decided to present just RMSE for simplicity (we reach similar conclusions with NSE and KGE). We agree that the metrics that assess performance of low flows would be a particularly useful addition.
Changes to manuscript: We have tabulated performances across a range of metrics ***[LINES 318 – 322]*** for each reservoir in a table supporting Figure 8 ***[TABLE 1, LINE 575]***.

Referee Comment: A final, general comment is that in the absence of pointers on what the forecast information is, the forecast information might well be the expected average inflows conditions – involving no actual forecast at all. This should be clarified.
Author Response: We can confirm that the process completely avoids inferring as forecasts any operations tailored to average seasonal inflow conditions. Operations tailored to average inflows are a function of time-of-year and can therefore be intercepted by performing the forecast derivation on individual weeks (see short comment posted in immediate response to your review as well as the rewrite of the method section).
Changes to manuscript: We have rewritten this section in the manuscript to demonstrate clearly that our procedure avoids detecting foresight in operations as a result of expected average inflows ***[LINES 126 – 137]***.

Minor comments:

- Line 59: please replace "hydrology" by "hydrological" ***[done – LINE 62]***.
- Line 93: mention that October 1st is the start of the hydrological year ***[done – LINE 96]***.
- Line 106: it would be good to tell right there (maybe with an equation) how exactly fit is computed, and justify choice of formula ***[done - LINES 109 – 112]***.
- Section 2.4 and line 271: it would be useful to precisely define F1 score, precision and recall ***[done - LINES 590 – 596]***.

Reviewer 2

Referee Comment: In this submitted manuscript, the authors applied a conceptual method to analyze 316 dams and reservoirs in the U.S. with respect to the roles of forecast information in driving the discharge operations. Using the proposed “horizon curves”, authors specifically analyzed the relationship of forecast information and operation for four key dams, in order to test whether the proposed method could improve the modeling capability of large-scale hydrological studies with the interference of reservoirs and dams. The study was originated from the fact that water managers nowadays will rely more and more on hydrological forecasts as the information of forecast range, resolution, and accuracy have been improved by various methods. However, it is still unknown how important and how influential a forecast could essentially improve the reservoirs and dams operations. One of the contributions of this study is to analyze a large number of dams in the United States based on limited reservoir operation data. In addition, a new concept of “horizon curves” has been proposed by authors. Using the proposed method, this study also tries to answer the question of “how and when do forecasts applied in the field of reservoir operations”. In general, the scope of the submitted manuscript is indeed very interesting, and the main contribution & novelty lies in the invention of the concept of “horizontal curve” for reservoir operations. However, the reviewer thinks there are a few key assumptions are questionable when authors develop the “horizon curve” method. Those assumptions are subject to verification and further investigation. In addition, the reviewer also finds the organization of the manuscript is confusing, and few paragraphs in the methodology section are hard to follow due to missing steps or information.
Author Response: Thank you for your constructive review. We are confident that we can address each of your concerns through clearer method description.

Referee Comment: Methodology Justification (Line 85-86) The proposed approach is based on the assumption that 1) “the future observed inflows (perfect forecast) may act as a proxy for the actual forecast available to the operator at the time of deciding how much water to release”. However, in reality, reservoir operators never trust a single forecast, at least the forecast uncertainty needs to be considered when making any release decision. More importantly, most of the releases are pre-defined by the reservoir “rule curves” with limited influences from the forecasts. Regardless of the forecasts in different ranges and accuracy, reservoir operators always and have to releases a certain amount of water at a certain time following the “rule curves”. Therefore, the reviewer is unclear how the forecast information based on the “horizon curves” could actually interact with the existing operating rules. The manuscript seems to omit this linkage between forecasts and the hard rules reservoir operators must follow. The rule curves are even more important in terms of mid to long-term operations, which is the same time range this study has been focused on. Different reservoirs have different rule curves, and it would vary from one reservoir to another. The proposed method of “horizon curves” seems to be a universal approach for any reservoirs. Reviewer is wondering the applicability of the “horizon curves” as each reservoir will have different settings and “rules” to follow as regulated by USACE or relevant water agencies. How does the proposed “horizon curves” could address different reservoir regulations and functions, such as hydropower reservoir vs. flood control reservoir vs. water supply reservoir vs. environmental demands?

Author Response: Thank you for this comment as it allows us to clarify the application of horizon curves. We agree that we ought to show how the two-stage release function we propose aligns with rule curves and reservoirs that serve multiple functions. Let's first assume that forecasts are not used at all and that we simply want to use the storage volumes to set the release for any given week of the year (as in archetypal rule curve). Our scheme actually allows us to do this very effectively. The two-stage piecewise model provides the flexibility to represent two situations: (a) the reservoir is above the guide-curve, in which case one would expect the operator to respond by releasing water to draw the reservoir back down (with higher release for higher storage levels—allowed for by the right-hand slope of the piecewise function); and (b) the reservoir is below the guide-curve, in which case the operator would wish to cut back the release significantly to allow the reservoir to refill. For (b), the operator would be constrained by the fact that release cannot be negative and that some environmental flow will normally be required, so we add a constraint to our model so that the slope for (b) must be less than for (a). Assuming the operator works only to meet a guide-curve based on storage levels and time of year, our model is ideal. The breakpoint of the piecewise function on the x-axis (water availability) essentially represents the reservoir guide-curve level (since water availability is just storage volume when there is no inflow forecast). Since these rules are optimized to fit observations for each water week and for each reservoir individually, they do indeed account for the differences across the year and across dams. The model is trained on observed decisions, so is agnostic as to whether the reservoir is used for flood control, irrigation, hydropower, etc. It mimics how water is released in practice, so will in effect capture any of these purposes. We must also recognize that these rules are somewhat flexible in the sense that operators will deviate from them depending on forecast information available. Our scheme is designed to allow us to integrate forecast information in the rule-based system. The difference is that the rule is no longer a function of current storage, but becomes a function of current storage plus the inflow out to various candidate horizons, with the candidate horizon offering the best fit to observed decisions taken as the assumed operational horizon in the inferred horizon curve. We agree that operators are more likely in practice to use a forecast ensemble than a deterministic forecast. Given the large scale of our study and the intended application (ultimately a CONUS-scale hydrological and river-routing model) we require a simple proxy for the forecast information available to the operator. Our results demonstrate that the actual, future inflow serves this purpose well in many cases.
Changes to manuscript: We have amended the method section to explain how our chosen model is compatible with reservoir guide-curves used in real-world operations for a variety of purposes ***[LINES 114 – 125]***. We have also added to the discussion to highlight the limitation that our model is based on the assumption of deterministic forecast-use ***[LINES 345 – 346]***.

Referee Comment: The steps of horizon curve method (Line 80-120) The reviewer cannot fully understand the whole process of deriving the horizon curve. For example, in line 98, the authors mentioned the "release-availability" function for the first time in the manuscript and then briefly explained the definition of "availability a". How do the authors define "release-availability" here? How did authors construct the functions of "release- availability"? The possible releases must be from the existing operating rules to prevent overtopping and dead-pool of reservoir storage. Where do authors obtain such information in a national scale? This is a term again not commonly used by water managers, and more explanations would be needed. The authors also wrote, "The inferred policy function fitted to these data is a piecewise linear model with a single breakpoint" in line 99 and the reviewer is wondering what does the "policy function" here refer

to? And what do “these data” referred to as? In general, the reviewer thinks this section is hard to follow given lots of non-common terms were used. Those wordings may make sense to authors themselves, however, it is not apparent to water managers and operators. Please re-check some of the literature and especially reservoir operation reports to further explain how the proposed method is constructed in detail. A flowchart or additional figure may be added to explain the steps of creating this horizon curves.
Author Response: Our model is indeed quite complex. Figure 1 was designed to help the reader in this regard, but on reflection we agree that the explanation would be enhanced with a flow chart outlining the process and data used at each stage. The release-availability function is the key to the whole approach. This is simply a relationship (derived for each water week and defined by a broken linear model with two lines and two slopes) that specifies the water release as a function of water availability. These are constructed using observed records of release, storage, and inflow—so the releases are from existing operations designed to prevent overtopping and dead-pool of reservoir storage. We obtain these records from five sources: US Army Corps of Engineers, US Bureau of Reclamation, US Geological Survey, California Data Exchange, and Texas Water Development Board. These are listed in the experimental setup of the manuscript. We used “policy function” and “release-availability” function interchangeably, which we agree is confusing for readers and should be amended.
Changes to manuscript: We have defined the release-availability function more clearly ***[LINES 100 – 101; 103 – 104; 109 – 112]*** (keeping terminology consistent throughout) and have replaced Figure 1 with a flow diagram to guide the reader through process of deriving the horizon curve in an example case ***[PAGE 19]***.

Referee Comment: The use of Random Forest Classifier (Line 160 - 170): There are few nested issues about the description on the use of Random Forest Classifier, experiment setting, and how will these experiment settings lead to a conclusion related to the forecast information and reservoir operation. First, authors should point out what are the “features” and “target” when using Random Forest Classifier. The authors mentioned there are 26 features without a tabular form to let readers know what those are. In addition, the “target” used in RF is still unclear. Did the authors intend to figure out which feature has the most important influences on release decisions? Or did the authors intend to classify reservoirs according to their correlation between discharge and inflow fore- casts? And how was this realized in RF? The description here reads very short and is not comprehensive. Reviewer is confused about what has been classified based on what inputs, as well as how this experiment setting would lead to a certain conclusion. At least a few additional paragraphs would be necessary to explain the experiments here.
Author Response: Thank you. We did indeed define the target, but we referred to it as the “response variable” in the method (“*The response variable is a Boolean of whether there is evidence for significant forecast contribution or not*.”) In other words, the target is a simple TRUE/FALSE for whether there is evidence for forecast use in the horizon curve of each dam. The point of the RF analysis is thus to understand if there are features of dams (storage capacity, etc) that would be associated with detected forecast use. We agree that terminology should be made consistent and we expect that with the target clarified this part of the study will be much easier to follow.
Changes to manuscript: We have listed all 26 input features of the RF classification ***[TABLE A1]*** and have adjusted the text for consistency throughout method and results ***[LINE 164]***. We

have also provided additional detail on the classification within the Method secftion ***[LINES 162 - 173]***.

