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Evaluation of Seasonal Streamflow Forecasting

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ABSTRACT

Long-term streamflow forecasts are essential for optimal management of water resources for various demands, including irrigation, fisheries management, hydropower production and flood warning. In this paper, a probabilistic forecast framework based on Ensemble Streamflow Prediction (ESP) technique is presented, with the basic assumption that future weather patterns will reflect those experienced historically. Hence, past forcing data (input to hydrological model) can be used with the current initial condition of a catchment to generate an ensemble of flow predictions. The present study employs the ESP-based approach using the TopNet hydrological model. The objective of this present paper is to evaluate and assess the uncertainty due to initial condition of the catchments and forcing (meteorological input to the model) data for (ESP) based streamflow forecasting using the TopNet hydrological model in New Zealand catchments. An ensemble of streamflow predictions which provide probabilistic hydrological forecasts, reflecting the intrinsic uncertainty in climate, with lead time up to three months is presented for the four catchments on New Zealand's South Island. Verification of the forecast over the period 2000-2010 indicates a Ranked Probability Skill Score of 23% to 69% (over climatology) across the four catchments. In general, improvement in ESP forecasting skill over climatology is greatest in summer for all catchments studied. The major uncertainty associated with ESP forecast is combination of uncertainty due to initial state and climate forcing. The analysis indicates that the sensitivity of flow forecast to initial condition uncertainty depends on the hydrological regime experienced by the basin during the forecast period. On average, the relative importance of initial condition is greatest within two weeks to months of the start of the simulation for all catchment and all season. After this time period uncertainty in forecast is mainly due to uncertainty in forcing data. Finding of this study can be valuable tool for water resource managements.

Keywords

Long-term forecast, Streamflow, ESP, Probabilistic forecast

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NTRODUCTION

Streamflow forecasts are essential for optimal allocation of water supplies for various demands that include irrigation for agriculture, habitat for fisheries, hydropower production and flood warning. A long-range forecast is essential for any water resource planning because long-range/seasonal streamflow forecast can help water manager for optimal management of water resources and allow them to take timely decision to assesses the risk of alternative water use and management strategies (Robertson et al., 2013).

Common approaches to seasonal-to-interannual (long-term) streamflow forecasting include simple statistical methods(Garen, 1992; Piechota et al., 1998; Svensson, 2016) (e.g. using regression equations to predict seasonal streamflow via observations of snowpack and precipitation) or Ensemble Streamflow Prediction (ESP) techniques (Chen and Brissette, 2015; Day, 1985; Singh, 2016; Wood and Lettenmaier, 2008) using empirically or physically based hydrologic model simulations initialized by estimates of state variables such as snowpack or soil moisture. Although approaches using regression equations are relatively inexpensive to implement and maintain, and have been demonstrated to perform well in settings where snow is major component of the hydrologic cycle, there are several reasons to prefer more sophisticated approaches that use hydrologic simulation models. Perhaps the most compelling of these relates to concerns about parameter stationarity during extreme events (e.g. due to changing baseflow conditions during long droughts) or in the context of climate change. The ESP approach also provides explicit spatial information about the initial hydrologic state (e.g. maps of snowpack or soil moisture anomalies), it directly simulates an ensemble of streamflow time series which can be fed into planning models at a range of time scales, and it quantifies a wider range of uncertainties in the forecasts (e.g. related to both volume and timing) in a more direct and easily interpreted manner than statistical forecasts. The usefulness of regression based approaches in New Zealand is also limited by the lack of a comprehensive snowpack monitoring system (Hendrikx et al., 2009). This limitation is not as important when employing ESP approaches, because the hydrologic models themselves can be used to simulate the hydrologic state variables using observed temperature and precipitation data as the inputs. For these reasons, we have elected to explore the performance of an ESP forecasting system in this paper, rather than regression based approaches.

Several small-scale streamflow forecasting systems have been implemented in individual river basins at various times in New Zealand (e.g. Purdie and Bardsley (2010)), and a more comprehensive, qualitative system based primarily on precipitation monitoring and review by a panel of experts is currently used to estimate streamflow for the coming year in a number of rivers (NIWA, 2016). These existing approaches notwithstanding, New Zealand currently does not have a centralized, comprehensive, and state-of-the-art seasonal-to-interannual streamflow forecasting system in place to support water management decisions. A number of fundamental research tasks must be carried out before such a system can be designed and implemented including: hydrologic model development and implementation, preparation of historical meteorological data sets, model calibration for individual river basins, evaluation of the importance of various forecast and/or observed physical drivers that inform the forecasts (such as future precipitation and temperature, soil moisture, snowpack, El Nino Southern Oscillation (ENSO), etc.), design and implementation of monitoring systems to support forecasts, and retrospective evaluation of hindcasts of historical streamflows at various lead times and times of year to determine the error characteristics and appropriate times of year for the forecasts.

As an exploratory study, we have elected to implement and evaluate in detail an experimental Ensemble Streamflow Prediction forecasting system over two specific river basins on the South Island of New Zealand (Figure 1). In the Upper Waitaiki basin our study will focus on the Ahuriri, Hooker and Jollie catchments, while the Rangitata River basin is modeled as a whole. These rivers were chosen for two reasons: a) both have good quality observed streamflow and snowpack information over a long-time period to support hydrologic modeling efforts and b) skillful forecasting systems would benefit water resources management applications (hydropower production and marketing, and irrigation respectively). Also New Zealand's National Institute of Water and Atmospheric Research (NIWA) has easy access to hydrologic information and data for the Waitaki and Rangitata basins from past field campaigns (Clark et al., 2011) and previous application of snow/rainfall - flow models (e.g. Woods (2009)).

The objective of this study is to evaluate and asses forecasting uncertainty due to initial condition of the catchments and forcing (meteorological input to the model) data for ESP-based streamflow forecasts using the TopNet hydrological model in New Zealand catchments.

