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Using hydroclimatic extremes to guide future hydrologic predictions

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Abstract

There are growing numbers of studies on climate change impacts on forest hydrology but limited attempts have been made to use current hydroclimatic extremes to constrain future climatic conditions. Here we used historical wet and dry years as a proxy for expected future extremes in a boreal headwater catchment. Hydrologic modelling assessments showed that runoff could be underestimated by at least 35% when dry year parameterization was used for wet year conditions. Uncertainty analysis showed that behavioural parameter sets from wet and dry year separated mainly on precipitation related parameters and to a lesser extent on parameter sets related to landscape processes. While inherent uncertainty in climate models still drives the overall uncertainty in runoff projections, hydrologic model calibration for climate impact studies should be based on years that best approximate future conditions to constrain uncertainty in projecting future conditions.

Keyword: Boreal forest, boreal hydrology, climate change, uncertainty assessment, hydroclimatic extremes

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1 Introduction

There are growing numbers of studies on climate change impacts on forest hydrology but these are usually based on long-time series that depict average system behaviour (Bonan, 2008; Lindner et al., 2010: Tetzlaff et al., 2013). As a result, limited attempts have been made to use current hydroclimatic extremes to assess plausible future conditions. These trends in predictive uncertainty might continue beyond our current projecting capability if the level of human activities and greenhouse gas emission continues. Increasing numbers of studies are showing the importance of ensemble projections to create a matrix of possible futures, where the mean provides a statistically more reliable estimate (Bosshard et al., 2013; Dosio and Paruolo, 2011; Oni et al., 2014a; Raty et al., 2014) instead of using a single climate model to represent the future. This has helped in part to constrain the predictive uncertainty and/or uncertainty in precipitation downscaling that is still larger than that of temperature (Teutschbein and Siebert, 2012). This inherent uncertainty might further increase in the warmer future in northern latitudes and high altitude catchments as precipitation dynamics become less consistent due to a shift in winter precipitation patterns toward rainfall dominance (Berghuijs et al., 2014; Dore, 2005).

It is unequivocally believed that climate is a first order control on watershed hydrology (Oni et al., 2015; Vörösmarty et al., 2000). As a result, runoff has become a central feature in the modelling community (Futter et al., 2014; Lindström et al., 2010) to understand watershed responses to both short and long term environmental changes (Wellen et al., 2014). Conceptualization of many of these hydrologic models has been based on average long term natural rainfall-runoff processes. However, average conditions may not best reflect processes operating under changing conditions. As a result, all models have their inherent uncertainties that can be amplified when projecting future conditions. The predictive uncertainties resulted from hydrologic models is due in part to issues of conceptualization, scaling and connectivity of processes between the landscape mosaic of a watershed (Tetzlaff et al., 2008; Ren and Henderson-Seller, 2006). No consensus has yet been reached regarding whether the uncertainty due to differences in hydrologic model structures and/or calibration strategies would be greater than the unresolved uncertainty inherent in climate models when projecting hydrologic conditions in boreal ecozones.

Although climate change is a global phenomenon (IPCC, 2007), it will likely also alter local catchment water balances (Oni et al., 2014b; Porporato et al., 2004). Prolongation of drought regimes or increasing frequency of storm events observed in different parts of the world (Dai, 2011; Trenberth, 2012) calls for greater attention on how to constrain uncertainty in predicting extreme events. While the frequency of hydroclimatic extremes might be low under present day conditions (Wellen et al., 2014), there could be intensification of precipitation events globally as climate changes (Chou et al.,

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2013). Otherwise, preparations for future hydroclimatic extremes could be undermined by our inability to properly simulate or project new conditions expected in the future.

One way to constrain the uncertainty in hydroclimatic projections is to utilize historical wet and dry years as a proxy for the future conditions expected as climate changes. Here we used hydrological and meteorological observations in dry and wet years in a long term monitored headwater catchment in northern Sweden. The objectives of this study were to: 1) to utilize long term field observations to gain insights into present extreme hydroclimatic behaviour; 2) to model the extreme behaviour using multi-criteria goodness-of-fit metrics; 3) to quantify the uncertainty in our current predictive practices that is based on long term series; 4) to conduct a robust parameter uncertainty assessment that will help to gain further insights into plausible differences in hydrologic behaviour in dry and wet years; and 5) to use an ensemble of climate change scenarios to test whether our current predictive uncertainty regarding future extremes could be attributed to inherent uncertainties in climate models or be driven by differences in hydrologic model calibration strategies.

2 Method

2.1 Study site

This modeling exercise was carried out in Svartberget (64° 16′N, 19° 46′ E), a 50 ha headwater boreal catchment part of the Krycklan experimental research infrastructure in northern Sweden (Fig. 1) (Laudon et al., 2013). Svartberget has two headwater streams, one of which drains a completely forest landscape while the other drains a headwater mire. The catchment has a long term mean annual temperature of about 1.8°C. The minimum temperature of -9.5°C occurred in January and maximum temperature of 14.5°C occurred in July. The catchment receives a mean annual precipitation of 610 ± 109 mm with more than 30% falling as snow (Laudon and Ottosson-Löfvenius, 2015). Snow cover usually lasts between November and May (Oni et al., 2013). The catchment has a long term mean annual runoff of 320 ± 97 mm with subsurface pathways dominating the delivery of runoff to streams. Spring melt represents the dominant runoff event in the catchment and lasts 4 to 6 weeks. Modelling results presented here were based on the long-time series of precipitation, air temperature and runoff from a weather and flow monitoring station at the outlet of Svartberget. Forest cover includes a century old Norway spruce (*Picea abies*) and Scot pine (*Pinus sylvestris*) with some deciduous Birch species (*Betula spp*). *Sphagnum sp* dominates the mire landscape. Svartberget has gneissic bedrock overlain by compact till of about 30 m thickness to the bedrock. The catchment elevation ranges from 235-310 m above sea level and was delineated using DEM and LIDAR (Laudon et al., 2011).