Referee Comment: data segmentation (Line 160 - 170): Since the methodology used here is Random Forests as one of the machine learning tools, the reviewer is wondering whether there is an overfitting issue? Traditionally, the data should be split into training, validation and test periods to verify there is no overfitting. However, authors only did a training and a test without validation. It is likely the model is overfitted and more experiments on different folds are necessary to justify the proper use of random forests.
Author Response: The traditional machine learning methodology uses training data to train a model, uses validation data to tune model hyperparameters, and uses testing data to evaluate model performance. We agree that if a sole testing set is used for both hyperparameter tuning and model evaluation, the model may be biased and prone to over-fitting. But in our case, the only two hyperparameters tuned (number of trees and maximum tree depth) are not adjusted to achieve best testing score, but instead determined in reflection of our small dataset: maximum tree depth is limited to 3 levels to reduce model complexity, and we choose a considerably large number of trees of 1000 to reduces the model variance and hence reduce overfitting (the larger the number of trees, the lower the ensemble model variance). Additionally, we repeated the experiments 200 times with different splits, each time train the model from scratch on training data and evaluated the model performance only on unseen testing data. We are therefore confident the model is not overfitted.
Changes to manuscript: We have added the additional details of the Random Forest experiment design into the draft (including measures taken to avoid overfitting) ***[LINES 177 – 180]***.

Referee Comment: Gini index Line 305: Can the authors define what is the "Gini impurity of the tree"? Some examples and references using this index would be helpful.
Author Response: Thanks for the request for clarification. Gini impurity, like entropy, describes the heterogeneous state of a system and is formally calculated as $\sum_{\boldsymbol{i}=\mathbf{0},\mathbf{1}} \boldsymbol{P_i} * (\mathbf{1} - \boldsymbol{P_i})$ in a binary classification tree node, where $\boldsymbol{P_i}$ is the fraction of samples that belongs to class $\boldsymbol{i}$ in this particular node. The feature importance score is calculated as the percentage of Gini impurity decrease because of the particular feature, averaged across the forest. The sum of all feature importance scores equal to 1.
Changes to manuscript: We have added new text to explain Gini impurity (including the equation) and how it is used to calculate feature importance ***[LINES 181 - 187]***.

Inferred inflow forecast horizons guiding reservoir release decisions across the United States

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Abstract. Medium to long-range forecasts often guide reservoir release decisions to support water management objectives, including mitigating flood and drought risks. While there is a burgeoning field of science targeted at improving forecast products and associated decision support models, data describing how and when forecasts are applied in practice remains undeveloped. This lack of knowledge may prevent hydrological modelers from developing accurate reservoir release schemes for large-scale, distributed hydrology models that are increasingly used to assess the vulnerabilities of large regions to hydrological stress. We address this issue by estimating seasonally-varying, regulated inflow forecast horizons used in the operations of more than 300 dams throughout the Conterminous United States. For each dam, we take actual forward observed inflows (perfect foresight) as a proxy for forecasted flows available to the operator, and then identify for each week of the year the forward horizon that best explains the release decisions taken. Resulting "horizon curves" specify for each dam the inferred inflow forecast horizon as a function of the week of the water year. These curves are analyzed for strength of evidence for contribution of medium to long-range forecasts in decision making. We use random forest classification to estimate that approximately 80% of large dams and reservoirs in the US (1553±50 out of 1927 dams with at least 10 Mm^3 storage capacity) adopt medium to long-range inflow forecasts to inform release decisions during at least part of the water year. Long-range forecast horizons (more than six weeks ahead) are detected in the operations of reservoirs located in high elevation regions of the Western US, where snowpack information likely guides the release. A simulation exercise conducted on four key Western US reservoirs indicates that forecast-informed models of reservoir operations may outperform models that neglect the horizon curve—including during flood and drought conditions.

1 Introduction

Dams regulate nearly all rivers in the United States. They generate more than half of US renewable electrical power, protect thousands of communities against damaging floods, and supply copious water for the nation's irrigated agriculture and urban water systems (US Army Corps of Engineers, 2015; Bureau of Reclamation, 2016). To provide these essential services, dams must be operated efficiently for uncertain hydrological conditions days and weeks ahead. Water managers thus rely increasingly on reservoir inflow forecasts to guide water release decisions (Gong et al., 2010; Brown et al., 2015; Boucher and

Ramos, 2018)—and will continue to do so as the range, resolution, and quality of hydrological forecast products continue to advance (e.g., Wang and Robertson, 2011; Yuan et al., 2015; Bennett et al., 2016). Inflow forecasts are valuable because they help operators manage difficult trade-offs. For example, the threat of drought is best addressed with maximum stored water, while the threat of flooding requires spare storage capacity for capturing water. Knowledge as to the likelihood of either hazard is thus indispensable when deciding how much water to hold in storage. This is why, for instance, the depth of upstream winter snowpack in high Western US headwaters, which provides a strong indication of the volume of water likely to enter a reservoir in the spring, guides operators on how much water to hold in storage early in the year (Garen et al., 1992).

While we know that inflow forecasts are useful, our understanding of their precise contribution to water release decision making across a large number of dams is limited. Lack of detailed reporting of operational rules and guidelines means the science community remains largely uniformed on a number of key details, such as typical forecast lead times adopted, and times of year when forecasting is deemed most important. To our knowledge, these data have yet to be collected through any qualitative or quantitative research study conducted at national scale. Lacking accurate operational data and associated decision-making schemes, large-scale, distributed hydrology models (e.g., Van Vliet et al. 2016, Wada et al. 2016; Voisin et al. 2013b; Voisin et al., 2017; Vernon et al., 2019; see Nazemi and Wheater, 2015 for a review) are liable to misrepresent the influence of human water management on river flows (Yassin et al., 2019), including during extreme flood and drought conditions. The applications of these models—increasingly, large-scale multisectoral planning studies aiming to predict stresses on water, energy, and food systems—may in-turn suffer mischaracterization of human systems' exposure to hydrological risks.

This paper asks whether the use of forecasts in real-world operations can be inferred (i.e., back-calculated) from historical records of reservoir storage, inflow, and release. We suggest that the contribution of forecasts to decision making at a given dam can be described quantitatively through construction of seasonally-varying estimates of regulated inflow forecast horizons adopted by the operator (herein termed the dam's "horizon curve"—a novel concept introduced in this paper). To test this hypothesis, we attempt to infer the horizon curves and associated water release policies for a sample of 316 dams and reservoirs in Conterminous United States. Since horizon curves are derived empirically for each dam using observed (i.e., regulated, non-natural) inflows and releases, the estimated horizons are attributed to a water forecast that could be derived from any source of information, including meteorological, climatological, and hydrological predictions, as well as knowledge of planned water management, such as scheduled releases from a large dam upstream. The approach is therefore agnostic to the possible sources of information that an operator may deploy to predict future inflow. We explore how the inferred horizon curves vary across dams, and then interpret some of the dominant as well as unexpected operator behaviors by focusing on particular cases. By labeling each dam's horizon curve according to whether or not it provides compelling evidence for medium-range inflow forecast use in operations, we identify (using random forest classification) the dam and reservoir characteristics that are conducive forecast-informed operations. Finally, simulations at four key dams are used to test whether the horizon curve could lead to improved representation of water management in large scale hydrological models.

2 Method

2.1 Justification for the concept of a horizon curve

Several factors determine whether and how foresight informs water release decisions, and these factors vary widely across dams. For example, the value of an inflow forecast may depend on the characteristics of the reservoir. There are diminishing returns in low-memory reservoirs (low storage capacity relative to inflow) and for certain operating purposes (Georgakakos and Graham, 2008; Graham and Georgakakos 2010; Zhao et al., 2012; Anghileri et al., 2016; Turner et al., 2017). If the reservoir characteristics are suitable, the operator's decision to adopt a forecast-informed release policy will then depend on perceived forecast reliability and how that reliability varies throughout the year (Rayner, 2005; Whateley et al., 2014). Forecast reliability, in turn, depends on the available predictive information. An operator might rely on upstream water storage (e.g., soil moisture, snowpack, lake levels) (Shukla and Lettenmaier, 2011), hydrological regime state (Turner and Galelli, 2016), climate indices and teleconnections (Yang et al., 2017; Libisch-Lehner et al., 2019), weather forecasts (Georgakakos et al., 2005; Shukla et al., 2012; Nayak et al., 2018), current river flow rates (Hejazi et al., 2008), knowledge of planned water releases from upstream dams, and perhaps some or all of these in combination (Denaro et al., 2017). This enormous scope for variability in forecast quality and application across dams means there is no obvious way to identify the actual operationalized forecast, or indeed the model used to assimilate it into decision making, for a given system without insight into individual agencies' models and data preferences. Large-scale hydrology models may encompass several hundred dams, so acquiring this insight through qualitative survey would be a major challenge. We therefore propose a practical, empirical approach to inferring—or back-calculating—seasonally-varying forecast horizons adopted in dam and reservoir operations.

2.2 Derivation of horizon curves

To characterize the contribution of forecasts to release decisions across a large sample of dams, we adopt a simple, regression-based method that can be applied to any reservoir for which observational daily time series of storage volumes and at least one of inflow or release are available. The approach returns for any dam a signature of the inferred regulated inflow forecast horizon over the water year (the horizon curve) as well as an associated inferred operating policy describing how future inflow out to those horizons informs the release and depending on time of year. To achieve this, we must first assume that the future observed inflows (perfect forecast) may act as a proxy for the actual forecast available to the operator at the time of deciding how much water to release (the limitations of this necessary assumption are covered in the Discussion section). If this holds, and if regulated inflow forecasts contribute substantially to the release decision amidst other rules and constraints, then the future inflow would better indicate the observed release decision than the current inflow. In other words, the operational forecast horizon is assumed to be the one that best explains the release decision taken. No prior assumption of forecast use is needed, because the method identifies for each dam whether a forward inflow horizon substantially informs the release decision.