The approach taken here is to run TopNet hydrological models with 38 years of historical climate forcing data and current initial Conditions (ICs). From the collection of model runs (the ensemble), probability distributions can be derived to produce probabilistic flow forecasts, capturing the intrinsic uncertainty in weather or climate. An ESP-based hydrological forecast with lead time up to three months is presented here as the relative importance of initial state variables (such as soil moisture and snowpack) and future precipitation and temperature as fundamental drivers of uncertainties in forecasts are evaluated for different seasons for selected rivers in South Island of New Zealand.

METHODOLOGY

ESP based forecasting Technique

The ESP forecast technique assumes that meteorological events that occurred in the past are representative of events that may occur in the future. In ESP forecasting, an ensemble of potential future flow records is simulated to create a range of possible flow scenarios (Day, 1985; Wood and Lettenmaier, 2008). The basic assumption of the ESP forecast is that historical meteorological data like precipitation and temperature in an area are reasonable representation of conditions which might be expected to reoccur in that area in the future. An additional assumption is that hydrological process occurring in the area can be accurately represented by a hydrological model (Twedt et al., 1978; Wood and Schaake, 2008). In an ESP forecast system, the hydrologic model is used to first simulate real-time flow conditions up to the date and time of the forecast. The pre-forecast period simulation is driven by near recent and real-time climate input data. A minimum of one year of pre-forecast simulation is recommended to get the representative initial condition of a catchment at the time of the forecast. The hydrologic model is then run numerous times to create a set of possible flow records of the forecast period. All the simulated flow records (or traces) have the same simulation starting and ending dates that span the forecast period. The traces are created using the same real-time initial conditions, which include snow, soil moisture, and flow on the day of the forecast. However, each trace is simulated using climate input data from a different year in the historical record. Applying weather for different years to the present conditions allows extremes of weather in the region at this time of the year to be captured. The resulting traces give an idea of the range of possible flows. Once several scenario hydrographs are calculated, the results can be used to generate probabilistic streamflow values.

The ESP forecast can be summarised as follow.

1. Calibrate the hydrological model on observed data
2. Run the hydrological model up to the forecast date using current climatic data and store the initial state of the catchment

Table 1 TopNet model parameters which need calibration, description and allowed range for the parameter multiplier

Parameter	Description	Initial	
		Min	Max
topmodf	TOPMODEL f parameter (m^{-1})	0.001	2
hydcon0	Saturated hydraulic conductivity (ms^{-1})	0.01	9999
swater1	Drainable water(m)	0.05	20
swater2	Plant-available water(m)	0.05	20
dthetat	Soil water content(m)	0.1	10
overvel	Overland flow velocity (ms^{-1})	0.1	10
gucatch	Gauge under-catch for snowfall(-)	0.5	1.5
th_accm	Threshold for snow accumulation(K)	272.16	275.16
th_melt	Threshold for snow melt (K)	272.16	275.16
snowddf	Mean degree-day factor for snow melt (mm K-1 day-1 = kg m-2 K-1 day-1)	0.1	7.5
minddfd	Minimum degree-day-factor day (julian day: 1 to 366)	1	366
maxddfd	Maximum degree-day-factor day (julian day: 1 to 366)	1	366
snowamp	Seasonal amplitude of degree-day factor for snow melt (mm K-1 day-1 = kg m-2 K-1 day-1)	0	7.5
cv_snow	Coefficient of variation in sub-grid SWE(-)	0.5	1.5
r_man_n	Manning's n(-)	0.1	10

Table 2 Modeled high, medium and low flow years for the different catchments

	Rangitata	Ahuriri	Jollie	Hooker
high	1983	1983	1983	1998
medium	1987	1999	1996	1993
low	1985	1989	1989	1985

3. Select historical meteorological data for the same season of the forecast is required.
4. Run the hydrological model using the current initial condition and different historical years forcing data selected in Step 2 for the forecast season.
5. Make probabilistic forecast from the ensemble member from Step 3.
6. Make different probabilistic forecast products.
7. Verify the forecast and report the skill of the forecast.

As ESP forecasts use current initial conditions and forcing from observed meteorological data in past years (Day, 1985), streamflow forecast uncertainty is due to errors in specifying hydrologic initial conditions (i.e. soil moisture, depth to groundwater, state of the snow pack), meteorological (temperature and precipitation) forcing errors and internal model structural errors (Wood and Schaake, 2008).

Forecast Verification

Streamflow forecasts cannot be used in full confidence without a proper verification. ESP verification is intended to give an indication of the quality of the basin calibration and resulting predictive ability. However due to the probabilistic nature of ESP forecasts, verification is a difficult task as compared to deterministic forecast. Verification of deterministic forecasts is done by judging how well the forecast matches the observed streamflow for an event. Comparing the mean of ESP forecasts with observed discharge cannot be a robust test for the verification of the forecast. Probabilistic (ESP) forecasts provide a forecast distribution and do not have a single value against which to compare the observed streamflow. As a result, ESP verification is performed with respect to climatology and observed discharge. Climatology forecasts were generated from the historical observed flow over the evaluation periods.

To avoid including a "perfect" forecast of observed meteorological driving data, the ensemble member associated with the observed water year is excluded from the ensemble (i.e. 37 ensemble members are available for each retrospective forecast date and lead time). Ranked Probability Score (RPS) can be used to determine how well the probability forecast predicted the category that the observations fell into (Epstein, 1969; Murphy, 1969). Relative performance of the forecast over baseline (i.e. climatology) is determined using Ranked Probability Skill Score (RPSS).

The Ranked Probability Score and Ranked Probability Skill Score is given by following equation

$$RPS = \sum_{i=1}^{n}[P(forecast < i) - P(observed < i)]^2 \qquad (1)$$

$$RPSS = 1 - \frac{RPS}{RPS_{climatology}} \qquad (2)$$

Where P (forecast) is the forecast exceedance probability and P (observed) is the observed exceedance probability. RPS is bounded by 0 and 1 and a score of zero indicates a perfect forecast. Whereas RPSS is bound by - ∞ to 1, with 0 means no skill compare to climatology.

Evaluating the importance of initial state and forcing (meteorological Input to model) data on streamflow forecast

Uncertainty in ESP forecasts is due to errors in specifying hydrologic initial conditions (i.e. soil moisture, depth to groundwater, state of the snow pack), meteorological (temperature and precipitation) forcing errors and internal model structural errors (Wood and Schaake, 2008). As a result, the initial state of a basin may have a pronounced effect on model discharge in the following time steps.