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2.2 Climate downscaling

We used 15 different regional climate models (RCMs) from the ENSEMBLES project (Van der Linden and Mitchell, 2009) in the downscaling and analysis presented here (Table 1). All the RCMs had a resolution of 25 km and were under A1B emission scenarios. Precipitation and temperature values (2061-2090) were obtained by averaging the values of the RCM grid cell with center coordinates closest to the center of the catchment and of its eight neighboring grid cells. Due to the coarse resolution of global climate data, we bias-corrected each RCM using precipitation and air temperature data from a weather station (1981-2012) located within the Svartberget catchment. The distribution mapping method was used for bias-correction of the 15 RCMs presented here. This was achieved by adjusting the theoretical cumulative distribution function (CDF) of RCM-simulated control runs (1981-2010) to match the observed CDF. These were then applied to adjust the RCM-simulated scenario runs for the future (2061-2090). Downscaling or RCM bias corrections presented here were fully described in Jungqvist et al. (2014) and Oni et al. (2014, 2015).

2.3 Modelling and analysis

PERSiST is a semi-distributed bucket type rainfall-runoff model with a flexibility that allows modelers to specify the routing of water following the perceptual understanding of their landscapes (Futter et al., 2014). This feature makes PERSiST a useful tool to simulate streamflow from landscape mosaic patches at a watershed scale. The model operates on a daily time scale with inputs of precipitation and air temperature. The spatial interface requires an estimate of area, land cover proportion and reach length/width of the hydrologic response units. In the PERSiST application presented here, we used three buckets to represent the hydrology of Svartberget. These include snow, upper soil and lower soil buckets. In the snow routine bucket, the model utilized a simple degree day evapotranspiration and degree day melt factor (Futter et al., 2014). Although the maximum rate of evapotranspiration could be independent of wet and dry years as used in this study, the actual rate of evapotranspiration could be influenced by the amount of water in the soil and by an evapotranspiration adjustment parameter. The latter is an exponent for limiting evapotranspiration that adjusts the rate of ET (depending on water depth in the bucket or how much is evapotranspired). The snow threshold partitions precipitation as either rain or snow. The model also simulates canopy interception for snowfall and rainfall to the uppermost bucket.

The quick flow bucket simulates surface or direct runoff in response to the inputs of rainfall or snowfall as a function of soil moisture saturation. Partitioning of the runoff generation process between the quick flow and lower soil buckets (upper and lower) is defined in the square matrix (Table 2). The evapotranspiration adjustment parameter sets the rate at which ET can occur when the soil is no longer able to generate runoff and this was set to 1 in the upper soil box. Maximum

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capacity is the field capacity of the soil that determines the maximum soil water content held. The time constant specifies the rate of water drainage from a bucket and requires a value of at least 1 in PERSiST. The relative area index determines the fraction of area covered by the bucket and is also set to 1 for our simulations. Infiltration parameters in each bucket determine the rate of water movement through the soil matrix. The model is based on series of first order differential equations that are solved sequentially following the bucket order in the square matrix. More detailed information about PERSiST parameterization and equations is provided in Futter et al. (2014). Parameter values and ranges used in the Monte Carlo analysis are listed in Table 3.

The model was calibrated against streamflow to generate present day runoff conditions. Initial manual calibration was performed on the entire time series to minimize the difference between the simulated and observed runoff. The manual calibration also helps to identify a suite of parameters and their ranges to be used in the Monte Carlo analysis by varying each parameter value such that the Nash-Sutcliffe (NS) value for the overall period of simulation dropped close to zero. This helped to determine the ranges to use in the Markov Chain Monte Carlo (MCMC) analysis for the wet and dry year simulations. The MCMC tool utilizes the Metropolis-Hasting algorithm and was described in Futter et al. (2014). The best parameter sets (top 100) were selected based on highest NS statistics from untransformed/log transformed data and other performance metrics (e.g. variance of modeled/observed series, absolute volume difference, root mean square and R^2). These top 100 parameter sets are referred to as behavioural parameters henceforth. The behavioural parameters were subjected to further analyses to determine hydrologic behaviour in dry and wet years. These include the cumulative distribution function (CDF) of behavioural parameters to determine the sensitive parameters and discriminant function analysis (DFA) to determine the dominant parameter(s) that separate the hydrology of wet from dry years. Wet years were defined as the hydrologic years with runoff exceeding 430 mm/yr or 40% higher than average annual runoff (1995, 2002, 2005 and 2010). Dry years were defined as the hydrologic years with runoff less than 150 mm/yr or less than 50% of average annual runoff (1987, 1992, 2000 and 2001). Hydrologic year was September 1 of a year to August 31 of the following calendar year. The bias corrected future climate series from ensemble of climate models (Table 1) were used to project future extremes using different goodness of fit metrics.

3 Results

3.1 Analysis of long term climate and hydrology series

Preliminary analysis showed that the Svartberget hydroclimate was highly variable and thus helped to partition the long term series into dry and wet years (SI 1). As a result, both dry and wet year conditions were different in terms of climate and cumulative runoff patterns. The cumulative distribution of the dry/wet year series (Fig 2a) showed that dry year precipitation (462 ± 102 mm) was only 64% of precipitation observed in wet year (716 ± 56 mm). Similar patterns were observed in runoff dynamics (Fig. 2b) where total runoff in dry years (129 ± 35 mm) was 29% of total runoff observed in wet years (449 ± 19 mm). Runoff response was 63% of total precipitation that fell in wet years and 28% of precipitation in the dry year regime. These were summarized in Table 4. Mean annual temperature was 2.4 °C in wet versus 1.8 °C in dry years.

When assessed on a seasonal scale, both precipitation and runoff were higher in almost all months in wet compared to dry year condition (Fig. 3) but differed in terms of seasonal patterns. While runoff peaked in May in both wet and dry years reflecting spring snowmelt dynamics that characterize Svartberget, runoff magnitude differed. Peak precipitation events occurred in summer months with additional autumn peaks in wet year. However, there was a shift in precipitation patterns with lowest precipitation depth occurring between February/March in dry year compared to April in wet year. Result also showed that temperature in wet and dry years were similar on average, while winter months were generally slightly warmer during wet years and summers slightly warmer in dry year (Fig 3c).

