Reply to reviewer comment hess-2017-340-RC1

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General referee comment:

There is an urgent need to improve the safety and operation of impoundments in Central Asia, yet hydrometeorological data to support inflow forecasting and water management are in short supply. This manuscript seeks to address these needs by developing a standard multiple linear regression model of melt season (April-September) discharge in 13 catchments. Forecasts are based on suites of predictors (precipitation, temperature, snow cover and composite variables) in January to June, and tested using a cross-validation technique applied to 16 years of monthly data. Following an exhaustive evaluation of all possible permutations of monthly and averaged predictors, best-performing models, and 20 near-optimal models are retained. The attendant mix of predictors and uncertainty bounds are then examined for months leading up to and at the start of the forecast season. Variations in forecast skill are qualitatively linked to catchment characteristics.

The overall approach to model development is necessarily pragmatic given the data and technical constraints of the region. Despite the simplicity of the approach, high explained variance (R2) is reported and the authors have bounded forecasts using envelopes of predictor suite uncertainty. However, it is unclear whether the underpinning data comply with the assumptions of the MLR model (i.e. linearity of relationships, homoscedasticity, no outliers, normally distributed and uncorrelated residuals). Furthermore, given the small number of cases (16) and relatively large number of independent variables (4) it is essential that significance levels and adjusted R2 values are reported for all retained MLR models. Significance of the model coefficients should also be tested and any insignificant variables removed. In some models, the predictor variable (e.g. May discharge) is not fully independent of the forecast variable (April to September discharge).

On this basis, publication is recommended subject to the following major revisions, minor corrections and clarifications.

We thank the referee for the critical and constructive comments. We provide detailed answers and justifications below, were the main comments are listed.

Main comments

[Abstract] Please incorporate more headline results, such as the range of forecast skill for forecasts issued before the onset of the main melt season, as well as typical forecast biases.

The suggestion has been taken up and the abstract reads now as follows:

The semi-arid regions of Central Asia crucially depend on the water resources supplied by the mountainous areas of the Tien Shan, Pamir and Altai mountains. During the summer months the snow and glacier melt dominated river discharge originating in the mountains provides the main water resource available for agricultural production, but also for storage in reservoirs for energy generation during the winter months. Thus a reliable seasonal forecast of the water resources is crucial for a sustainable management and planning of water resources. In fact, seasonal forecasts are mandatory tasks of all national hydro-meteorological services in the region. In order to support the operational seasonal forecast procedures of hydro-meteorological services, this study aims at the development of a generic tool for deriving statistical forecast models of seasonal river discharge. The generic model is kept as simple as possible in order to be driven by available meteorological and hydrological data, and be applicable for all catchments in the region. As snowmelt dominates summer runoff, the main meteorological predictors for the forecast models are monthly values of winter precipitation and temperature, satellite based snow cover data and antecedent discharge. This basic predictor set was further extended by multi-monthly means of the individual predictors, as well as composites of the predictors. Forecast models are derived based on these predictors as linear combinations of up to 3 or 4 predictors. A user selectable number of best models is extracted automatically by the developed model fitting algorithm, which includes a test for robustness by a leave-one-out cross validation. Based on the cross validation the predictive uncertainty was quantified for every prediction model. Forecasts of the mean seasonal discharge of the period April to September are derived every month starting from January until June. The application of the model for several catchments in Central Asia - ranging from small to the largest rivers (240 km^2 to 290,000 km^2 catchment area)– for the period 2000-2015 provided skilful forecasts for most catchments already in January with adjusted R^2 values of the best model in the range of 0.3 – 0.8. The skill of the prediction increased every following month, i.e. with reduced lead time, with adjusted R^2 values usually in the range 0.8 – 0.9 for the best and 0.7 – 0.8 for the ensemble mean in April just before the prediction period. The later forecasts in May and June improve further due to the high predictive power of the discharge in the first 2 months of the snow melt period. The improved skill of the model ensemble with decreasing lead time resulted in very narrow predictive uncertainty bands at the beginning of the snow melt period. In summary, the proposed generic automatic forecast model development tool provides robust predictions for seasonal water availability in Central Asia, which will be tested against the official forecasts in the upcoming years, with the vision of operational implementation.

[Table 1] Add additional information on the mean annual precipitation, temperature and winter snow cover area in each catchment.

Thanks for the suggestion. We will extend Table 1 as shown below.

Table 1: List of the catchments for which prediction models are derived with discharge (Q) and meteorological gauging stations used for the prediction. Note that Charvak, Andijan and Toktogul are reservoir inflows summing several tributary inflows. For the Charvak reservoir the mean temperature and precipitation data of three meteo stations located in the catchment was used. Latitude and longitudes are in decimal degrees (WGS84). Q mean seasonal is multiannual mean seasonal discharge from April to September for the period 2000-2015. Mean annual P ist the mean annual precipitation sum of the meteo station for the period 2000-2015. Mean annual T is the mean annual mean temperature of the meteo station for the period 2000-2015. Mean winter SC is the mean of the mean daily snow coverage of January to February for the period 2000-2015.