In order to estimate the importance of errors in hydrologic initial conditions as sources of streamflow forecast uncertainty, initial conditions are varied at the beginning of the period of simulation (termed as reverse ESP) for each catchment. As a result, an ensemble of streamflow time series is created for a specific starting month, based on the ensemble of initial conditions modelled at the start of that particular month. The uncertainty in streamflow forecasts due to error in initial conditions is estimated with seasonal ensemble spread, which is defined as follows. First, the normalized forecast anomaly for ensemble member *i* is:

$$MS(i) = \sum_{over\ season} \frac{(Q_{sim} - Q_{ens(i)})}{\sum_{over\ season} Q_{sim}} \quad (1)$$

Where, MS is measure of spread. Q_{sim} is the modeled discharge for a given time period, $Q_{ens(i)}$ is streamflow corresponding to ensemble member *i.* We have defined this anomaly in terms of the total flow over a season, but it would be possible to use other measures of anomaly, if the interest was in forecasting high flows, or low flows, rather than the total flow in the season. The standard deviation of the MS values over one ensemble is a measure of the seasonal ensemble spread. If the spread in MS is large, then the forecast is sensitive to initial conditions and if the spread in MS is small then the forecast is not sensitive to initial conditions.

In order to estimate the importance of errors in meteorological (temperature and precipitation) forcing as sources of streamflow forecast uncertainty, the hydrological model was run with a range of past forcing data with current initial conditions for period of simulation for each catchment. The standard deviation of the MS was used to measure the spread of the ensemble.

Using ESP, we can evaluate the relative effect of future precipitation and temperature uncertainties on the streamflow forecast. While using Reverse ESP (different initial condition but same forcing data) we can examine the relative effects of the initial state conditions on the future streamflow forecasts. The spread of ESP and reverse ESP is used as measure of uncertainty. The wider the spread (higher the standard deviation of MS) more the uncertainty. For the sake of simplicity, the results will be presented for high, medium and low flow years for all catchments.

STUDY AREA AND MODEL

Study Area

The four catchments selected for this study were Rangitata (1469 km^2), Hooker (105 km^2), Jollie (141 km^2), and Ahuriri (568 km^2) located in South Island, New Zealand (Fig. 1). Catchment areas range from 100 to 1500 km^2. The catchments are similar in topography, land cover and climate, as they are all on leeward side of the Southern Alps. However, they span a range of distances from the main divide and rainfall shadow affects their precipitation and snow water storage to varying degrees. The mean annual precipitation varies across the catchments from 1.77 m (Ahuriri) to 8.57 m (Hooker) as well, flow generation processes differ for these catchments. Rangitata and Ahuriri are rainfall dominated catchments, whereas Jollie and Hooker are snow dominated. The mean annual runoff ranges from 8 m^3/s to 98 m^3/s.

Meteorological Driving Data

Topographically adjusted, daily time step, 0.05 degree latitude/longitude (~5km resolution) operational gridded meteorological data (daily precipitation and maximum, minimum temperature, and daily potential evapotranspiration) were extracted from the Virtual Climate Network (VCN) of National Institute of Water and Atmospheric Research (NIWA) over the period 1972-2010 (Tait et al., 2006; Tait and Woods, 2007). Because the sub-basin elements in the hydrological model have about the same resolution as the gridded meteorological data set and that the interpolation process used to create the gridded meteorological product tends to spatially smooth the data, a simple nearest-neighbour re-gridding approach is used to produce driving data for each sub-basin element in the hydrological model. Although the driving data are input to the hydrologic models at daily time step, the hydrological model internally disaggregates the data to hourly time step (Clark et al. 2008). The physical catchments characteristics was derived from River Environment Classification (REC)

