Forecasting reservoir inflows using remotely sensed precipitation estimates: a pilot study for the River Naryn, Kyrgyzstan

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Forecasting reservoir inflows using remotely sensed precipitation estimates: A pilot study for the River Naryn, Kyrgyzstan.

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Abstract
This study explores the feasibility of applying remotely sensed precipitation estimates (in this case from the Tropical Rainfall Measuring Mission [TRMM]) for forecasting inflows to the strategically important Toktogul reservoir in the Naryn basin, Kyrgyzstan. Correlations between observed precipitation at Naryn and 0.5° TRMM totals is weaker for daily \( r=0.25 \) than monthly \( r=0.93 \) totals, but the Naryn gauge is representative of monthly TRMM precipitation estimates across ~60% of the basin. We evaluate predictability of monthly inflows given TRMM estimates, air temperature, and antecedent flows. Regression model skill was superior to the Zero Order Forecast (mean flow) for lead times up to three months, and had lower errors in estimated peaks. Over 80% of the variance in monthly inflows is explained with three month lead, and up to 65% for summer half-year average. The analysis also reveals zones that are delivering highest predictability and hence candidate areas for surface network expansion.

Key words
Remotely sensed precipitation, river flow forecast, Toktogul reservoir, regression model
1 Introduction

Early river flow forecasting systems relied on accurate ground based measurements of precipitation at meteorological stations – a basic input requirement that is still difficult to achieve in data sparse and/or physically remote regions (Artan et al., 2007). Partial information on precipitation variation in space and time continues to limit the development of flow forecasts for infrastructure operation and hazard warning (Bitew et al., 2012; Kekete et al., 2004). Even where data exist, absence of treaties for information sharing can hinder modelling and management of extreme events in transboundary situations (Hossain, 2007).

Remotely sensed, near real-time precipitation estimates have the potential to address these shortcomings (Hughes, 2006; Su et al., 2008; Collischonn and Pante, 2011) and may offer particular advantages for strengthening flow forecasts for large, transboundary river basins (Balthrop and Hossain, 2010). These capabilities have attracted growing attention from researchers and national agencies alike, with short-term flood forecasting models utilising passive microwave data for both precipitation and discharge estimation (e.g., Hopson and Webster, 2010; Hirpa et al., 2013).

The purpose of this paper is twofold. First, we assess the accuracy of a remotely sensed precipitation product for a strategically significant river basin in Central Asia. Second, we investigate the potential for river flow forecasting based on remotely sensed precipitation, surface temperature and gauged discharge, over monthly to seasonal horizons. We evaluate the data and forecasting techniques using flows in the Syr Darya, Kyrgyzstan upstream of the Toktogul reservoir. This system was chosen because of the importance of the basin as a ‘water tower’ for sustaining livelihoods downstream (Immerzeel et al., 2010). In addition to socio-economic challenges the region also faces a range of geophysical and meteorological hazards. Earthquakes and landslides are common in the Tien Shan, with most of the population of Kyrgyzstan living in areas of high or very high seismic hazard (UNDP, 2012). The primary meteorological hazard in the Syr Darya is flooding, which can be exacerbated by reservoir operations (UNDP, 2012).

The following section provides more background to the pilot study region and data. Section 3 describes the methods used to evaluate satellite products, and to build
statistical forecast models of reservoir inflows, drawing on input data from different scales and locations within the basin. Section 4 presents the results of these analyses, and Section 5 offers interpretations of model skill based on the hydrometeorological processes within the basin. Finally, section 6 briefly considers the transferability of the approach beyond the Naryn-Syr Darya cascade and offers suggestions for further research.

2 Study area and data

The Naryn basin is located in the Central Tien Shan mountain range of Kyrgyzstan, the headwaters of the Syr Darya River (Figure 1). The Syr Darya is one of two major rivers (along with the Amu Darya) that supplies water to the Central Asian Republics. The basin area of the Naryn is 55,944 km² with an elevation range of more than 4,000 m including major mountain belts such as the Kyrgyz Range in the north, Talas Ala Toosu and Fergana ranges in the southwest (Kriegel et al., 2013). The Naryn is fed by a major tributary below Song Kol Lake which runs during the melt season (April to September). Land cover is mainly grass and shrub, with pastoral farming on mountain sides, and some arable crop and hay production in valleys sustained by irrigation.