	catchment	discharge station	Q deg. lat	Q deg. long	meteo station	meteo deg. lat	meteo deg. long	meteo altitude [m]	catchment area [km^2]	Q mean seas. [m^3/s]	mean altitude [m]	mean ann. P [mm]	mean ann. T [°C]	mean winter SC [%]
1	Uba	Shemonaikha	50.620	81.880	Shemonaikha	50.620	81.880	300	9324	269.2	740	460	3.6	69.2
2	Ulba	Perevalochnaya	50.033	82.843	Oskemen	50.030	82.700	375	5080	151.4	950	483	3.8	87.7
3	Chirchik	Charvak	41.626	69.969	Chatkal	41.822	71.097	2300	10903	346.21	2575	708	5.5	97.3
					Oygaing	42.000	70.633	1620	10903					
					Pskem	41.861	70.384	2220	10903					
4	Talas	Kluchevka	42.581	71.836	Kyzyl-Adyr	42.616	71.586	1764	6663	19.62	2424	327	9.0	72.1
5	Ala-Archa	Kashka-Suu	42.650	74.500	Baytik	42.670	74.630	1579	239	8.83	3288	559	3.2	79.6
6	Chu	Kochkor	42.250	75.833	Kara Kuzhur	41.930	76.300	855	4961	34.53	2934	253	1.1	59.4
7	Chilik	Malybai	43.494	78.392	Shelek	43.597	78.249	600	3964	70.67	2603	274	11.0	74.5
8	Charyn	Sarytogai	43.553	79.293	Zhalanash	43.043	78.642	1690	7921	59.06	2260	507	6.1	82.4
9	Karadarya	Andijan	40.814	73.257	Ak-Terek	40.365	74.222	1190	11670	186.21	2663	913	9.5	82.4
10	Naryn	Toktogul	41.760	72.750	Naryn city	41.460	75.850	2040	51926	653.13	2850	374	-5.8	88.0
11	Upper Naryn	Naryn city	41.460	75.85	Tien Shan	41.910	78.210	3614	10343	168.64	3546	345	-5.8	91.0
12	Amudarya	Kerki	37.842	65.23	Kerki	37.842	65.230	237	287714	2551.02	2578	173	17.9	56.7
13	Murgab	Takhta Bazar	35.966	62.907	Takhta Bazar	35.966	62.907	354	35767	40.13	1707	217	18.2	37.5

[Section 2.1] Explain the method and purpose of the hierarchical clustering. What metrics were used to compare catchments and to establish cluster membership? The three clusters should be linked much more explicitly to subsequent discussions of predictor sets (in section 4.2).

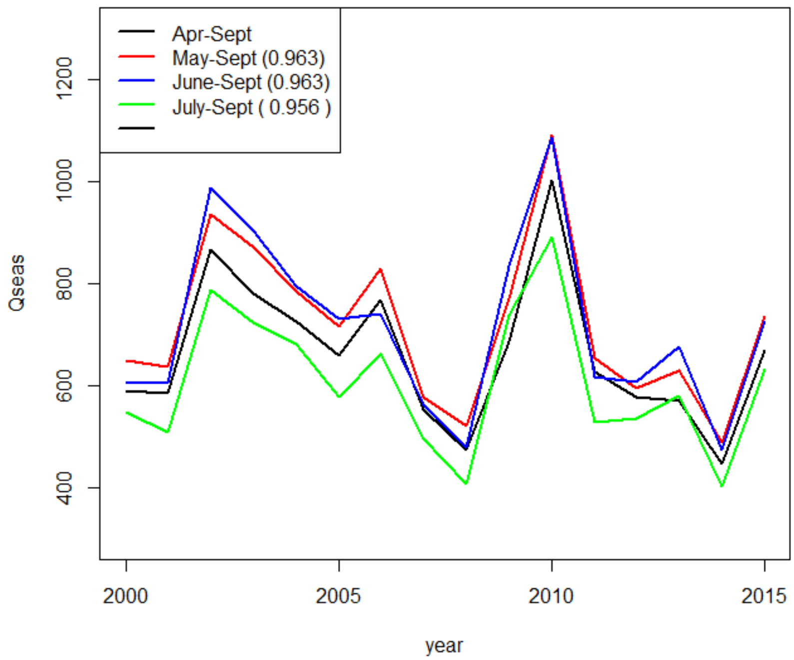
We want to show that the different catchments show some differences in the inter-annual variability of the seasonal discharge. This is important, because if all catchment would have the same inter-annual variability, the discharge could theoretically be equally well forecasted with meteorological variables from other catchments with the same variability. This would mean in turn, that the presented ability of the approach to predict the seasonal discharge for the selection of different catchments would provide no additional evidence for the suitability of the approach as a single test case. Cluster memberships were established based on the dissimilarities of the correlation between the seasonal discharge time series of the different catchments, i.e. basically on the similarity/dissimilarity of the variability of the seasonal discharge as shown in Figure 2. The cluster algorithm starts by assigning a single cluster for each catchments, and starts to reduce the number of clusters by joining the most similar clusters. For the construction of the clusters the Ward algorithm was chosen, which minimizes the variability within the clusters and maximizes the variability between the clusters. This is a standard procedure. Details on this can be found in any statistical textbook.

[Section 3] How significant are evaporative losses from the catchments and how might this component of the water balance be represented within MLR models?

The catchments presented are all mountainous catchment with a cold climate and fast flowing rivers. The evaporative losses from the rivers are thus expected to be low, and do not substantially influence the seasonal discharge to be predicted. Evaporative losses from reservoirs are more likely, but all catchments in the study are without reservoirs (except the Nurek dam in Amudarya, whos influence is negligible in this large catchment. See also reply to short comment SC1), or represent inflows into reservoirs. And in general, evaporative losses are difficult to observe directly and thus to include in the MLR models. Moreover, we do not believe past evaporative losses would have a high predictive power for future discharge. Evaporation is strongly related to radiation/temperature and past temperature is already included as a potential predictor into the MLR models.

[Section 3.1] To maintain independence of the predictors, only variables up to March should be used to build models of April-September discharge. After March, the forecast period should be progressively reduced. For instance, predictors between January and April could be used to build models of May-September discharge, January to May variables for June-September discharge, and so forth. Results from models with overlapping predictors and forecast variable should be removed.