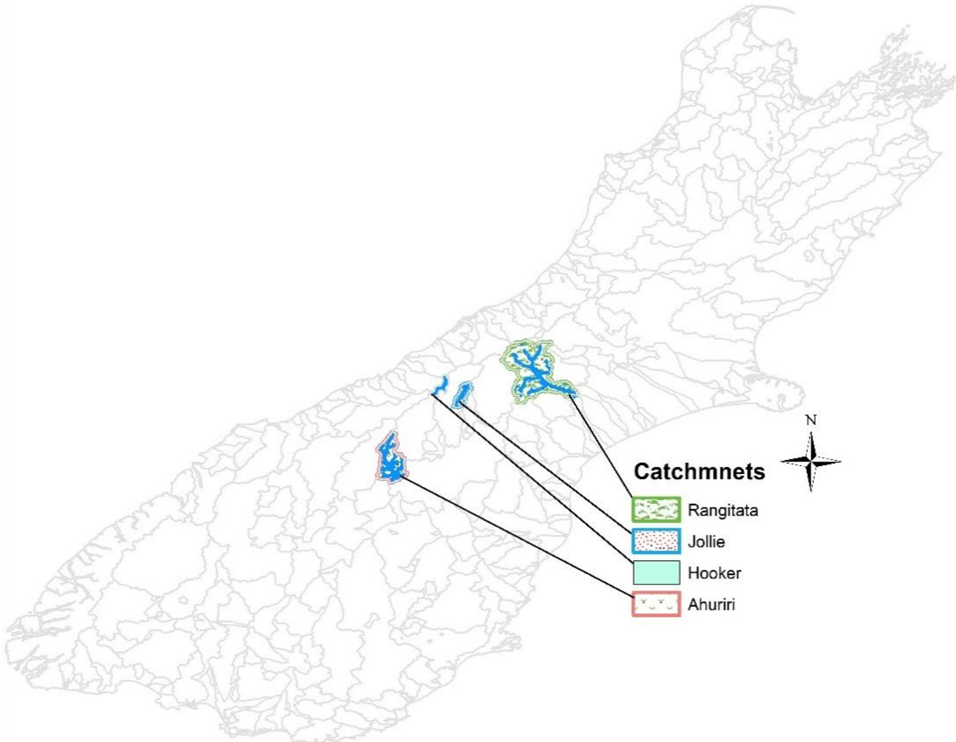

Figure 1 The location of four selected catchments

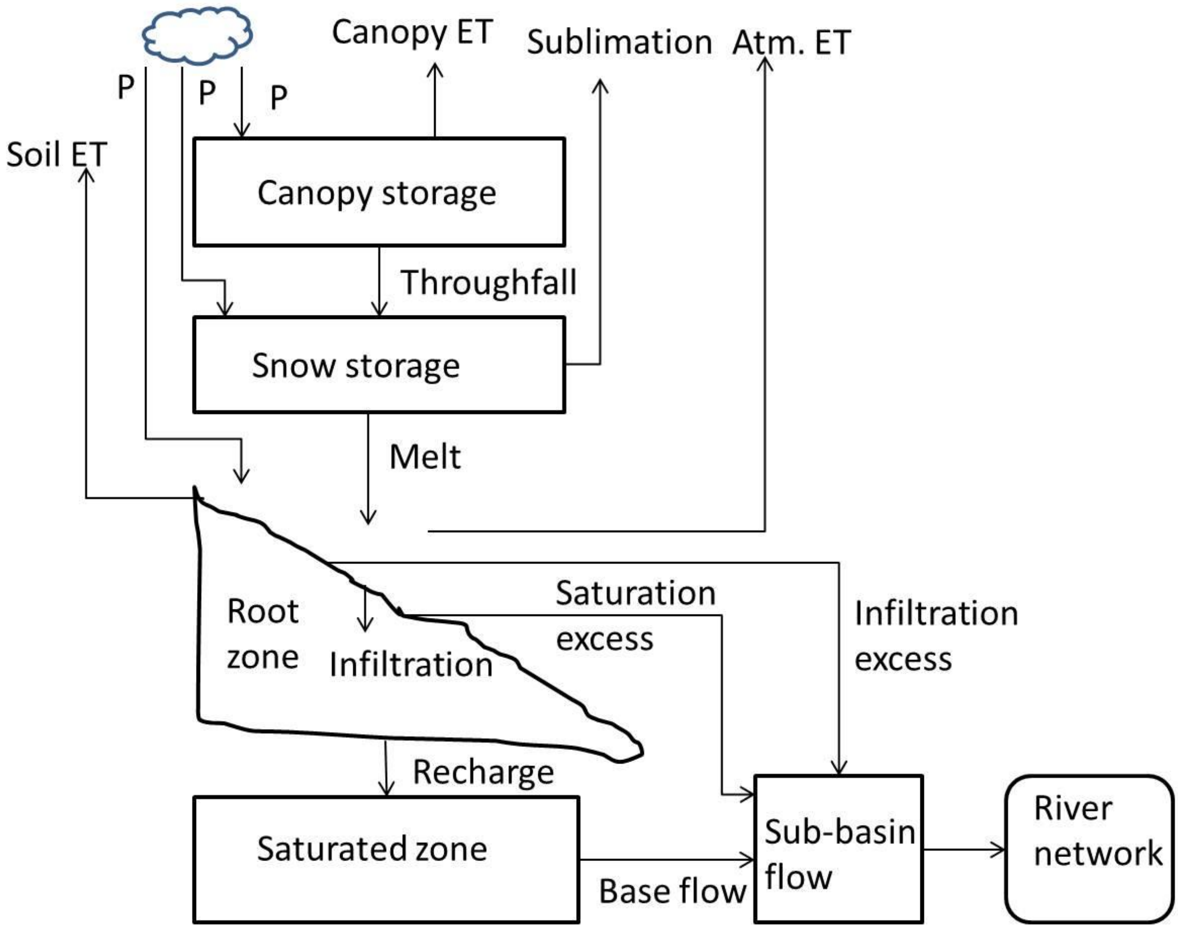

Figure 2 Systematic Representation of TopNet model structure (Singh and Dutta, 2017)

river network (Snelder and Biggs, 2002), the lithology and soil drainage from “New Zealand Land Resource Inventory” (NZLRI) (Newsome et al., 2000), The land use grid was derived from the New Zealand Land Cover Database (S. Thompson, 2003).

Model

TopNet is a semi-distributed hydrological model which simulates catchment water balance and river flow. It was developed using the TOPMODEL (Beven and Kirkby, 1979) concepts for parameterization of soil moisture deficit using a topographic index to model the dynamics of variable source areas contributing to saturation excess runoff (Bandaragoda et al., 2004; Beven and Kirkby, 1979). TopNet models a catchment as a collection of sub-watersheds, linked by a branched river network (Clark et al., 2008). Flow is routed through the river network using kinematic waves using the shock-fitting technique of Goring (1994). Modelled streamflow is generated in 3 ways:

- rain falls on a location where soil water storage equals its capacity (Saturation excess runoff')
- rain rate exceeds infiltration rate ('Hortonian runoff')
- saturated zone discharge into stream (baseflow)

TopNet assumes that available soil water storage can vary within a sub-watershed because of topographic effects - valley bottoms and flat places are wetter than ridges. TopNet provides a prediction of flow in each modelled reach within a catchment (Bandaragoda et al., 2004; Clark et al., 2008; Ibbitt et al., 2000). The model inputs are rainfall and temperature time series (e.g at hourly time steps, with rain from one or more locations), relative humidity, solar radiation, and maps of elevation, vegetation type, soil type and rainfall patterns. These map data are used with tables of model parameters for each soil and vegetation type, to produce initial estimates of the model parameters. A schematic representation of the model is given in Figure 2. TopNet has 31 parameters to define the hydrological processes of a catchment. Where possible, parameter values are determined from physical catchment properties; however, 15 parameters (Table 1) typically require calibration. During calibration, TopNet model uses a spatially constant multiplier for each parameter, to adjust the parameters while retaining the relative spatial pattern obtained from the soil and vegetation data (Bandaragoda et al., 2004). This procedure is necessary to reduce the dimensionality of the calibration problem.