3.2 Future climate projections

Results showed that there was less agreement between the observed series and uncorrected individual RCMs (SI 2a, b). However, bias correction helped to reduce the uncertainty by providing a better match for the ensemble median of the air temperature and precipitation with their corresponding observed series (SI 2c, d). Results showed that ensemble median performed better in fitting the observed air temperature than precipitation. Results also showed a possible increase in air temperature by 2.8-5°C (median of 3.7°C) and possible increase in precipitation by 2-27% (median of 17%). Although precipitation and temperature were projected to increase throughout the year, the temperature changes would be more pronounced during winter months irrespective of whether it was a dry or wet year (Fig. 3c). However, projected changes in precipitation followed similar patterns to historical wet year with more precipitation expected between late winter months through spring (Fig. 3a). Result also showed that the winter period with temperature below 0°C could be shortened as climate warms in the future (SI 2).

3.3 Model calibrations and performance statistics

Model behavioral performance followed similar patterns when metrics such as R^2, NS and log NS were used (SI 3a-c) and could be used interchangeably to measure model performances. The model performed better when calibrated to wet and dry conditions (compared to long term) using NS metrics (SI 3b, c). Although no major improvements to model efficiency above NS of 0.79 and 0.81

were obtained in dry and wet years, respectively, we obtained a wider range of model performances in wet relative to dry year. The patterns of other performance metrics were different as we observed the highest RMSE in dry year and lowest RMSE in wet year condition (SI 3d). There was minimum AD range in the long term record and maximum range in dry year (SI 3e). Model performances based on the Var metric also showed the largest variability in dry year compared to the long term record and least Var in the wet year (SI 3f).

3.4 Runoff simulations and behavioural prediction range

Using the best performing parameter sets based on the NS statistic as an example, the model performed well in simulating the interannual runoff patterns but underestimated the peaks (SI 4). When resolved to their respective dry and wet year components, the model performed better in simulating runoff conditions in wet year despite its larger data spread and higher spring peaks than the dry year regime (SI 5). When parameterization for dry year was used for runoff prediction in wet years, runoff was underestimated by 35% due to significant uncertainty that stemmed from growing season months (Fig. 4). Modelling analysis presented here also showed that no single metric can be an effective measure of model performance under extreme conditions depicted in dry and wet years (Fig 5a- c). However, utilizing a behavioural mean of these different performance metrics (Fig. 5d-f) appeared to be a more effective way of calibrating to extreme hydroclimatic conditions. While the behavioural mean performed better in simulating runoff dynamics in winter through spring in the long term record and significantly reduced the uncertainty in dry and wet years, larger uncertainty existed in summer through autumn months in dry and wet year compared to the long term record.

3.5 Parameter uncertainty assessments

While we observed a wide prediction range from behavioural parameter sets (Fig. 5), we have limited information on the underlining processes. Therefore, we subjected the behavioural parameter sets to further analysis to identify sensitive parameters and plausible patterns of hydrologic processes that differentiate dry and wet years (Fig. 6). The cumulative distribution function (CDF) of behavioural parameter sets showed both rain and flow multipliers were sensitive parameters in dry year and tended toward lower ranges. The rain multiplier was less sensitive in wet years unlike the flow multiplier. Long term simulations showed no sensitivity to the rain multiplier but were sensitive to the flow multiplier. We observed similar patterns of behaviour to flow multiplier in all the three hydrologic regimes (Fig. 6b). Result also pointed to the sensitivity of interception in wet year but all the three hydrologic regimes showed similar patterns for the time constant (water residence time) in lower soil.

We subjected the pool of behavioural parameters in dry and wet year regimes to discriminant function analysis (DFA) to identify the key parameters that separate the extreme hydroclimatic conditions (Fig. 7). Result showed that both dry and wet years separated well in canonical space. However, the separation was driven mainly on quantitative parameters related to precipitation, interception and evapotranspiration on canonical axis 1 (Rmult, Int and DDE). The parameters separated to a lesser extent on processes related to snow parameters on canonical axis 2 (Smult, SM and DDM).

3.6 Quantification of uncertainty in hydrologic projections

We compared the effects of different performance metrics in wet and dry year regimes to constrain uncertainty in runoff projections under future hydroclimatic extremes in Svartberget catchment (SI 6). Results showed that differences in model representation of present day conditions might be minimal (compared to the observed) but a wide range of runoff regimes were projected in the future. We also observed small difference in the range of runoff projections (derived from minimum and maximum parameter sets) using different model performance metrics. Uncertainties inherent in climate models (as opposed to differences in calibration or performance metrics) appeared to drive the overall uncertainty in runoff projections to extreme hydroclimatic conditions. As wet year appeared to give more plausible projections of future condition expected in the boreal ecozone, and uncertainty in present day long term simulations is driven by dry year. We compared the runoff predictions using dry year parameterization to parameterization based on wet year to quantify our current predictive uncertainty. Results showed that future runoff could be under predicted by up to 40% if the projections are based on dry year parameterization alone (Fig. 8). Both parametrizations projected a shift in spring melt from May to April in the future. However, ensemble projections showed that summer months could be a lot wetter (based on wet year parameterization compared to dry year) and wet year spring peak could be up to 43% more compared to projections based on wet year ensemble mean.

4 Discussion

4.1 Insights from long term hydroclimatic series

Several studies have evaluated the impact of climate change on surface water resources (Berghuijs et al., 2014; Chou et al., 2013; Dore, 2005) but most of these were based on long term series that depict average system behaviour. However present day extremes, such as those derived from historical wet and dry years, can be used as simple proxies to gain insights that will aid our understanding of future hydroclimatic conditions. Using this approach we found that standard calibrations can result in underestimation of runoff by up to 35% due to high variability of hydroclimate series in northern boreal catchments. Several explanations can be offered for the high variability in the long term hydroclimate series at the study site. First, snowmelt hydrology is important in understanding the boreal water balances due to their location in a high latitude environment (Brown and Robinson,

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2011; Euskirchen et al., 2007; Dore, 2005; Tetzlaff et al., 2011, 2013). As a result, northern headwater catchments tend to show high variability (Brown and Robinson, 2011; Burn, 2008).