The Tien Shan mountain range has a continental climate with the main source of moisture originating from the Atlantic Ocean (Aizen et al., 1995a). Several weather systems meet over the region, including westerly air streams, the Siberian anticyclone and south/south-westerly cyclonic circulations (Aizen et al., 1995a; 2001). The mountains prevent penetration of moisture into central areas resulting in low winter precipitation, with maximum totals typically occurring in June and July (Aizen et al., 1995a; 1996). Orographic factors produce a general decrease in precipitation and temperature along a north-west to south-east gradient (Sorg et al., 2012, Karaseva et al., 2012). Temperatures vary from 30°C in the western valleys in summer to -25 °C in the glacierised regions in winter, but values as low as -50 °C have been recorded in the Ak-Say valley. Snow depth is dependent upon aspect relative to the western air masses, and an average melt season of ~70 days has been observed in northern parts of the region (Aizen et al., 1995a; b).
The Naryn River has mean annual discharge of 13.8 km$^3$ with more than 50% of the flow originating from snow and glacier melt (Savoskul et al., 2003). The Syr Darya has been extensively managed to re-allocate water to satisfy the needs of countries through which it flows (Kyrgyzstan, Uzbekistan, Tajikistan and Kazakhstan). Six large and several smaller reservoirs were built along the Syr Darya by the Soviet Union, providing a total storage capacity of ~35 km$^3$ (Savoskul et al., 2003). These reservoirs have contributed to a management system described as one of the most complicated in the world (Raskin et al., 1992).

Water diversions from the Syr Darya have contributed to the Aral Sea losing two-thirds volume since 1957 (UNEP, 2008). Contention also surrounds the differing interests of Kyrgyzstan to release water for hydropower generation during the winter, versus downstream needs of Uzbekistan and Kazakhstan for irrigation in summer (Karaev, 2005). During the Soviet era such energy-water trade-offs were managed centrally (Hodgson, 2010); post-independence Kyrgyzstan has increased the volume of water released from Toktogul during winter months for hydropower to reduce the risk of black outs (Umaraliev, 2012). Attempts have been made to resolve these competing interests (Kraak, 2012a) with operation of Toktogul reservoir central to such discussions due to the immense storage capacity (19.5 km$^3$) and position of the impoundment within the system (Figure 1).

2.1 Remotely sensed precipitation

UNDP (2012) concluded that as well as greater regional cooperation, there is also a need to strengthen monitoring and modelling capacity in the region. Remotely sensed precipitation data offer a means of filling these gaps. Several satellite precipitation products are available including: the Tropical Rainfall Measuring Mission (TRMM) and its successor the Global Precipitation Measurement (GPM) Core Observatory (launched February 2014)$^1$; Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN); and NOAA Center for Satellite Applications and Research (STAR).

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This study demonstrates proof of concept using the TRMM Multi-satellite Precipitation Analysis (TMPA) but our approach is applicable to other sources of remotely sensed data. The TRMM product was constructed in four stages (NASA, 2011). First, microwave precipitation estimates are calibrated and combined; second, infrared precipitation estimates are created with the aid of the calibrated microwave precipitation estimates; third, microwave and infrared estimates are combined; and fourth, rain gauge data are incorporated into the final estimate. Microwave precipitation estimates are collected by multiple satellites (TRMM, DMSP, Aqua and NOAA) which cover the area between 50°N and 50°S. Infrared data are collected by the TRMM satellite and provides high temporal and spatial coverage. Rain gauge data used in TRMM were obtained from Global Precipitation Climatology Centre (GPCC) and the Climate Assessment and Monitoring System (CAMS) (Huffman et al., 2007; Huffman and Bolvin, 2013).