We agree, in order to guarantee independence of the predictors from the predictand this would be the appropriate procedure enabling a fair comparison of the skill of the forecasts before and during the vegetation period. But this is not the purpose of the presented study. We rather aim at providing the best possible forecasts with the given data at hand. As shown in the results and discussion, the observed discharge values (antecedent discharge predictors) from the start of the vegetation period have a high predictive power for the whole vegetation period. Therefore these should be used for the prediction, particularly when a possible application in operational forecast is considered. Besides this, the results would very likely not change much, because the seasonal discharge for April to September is highly correlated to the seasonal discharges for shorter periods. The following figure shows this exemplarily for the Naryn basin. The shorter seasonal mean discharges are very similar to the whole vegetation period April to September, and are highly correlated. The numbers in the legend show the linear correlation coefficient. All correlations are highly significant (p-values $< 10^{-8}$). This means that the performance of models predicting only the discharge ahead is pretty much identical to the presented performance.



Moreover, the presented approach is in line with the official forecast procedures in the Central Asian hydromet services. In order to obtain acceptance of the proposed method in the services and their use in the official forecast procedures it is advisable to follow the prescribed procedures. It is required from the Hydromet Services to issue updated (corrected) forecasts, which include the entire vegetation period (April-September), The water regulation procedures and e.g. agricultural yield estimation are traditionally based on bulk numbers for the entire period. If these procedures are not followed, the obtained results, which are better than the forecasts issued with the existing procedures, might not be implemented and come into practise, and thus a chance would be missed to bring research results into application.

[Section 3.2] More rigour is needed in testing for violations of MLR assumptions (i.e. linearity of relationships, homoscedasticity, no outliers, normally distributed and uncorrelated residuals). This could be captured in tabular format with a matrix showing which assumptions (if any) are violated in each catchment.

The general answer to this comment is: no, the discharge generation in the catchments is not linear, particular if all relevant processes are considered. This has been shown in many hydrological studies. However, this does not mean that linear models cannot be applied. In fact, runoff generation can be approximated by linear models. This has been proven by the many hydrological modelling studies based on linear concepts, e.g. linear storage models. Moreover, hydrological processes can be even better approximated on longer time scales, or on larger spatial scales. This is the basis for the still wide spread use of linear regression in (seasonal) forecast studies (Seibert et al., 2017;Delbart et al., 2015;Dixon and Wilby, 2015).

Furthermore, if the processes to be described show significant non-linear features, using linear models will result in low(er) performance. Predictions and model performance cannot be improved by linear models if processes are non-linear. We thus argue, that the use of linear regression for seasonal forecasts as presented is justifiable by these general considerations, and is actually supported by the good results obtained.

However, we also tested the MLR assumptions as suggested by the reviewer in order to show that our general argument holds, i.e. that the seasonal runoff generation in Central Asia can be approximated with linear models.

First we tested if the residuals of the models are normally distributed with the Shapiro-Wilk test for normality. Doing so, one has to bear in mind that this test is based on a sample size of maximal 16 values for each model only, so the test may not provide meaningful results. The table below shows the test result for every model, catchment, and forecast month. Note that the test was performed for a new set of models, where models with insignificant predictors were removed (cf. comment below). A "1" indicates a normal distributed residuals, "0" not normal distributed residuals. "NA" indicates that no more models with significant predictors could be found. For every forecast month up to 20 indices are given. The table shows that for most of the models (89.5%) the test was positive, i.e. the residuals are normally distributed, even for this rather low and possibly not representative sample size.

Test for normal distributed residuals, for every catchment, prediction month, and selected 20 models						
1 = normal distributed, 0 = not normal distributed, NA = no valid model found						
	January	February	March	April	May	June
Uba	11111111111111111111	10101011011010010110	10000111011100001011	11111111111111101110	11111111111111111111	11111111111111111111
Ulba	11111111111111111111	11110111011111011110	11101111111111111111	11111111111111111111	11111111111000010000	11111111111111111111
Chirchik	1111111110101111111 NA	11111111111111111111	11111111111111111111	11111111111111110100	00000111100000000001	00111001110111111111
Talas	11111111111000111111	11111111111011111111	11111111111111111111	11111111111111111111	11111111111111111111	10101110111111111001
Ala-Archa	11111011111100111111	10110111111111111011	11101111111111001111	11111111111111111111	11101101011111110111	11111111111111111111
Chu	1111011111111 NA NA NA NA NA NA NA	11101111111111111111	11111111111111111101	11110001101111110011	11111111111111011111	11111111111111111111
Chilik	11111111111111111111	11111111111111111111	10111111011011111111	11101111101111011111	11101010111011101100	11111111101001110101
Charyn	11111111111111111111	11111111111111111111	11111111111111111111	11111111111111111111	11111111111111111111	11111111111111111111
Karadarya	11111111111010111110	11111111111111111111	11111100011101110110	11111111111111110111	11111111111111111111	11101110011001111100
Naryn	11111110111111111111	11111111111111111111	11111111111111111111	11111111111111111111	11100111110111111111	11111111110111111111
Upper Naryn	11111111111111111111	11111011100011111111	00101111111111111110	11111111111110111111	11111100001111111111	11111111111111111111
Amudarya	1111111111111 NA NA NA NA NA NA NA	11111111111111111111	11111111111111111111	11111101111111111111	11111111101111011110	11111111111111111111
Murgap	11111111111111111101	11111111111110111111	11111111111110111111	11111111101110011101	11111111110111101111	11111010011111101101

Next we tested if the residuals are independent applying a test for autocorrelation with lag 1 at significance level p = 0.05. In the table below a "0" indicates independence, a "1" dependence. It shows that 95.8% of the models have independent residuals.