For a given dam or reservoir, the procedure is executed as follows (as illustrated in Figure 1). First, daily time series of inflow and release rates are aggregated to weekly volumes (in million cubic meters) by water week, with week 1 starting 1st October—the start of the hydrological year. The weekly timestep allows us to reasonably back-calculate inflow or release (if either is missing) from change in storage, using conservation of mass and assuming negligible evaporation and other losses (such estimates are not reliable at the daily scale because storage and flow variables tend to be reported as daily averages). This gives us a much larger sample of dams to work with. Then, for each water week, the interannual values of starting storage, release, and inflow are used to fit release-availability functions (i.e., relationships that specify the water release decision as a function of water available) for multiple candidate future inflow horizons, where in each case the availability, *a*, is computed as the starting storage plus the cumulative future inflow out to horizon *h* weeks (see example in Figure 1). The inferred release-availability function fitted to these data is a piecewise linear model with a single breakpoint. This model provides appropriate flexibility to account for the typical behavior of operations, wherein an excess of incoming water may be addressed with a comparable increase in the release (leading to a relatively sharp positive slope on the right-hand side of the function), while a lack of water must be satisfied by a reduction in the release, which cannot be negative and which is often bound by a requirement to provide environmental flows (leading to a flat or low-gradient positive slope on the left-hand side of the function). These piecewise functions are fitted to observed release and availability data for all possible horizons in increments of one week (with x-axis availability, *a*, recomputed for each horizon). Functions may be fitted for a given set of breakpoint coordinates by performing linear regression on either side of the breakpoint; the breakpoint coordinates themselves can be optimized for minimum sum of squares in the model residuals. Once functions are fitted for all candidate horizons, the horizon offering the closest fit to observed decisions is selected as the operational horizon for that water week of the year (subject to some conservative adjustments described below).

A desirable feature of this model is its compatibility with archetypal rule curves often implemented in practice. To demonstrate this compatibility, let us first assume that forecasts are not used at all and that the operator uses seasonally-varying storage targets to decide on how much water to release. Our scheme allows us to mimic this type of operation very effectively. The two-stage piecewise model provides the flexibility to represent two situations: (a) the reservoir is above the guide curve, in which case one would expect the operator to respond by releasing water to draw the reservoir back down (with higher release for higher storage levels—allowed for by the right-hand slope of the piecewise function); and (b) the reservoir is below the guide curve, in which case the operator would wish to cut back the release significantly to allow the reservoir to refill. The breakpoint of the piecewise function on the x-axis (which, absent the forecast, is simply water in storage) essentially represents the traditional reservoir guide-curve level, and the slopes either side of the function specify how the operator behaves in either situation. Our scheme is of course also designed to allow us to integrate forecast information in the rule-curve system. The difference is that the rule is no longer a function of current storage, but becomes a function of current storage plus the inflow out to various candidate horizons.

A conceptually similar piecewise model is presented in Yassin et al. (2019) with the fundamental difference that the process omits forecasts and is therefore based on climatology and current storage and inflow conditions. Importantly, because our algorithm is also computed for individual weeks, it ensures that the effects of operational decisions driven by long term average water availability conditions are intercepted and removed when supporting the horizon curve determination. For example, a simple operating rule designed to accommodate typical high flows delivered in springtime would not lead to detection of a forecast horizon in our procedure. The reason is that such actions are a function of time of year rather than forecasted flow. High releases to create a flood pool in anticipation of typical springtime flows can be implemented in reservoir rules without foresight, for example by releasing high volumes of water each March. Foresight would only be detected if there were clear evidence of the flood buffer being adjusted based on a forecast of the inflow and its deviation from normal conditions for that time of year. This behavior has been confirmed through a simple simulation exercise to check for the unwarranted detection of horizons beyond current-period in a synthetic reservoir with a seasonally-varying operating rules that are not explicitly forecast-informed.

2.3 Experimental setup

For this study we compile daily observed storage, inflow and release time series for more than 900 dams and reservoirs in Conterminous United States (sources are US Army Corps of Engineers, US Bureau of Reclamation, US Geological Survey, California Data Exchange, and Texas Water Development Board; see acknowledgements). In cases where only storage data are available, releases are obtained from USGS streamflow gauges immediately downstream of the dam. After addressing minor gaps (ten continuous days or less), we remove incomplete, short (less than ten years' continuous data) and duplicate records, leaving a set of 316 dams with sufficient data for creating horizon curves. These dams represent a range of operating purposes and reservoir storage sizes and are well distributed across the Conterminous United States west of the Mississippi River (Figure 2). We then create a horizon curve for each dam following the steps outlined above and in Figure 1. Piecewise functions are fitted to each water week (1, 2, … 52) and future inflow horizon (1, 2, … 30 weeks) combination for each dam (total of $52 \times 30 = 1560$ functions fitted for each dam) by identifying the function breakpoint coordinates that minimize root mean squared error, achieved using a numerical optimization algorithm designed for derivative-free, non-linear problems (Powell, 2009) and found to perform efficiently in our testing. To avoid overfit to unrealistic operating policies, the piecewise functions are constrained such that both slopes are non-negative and that the right-hand slope exceeds the left-hand slope. We wish to avoid inferring forecast contribution in cases where the evidence is marginal relative to lower horizons or no-forecast cases. We therefore infer forecast contribution only when the policy for forecast horizon h results in a substantially better fitting policy (> 0.1 increase in R^2) relative to forecast horizon $h - 1$. In other words, when the strongest policy fits are similar across a range of horizons (say, an increase in R^2 of less than 0.1 between horizons of 6 and 7 weeks ahead), the lowest of these horizons (6 weeks ahead) is assumed to drive the release decision. Given the imperfections of the process, a degree of noise is to be expected in the derived horizon curve for any dam. This is addressed by de-spiking each horizon curve and then smoothing using a locally-weighted smoothing spline (Cleveland, 1981). All of these calculations and assumptions are made freely available through an open code repository (www.github.com/IMMM-SFA/horizon).

2.4 Classification of horizon curves

With the horizon curves derived, we use Random Forest classification (Ho, 1995) to identify features of dams associated with detection of significant medium to long-range inflow forecast contribution in the horizon curve. The classification not only supports the interpretation of the results but also allows exploring the potential extrapolation of horizon curves to dams with no observed data. In this analysis the target response variable is a simple Boolean (true/false) of whether there is evidence for significant forecast contribution or not. This first requires a definition of what constitutes significant forecast detection in the horizon curve. One can anticipate that many horizon curves could contain only very weak evidence for foresight in operations (e.g., a horizon curve in which periods of apparent forecast-use are sporadic and with short lead times). Ideally, these should be labelled as non-significant horizon curves. Unfortunately, separating these low-evidence cases from the others is a rather arbitrary exercise. We label a horizon curve as significant (meaning containing sufficient evidence for medium-to-long range forecast horizons) if it contains an unbroken, three-week period with operating horizons of at least two weeks ahead, and with the coefficient of determination of the release-availability functions associated with those horizons exceeding 0.5. Relaxing these thresholds would of course result in more dams being categorized as significant (and vice versa), so we take the additional step of performing sensitivity to changes in these thresholds (with relevant results included in Appendix A).

The candidate explanatory features in this classification analysis include dam and reservoir specifications, operating purposes, and various statistics describing the inflow and storage time series (variability, autocorrelation, etc., at various time scales)—a total of 26 features (listed in Table A1).

It's essential that a Random Forest classification scheme is set up to avoid the possibility of overfitting. Here we set the number of trees to 1000 and limit the number of decision layers to a maximum of three. A bootstrap is used to repeat Random Forest generation 200 times with different training-test splits. In each case, a different random sample of 70% of dams constitute the training set while the remaining 30% are used as unseen testing data for validation and evaluation. Feature importance is then determined using the "Gini impurity" of the tree (Friedman et al., 2001). Gini impurity, like entropy, describes the likelihood of an incorrect classification of the heterogeneous state of the system. It is formally calculated as:

$$\sum_{i=0,1} P_i \times (1 - P_i) \qquad \text{Equation 1}$$

where P*i* is the fraction of the samples that belongs to class i in the binary classification tree node. The feature importance score is then calculated as the percentage decrease in Gini impurity, averaged across the forest. The sum of all feature importance scores is equal to 1.

2.5 Practical application of the horizon curve in a reservoir simulation

The intended application of the horizon curves is to enhance reservoir release schemes of large-scale, distributed hydrological models incorporating water management specifically in anticipation of flood and drought events. The derivation of horizon curves involves determining the horizon that leads to the best-fit operating policy (release as a function of available water) at weekly intervals, leading to a relatively high-resolution dataset that could be deployed in these models. A regional-scale hydrological simulation lies beyond the scope of the current study and is being conducted in ongoing research. Nonetheless, we can explore the potential improvements that a forecast-driven model might proffer by conducting offline, single reservoir simulations forced with observed inflows. For each of four significant, large storage dams in the Western United States, we perform the horizon curve derivation procedure as outlined above. The chosen dams are Grand Coulee (Columbia River), Glen Canyon (Lake Powell, Colorado River), Shasta (Sacramento River, California), and Dworshak (Snake River), which represent a set of diverse storage capacity, flow seasonality and level of regulation in inflows. For each water week and selected horizon there is an associated piecewise function that specifies a release decision as a function of water availability (storage volume plus cumulative future inflow out to the duration of the horizon). Simulation is performed using observed inflow and storage levels. This means errors in the release are not allowed to accumulate through storage, providing the cleanest test of overall decision accuracy across all data points. Further testing that allows storage error accumulation and includes the effects of inflow bias lies outside the scope of this work and is being conducted in ongoing research. To compare results against a release policy that neglects forecasts, we use the same format of piecewise models but instead train them with a uniform horizon of one week ahead for all weeks of the year. This means the benchmark operating policy is a function of current storage plus current inflow (with the model varying by week).