RESULTS

Hydrologic Model Calibration and Evaluation

A TopNet model was calibrated for each river basin. Each TopNet model was calibrated at the most downstream gauging station in the catchment. The wetness index and flow distance distributions for each sub-basin are derived from a 30m digital elevation model (DEM) and the initial model parameters for each sub-basin are estimated using soil and vegetation maps. The spatial distribution of initial model parameters at the sub-basin scale is provided to the model before calibration (Bandaragoda et al., 2004). During calibration, TopNet model uses a multiplier for each parameter except the snow related parameters to adjust the parameters while retaining the relative spatial pattern obtained from the soil and vegetation data (Bandaragoda et al., 2004). The 15 parameters (seven soil related, seven snow related and one routing related) were calibrated over the time period 1998 to 2002 using the ROPE (RObust Parameter Estimation) algorithm (Bárdossy and Singh, 2008) using Log Nash-Sutcliffe coefficient as objective function. Model was validated over 2005-2008. Figure 3 shows the validation hydrographs for time periods 2005 to 2008 for the Rangitata River basin. The TopNet model under-predicts some flood events and over predicts others, but the dynamics of the model seem acceptable. The analysis of the calibration results for the remaining catchments

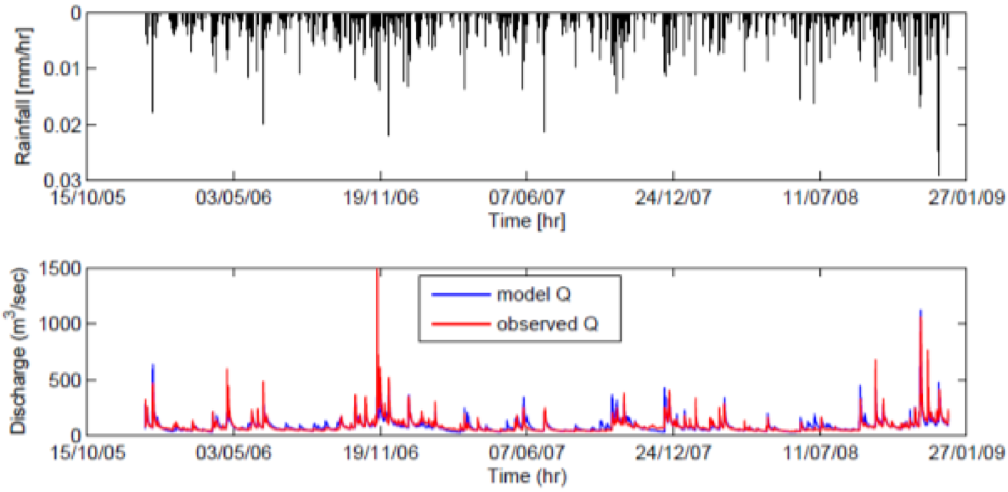

Figure 3 Observed and modeled hydrographs for Rangitata at Klondyke for validation time period, with catchment-mean climate forcing da

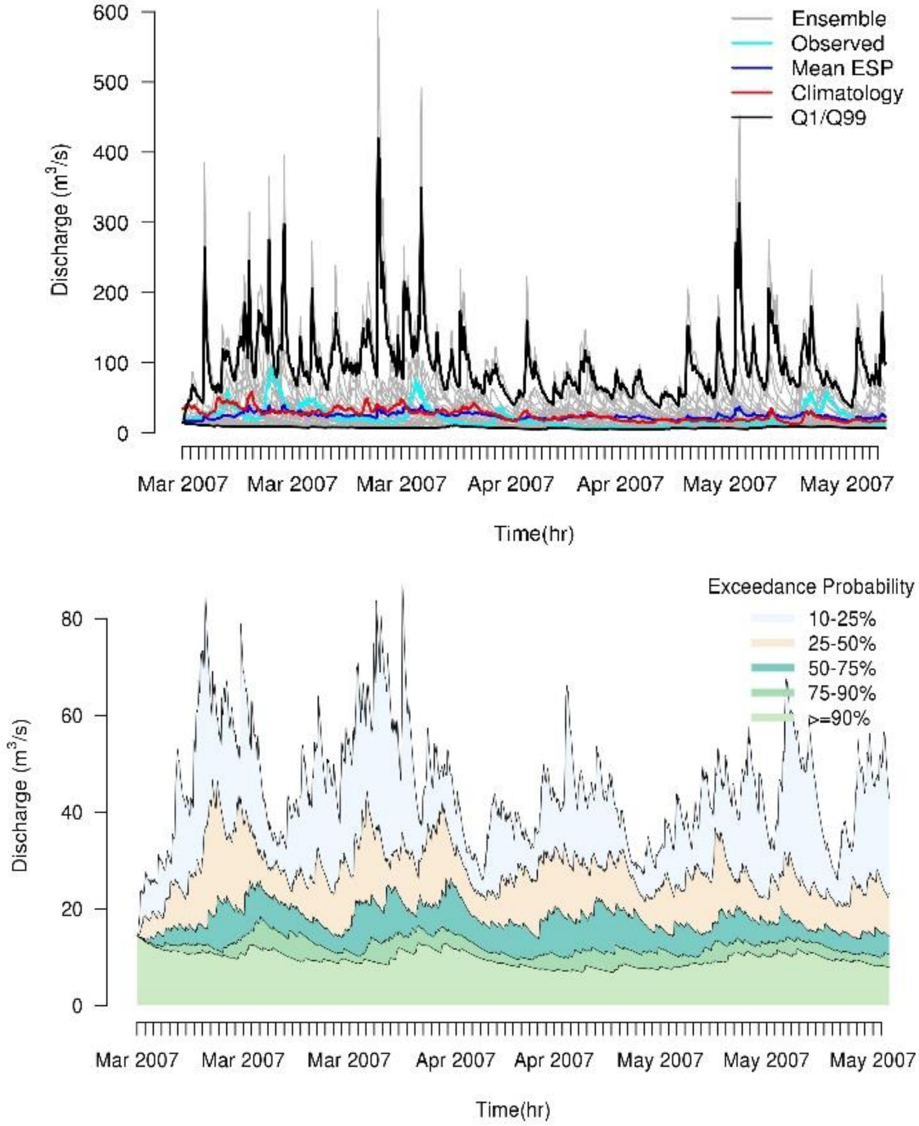

Figure 4 An example trace plot (top) and a probability plot (bottom) for Hooker catchment for forecast period March-May 2007