We observed annual runoff yield to be 63% of total precipitation that fell in the wet year compared to 28% of total precipitation in dry year. More runoff yield in the wet year regime could be as a result of near field capacity of the soils throughout the year, leading to greater propensity for runoff generation. This can also imply more winter snow accumulation during the long winter period, resulting in higher spring melt that drives the overall water fluxes (Laudon et al., 2004). Less runoff yield in dry year could be attributed to higher soil moisture deficit and relatively more important evapotranspiration rates (Dai, 2013).

We also observed differences in dry/wet year peak summer precipitation and a shift in the lowest precipitation in late winter/early spring. Despite the differences in precipitation, we observed similar patterns of runoff responses that only differ in terms of magnitude. This suggested that there was more effective rainfall (net available water) available to infiltrate, continuously recharge groundwater systems and generate runoff from upstream sources in wet year. Slightly warmer temperatures in summer months could drive more of growing season evapotranspiration in dry year. Small differences in temperature regime in wet and dry year, unlike precipitation, also explained why larger uncertainty still exists in precipitation downscaling using any scenario-based GCM as observed in SI 2.

4.2 Multi-criteria calibration of hydrological models

There has been considerable discussion about the calibrating procedure in the hydrological modelling community (Andreassian et al., 2012; Boij and Krol, 2010; Efstratiadis and Koutyiannis, 2010; Krause et al., 2005; Price et al., 2012). One of the key reasons for this is the difference in goodness-of-fit measures utilized in each model (Pushpathala et al., 2012). The most common strategy is to calibrate hydrologic models using the Nash and Sutcliffe (NS) statistic (Nash and Sutcliffe, 1970). However, many modelers believe that the NS-based method alone tends to underestimate variance in modelled time series as this metric could be biased toward high or low flow periods (Futter et al., 2014; Jain and Sudheer, 2008; Pushpalatha et al., 2012). This is leading us to use of multi-criteria statistics in model calibrations to constrain predictive uncertainty in our hydrologic projections to extreme hydroclimatic events. Therefore, multi-criteria calibration objectives that assessed model performances using different goodness-of-fit metrics could aid our understanding of hydrologic behaviour to extreme hydroclimatic conditions in boreal catchments. Our observation of differences in model performances in terms of NS and other metrics presented here is expected as a three box model proposed by Seibert and McDonnell (2002) similarly showed good fit for NS but poor fit using

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other metrics. However, lower model performance (based on NS) for the long term record is explainable as most hydrologic models are based on average system behaviour represented by long term rainfall-runoff processes (Futter et al., 2014; Oni et al., 2014b; Wellen et al., 2014).

The lower range of model performances in calibrating to the observed runoff in dry years is an indication of variable runoff generation processes associated with this wetness regime. Dry years cause drought-like conditions (Dai, 2011; Mishra and Singh, 2010) as a result of less water availability that reduce hydrologic connectivity within the catchment. However, the model performed better when applied to wet and dry years individually compared to the long term record based on NS statistics. This suggested that the mechanisms driving hydrologic processes in dry and wet years might be similar but their relative magnitude differs from long term average conditions (Grayson et al., 1997). Better performance to extreme conditions (compared to average long term) can also be attributed to the fact that NS or log NS are believed to be biased towards high flows and baseflow, respectively (Futter et al., 2014; Jain and Sudheer, 2008; Pushpalatha et al., 2012).

However, NS statistics alone are not enough to assess model performances in climate-sensitive boreal headwater streams such as Svartberget. Other metrics such as the RMSE showed that dry year could be a major driver of the uncertainty we observed in simulating the long term record. A possible explanation could be that the soil moisture deficit is larger in dry year, leading to soil matrix or vertical flow (Grayson et al. 1997) that can only generate runoff after filling soil pore spaces (McDonnell, 1990). For example, soil pore spaces are usually not close to saturation under dry condition due to 1) intermittent precipitation events throughout the year and 2) several patchy source area of high water convergence that are characterized by local landscape terrain or soil properties (Fang and Pomeroy, 2008; Jencso et al., 2009). Also higher rates of evapotranspiration coupled with low precipitation can contribute to a more spatially decoupled runoff and antecedent soil moisture conditions in dry years (Dai, 2013; Vicente-Serrano et al., 2010). Therefore, no single model performance metric can be effective in simulating the hydrology of extreme conditions, as our results showed that the mean of behavioural metrics outperformed any individual metric in dry and wet years under present day conditions.

4.3 Parameter sensitivity in dry and wet year regimes

Despite the fundamental issues of parameter equifinality (Beven, 2006) in models like PERSiST, more complex models have been shown to perform better in simulating runoff dynamics at the watershed scale (Li et al., 2015). The robust uncertainty assessment conducted here showed that extensive exploration of model parameter spaces could give some hints as to how hydrologic behaviour differs between wet and dry year regimes. A possible explanation for the non-sensitivity of the rain multiplier in wet year could be attributed to a more consistent or stable precipitation feeding the system throughout the year compared to intermittent precipitation in dry year (Fang and Pomeroy, 2008; McNamara et al., 2005). This can explain the smaller spring peak that characterizes the dry year regime or its non-sensitivity to interception unlike what characterize wet year regimes.

However, sensitivity of the lower soil time constant followed similar patterns in dry and wet years unlike the upper soil box. Therefore, we could expect faster flow and higher runoff ratio in the wet years due to rapid response to precipitation events and more macropore flow (Peralta-Tapia et al., 2015). This can lead to steady runoff generation due to 1) near saturation of soils and 2) greater connectivity between stream channels and upland areas (Bracken et al., 2013; Ocampo et al., 2006) that become disconnected in dry year. However, the patterns of the flow multiplier parameter suggested that both extreme conditions followed similar runoff generation processes. These suggested that the main physical mechanism to explain parameter sensitivity and hydroclimatic behaviour to extreme conditions were related to differences in their precipitation patterns rather than landscape-driven hydrologic processes.