3 Results

3.1 Horizon curves for 316 dams

We group resulting horizon curves according to the timing of peak horizon (i.e., the week of the year when the maximum forecast horizon is used) within the water year and then order within each group by magnitude of peak horizon. Resulting horizon curves are displayed in Figure 3. Of the 316 horizon curves derived, use of foresight is detected in 283 cases (i.e., 283 cases in which at least one week of the year contains a detectable horizon of at least one week ahead of the current week). This equates to 90% of dams studied. The remaining 33 dams have completely flat horizon curves—suggesting that the releases from these dams are guided at all weeks of the year using information on currently available water alone. Perhaps surprisingly, the timing of the peak horizon varies widely across dams. Horizon peaks occurring toward the end of the water year tend to be short-lived, lasting three or four weeks. In contrast, horizons detected in earlier in the year (from weeks 9 through 25, or mid-December through early April) are often drawn out, lasting a number of months.

While no two horizon curves are identical, some consistent and intelligible patterns emerge. Flat horizon curves with consistent horizons of one week (which should be interpreted as the current period inflow—or no forecast use) and consistently strong policy fits ($R^2 > 0.9$) are found for run-of-river hydropower facilities, such as Ice Harbor Lock and Dam, on the Columbia River, Washington (Figure 4a). These dams have very low storage relative to inflow (typically a day's flow or less), meaning forecasts of more than a few days ahead are superfluous. At a weekly resolution, inflow is close to outflow, so we observe a near-perfect relationship between release and current water availability, and progressively weaker relationships as the horizon is extended. Though unsurprising, this result is satisfying because it demonstrates that cases where forecasts certainly do not influence the decision are easily identified as such by the derivation procedure.

Evidence for week-ahead horizons begins to emerge as we move to reservoirs with slightly longer memory (Figure 4b). Orwell Dam, Minnesota, for example, impounds a small, upstream reservoir (~25 Mm3) used for flood control and municipal water supply. Storage capacity is about five percent of annual inflow. Here we infer week-ahead forecast use during a few periods of the latter half of the water year. The region is prone to summer thunderstorms, so perhaps severe weather warnings during these weeks have, on occasion, prompted operators to lower reservoir levels to increase the flood buffering volume.

In cases where long-range forecasting is inferred (defined here as four consecutive water weeks with a horizon of six weeks or more), horizon curves tend to be n-shaped: low during the beginning and end of the water year, with a significant rise emerging in winter or early spring and then fading off by early summertime. These cases are indicative of snowpack driven forecasting. Operations at Glen Canyon Dam (Lake Powell) exemplify this behavior (Figure 4c). Here we observe inferred forecast horizons increasing rapidly by the start of the calendar year—neatly coinciding with the first issue of April-July streamflow forecasts provided by the Colorado River Basin Forecast Center—and then slowly declining in horizon as the snowmelt season approaches. Similar examples include Jackson Lake, Wyoming (Figure 4d), and Bridgeport Reservoir, California (Figure 4e), for which the inferred horizon rises at the onset of the snowmelt season (early April) for the Rockies and the High Sierra, respectively. Perhaps in these cases early-year forecasts are too unreliable to inform releases. Or perhaps early-year forecasts do inform releases, with the policy undetected here due to the uncertainties or conservative assumptions embedded in the derivation procedure (e.g., use of actual observed future flow instead of the actual forecast available to the operator).

Some horizon curves require more in-depth interpretation. A few dams follow the same snowmelt-driven forecast behavior described above, but also appear to use significant foresight during fall (i.e., at the start and end of the water year). This may indicate use of seasonal water outlooks informed by ENSO, which improves the skill of winter precipitation forecasts in the region (Yang et al., 2018). Canyon Ferry, Montana (Figure 4e), and Millerton Lake, California (Figure 4f), are two such cases, although we must be careful not to conflate climate forecasts with other possible sources of foresight. Millerton Lake lies below a cascade of dams on the San Joaquin River; coordinated operations, rather than hydrological forecasting, may provide the foresight to guide releases. Indeed, it appears that in other cases the guiding information comes not from any hydrological or meteorological forecasts, but from simple knowledge of planned upstream water management decisions. Agate Dam and Reservoir (Figure 4g) depends almost exclusively on diverted water from upstream storage via a canal system. Close inspection of release decisions reveals very clear correlations between release and future inflow at specific points in the water year. The January release is typically zero, with the two exceptions: 2002 and 2017. For both years the currently available water at the time of those releases is normal, but the cumulative future (diverted) inflow is well above average, suggesting that releases from this dam are closely coordinated with planned upstream diversions. Generally, we may assume that if a dam depends almost entirely on the water management decisions from upstream reservoirs, and if those decisions can be planned weeks ahead in advance, then the inflows can be known with a high degree of accuracy and could be used to guide decisions. Knowledge of upstream water management decisions (either dam releases or perhaps planned abstractions for irrigation or other purposes) rather than hydrological or meteorological forecasting may explain much of the operational foresight detected in summer months at several dams (week 40 onwards in Figure 3).

Correlation between current release and future inflow need not always imply that the release is driven by knowledge of future inflow. It could be that the future inflow is driven by the release. Suppose for instance that a dam is called upon to release significant volumes of water over an extended period of time to address water quality concerns, resulting in a significant drawdown below the reservoir guide curve. This release event could trigger an upstream operational response to refill the downstream reservoir, perhaps over a period of several weeks. Complex coordinated operations of this sort are bound to create a myriad of uninterpretable wrinkles in the horizon curves derived. These complexities highlight the enormity of the challenge faced large-scale hydrological modelers trying to represent human water management actions without information on the actual operating schemes deployed in practice.

3.2 Features of dams with significant horizon curves

We applied the significance test described in section 2.2 on the horizon curves. Of the 316 dams studied, 256 (82%) are classified as having a significant horizon curve after applying these criteria. Relaxing these thresholds would of course result more dams being categorized as significant (and vice versa), so we take the additional step of performing sensitivity to tightening and relaxing of thresholds (results presented in Appendix A). After applying the classification scheme described in section 2.3, dam and reservoir features that best determine whether the horizon is significant are: the storage ratio of the dam (storage over mean annual inflow), the annual inflow volume, the average timing (within the water year) of minimum reservoir storage, dam elevation above sea level, and variability of storage and inflow time series at interannual and seasonal resolution (Figure 5). The storage ratio determines the memory of the system; forecasts do not contribute to release decisions for reservoirs with low storage ratio, as reported above with respect to run-of-river hydropower dams. As such, the storage ratio—

and related features such as mean annual inflow and storage capacity—are among the most important variables in determining horizon curve significance (Figure 6a). Neither the dam's primary purpose (water supply, hydropower, irrigation, flood control, etc.) nor the source of data (US Army Corps, US Bureau of Reclamation, etc.) provide predictive capability in the random forest classification scheme.

Features describing water week with minimum storage, within-year variability of storage levels, and dam elevation may all be significant because they indicate the likelihood of a snowmelt driven regime. Spring snowmelt reservoir refill patterns are typical of high elevation dams (Giuliani and Herman, 2018). Snowpack volumes are the most reliable source of long-range streamflow forecast skill in snowmelt-dominated Western United States (Day 1985, Pagano et al., 2014), so one should expect that features like elevation become more important in determining whether long range forecasts contribute. This indeed appears to be the case. If we group horizon curves into separate categories based on the longest forecast horizon observed, we find that long-range forecasts (six to eleven weeks ahead) and seasonal forecasts (twelve weeks ahead or more) typically contribute to the release decisions of high elevation dams and reservoirs (>1000 meters above sea level) (Figure 6b). Long range and seasonal horizons are found in approximately 35 % of dams with elevation below 500m above sea level, compared with 46% of dams in the 500 – 1000m category, and more than half of dams in the 1000 – 1500m and > 1500m categories. Corroborating this finding, in the months leading up to the snowmelt season (weeks 9 through 25, Figure 3) we observe prolonged inferred horizons that reflect the long period of snowpack accumulation during which long-range foresight is available.

The random forest classification scheme can be used to infer whether or not dams and reservoirs outside of the study sample are likely to apply medium to long-range forecast horizons. To extrapolate our results across all large dams (greater than 10 Mm3 storage capacity) in the Conterminous United States (1927 large storage dams in total), we re-train the Random Forests classification model using features that are available for all dams represented in the Global Reservoir and Dams (GRanD) database (Lehner et al., 2011). To this we add two additional features describing the number and accumulated storage of upstream dams (created from watershed mapping). Data describing the variability and autocorrelation of the inflow and storage time series are unrepresented in the GRanD, so must be excluded from the classification model. This turns out to be unproblematic; a Random Forest trained with only the storage ratio, elevation above sea level, mean annual inflow, storage capacity, and number of upstream dams is sufficiently accurate in validation, with strong scores of 0.91, 0.89, and 0.94 achieved for the common accuracy metrics of F1 score, precision and recall, respectively (see Appendix for mathematical definitions of these scores). The fact that these scores are achieved without the additional features suggests that these features may be redundant with others represented in the pared-down feature set. We use this pared down model to extrapolate our results for all dams in CONUS. The classification model estimates that 1553 ± 50 (90% confidence interval), or 82%, of large dams (storage capacity > 10 Mm3) are characteristic of dams with significant horizon curves. Inferred horizons are prevalent across large dams. Approximately 81% of CONUS dams with storage capacity greater than 100 Mm3 are estimated to have releases influenced by inflow forecasts; for dams with storage capacity greater than 1000 Mm3 (139 dams), the estimate is about 90%. Regions where inflow forecast-contribution is prevalent include mountainous regions of CONUS, such as the along the spine of the Rocky Mountains, the Sierra Nevada of California, Cascades of the Pacific Northwest, and the Appalachians to the east (Figure 7).