Two previous studies have evaluated TRMM products for the Tien Shan Mountains. One compared TRMM with every rain gauge in Kyrgyzstan (Karaseva et al., 2012); the other examined basins in the mid Tien Shan Mountain range (Ji and Chen, 2012). Both found that TRMM underestimated precipitation in mountainous areas and during heavy precipitation events, possibly due to difficulties in detecting shallow, orographic rainfall (Adler et al., 2003). Aspect was found to be an important factor with south facing slopes having higher accuracy and correlation compared with north facing slopes. However, there is low confidence in this finding because of limited data for south facing slopes (Ji and Chen, 2012). Karaseva et al. (2012) report low correlations in the vicinity of large lakes (e.g., Issyk Kul and Toktogul) due to contamination of the microwave signal by water bodies and mountains within the sensor footprint. Strongest correlations were found in the high plateaus, including for the Naryn gauge (Karaseva et al., 2012).

Rain gauge data are incorporated differently depending on aggregation period. The 3B43 (V7) (monthly precipitation estimate) is produced by first summing original three-hour values by calendar month. Second, monthly precipitation gauge analysis is used to create a large scale bias adjustment to the satellite estimates. Lastly, monthly gauge adjusted satellite estimates are combined directly with gauge precipitation via inverse error variance weighting to create the final product. The 3B42 (V7) dataset (daily precipitation estimate) is derived by scaling the original
three-hourly estimates so they sum approximately to the monthly gauge adjusted
satellite-gauge combination value calculated in step two of the 3B43 (V7) procedure
(Huffman and Bolvin, 2013). Henceforth, we refer to 3B42 (V7) as daily TRMM, and
3B43 (V7) as monthly TRMM.

Monthly and daily TRMM were obtained at 0.5° resolution from the TRMM Online
Visualisation and Analysis System (TOVAS) for every cell in the Naryn basin for the
years 1998 to 2010 inclusive. In addition, monthly and daily data were downloaded
for the same time period but at 0.25° resolution for cells within the 0.5° grid nearest
to the Naryn meteorological station (Figure 1).

2.2 Ground-based measurements

Daily meteorological and hydrological data were collected as part of a European
Bank for Reconstruction and Development (EBRD) project investigating downstream
consequences of climate change and flow regulation on the River Naryn (Wilby et al.,
2011). Daily precipitation totals and mean daily temperature were obtained for the
meteorological station at Naryn for the years 1981 to 2010 (Figure 1). This single
station was chosen for two reasons. First, an earlier analysis of all stations in
Kyrgyzstan showed that the correlation between TRMM and gauge precipitation was
strongest at Naryn (Karaseva et al., 2012). Second, the site is centrally located
within the Naryn basin, and the record is unbroken for the period over-lapping with
river flow data. Daily discharges were obtained for a site upstream of Toktogul for the
years 2000 to 2009. The inflow record has several months with missing data which
were filled by interpolating from monthly mean values.

3 Methods

The analysis proceeded in two stages. First, we evaluated the quality of daily and
monthly remotely sensed (TRMM) precipitation estimates in the vicinity of the Naryn
meteorological station. Second, we assessed the feasibility of forecasting monthly
inflows to Toktogul based on a blend of remotely sensed and ground-based
observations. Each step is described below.
3.1 Evaluation of TRMM products

We extend earlier analyses by comparing Naryn and TRMM precipitation at different spatial and temporal resolutions. We recognise that it is not possible to undertake a fully independent test of TRMM in data sparse regions because it is likely that data from available meteorological stations have been assimilated by the algorithm. Inspection of the gauges used for Kyrgyzstan confirms that this is the case\(^2\).

Consistent with other networks in the post-Soviet era, the number of gauges assimilated by TRMM declined from 23 (1998) to 12 (2010), but data for the station at Naryn was blended with other sites throughout our study period (Figure 2).

With these points in mind we investigated specific instances in which there are major discrepancies between TRMM and Naryn gauge data. Monthly mean and annual precipitation totals were calculated for the 0.5° TRMM cell overlying the Naryn meteorological station for the years 1998 to 2010. Likewise, cumulative precipitation totals and distributions were derived for the nearest 0.25° and 0.5° TRMM cells for the same period. The false alarm ratio was calculated for each month as the fraction of days on which TRMM detects precipitation but the gauge did not, divided by the total number of days on which TRMM measured precipitation (Scheel et al., 2011).