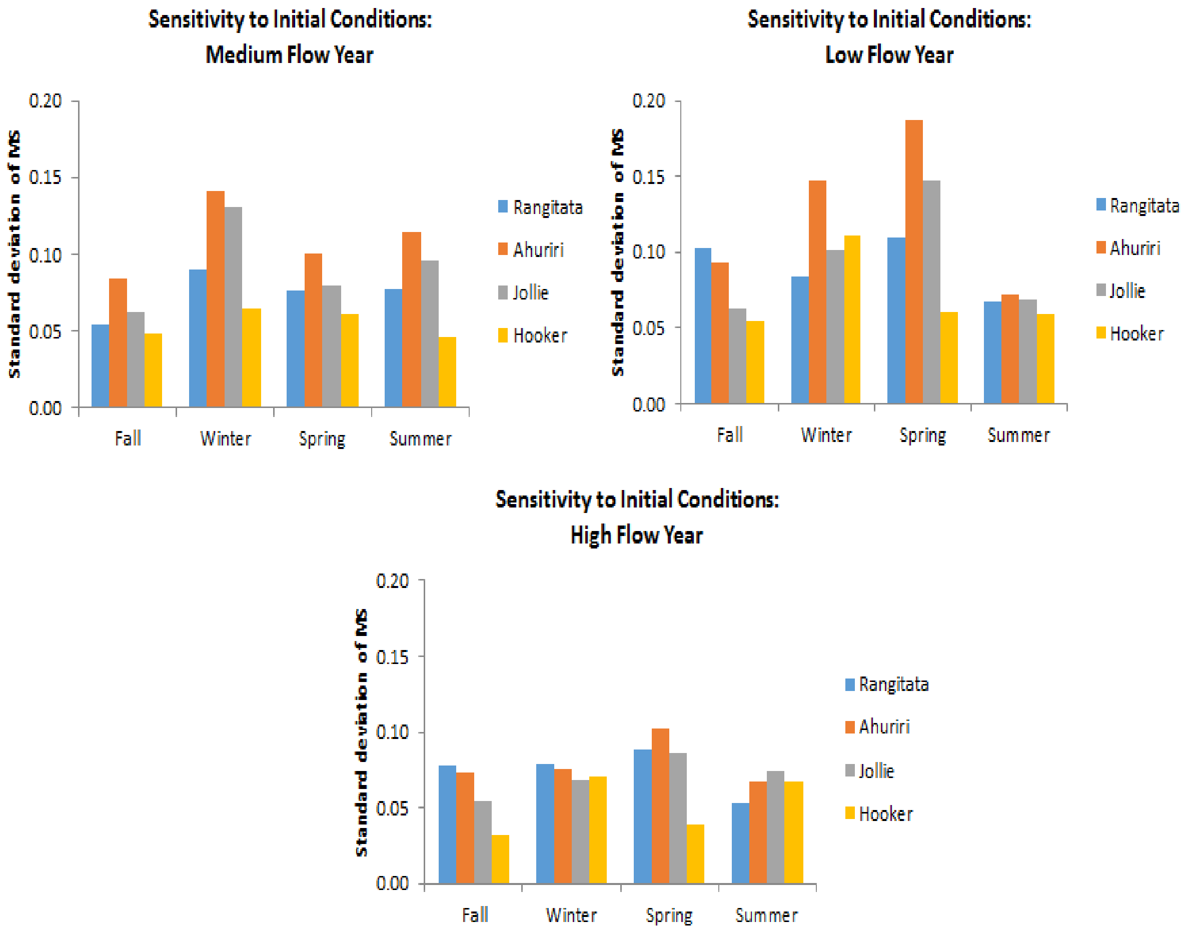

Figure 5 Sensitivity of initial condition on stream flow forecasting for low, medium and high water years for all the four season and all four catchments

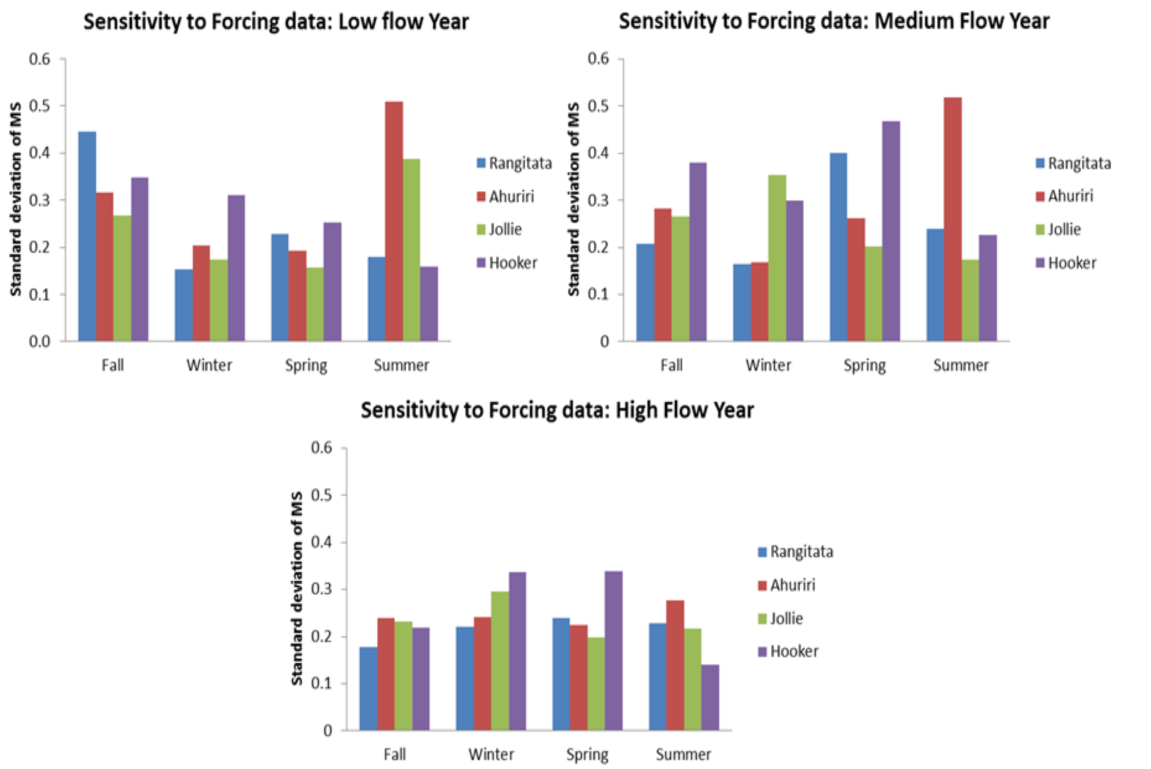

Figure 6 Relative importance of forcing data for different flow years for all the four catchments and seasons

provides similar conclusions and are not shown here.