3.3 Improvements in reservoir simulations using the horizon curve

Figure 8 displays policy simulation results for Grand Coulee, Glen Canyon, Shasta and Dworshak dams. The simulations are driven by actual observed inflow in each case. For each dam, results are shown for two simulations: simulated optimized piecewise policies assuming release to be informed only by current water availability, and simulated optimized piecewise policies using future flow as defined by the inferred horizon curve. These results demonstrate significant improvements in release decisions (relative to observation as measured by root-mean-squared error, RMSE) for the daily simulation, annual daily maxima, and annual average 90-day minima time series of releases, as well as for the transformed RMSE (TRMSE), wherein the simulated and observed releases are first transformed so that the result is weighted by performance during periods of low release (Box-Cox transform with exponent of 0.3, as adopted in van Werkhoven et al., 2009) (Table 1). This, and the maxima and minima assessments, are added to indicate performance improvements during flood and drought conditions. While some of these improvements are marginal (5 – 10% reduction in RMSE), one could hypothesize that there would be substantial differences in the representation of regional water management if such improvements were repeated across a large sample of dozens or perhaps hundreds of dams. Moreover, a marginal difference in a reservoir's capability to release or store water during an extreme event could imply a substantial difference in the downstream impact.

4 Discussion

The water management modules of large-scale hydrology models have to-date relied on relatively simple heuristics to simulate releases, such as monthly storage and release targets based on average climate (Hanasaki et al., 2006; Döll et al. 2009, Biemans et al., 2011; Solander et al., 2016; Voisin et al., 2013, 2017) or year-ahead, perfect foresight (Haddeland et al. 2006). Important nuances, such as the appropriate environmental release, are typically applied uniformly across all dams. The parameters of the 52 (weekly) piecewise release-availability functions (including detail of the forecast horizon) could inform a far more detailed and representative set of operating schemes with forward looking operations. This could be crucially important in many regions where inflow forecasts greatly enhance the reservoir's capability for flood and drought alleviation. Given the prevalence of forecast application, as suggested by this study, improved dam and reservoir models that represent intelligent operator response to anticipated reservoir inflows over seasonally-varying horizons within the myriad of other operational constraints should contribute to a better understanding of hydrological stressors on energy and food security that are increasingly linked to large-scale hydrological models (e.g., Van Vliet al. al. 2016, Wada et al. 2016; Voisin et al. 2013b; Hejazi et al. 2015, Voisin et al., 2018).

This approach to deriving a horizon curve is clearly not without limitations. Streamflow forecasts used in practice are often highly uncertain, so strong correlations between release and actual future observed inflow may be elusive, particularly for long-range forecast horizons. In theory, this issue could be addressed by using the actual forecasts available to operators to inform the availability axis of the candidate release-availability functions. In reality, these data are difficult to acquire—particularly for large-scale studies with many dams and reservoirs. Often the forecasts adopted will be probabilistic in the form of a forecast ensemble, rather than a deterministic forecast. In the present work, the actual observed future inflow is an imperfect yet practical alternative, and the results obtained suggest that it can be effective in many cases. Another challenge is selecting the correct study period. Ideally, a multi-decadal time series would be used to capture inter-annual variability in release and water available for all periods of the water year. The flipside is that the operating policy may have changed at some point in the last few years—it may be that new forecast products were introduced only the latter years of record, for instance. In such cases of non-stationarity in the policy it would be prudent to use only those latter, forecast-informed years of operation so as to avoid averaging away the forecast-use signal. Lacking prior knowledge of how or when forecasts may have been introduced, the practical approach is to discard operations prior to some cut-off year (in the present work we use 1995, but also test the robustness of this decision using cut-off years of 2000 and 2005). Non-stationarity in the inflows is not a limitation here; as long as the operating policy is consistent through time, then a wide range of possible inflow conditions would be desirable for determining the nature of that policy. A related problem is that the resulting models are not conducive to the type of rigorous validation exercise that has become standard in hydrological study. Apart from the problem that we are uninformed as to whether the policy of a given reservoir may have changed radically during the period of record, there are simply too few data points to support robust validation (~20 data points for 20 years of data, in a good case, which will contain perhaps only one or two flood or drought years to guide either side of the release-availability function). In the absence of long records of consistently-applied policy, it's vital to protect against over-fitting. We achieve this by constraining each piecewise function to an expected, archetypal form (see 2.3 Experimental setup), although the corollary is that the resulting functions may in some cases be over-constrained. They may lack the required flexibility to represent more complex operating rules applied in practice. Despite these limitations, we find that the approach arrives at convincing evidence for regulated inflow forecast contribution as well as a range of other interesting operator behaviors. While the associated release policies are likely to be highly imperfect models of actual operations, they potentially offer a significant advance on general, theory-driven rules currently adopted in state-of-the-art large-scale, distributed hydrological models (see Yassin et al., 2019, for a state-of-the-art review of existing approaches).

5 Conclusions

The use of foresight in reservoir release decisions can be interpreted without reported operating rules for individual dams and reservoirs. All that is needed is operational data—time series of storage and flows into and out of reservoirs—and an appropriate release-availability function that can be fitted to these data to test a range of candidate operational horizons. Our analysis is the first to use this idea to estimate the contribution of regulated inflow forecasts to reservoir releases across a large number of dams and reservoirs. The results provide a first national scale estimate of the existing contribution of monthly to seasonal flow forecast to release decisions. The general approach of horizon curve derivation is inhibited by a number of non-trivial challenges. These include identifying the appropriate operational period from which to build the curve, reconciling the differences between the forecast used by the operator and actual inflow over the horizon, and selecting appropriate thresholds for the indicating evidence for foresight contribution, such as the goodness-of-fit of the release-availability function. The single-breakpoint piecewise function adopted in this study is simple, but intelligible and, most importantly, effective for the purpose of identifying release policies driven by foresight of future inflow. And although the exactness of the horizon curves is undoubtedly impaired by the limitations noted above, our analysis supports some interesting conclusions.

First, we find that the use of operational foresight—determining what to do in the present with some foresight of what will happen in the coming weeks or months—is prevalent in US dam and reservoir management. We detect a significant contribution of regulated inflow forecasts of at least one week ahead in more than 80% of dams in our sample of 316 dams. A similar proportion is estimated when we extrapolate to a much larger sample of CONUS dams with capacity greater than 10 MCM. Second, our classification exercise highlights the potential to extrapolate horizon curves to data sparse reservoirs. Large dams and dams at high elevations appear more likely to adopt longer range forecasting, but aside from the general and obvious rule that run-of-river facilities cannot benefit from forecasts, it appears that dams of all sizes, purposes, and locations rely on some degree of medium-range foresight to guide operations. Detected foresight appears to derive from a wide variety of sources, including climate and weather forecasting, but also from coordinated operations between dams. Some particular patterns, such as snowmelt forecasting, are intelligible from the horizon curve shapes and the dam features (e.g., high elevation). The importance of forecasting to release decision making may be studied in future research to understand the role of rule curves, forecast accuracy, reluctance to adopt forecast into operations (see Rayner 2005), and other factor that may limit the value of forecast to release decision making. Whether a more detailed and accurate approach to identifying the source of information leading to forecast can be derived from operational data alone is also a challenge for future research. Classification models, such as Random Forests, may be useful for extrapolating not only the presence of a significant horizon curve, but also parameters of policy functions for reservoirs lacking the operational data to build a policy directly.

Our approach, as configured in this work, assumes that operators use release-availability functions based on cumulative forecasted inflow. In reality the forecasts may be assimilated in a different way. For example, many reservoir operators follow rule curves and release water according to a step-wise function, or they may deploy a threshold-based forecast across a range of horizons. While our approach is simple and intuitive, the integration of forecasts into decision making is a complex process and all subtleties might not be captured. Our study may motivate further work at a national scale into understanding how forecasts are integrated into decision making by dam operators. Application of horizon curves and their associated release-availability functions in regional-scale hydrological modeling is being tested in ongoing research and is expected to enhance the representation of water resources in spatially and temporally varying wet and dry conditions. This potential is demonstrated here through the implementation of horizon curves in the simulation of four key dams in the Western US. The operating policy information (i.e., release-availability function) derived in this work could also be explored on its own merits. For example, one could compare the lower limits of release across all time periods and dams to explore variation in environmental releases. Deriving new horizon curves for different periods of history may reveal changing preferences—such as points in time where environmental releases have increased, or the first introduction of forecast use in decision making.

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Initial weekly data for dam X

water_year	water_week	storage	inflow	release
1995	1	21912.28	106.926	143.067
1995	2	21876.14	129.735	173.277
1995	3	21832.60	134.630	136.480
1995	4	21830.75	136.138	144.032
1995	5	21822.85	105.121	153.597

[first five rows shown only]

Filter data for selected water week
Start: water week = 1

water_year	storage	inflow	release
1995	21130.99	101.040	209.463
1996	26282.50	151.631	263.014
1997	25191.24	136.081	296.187
1998	26519.82	199.549	346.703
1999	26643.17	170.019	297.808

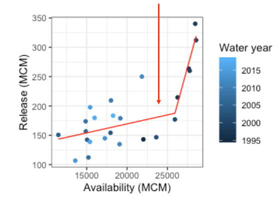
**availability =
storage + inflow forecast**

Select horizon and compute forecast and availability

Horizon = 1 (current week)

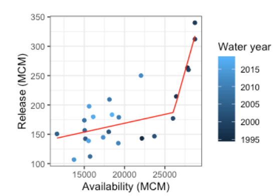
water_year	storage	inflow	release	inflow_forecast	availability
1995	21130.99	101.040	209.463	101.040	21232.03
1996	26282.50	151.631	263.014	151.631	26434.13
1997	25191.24	136.081	296.187	136.081	25327.32
1998	26519.82	199.549	346.703	199.549	26719.37
1999	26643.17	170.019	297.808	170.019	26813.19

Fitted piecewise function for **water week = 1** and **h = 1**



Horizon = 2

water_year	storage	inflow	release	inflow_forecast	availability
1995	21130.99	101.040	209.463	252.671	21383.66
1996	26282.50	151.631	263.014	287.712	26570.21
1997	25191.24	136.081	296.187	335.630	25526.87
1998	26519.82	199.549	346.703	369.568	26889.39
1999	26643.17	170.019	297.808	283.399	26926.57



…continue for all candidate horizons (1 – 30) and select the horizon resulting in **piecewise function** with **closest fit to data** (based on minimum squared residuals)

Repeat for all water weeks (1 – 52)

Horizon curve:

Figure 1 – Example of derivation of horizon curve for a given dam using piecewise linear functions fitted to release (*r*) availability (*a*) scatters. Best fit horizons (based on coefficient of determination) for each water week (i.e., each row of the release-availability plots above) are combined to create the horizon.