Test for autocorrelated (independent) residuals, for every catchment, prediction month, and selected 20 models, lag = 1						
1 = correlated, 0 = not correlated, NA = no valid model found						
	January	February	March	April	May	June
Uba	00000000001001000010	10001000000010111000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000
Ulba	10010101000000101001	01000011000100000010	00000000000000000000	00000000000000000000	00000000000000000000	11110101110010000000
Chirchik	0000000000000000000 NA	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000
Talas	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000
Ala-Archa	00000000000000000000	00000000000000001101	00000000000000000000	00000000000000000000	00000000000010000000	00000000000000000000
Chu	0000000000000 NA NA NA NA NA NA NA	00000000000000000000	01100000000000000000	00000000000000000000	00000000000000000000	00000110000000100000
Chilik	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	10001000000000000000	00000000000000000000
Charyn	00000000001000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000100
Karadarya	01000000010000010000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000
Naryn	00000000000000000000	00000000000000000000	00000000000000000000	00000000000000000000	00110000000000000000	00000000000000010000
Upper Naryn	00000000000000000000	00000000000000000000	00000100000000000000	00000000000000000000	00000011110000000000	11000000011000001010
Amudarya	0000000000000 NA NA NA NA NA NA NA	00000000000000000000	00000000000000000000	00000000000000000010	00000000000001000000	00000000000010000000
Murgap	00000000000000000000	10001000000000000000	00000000000000000000	00000001000000000000	10000000000000000000	00000000000000000000

Furthermore we applied the Breusch-Pagan test for heteroscedasticity. This test shows that 99.5% of the models have homoscedastic residuals.

Test for homoscedastic residuals, for every catchment, prediction month, and selected 20 models						
1 = homoscedasticity test (Breusch-Pagan test) passed, 0 = homoscedasticity test not passed, NA = no valid model found						
	January	February	March	April	May	June
Uba	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Ulba	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Chirchik	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 NA	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Talas	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 0 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Ala-Archa	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Chu	1 1 1 1 1 1 1 1 1 1 1 1 1 NA NA NA NA NA NA NA	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Chilik	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Charyn	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Karadarya	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Naryn	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 0 0 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Upper Naryn	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
Amudarya	1 1 1 1 1 1 1 1 1 1 1 1 1 NA NA NA NA NA NA NA	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1

In summary, we believe that the provided arguments and tests provide sufficient reason and arguments for the use of MLR models for the seasonal forecasts in Central Asia. The tables shown above can be included in an appendix to the manuscript.

[Section 3.3] Equations for the lmg algorithm should be provided, and the method of selecting predictors should be described more clearly. Significance of all model coefficients should be formally tested and any insignificant variables removed. All reported R2 values should be adjusted for sample size, and accompanied by a statement of significance. Then, only models that pass the specified level(s) of significance should be retained.

This comment refers to several section of the manuscript, not only section 3.3. The whole process of predictor selection and model fitting and model selection is described in sections 3.1 and 3.2. Section 3.3 describes the procedure of calculating the predictor importance, which is not relevant for model and predictor selection, but is rather a help for interpreting the selected models and their predictors. We answer to the different points referring to the different sections.

Section 3.1: The selection of the predictors used in the MLR models is described in this section. Additionally tables providing the selected predictors for each forecast month are given in the appendix. We actually think that this is clearly described, and do not see how to improve the description further. The reviewer comment does not provide guidance for this, while the second reviewer seems to be satisfied with our explanations. Therefor we will leave this section as it is, unless more information about what is unclear is provided.

Section 3.2: First, we did not report the significant levels in section 4 and Table 2, as we thought that it is actually obvious that models with such a high explained variance are highly significant, even for this limited sample size. We indicate the significance levels for the best models in Table 2 below, as well as the lowest significance of the selected 20 models for the mean performances.

However, we did not check the significance of the individual predictors in the models. We thank the reviewer for stressing this point. The model selection process has been modified in a way that only models with all predictors significant at $p = 0.1$ are retained. The selection of the models to be retained is still based on the PRESS value from the LOOCV. However, we weighed the PRESS by the number of years for which forecasts are available in order to reduce possible biases due to missing predictor values (i.e. reduced number of samples). This resembles a Predictive Residual Error Mean Squares.

Additionally the performance of the models is now reported in terms of adjusted R^2 values, as suggested. This lead to lower performance values mainly for the early forecasts, while the high performance of the late forecasts remain very high. Additionally we added the Mean Absolute Error MAE (relative to the mean seasonal discharge, just as the RMSE) to the performance plots in Figure 4, as requested by the second reviewer. Figure 4 is updated to the figure below, and Table 2 also reports now the adjusted R^2 values of the best LOOCV model and the mean of the selected models, where all predictors are significant at p = 0.1. In Figure 4 the green lines for the PRESS values is replaced by a brown line in order avoid red-green blindness problems, as suggested.

Table 2: Adjusted R^2-values of the best performing prediction models from the LOOCV for all catchments and prediction months. "best" indicates the single best model according to the LOOCV, "mean" indicates the mean percentage over the best 20 models according to the LOOCV. The adjusted R^2 values are associated with indicators for significance levels.