ESP forecast

To test the flow forecasting performance of the ESP forecast for Rangitata, Ahuriri, Jollie and Hooker catchments, the forecast model was run in hindcast mode for year 2000 to 2010 for different season. Results from all the catchments were similar, hence, the results from the Hooker catchment are presented here. The hydrological model runs on monthly cycles, with a 3-months forecast produced at each cycle. The forcing meteorological data was used from 1972 till date of the forecast. An example for an ESP based three month forecast for Hooker catchment is given in Figure 4. Verification of the forecast over the period 2000-2010 indicates a Ranked Probability Skill Score of 23% to 69% (over climatology) across the four catchments. In general, improvement in ESP forecasting skill over climatology is greatest in summer for all catchments studied. The ESP based forecast exhibited higher skill for a greater percentage of the forecasting period than climatology.

Uncertainties due to state variable on streamflow forecast

The relative importance of initial conditions as a source of uncertainty in hydrological predictability is different for each season of the year and each catchment. This uncertainty was access for low, medium and high water years (Table 2). Figure 5 indicates the sensitivity of the streamflow forecast to initial conditions in terms of a standard deviation of MS for low, medium and high water years for all the four season and four catchments. The analysis indicates that the sensitivity of flow forecast to initial condition uncertainty depends on the hydrological regime that will be experienced by the basin during the seasonal forecast period.

The maximum variation of flow due to initial state is associated with spring for the Rangitata, Ahuriri and Jollie catchments and winter for the Hooker catchment. At high flow water year, the initial conditions have much more impact during wet periods (summer and spring) as compared to medium and low flow water year. Analysis across the different catchments study indicates that flow forecasts are sensitive to the estimation of the initial condition and this sensitivity is highly dependent of the catchment, hydrological regime and season. The forecasts are generally more sensitive to initial conditions during the first month. This leads to some uncertainty on the year to use for the initialization of the model.

For the Rangitata catchment, initial conditions have less impact on forecast uncertainty in fall than in winter. Flow predictions for spring and summer seasons are the most sensitive to initial condition. In the Ahuriri catchment, during spring, winter and summer seasons there is more spread in ensemble flow, and hence uncertainty, due to initial conditions, while during fall the behaviour is similar to that of Rangitata. During high flow years, glaciated catchments (e.g. Hooker), the initial conditions have much more impact during summer and winter as compare to fall and spring.

For high flow years, initial conditions are important to provide reasonable summer flow forecasts. However, initial conditions seem to be unimportant for fall flow forecasts. This result is valid for both basins. The similarity behaviour of the two basins could be the result of the similar climatic conditions prevailing at the time.

For medium flow years, initial conditions are important to provide reasonable summer flow forecasts and seem to be unimportant in term of fall flow forecast. Result valid for both basin and it is not related to the climate condition at the time as both basin is using different climatic sequence.

For low flow years, initial conditions seem relatively unimportant to provide spring flow forecast across the basin. Reasonable estimates of initial condition are important for fall and summer flow forecast. Effect seems less important for winter in Rangitata but important for Ahuriri. The glaciated catchment, Hooker, does not have much effect of initial condition in