4.4 Drivers of hydrologic behaviour in dry and wet year regimes

Even though equifinality limits the use of CDFs alone in identifying all sensitive parameters, DFA of behavioural parameters gave further insights on plausible differences in wet/dry hydrologic behaviour when projected on canonical space. This suggested that hydrological model parameterizations calibrated to high flow associated with wet year differ from parameterizations for long term or dry conditions. Therefore, parameter separation primarily on quantitative parameters (Rmult, Int and DDE) related to rainfall and evapotranspiration on canonical axis 1 suggested that climate is a first order control of hydroclimatic extremes in the boreal forest. This is consistent with Wellen et al. (2014), who showed that extreme conditions could be triggered in a watershed when precipitation reaches a threshold that can initiate saturation overland flow. This is because soils are always near saturation capacity under prolonged wet conditions (Grayson et al., 1997). This can explain the increase in hydrologic model uncertainty in capturing the peak runoff events in wet years unless parameter ranges that combined different performance metrics are considered. Unfortunately, we might face a new challenge of increased precipitation ranges in the future as climate changes (Chou et al., 2013; Dore, 2005). The separation of wet and dry years on snow process related parameters (Smult, SM and DDM) to a lesser extent on canonical axis 2 suggested that indirect landscape influences on snow processes could be important but is a second order control on runoff response to hydroclimatic extremes. This agrees with Jencso et al. (2009), who showed that landscape mosaic structures with their unique source contribution areas control the overall watershed response.

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4.5 Implications for future climate projections

All the 15 RCMs considered in this study projected a range of plausible futures in the Swedish boreal forest. Irrespective of the model performance metrics, results suggested that the future could be substantially wetter and could make drought conditions less severe in boreal ecozones. This could explain the large uncertainty in projecting runoff under extreme wet conditions. For example, dry year and long term parameterization were similar and runoff was under-predicted by 35% under the present day condition when parameterization in dry year was used for wet year. This was due to large predictive uncertainty in runoff dynamics (Fig. 4) that resulted from high evapotranspiration rates during the snow free growing seasons in dry year. This suggests that wet year calibration could give more credible projections of the future in the boreal ecozone as the distribution of precipitation in wet year is closer to the precipitation pattern expected in the future. While our modelling results suggested negligible differences in runoff projections based on either dry year or long term parameterization, extreme hydrologic events related to wet conditions could become a more dominant feature in the boreal ecozone.

These have implications on future climate change as both dry and wet year parametrization showed a consistent shift in spring melt patterns from May to April (Fig. 8). This temporal advance in spring melt patterns could result from altered distribution of snowfall and rainfall patterns in the winter (Berghuijs et al., 2014; Dore, 2005), and may likely have effects on soil frost in the upper layer (Jungkvist et al., 2014) or change in evapotranspiration rates (Jung et al., 2010; Vicente-Serrano et al., 2010). Therefore, intensification of hydroclimatic regimes as climate changes in the future (Kunkel et al., 2013) could drive water quality issues to a new level in the boreal forest due to changes in the flux of organic carbon and aquatic pollutants. Furthermore, precipitation has been shown to have much larger biogeochemical implications for the boreal carbon balance than previously anticipated (Öquist et al., 2014).

The large spread of mean annual runoff projected by each RCM in wet years is an indication of less agreement between RCMs when predicting future conditions. This suggested that inherent uncertainty in climate models, rather than differences in model calibrations, drive the overall uncertainty in runoff projections. However, hydrologic model calibration for climate impact studies should be based on years that closely approximate future conditions to best constrain uncertainty in predicting extreme conditions.

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Table 1: List of RCMs from EU ENSEMBLE project used in study and their driving GCM.

No.	Institute	RCM	Driving GCM
1	**C4I**	RCA3	HadCM3Q16
2	**CNRM**	Aladin	ARPEGE
3	**DMI**	HIRHAM5	ARPEGE
4	**DMI**	HIRHAM5	BCM
5	**DMI**	HIRHAM5	ECHAM5
6	**ETHZ**	CLM	HadCM3Q0
7	**HC**	HadRM3Q0	HadCM3Q0
8	**HC**	HadRM3Q16	HadCM3Q16
9	**HC**	HadRM3Q3	HadCM3Q3
10	**ICTP**	RegCM	ECHAM5
11	**KNMI**	RACMO	ECHAM5
12	**MPI**	REMO	ECHAM5
13	**SMHI**	RCA	BCM
14	**SMHI**	RCA	ECHAM5
15	**SMHI**	RCA	HadCM3Q3

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Table 2: Square matrix used to partition runoff generation between buckets in PERSiST application presented here. For example, we conceptualized that 40% of the precipitation inputs are retained in the upper box, 60% are transferred to the lower box and 0% are transferred to the groundwater (row 2)

	Upper box	Lower box	Groundwater
Upper box	0.4	0.6	0
Lower box	0	0.5	0.5
Groundwater	0	0	1

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Table 3: Parameter notations, descriptions and ranges used in the MCMC analyses in this analysis

	Notation	Parameter description	Min	Max	Units
SNOW	SMt	Snowmelt temperature	-3	5	°C
	ISD	Initial snow depth	40	120	mm SWE
	DDM	Degree day melt factor	1	4	mm °C day^{-1}
	DDE	Degree day evapotranspiration	0.05	0.3	mm °C day^{-1}
	GDT	Growing degree threshold	-3	3	°C
	Smult	Snow multiplier	0.5	1.5	-
	RM	Rain multiplier	0.5	1.5	-
	CI	Canopy interception	0	4	mm day^{-1}
UPPER BOX	IWD_1	Initial water depth	40	100	mm
	RWD_1	Retain water depth	100	250	mm
	Infilt_1	Infiltration	1	15	mm day^{-1}
	DRF	Drought runoff fraction	0	0.5	-
	REI	Relative evapotranspiration index	1	1	-
	EA_1	Evapotranspiration adjustment	1	10	-
LOWER BOX	IWD_2	Initial water depth	80	250	mm
	Infil_2	Infiltration	1	15	mm day^{-1}
	RWD_2	Retain water depth	200	200	mm
	TC_2	Time constant	2	50	days
	EA_2	Evapotranspiration adjustment	0	0	-
	InunT_2	Inundation threshold	80	150	mm
GROUNDWATER	IWD_3	Initial water depth	80	250	mm
	Infilt_3	Infiltration	0.1	10	mm day^{-1}
	EA_3	Evapotranspiration adjustment	0	0	-
	RWD_3	Retain water depth	250	250	mm
	TC_3	Time constant	2	50	days
REACH	a	Flow multiplier	0.004	0.762	-
	b	Streamflow exponent	0.01	0.98	-
	ST	Snow threshold temperature	-2	3	°C

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Table 4: Quantification of runoff and precipitation dynamics in wet and dry year using the observed series and simulated series from PERSiST

	Observed series (%)	Simulated series (%)
Precipitation proportion (dry:wet year)	64	
Runoff proportion (dry:wet year)	29	29
Runoff response to precipitation events		
Dry year	28	30
Wet year	63	66

Figure 1: Map of Svartberget; a long term monitored headwater catchment in northern boreal ecozone of Sweden. The catchment (50ha) drains terrestrial area that consist of forest (80%) and upland mire (20%). Streamflow measurements were taken at downstream confluence point .