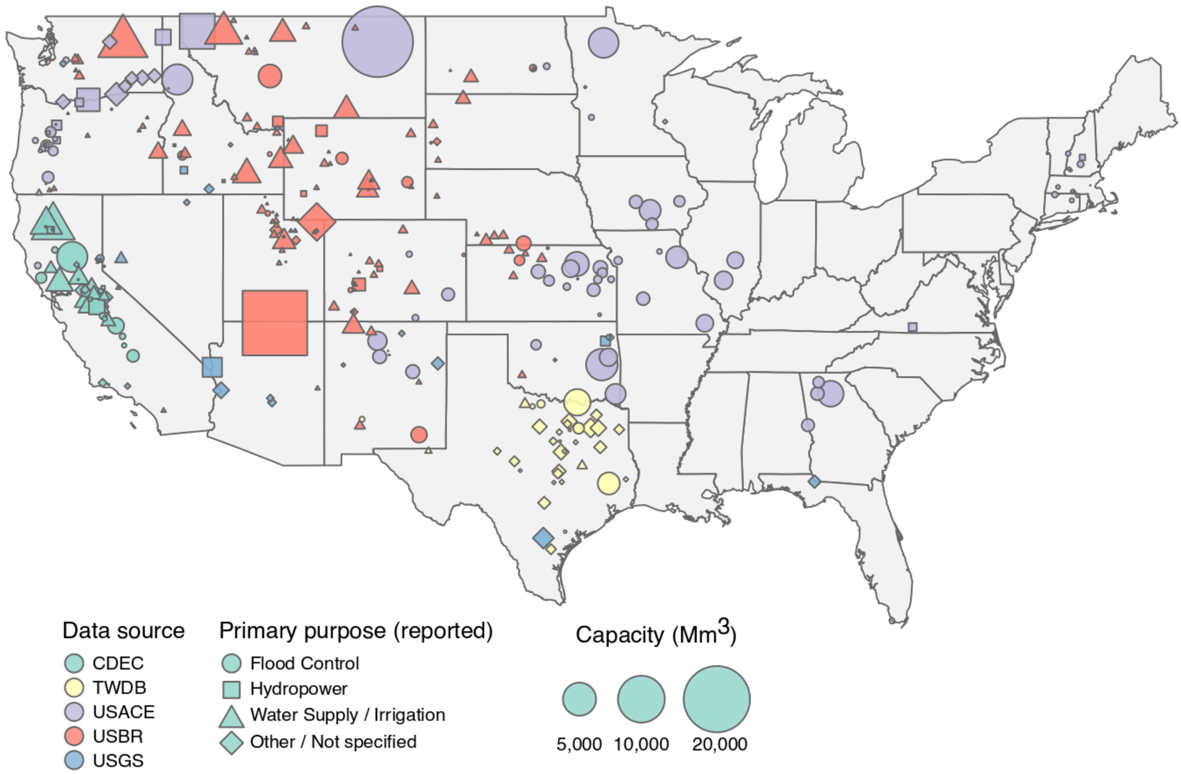


Figure 2 – Dams included in forecast use signature analysis (n = 316). Data sources are California Data Exchange (CDEC), Texas Water Development Board (TWDB), US Corps of Engineers (USACE), US Bureau of Reclamation (USBR) and US Geological Survey (USGS).

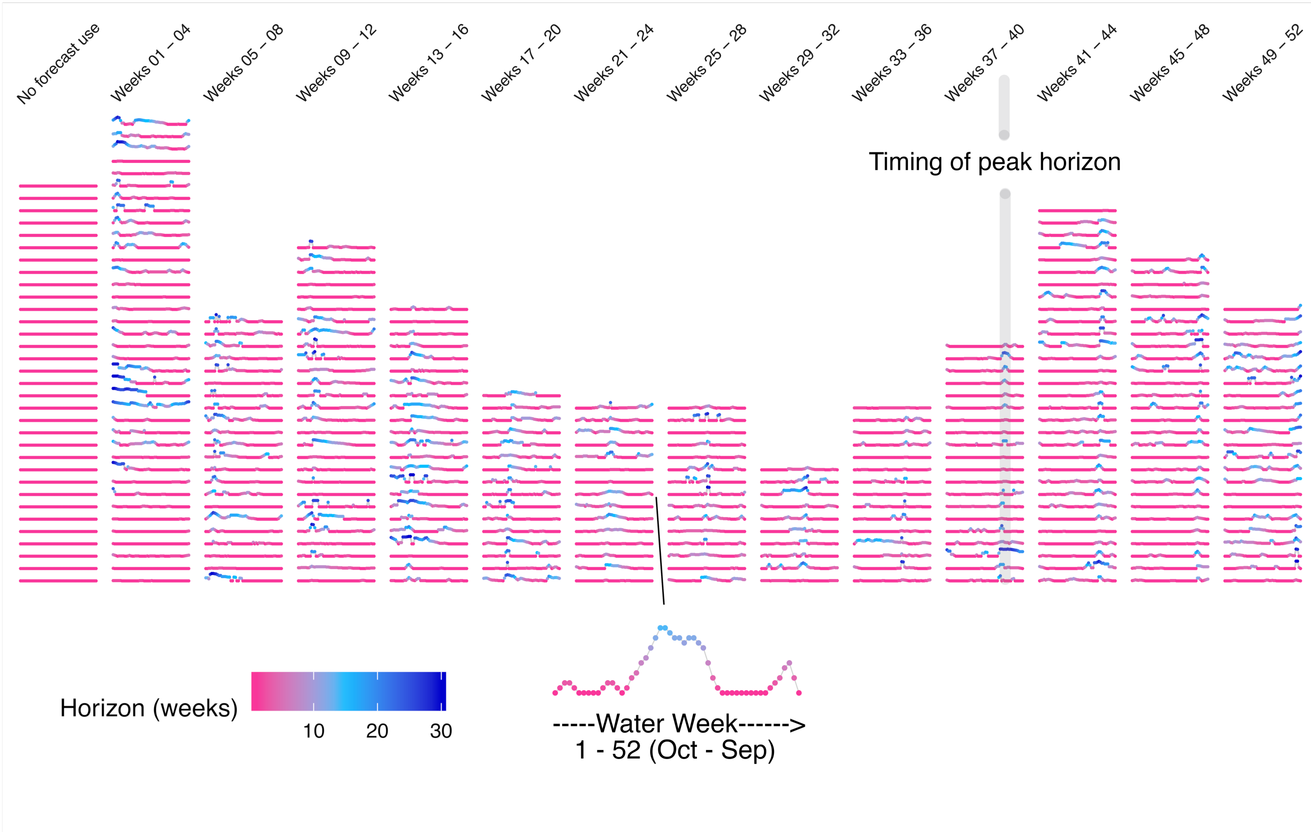


Figure 3 – Horizon curves for 316 dams, binned according to timing of peak horizon (i.e., the week of the water year where the longest-range foresight horizon is detected). Each signature specifies the inferred operational horizon from water week 1 (week commencing 1st October, at the left of forecast use signature) to 52 (week commencing September 24th, at the very right of the forecast use signature).