		January		**February**		**March**		**April**		**May**		**June**	
		best	*mean*	best	*mean*	best	*mean*	best	*mean*	best	*mean*	best	*mean*
1	**Uba**	0.678 ++	0.511 ++	0.824 +++	0.714 +++	0.842 +++	0.743 +++	0.811 +++	0.790 +++	0.823 +++	0.804 +++	0.959 +++	0.951 +++
2	**Ulba**	0.624 o	0.429 +	0.714 +++	0.444 +	0.781 +++	0.672 ++	0.869 +++	0.811 +++	0.943 +++	0.932 +++	0.983 +++	0.975 +++
3	**Chirchik**	0.253 ++	0.278 --	0.594 +++	0.556 ++	0.650 +++	0.593 ++	0.891 +++	0.884 +++	0.945 +++	0.941 +++	0.971 +++	0.964 +++
4	**Talas**	0.669 +++	0.408 +	0.794 +++	0.703 +++	0.808 +++	0.728 +++	0.823 +++	0.787 +++	0.886 +++	0.852 +++	0.961 +++	0.954 +++
5	**Ala-Archa**	0.393 +	0.353 o	0.597 ++	0.431 o	0.758 +++	0.524 +	0.761 +++	0.623 ++	0.739 +++	0.624 ++	0.837 +++	0.738
6	**Chu**	0.274 +	0.260 --	0.709 +++	0.440 o	0.903 +++	0.729 +++	0.680 +++	0.569 ++	0.800 +++	0.740 +++	0.887 +++	0.862 +++
7	**Chilik***	0.865 +++	0.818 ++	0.856 +++	0.787 ++	0.910 +++	0.873 +++	0.757 +++	0.770 ++	0.880 +++	0.805 +++	0.933 +++	0.821 +++
8	**Charyn**	0.643 +++	0.503 +	0.844 +++	0.786 +++	0.792 +++	0.765 +++	0.873 +++	0.810 +++	0.949 +++	0.944 +++	0.985 +++	0.975 +++
9	**Karadarya**	0.573 ++	0.449 +	0.589 +++	0.411 ++	0.880 +++	0.845 +++	0.976 +++	0.968 +++	0.977 +++	0.979 +++	0.981 +++	0.973 +++
10	**Naryn**	0.782 +++	0.679 +++	0.657 +++	0.657 +++	0.844 +++	0.800 +++	0.853 +++	0.819 +++	0.906 +++	0.887 +++	0.924 +++	0.899 +++
11	**Upper Naryn**	0.832 +++	0.810 +++	0.898 +++	0.850 +++	0.916 +++	0.897 +++	0.947 +++	0.923 +++	0.858 +++	0.847 +++	0.950 +++	0.947 +++
12	**Amudarya**	0.213 +	0.304 +	0.841 +++	0.691 +++	0.857 +++	0.840 +++	0.878 +++	0.839 +++	0.897 +++	0.876 +++	0.983 +++	0.972 +++
13	**Murgap**	0.465 ++	0.367 o	0.757 +++	0.551 +	0.802 +++	0.642 ++	0.807 +++	0.700 ++	0.970 +++	0.960 +++	0.997 +++	0.993 +++

* the performance of Chilik is not representative and comparable to the other catchments due to too many missing discharge and predictor data.

Significance p: +++ = 0.01, ++ = 0.05, + = 0.1, o = 0.2, -- = >0.2; for mean the lowest significance of the model ensemble