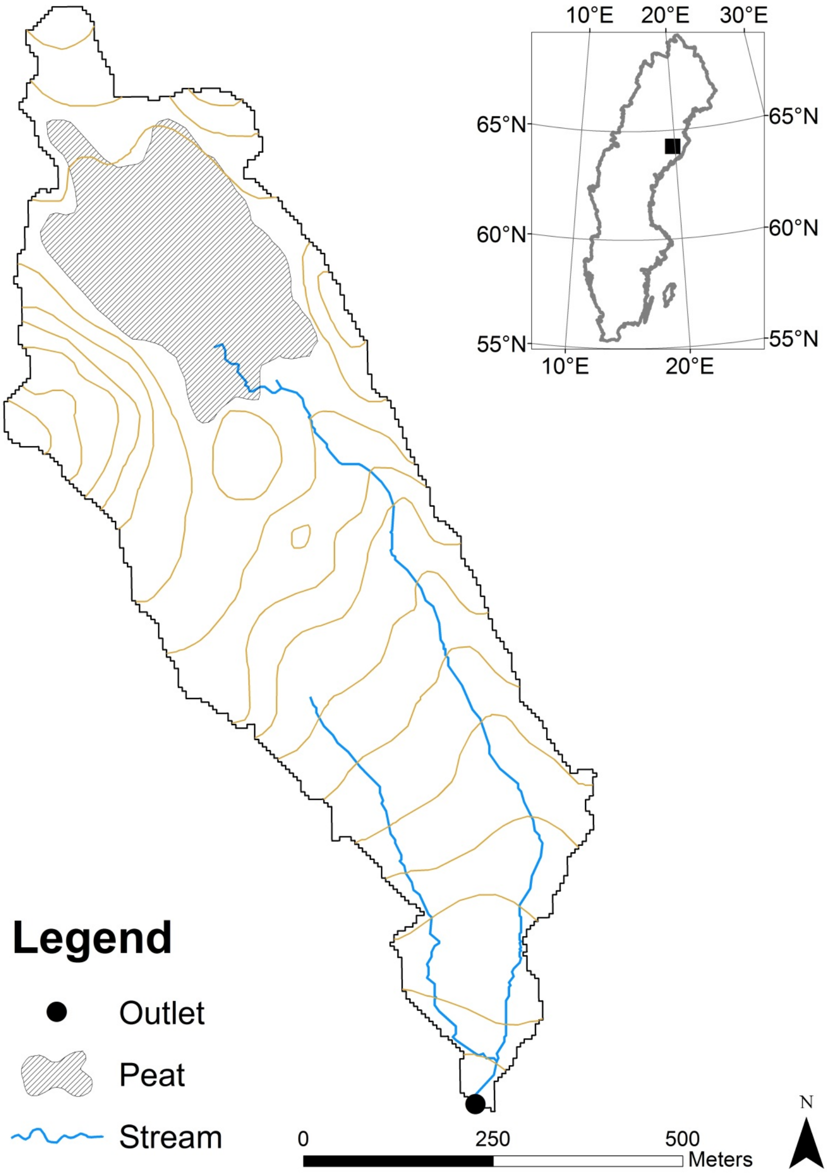

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Figure 2: Cumulative plots of (a) precipitation and (b) runoff in dry (1995, 2002, 2005 and 2010) and wet (1987, 1992, 2000 and 2001) hydrologic years. Hydrologic year represent September 1 (day 1) to August 31 of the following year (day 365).

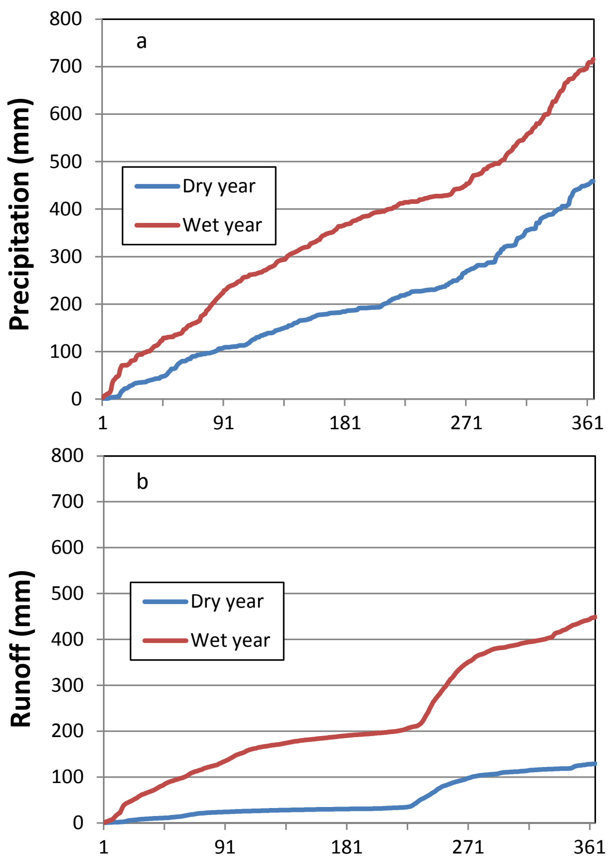

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Figure 3: Seasonal patterns of (a) precipitation in dry and wet years versus ensemble mean of future precipitation projections, (b) runoff dynamics in dry and wet year and (c) temperature in dry and wet years relative to ensemble mean of future temperature projections.