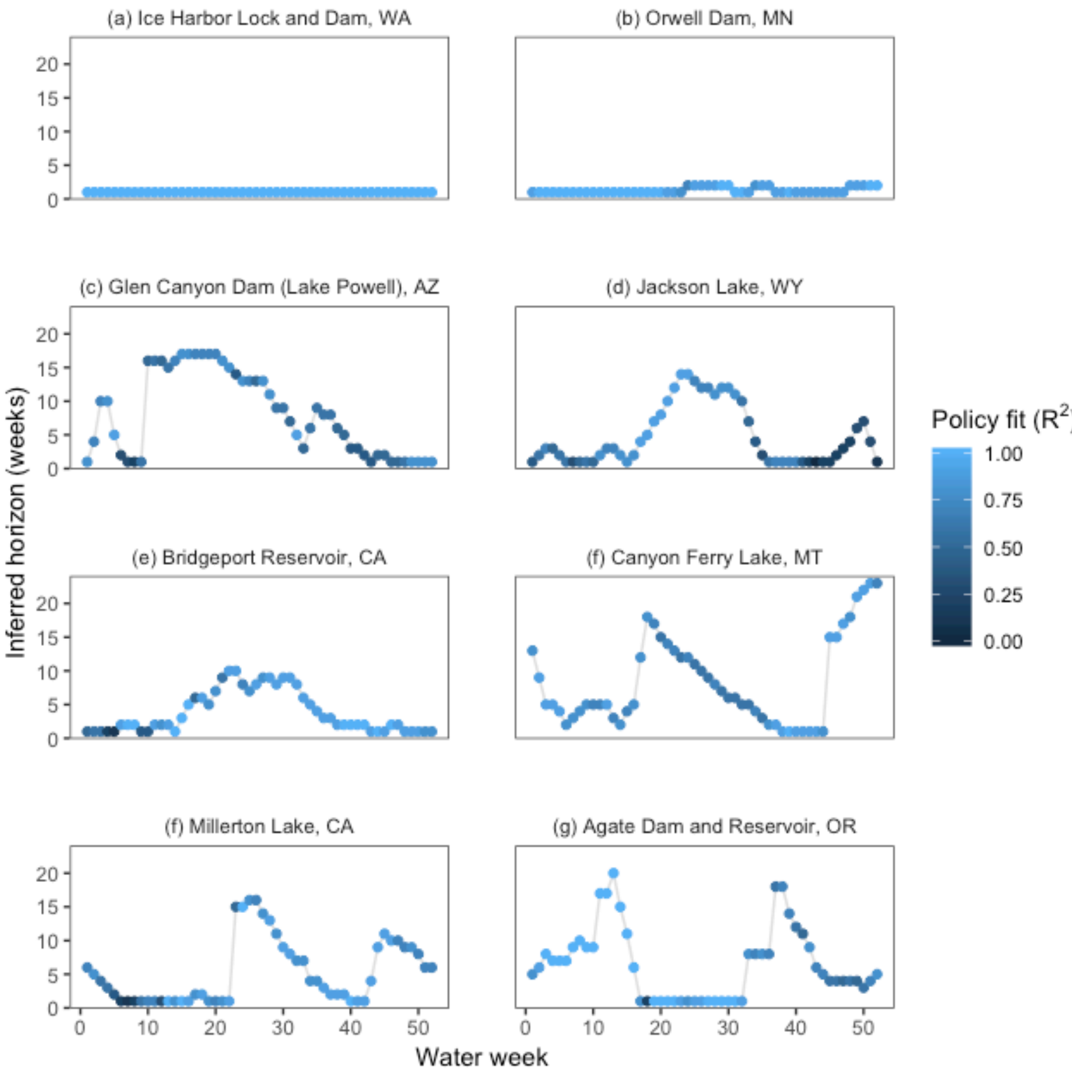
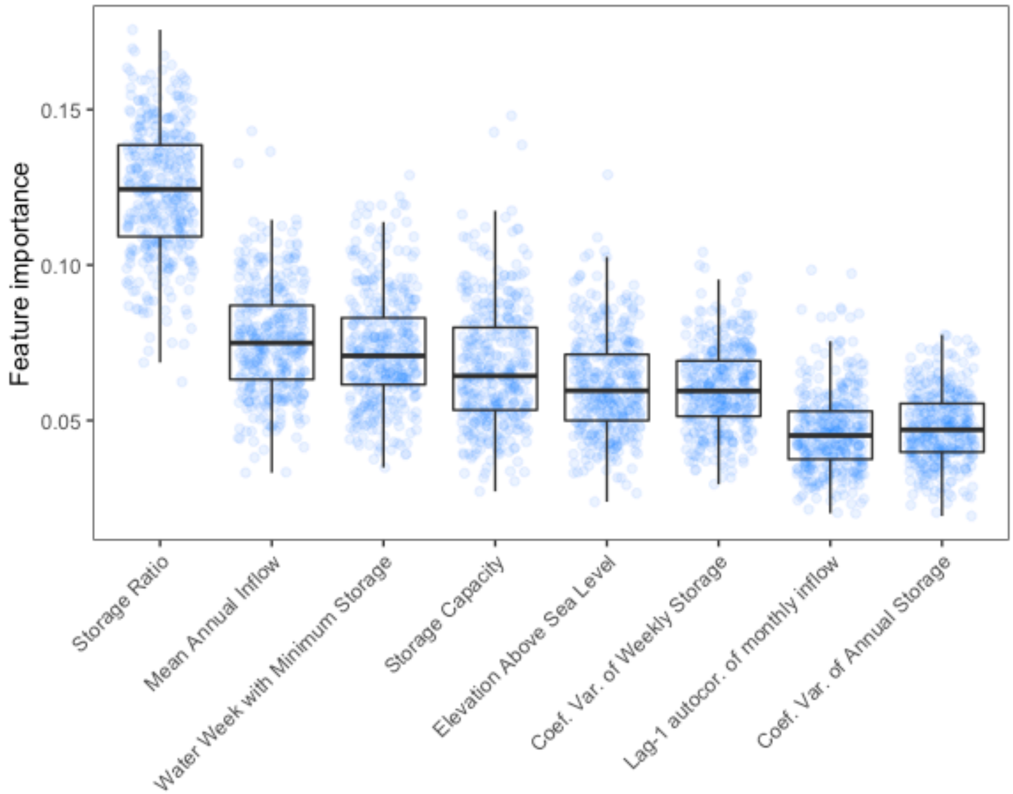
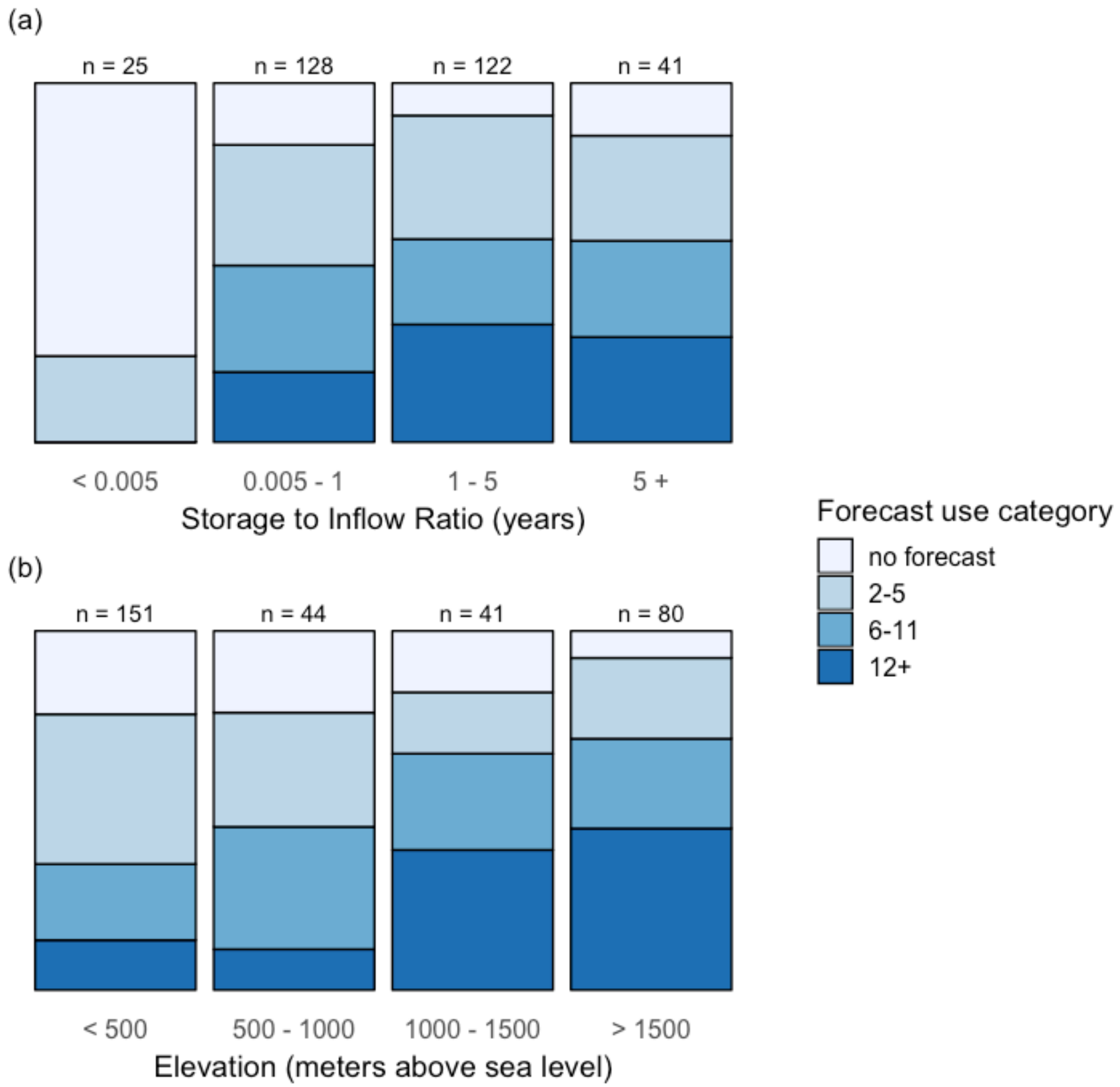


Figure 4 – Inflow forecast use signature examples for eight dams located throughout Western United States. The policy fit refers to the coefficient of determination (R^2) of the release-availability relationship for the best-fit horizons.