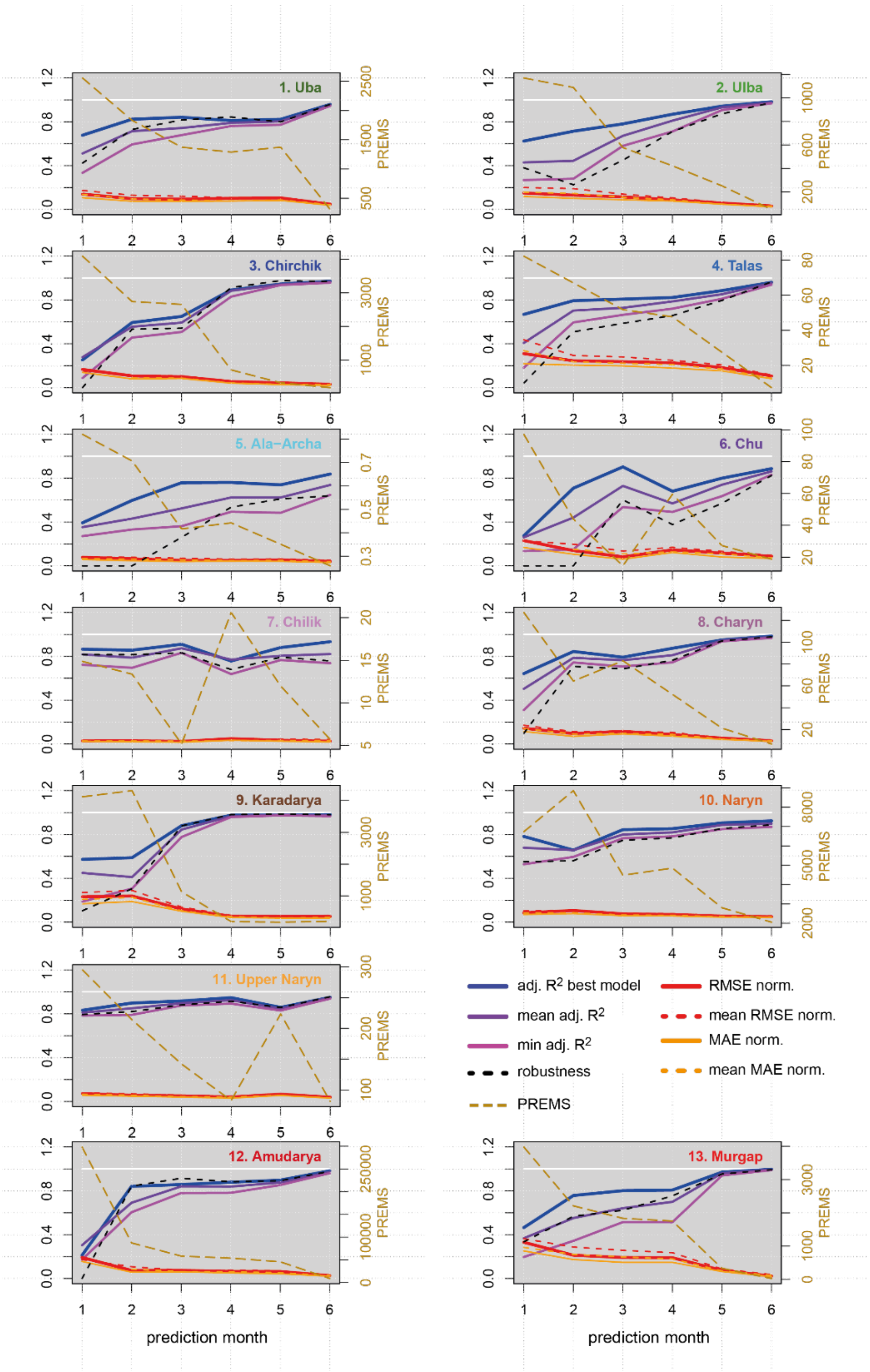

1. Uba
2. Ulba
3. Chirchik
4. Talas
5. Ala−Archa
6. Chu
7. Chilik
8. Charyn
9. Karadarya
10. Naryn
11. Upper Naryn
12. Amudarya
13. Murgap
PREMS
prediction month
adj. R^2 best model
mean adj. R^2
min adj. R^2
robustness
PREMS
RMSE norm.
mean RMSE norm.
MAE norm.
mean MAE norm.

Figure 4: Performance of the prediction models for the different catchments and prediction months. Adj. R^2 best model is the adjusted R^2 of the single best LOOCV model, mean adj. R^2 is the mean adj. R^2 of the best 20 LOOCV models, min adj. R^2 is minimum adj. R^2 of the best 20 LOOCV models, robustness is mean LOOCV-adj. R^2 of the best 20 models divided by the mean adj. R^2, RMSE/MAE norm. is the root mean squared error/mean absolute error of the single best model normalized to mean multi-annual seasonal discharge, mean RMSE/MAE norm is the mean root mean square error/mean absolute error of the best 20 LOOCV models normalized to the multi-annual seasonal discharge; PREMS is the predictive residual sum of squares (PRESS) of the single best model, divided by the number of prediction months.

Section 3.3: The analysis of predictor importance is performed after the best models are selected, i.e. it has no influence on the predictor and model selection. The *lmg* algorithm calculates how much of the overall explained variance is explained by the individual predictors of the selected models. This is principally performed by re-running the model with a single of the selected predictors and calculating the explained variance. Then the other predictors are added and the gain in explained variance is determined (->sequential R^2s). Then the importance of a predictor is given either as percentage of the overall explained variance, or as absolute fraction of explained variance. However, in this procedure the sequence of predictors influences the explained variance. In other words, it matters with which predictor the importance analysis starts. The lmg algorithm tests all predictor orderings and calculates the mean importance of every ordering in order to overcome the problem of predictor ordering in sequential R^2s. More details are given in the reference provided. We will add some sentences as above for explanation in the revised manuscript.

[Table 2] Report only adjusted R2 values for the overall best, and 20 best models. Results for forecasts issued in April, May and June should only cover the periods May-September, June-September and July-September respectively. The legend should be updated accordingly.

Adjusted R2 values are now reported in Table 2 and Figure 4 (see above). However, as already explained in an earlier answer, we would keep the current procedure, because of the high correlation of the seasonal and sub-seasonal mean discharge and for better transfer into operational practice in Central Asia.

[Section 4.1] The discussion of predictive uncertainty should acknowledge other components, including from data quality, choice of model type/ structure, choice of objective unction(s), model parameters. As noted, the uncertainty bands associated with the 20 best models reflect the number of models retained. When more stringent tests of model skill are applied (see comments on section 3.3 above), fewer models may pass. In any event, the criteria for model inclusion within the ensemble used for uncertainty estimation should be stated explicitly.

The criteria for model inclusion in the ensemble is as stated the best model performance in the cross validation, i.e. the lowest PREMS (=PRESS divided by the number of years for which forecasts can be made by the individual models) value. However, the number of models for the ensemble is set subjectively to 20. This selection is aiming at obtaining a sufficient number of models for an ensemble evaluation of the forecasts. With the newly set restriction on model selection (only models with significant predictors), a few ensembles, particularly for the January prediction have less than 20 models, because not enough models fulfilling the new selection criteria could be identified. There is actually no rule for the number of ensembles members applied. We left sufficient amount of freedom for this, in order to enable an expert selection of models by the forecasters of the Central Asian hydromet services. The forecasters have a lot of experience with their catchments, and can decide better which forecasts are valuable for them. The forecasters check every model retained for their performances (qantitatively and qualitatively), and select the models accordingly. This means that in practice less models that the 20 presented in the manuscript might be selected, or even more. Another possible rule for ensemble model selection could be to set a threshold in explained variance for the model. However, due to the high explained variances, the threshold must be very high in order to reduce the ensemble members. A fixed R^2 threshold would more likely increase the ensemble members in most cases.

We will explicitly discuss other uncertainty sources. Other uncertainty sources are, as mentioned, model structure, which is rather low given the high explained variances; data sources, which is not quantifiable, but might be high, particularly the discharge data; and performance criteria for selecting the best models. This last aspect has actually been tested, but is not included in the manuscript in order to keep the manuscript concise. Using other performance criteria as PRESS for model selection usually results in slight different selection of best models, and often in a different order of the best models. The best PRESS model is not necessarily the best cross validated R^2 model. However, as this mainly affects the ordering of the best models, the results in terms of ensemble predictions, if unweighed as presented, will remain the same. In order to illustrate this, we will some sentences in the manuscript. We could also provide tables with further performance criteria (R2, adj., R2, SSQ, MAE, central Asian performance criteria, all for cross validation and full models) for every selected model, forecast month and catchment in the appendix. This will, however, result in 13 x 6 wide tables, i.e. in quite a long appendix. We would abstain from including this bulk of data into the manuscript, unless the editor explicitly requests this.