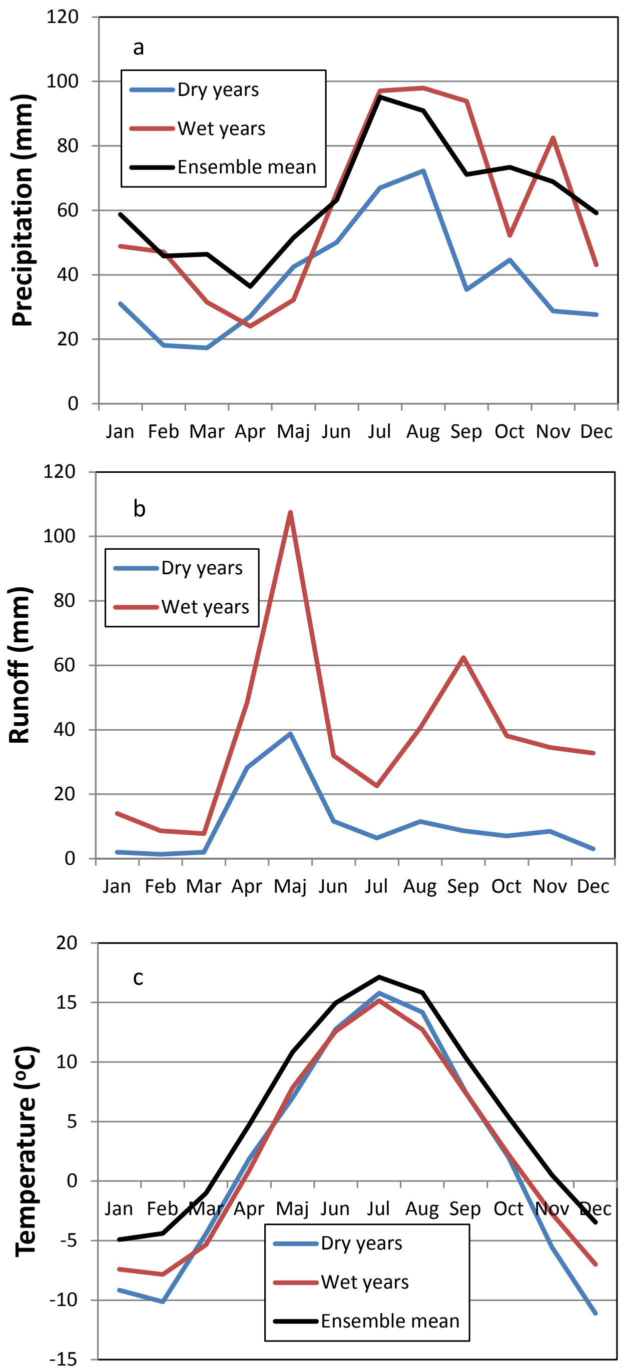

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Figure 4: Quantification of predictive uncertainty in runoff simulations when best parameter set (based on NS) calibrated for dry year was used for wet year.

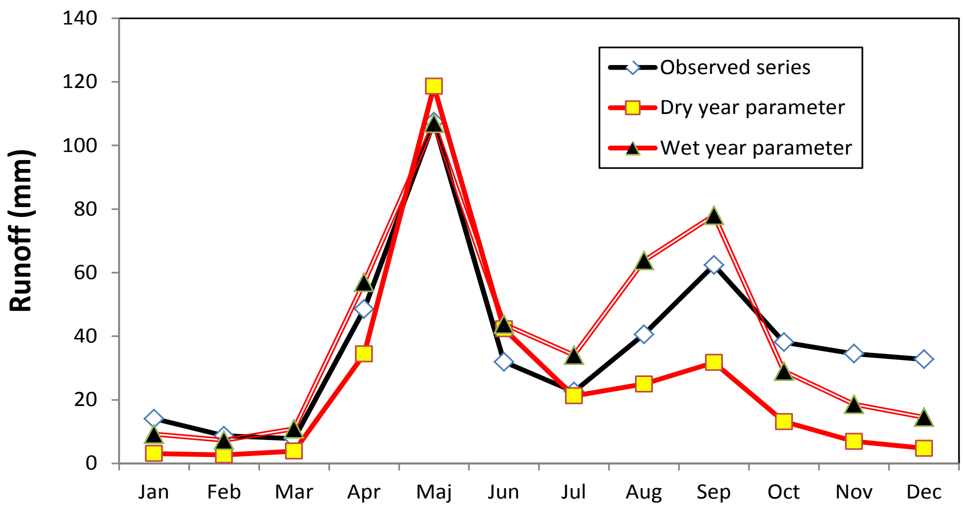

Figure 5: Summary plots showing prediction range of seasonal runoff dynamics using different performance metrics in a) dry year, b) wet year and c) long term. (d) to (f) show the corresponding model performances using behavioural mean of the metrics in (a) to (c).