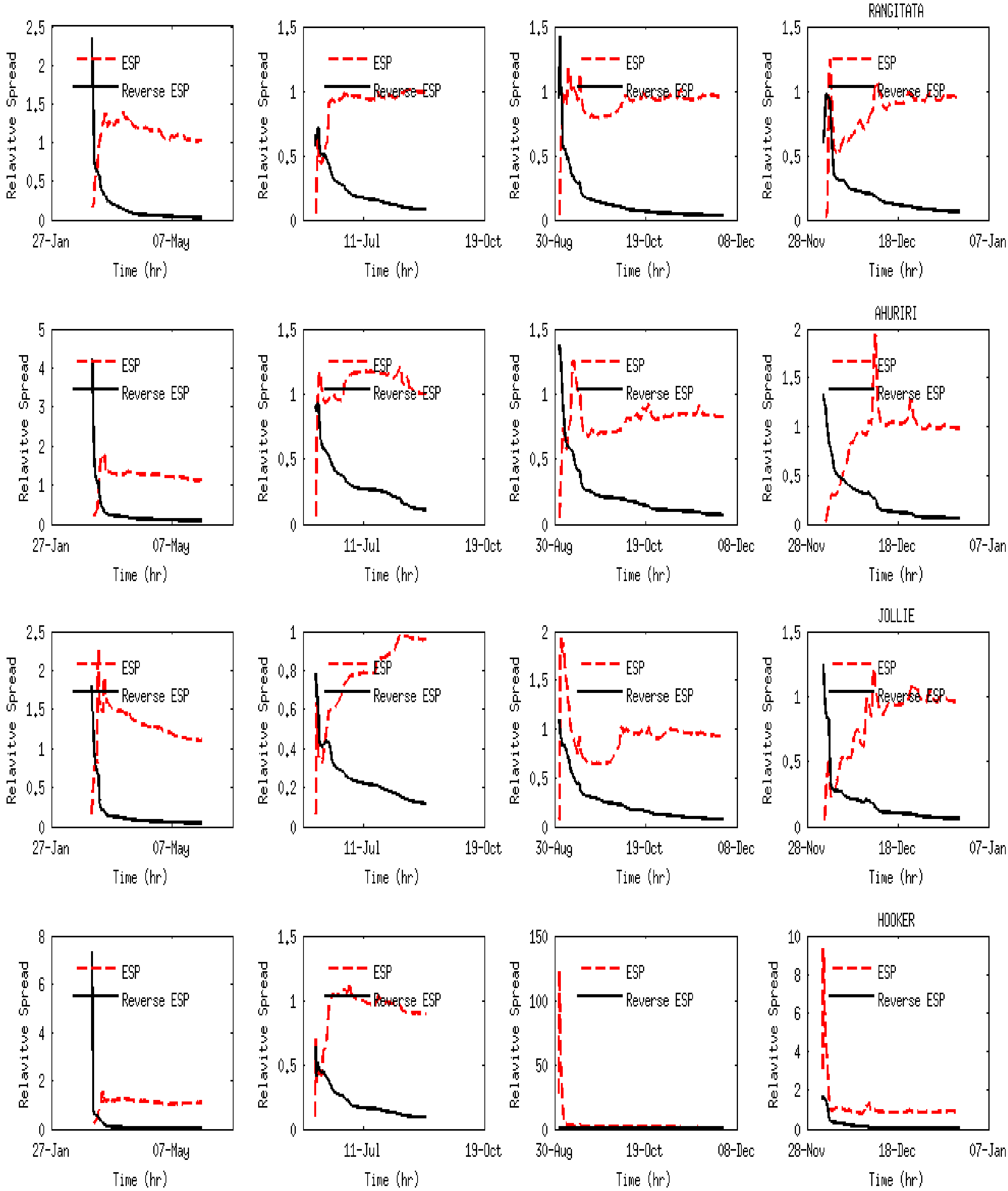

Figure 7 Variation during each forecast of the average relative spread from ESP and Reverse ESP for Rangitata, Ahuriri, Jollie, and Hooker catchments (top to bottom), for forecasts starting in Fall, Winter, Spring and Summer (left to right). In most cases, by two weeks into the forecast period, the ESP spread is larger than the reverse ESP spread.

summer. This may be due to effect of snow melt from the catchment during summer.

Uncertainties due to forcing data on streamflow forecast

In order to estimate the importance of error in hydrological forcing data, such as precipitation and temperature as a source of stream flow forecast uncertainty, ESP forecasts are prepared for each catchment. As a result, an ensemble of flow forecasts is created for specific months, based on the ensemble of past forcing data. Figure 6 shows the sensitivity of stream flow forecasts to forcing data as a standard deviation of MS for low, medium and high water year for all seasons and catchments. The analysis indicates that the sensitivity of flow forecast to forcing uncertainty depends on the hydrological regime that will be experienced by the basin during the seasonal forecast period. Ensemble spread due to uncertainty in forcing data tends to be lower in years with higher flow than the medium and lower flow years in all catchments and seasons. The average ensemble spread due to uncertainty in forcing data is higher in Ahuriri catchment for all the seasons and flow conditions.

For high flow years, the uncertainty in forcing data tends to be equal for all the catchments and all four seasons. Although, the Hooker catchment exhibits greater forcing uncertainty in in winter and spring.

For medium flow years, the uncertainty in forcing data tends to be variable. Hooker catchment have greater influence in springs and Fall where as Ahuriri has greater effect in summer.

For low flow year, the uncertainty in forcing data tends to have less effect during winter and spring seasons than summer and fall.

Relative importance of state variable and forcing data on streamflow forecast

To evaluate the relative importance of hydrologic initial condition errors and climate forcing errors as sources of seasonal runoff forecast uncertainty, we use a framework described by previous studies (Paiva et al., 2012; Wood and Lettenmaier, 2008). Ensembles of forecasts generated with identical climate forcing data and a range of initial conditions are termed reverse ESP, whereas ESP is an ensemble of forecasts where uncertainty is due to forcing data. (Paiva et al., 2012; Wood and Lettenmaier, 2008) used climatological variance to evaluate the relative spread. The relative spread is calculated as ratio of MS of ESP or Reverse ESP to MS of climatology. Although effects of initial conditions are found in all of the catchments, results show to be different for each catchment and for each season. The uncertainty associated with initial condition appears to be more important for wet periods. The spread of the ESP ensemble is higher for springs than others. On an average, the cross over time for ESP and reverse ESP is after two weeks to months (Figure 7). This implies that (on average) relative importance of initial condition two weeks to months for all catchment and all season. After this time period uncertainty in forecast is mainly due to uncertainty in forcing data. As similar conclusion was made by Svensson (2016).

Uncertainty associated with ESP forecast is mainly combination of both uncertainty due to initial state and climate forcing. In general snow coverage of catchments have great influence on initial condition of that catchment. This is simply because soil moisture level of snow dominated catchment is higher than other catchments. Moreover, soil moisture level of catchment has great influence in flow generation. The analysis of relative importance of initial conditions vs climate forcing show that the importance of both source of uncertainty is different for different catchment and different season. This can be due to reason that initial state estimation for different catchment is different when some catchment has high snow coverage than others.

The major limitation of hindcast based EPS forecast is quality of the past data on which the data based is made. If quality of the data is not good, we will end up with more uncertainty in our forecast. The other limitation in present study is not using the climate index to weight the ensemble members.

CONCLUSION

This study focused on effect of initial condition on ESP method for seasonal streamflow forecasts. ESP forecast uses conceptual hydrologic models to forecast future streamflow using the current hydrological conditions such as soil moisture, snow water equivalent, depth to ground water, with historical meteorological data (Day, 1985). The analysis indicates that the sensitivity of flow forecast to initial condition uncertainty depends on the hydrological regime experienced by the basin during the forecast period. Maximum variation of flow due to initial state is in spring, hence the initial state has more pronounced effects on spring than another season. On an average, the cross over time for ESP and reverse ESP is after two weeks to months. This indicates that (on average) the relative importance of initial conditions is greater within the first two weeks to months of the simulation for all catchment and all season. After this time period uncertainty in forecast is mainly due to uncertainty in forcing data. Since climate change is expected to result in increased variability of climate forcing, climate change may impact the quality of ESP-based forecasts. Hence, further research is needed to establish the impact of climate change on ESP forecast.

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