[Section 4.3] Add a paragraph on the specific operational decisions that are already, or could be, supported by seasonal discharge forecasts in Central Asia.

A lot of management and strategic decisions are based on seasonal forecasts of water availability in CA. The main consumer of water resources in the Aral Sea basin is the agricultural sector with has one of the world's largest irrigation systems (Dukhovny and de Schutter, 2011). Very important decisions based on water availability forecasts are the planning of agricultural production crop types and water allocation through the irrigation network. Also the estimation of agricultural yield is related to water availability and is needed for country income planning that heavily depends on agricultural export in some countries.

[Conclusions] Note that seasonal forecasting of precipitation could provide useful in-formation in catchments and years with relatively little winter snowpack accumulation. Seasonal and sub-seasonal forecasts of extreme rainfall could also be important for hazard management (floods, landslides) and dam safety. Note also that the winter precipitation, summer melt situation applies in the Western U.S. too. Add a paragraph on further research opportunities.

Thanks for the suggestions. We will discuss the possibility of the forecasts for hazard management on more detail.

However, seasonal forecasts of precipitation in Central Asia are difficult and very uncertain. We have studied this in another publication (Gerlitz et al., 2016). We showed, that winter precipitation amounts are highly related to tropical and extratropical circulation modes (such as ENSO and NAO) and thus exhibit a certain degree of predictability. In contrast, summer precipitation in Central Asia is usually convective, i.e. is triggered by surface heating and associated atmospheric instability. Summer precipitation sums are composed of few single events (occasionally of high intensity) which, however, are rather randomly distributed and non-predictable.

Minor corrections and clarifications

[P1, L19] Note that seasonal forecasts can also contribute to improved dam safety.

Thanks for the hint. We will add this in the introduction.

[P1, L31] State the range of river catchment areas.

Will be included.

[P2, L7] Typo “The Central Asian region. . .”

Will be corrected.

[P2, L25] Omit “actually”.

Will be omitted.

[P3, L4] Provide full publication details for the Hydromet Services questionnaire.

The questionnaire was project internal and not published. This was a prerequisite for participation in the questionnaire. The replies to the questionnaires were rather heterogeneous and were further elaborated and specified in the dialogue with the Central Asian forecasting specialists during a workshop. It would, however, go far beyond the scope of this manuscript to compile and publish the detailed answers of the questionnaires and interviews. The content of the questionnaire would also neither improve the quality of the manuscript, nor change the focus, but rather distract the focus.

[P4, L27] Typo “catchmentss”.

Will be corrected.

[P4, L27] Note that some of the catchments are nested (i.e. not independent) such as the Upper Naryn and Naryn, so the actual sample size is smaller than 13.

This comment applies for the Naryn basin only. The catchments were nested in order to analyse if the method also works for high alpine catchment such as Upper Naryn with a high degree of glacierization. We will state this in the revised manuscript.

[P7, L12] Non sequitur – please clarify why the need for cross-validation and hierarchical clustering follows from the observation that the discharge regimes vary between catchments.

Thanks for spotting this. The sentences will be changed in “This plot indicates similar but also different inter-annual variability patterns of the different catchments. In order to distinguish between similar and different inter-annual variabilities cross-correlations of the seasonal discharges are calculated and hierarchically clustered (Figure 3).”.

[P10, L20] Presumably all variables used in composites (e.g. temperature and precipitation) are normalized by their mean and variance such that they have equal weight in the MLR model?

No, the variables in the composites were simply multiplied.

[P11, L4] Provide the equation for the Predicted Residual Error Sum of Squares (PRESS). Note also that had a different objective function been selected, different sets of predictors might have emerged.

We will include the following description of PRESS:

“The PRESS residuals are defined as $e_{(i)} = |y_i - \hat{y}_{(i)}|$ where $\hat{y}_{(i)}$ is the regression estimate of y_i based on a regression equation computed leaving out the i^{th} observation. The process is repeated for all n observations resulting in:

$PRESS = \sum_{i=1}^{n} {e_{(i)}}^2$ “

And yes, a different objective criteria might result in a different set of models, but in most cases usually in a different order of the best models. We commented on this earlier. We argue that PRESS is the most appropriate selection criteria, because a desirable forecast would reduce the residuals to a minimum in cross validation.

Moreover, we now normalized the PRESS by the number of years for which forecasts could be made by the individual models in order to avoid biases caused by missing predictor values. This resembles a Predictive Residual Error Mean of Squares, which we term PREMS.

[P11, L14] Please clarify “a set of specific models of the best models”.

This refers to the option of selecting individual models by experts of the catchments, i.e. the responsible forecasters in CA. some models might have acceptable performance criteria, but the temporal dynamics might be not acceptable. Or, some models might show high performance, but have too many missing predictors resulting in a spurious good performance. Such models can be excluded from the ensemble by the forecasters.

[Figure 4] Improve legibility by removing the grey background from each panel. Avoid use of red with green lines as these will be indistinguishable for some readers.

The green line for PRESS (now PREMS) has been replaced be a beige/light brown dashed line. We would actually keep the grey background, because we believe that this supports the legibility and enhances the graphical appearance. Because the other reviewer did not comment on this, we would ask the editor to decide whether the background should be changed or not.

[Table 3] Explain how the number of "good" forecasts can be higher for the mean than for the best model in some catchments (e.g. Uba, January).