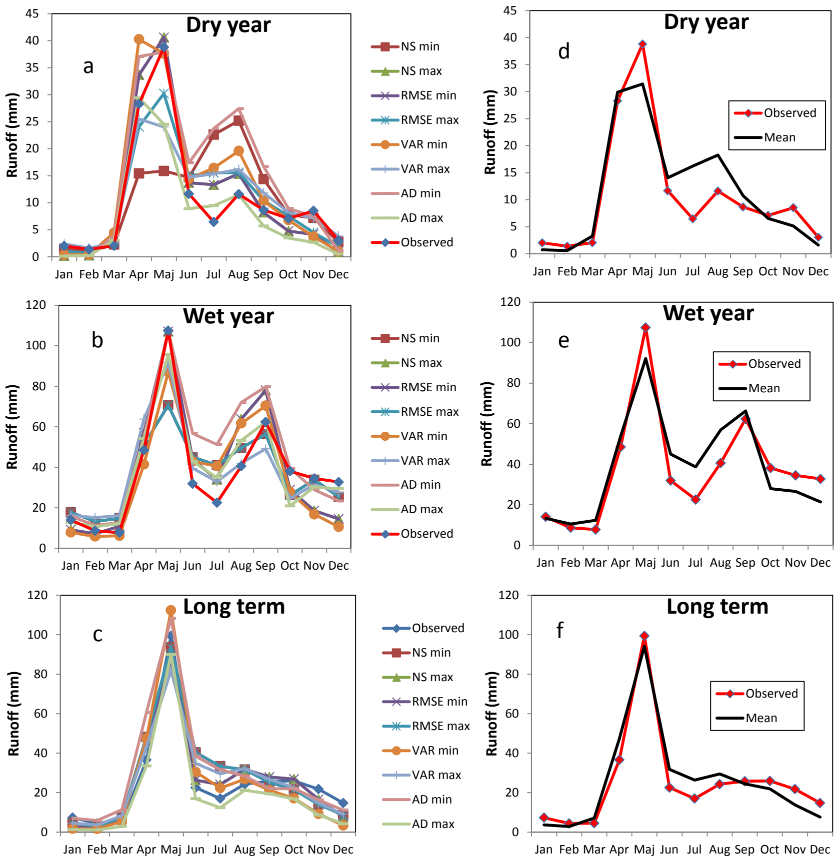

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Figure 6: Cumulative distribution function (CDF) of behavioural parameters (top 100 iterations from the MCMC) in wet and dry years versus long term record. (a) is the rain multiplier, b) is the flow multiplier, c) is and d) is the lower soil time constant that defines water residence time in the lower soil box. A rectangular distribution (straight line plot) defines parameter behaviours that were not sensitive (not left- or right-skewed).

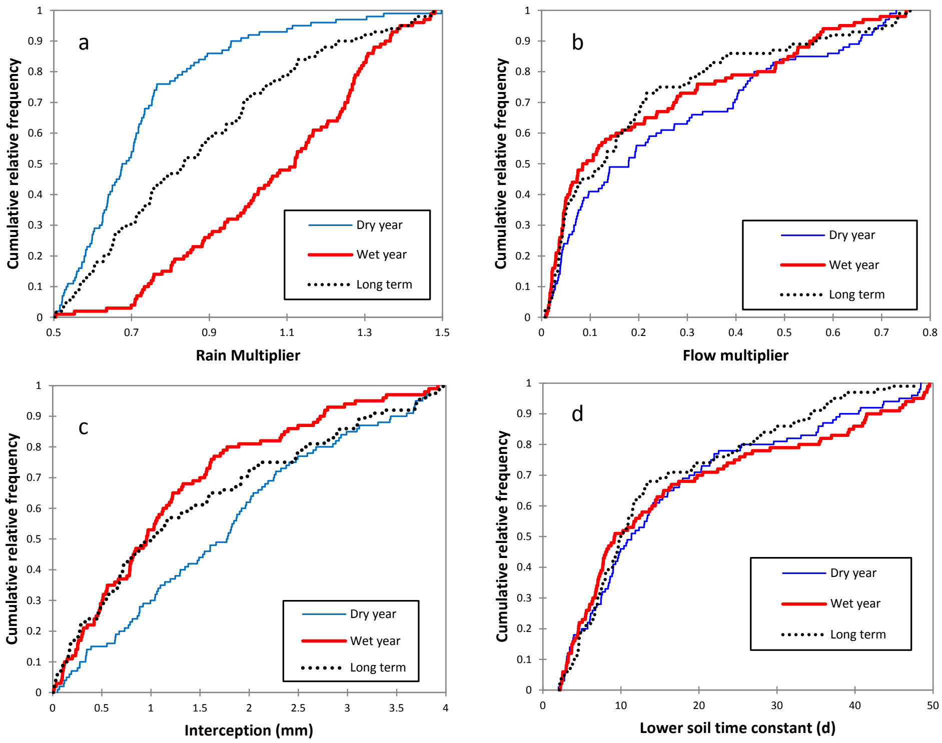

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Figure 7: Separation of the behavioural parameter sets (top 100 iterations from MCMC) in the dry and wet year hydrologic regimes using Discriminant Function Analysis (DFA). Wet and dry year hydrology separated mainly on parameters related to evapotranspiration (DDE), interception (Int) and rain multiplier (Rmult) on canonical 1. Parameters were separated on snow multiplier (Smult), snowmelt (SM) and degree day melt factor (DDM) on canonical 2. The circles represent normal 50% contours. Parameters are defined in Table 3

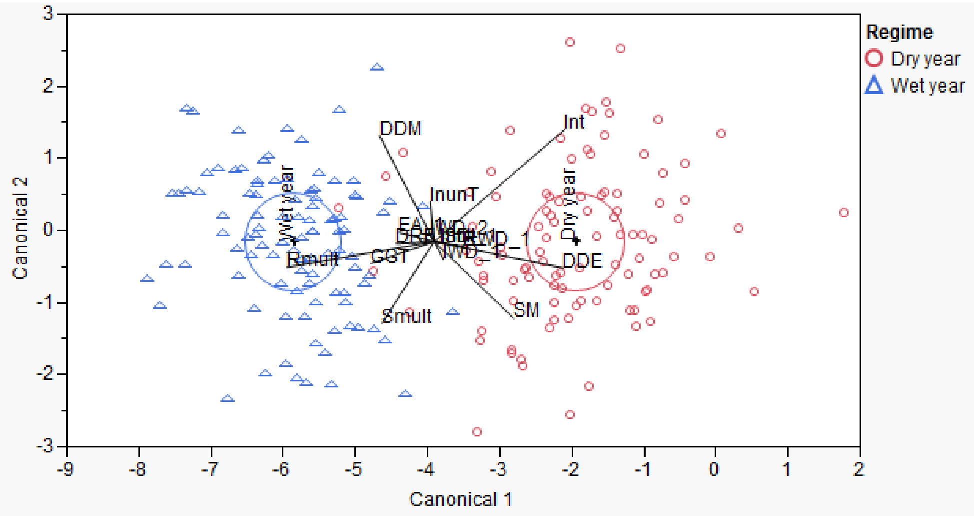

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Figure 8: Example of range of runoff projection using wet year parameterization that closely depicts the future versus projected range based on dry year parameterization that drives the uncertainty in long term series. The projected range was simulated to constrain uncertainty in extreme wet and dry conditions in the future using the behavioural parameter sets (top 100 iterations from MCMC) for each of the 15 RCM scenario considered here (100 parameters by 15 RCMs = 1500 runs each for dry and wet year). Ensemble mean represents the mean of the 1500 realizations while long term depicts mean of the long term series.