555 **Figure 5 – Distribution of feature importance across 400 random forests (eight features with highest median importance shown). The distribution is created by bootstrapping the random forest classification model with resampled training and test data. Boxplots give median and interquartile range.**



560 **Figure 6 – Stacked (100%) bars showing distribution of dams by detected forecast horizon within categories of (a) storage ratio and (b) elevation. Forecast use categories are: no forecast, 2 – 5 weeks ahead horizon, 6 – 11 weeks ahead horizon, and 12 weeks or greater horizon. Maximum detected horizon assumes that the horizon is detected in the forecast use signature for at least three consecutive weeks with policy fit (R^2) exceeding 0.5 in each week.**

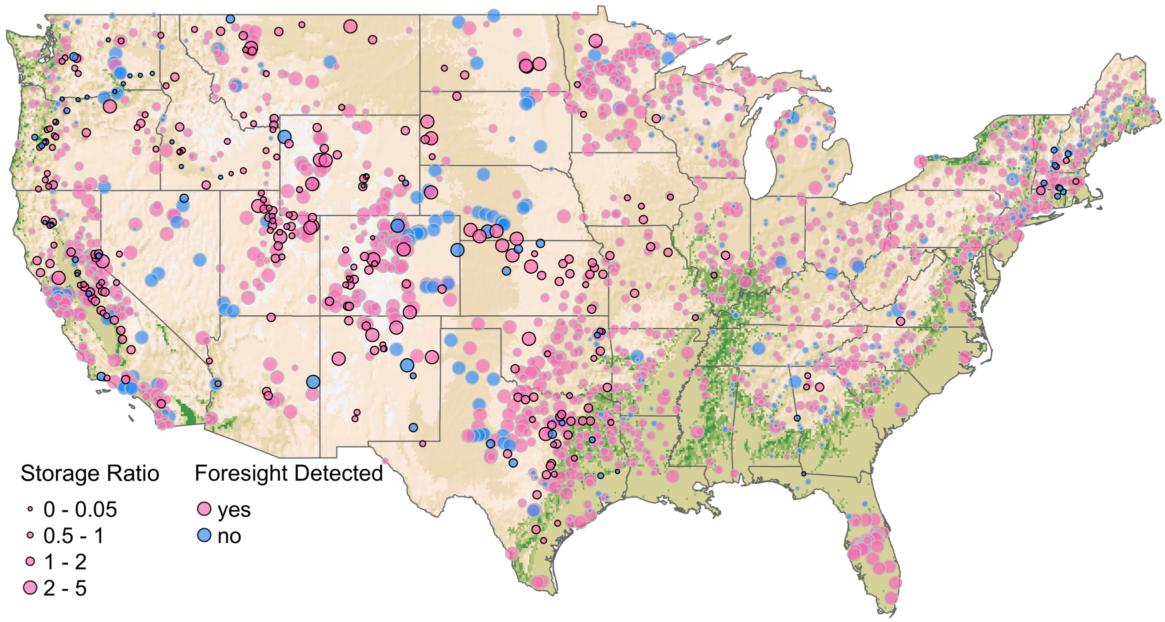


Figure 7 – Foresight-use for 1942 CONUS dams and reservoirs, based on forecast-use signatures (316 dams – black outlined circles) and out-of-sample, extrapolated estimates (gray outlined circles). Storage ratio (split into four categories) is storage capacity divided by the annual average reservoir inflow. Background shading gives land elevation.

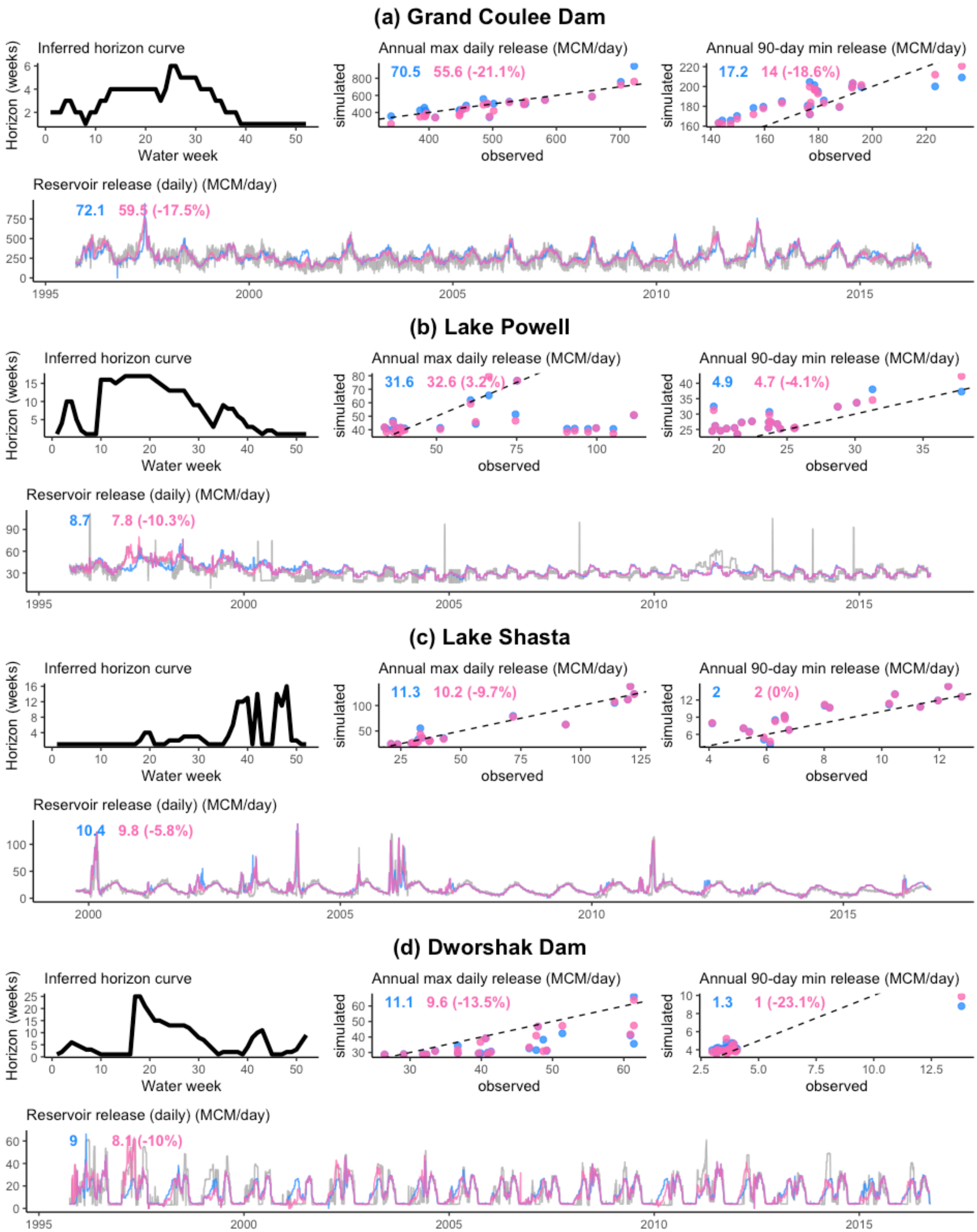


Figure 8 – Simulation performance improvements with horizon curves adopted. Blue represents forecast excluded; pink represents forecast included. Results given for four large storage dams, showing the inferred horizon curve, scatter plots for annual maxima and annual minima (90-day average) releases (representing performance during flood and drought conditions respectively) and the daily release time series. Numbers inside plot panels give RMSE scores relative to observation (% difference with horizon curve in parentheses).

Table 1 – Performance metrics for observed versus simulated daily release for two policies: "current week" (CW) neglects forecasts and instead uses piecewise release-availability functions trained on availability = storage + current inflow; "horizon curve" (HC) adopts the horizon curve and associated piecewise release-availability functions. Metrics assessed are RMSE of daily releases, RMSE of annual maxima of the daily releases, RMSE of annual 90-day minimum series, and Box-Cox transformed RMSE (TRMSE).

	Grand Coulee		Lake Powell		Shasta		Dworshak	
	CW	HC	CW	HC	CW	HC	CW	HC
$RMSE_{r\_daily}$	72.1	59.5 *(-17.5%)*	8.7	7.8 *(-10.3%)*	10.4	9.8 *(-5.8%)*	9.0	8.1 *(-10.0%)*
$RMSE_{r\_ann\_max}$	70.5	55.6 *(-21.1%)*	31.6	32.6 *(+3.2%)*	11.3	10.2 *(-9.7%)*	11.1	9.6 *(-13.5%)*
$RMSE_{r\_ann\_90dmin}$	17.2	14.0 *(-18.6%)*	4.9	4.7 *(-4.1%)*	2.0	2.0 *(-)*	1.3	1.0 *(-23.1%)*
$TRMSE_{r}$	1.58	1.28 *(-15.4%)*	0.68	0.62 *(-8.7%)*	1.12	1.06 *(-5.4%)*	1.25	1.12 *(-10.5%)*

Appendix

Table A1 – Sensitivity of results to change in number of consecutive weeks of horizon detected required to label a dam as having a significant horizon curve. The 26 features determined for each dam and included in this analysis are: dam elevation above sea level, dam purpose (a single categorical variable for primary purpose as well as seven Boolean variables indicating whether dam is used for water supply, irrigation, flood control, recreation, hydropower, ecological provision, and navigation respectively), dam latitude, dam longitude, reservoir storage capacity, storage ratio (i.e., storage to annual inflow ratio), coefficient of variation of storage (annual and weekly time series), mean annual inflow, coefficient of variation of inflow (annual and weekly) lag-1 autocorrelation of inflow (annual, quarterly, monthly, and weekly), average week of water year when minimum inflow occurs, average week of water year when maximum inflow occurs, number of dams upstream, total capacity of dams upstream.

Consecutive weeks of horizon detected required to label the horizon curve "significant"	Observed number of dams with significant horizon curve	Predicted number of dams >10Mm^3 with significant horizon curve	Top five predictive features for whether dam's horizon curve is significant, ordered by mean importance in random forest classification
2	277 (88%)	1677 ± 6 (87%)	***Storage ratio (0.15)*** ***Elevation (0.09)*** Mean ann. inflow (0.08) CV of weekly storage (0.06) Week of minimum flow (0.06)
3 (in study)	258 (82%)	1553 ± 50 (81%)	***Storage ratio (0.12)*** Mean ann. inflow (0.08) Week of minimum flow (0.06) Storage capacity (0.07) ***Elevation (0.06)***
4	223 (71%)	1219 ± 40 (63%)	***Storage ratio (0.09)*** Lag-1 ACF of mon. inflow (0.08) CV of annual storage (0.07) ***Elevation (0.06)*** CV of weekly storage (0.06)

Definitions of feature performance scores:

In validation of the classification model, True Positives (TP) is the number of correctly predicted TRUE values (i.e., forecast detected) while False Positives (FP) is the number of incorrectly predicted TRUE values (i.e., model predicts “forecast detected = TRUE” when it should be FALSE). Similarly, True Negatives (TN) is the number of correctly predicted FALSE values and False Negatives (FN) is the number of incorrectly predicted FALSE values.

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 = (2 × Precision × Recall) / (Precision + Recall)