As mentioned above, the best models are selected according to PRESS. In PRESS the residuals are squared, resulting in a different order and occasionally selection of the set of best models compared to a sorting based on absolute residuals, as the Mean Absolute Error MAE and the CA performance criteria defined in equation (1). This means that the best model according to PRESS is not necessarily the best model according to the CA performance criteria. This can result in more "good" forecasts according to the CA criteria on average for the selected ensemble model compared to the best model.

[P19, L22] Please clarify "possible lack of representativeness of the time series used for the "real" variability of the seasonal discharge in Central Asia".

This refers to the limited length of the time series used in this study, which might show a different variability compared to longer time series.

[P21, L7] Please clarify the sentence "This indicates that the predictor selection. . ."

We want to express that a) for the best models similar predictors are selected, i.e. that the predictor selection is not random and follows hydrological principles of runoff generation, and b) that the procedure of predictor selection for the models avoids the selection of correlated predictors from the same group, which could be a problem if the restriction in predictor selection were not set.

We will clarify this in the revised manuscript.

[Figure 7] Ideally the presentation and discussion of the predictors would be organized by the three clusters described in section 2.1.

This is a welcome suggestion. We will include references to the clusters in the revised manuscript. Also note that Figure 7 has slightly changed because if the updated model selection (only significant predictors), and because the importance is now quantified as absolute contribution to adjusted R^2 values:

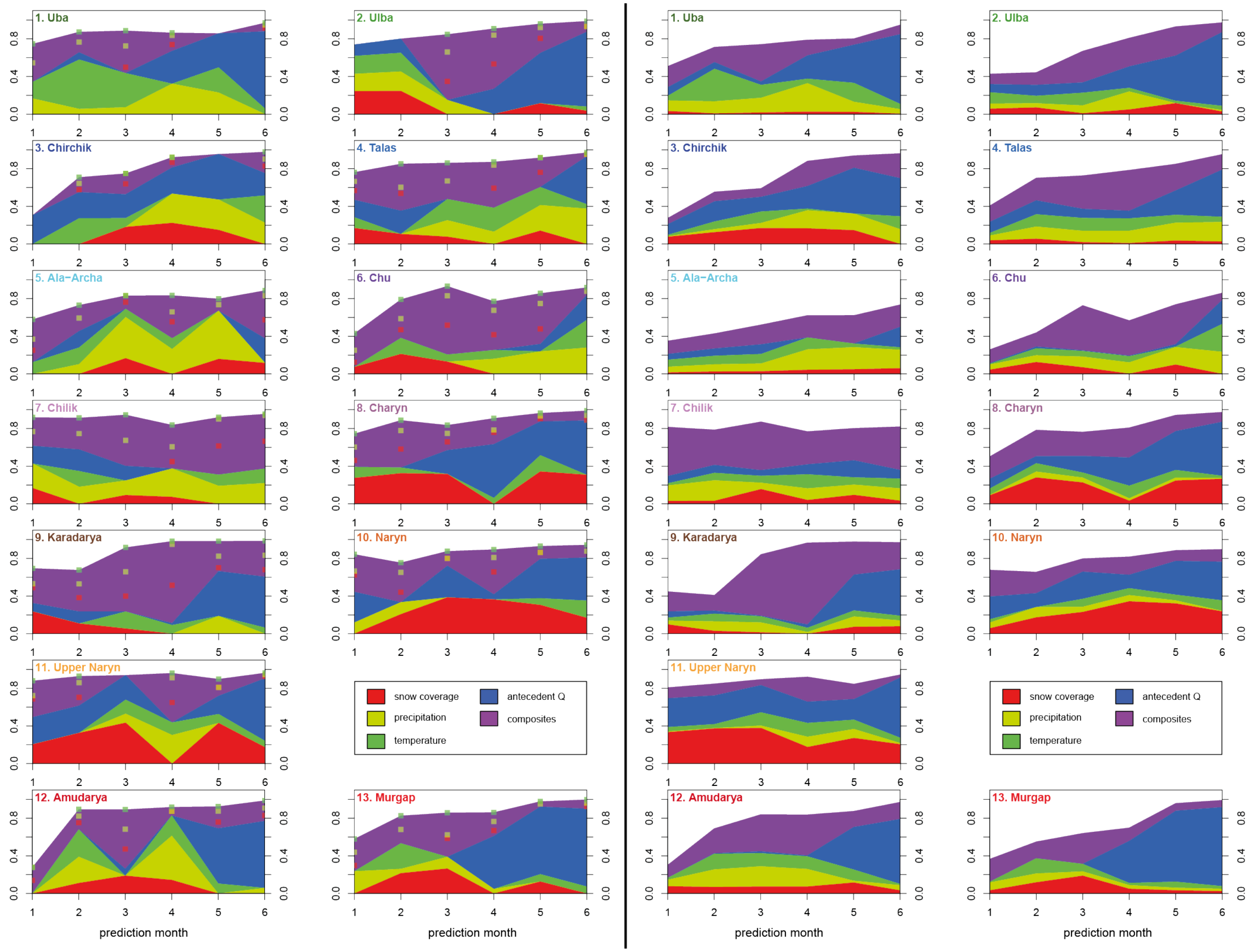


Figure 7: Importance of the predictors in the linear models as absolute contribution to the explained variance expressed as adjusted R^2 for all catchments and prediction months. Left: of the best LOOCV model; Right: on average for the best 20 LOOCV models. Squares in the left panel figures indicate the presence of the different predictors used in the composites: snow cover, precipitation and temperature, using the same colour codes as for the individual predictors.

[P24, L3] Typo “precipiutation”.

Will be corrected.

[P24, L25] Report only adjusted R2 values with accompanying significance level(s).

Will be done.

References:

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Dukhovny, V. A., and de Schutter, J. L. G.: Water in Central Asia: Past, Present and Future, CRC Press/Balkema,Taylor & Francis Group: London, UK, 2011.

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