Next, the non-parametric Spearman rank correlation coefficient was estimated using daily time series for the same cells. This was followed by a wider analysis of covariance across all cells in the Naryn basin in which data were stratified by calendar month and season. Finally, all cells, permutations of concurrent and lagged (0 to 3 months) TRMM precipitation, and moving averages (0 to 6 months) were correlated with monthly river flow at Toktogul. This was undertaken in order to identify the TRMM cell(s) and area(s) of the basin, lag interval \((t)\), and averaging period \((m)\) that potentially yield predictability of inflows.

3.2 River flow estimation

Following earlier studies we evaluated various combinations of predictor variable, averaging period and lag interval to develop multiple-linear regression models of

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\(^2\) The GPCC visualizer enables inspection of sites used in TRMM: http://kunden.dwd.de/GPCC/Visualizer
monthly inflow to Toktogul for the period May 1999 to July 2010 (Schär et al., 2004; Archer and Fowler, 2008; Magar and Jothiprakash, 2011; and Pal et al., 2013). Available monthly variables were precipitation and temperature observations at Naryn, basin average TRMM precipitation, lagged and time-averaged TRMM precipitation from individual cells, and dummy variable for month to capture the annual cycle (Table 1). The dummy variable regression weights give the flow anomaly with respect to a reference month (in this case December) once the influence of other predictors has been accounted for.

Regression modelling proceeded in two steps. First, the large number of lagged, time-averaged and spatially-explicit candidate variables was reduced to a smaller set of statistically significant, independent predictors. Second, the forecast skill of chosen predictors was determined using cross-validation. These stages ensure that the most parsimonious models, with out of sample forecast skill, are constructed.

We began by examining simple linear regression relationships between runoff in the summer snow melt season (April to September) as a function of individual predictors: year, precipitation, temperature and runoff in the preceding winter (October to March). This split-year approach has been applied to other runoff records in Central Asia and informs the preliminary selection of candidate predictor variables for sub-seasonal forecast models (e.g., Schär et al., 2004; Pal et al., 2013). Preferred monthly variables were then screened by stepwise multiple-linear regression, terminating at the point where inclusion of additional variables did not improve the amount of explained variance (when adjusted for sample size and number of predictors). Optimal sets of predictors of monthly discharge (Q) were identified for concurrent (t), one (t+1), two (t+2) and three (t+3) months lead time.

Regression model skill was then assessed using cross-validation by which monthly Q for individual years was predicted using models built on other years of data. For instance, flows for the year April 1999 to March 2000 would be predicted by a model calibrated on data for April 2000 to March 2010. Year-by-year a full series of predicted flows was built enabling validation against data not used in model calibration. Available records for Toktogul and TRMM permit cross-validation of 11 year-long segments of data, each with their own regression parameter sets. This provides a more stringent test of model skill than measures of calibration fit to the
whole data. Note that, however, an operational version of the model would be fit to
the selected predictor set using the entire record then recalibrated periodically as
more data become available.

All model predictions were benchmarked with respect to the Zero Order Forecast
(ZOF): the amount of explained variance that can be obtained from the simplest
possible model – in this case the long-term monthly mean flow. For comparability,
identical segments of data were used for estimating the long-term mean as those
entered into the 11 cross-validated regression models. The HydroTest tool (Dawson
et al., 2007) was used to derive five metrics of model forecast skill: Root Mean
Squared Error (RMSE); A Information Criteria (AIC); Nash-Sutcliffe Coefficient (NSC);
Percentage Error in Peak (PEP); and the Mean Absolute Relative Error (MARE).

4 Results

With the caveat about lack of full independency of data in mind, we first assessed
realism of TRMM precipitation estimates at different temporal scales using the gauge
data at Naryn. These data were then used to build and validate models of monthly
inflows to Toktogul with forecast horizons of up to three months.

4.1 Evaluation of TRMM products

When compared with gauge precipitation at Naryn, 0.5° TRMM estimates totals
during the accumulation (October to March) and melt-season (April to September)
with -1% and +11% bias respectively. The equivalent biases for the nearest 0.25°
TRMM cell are -2% and +5%. The largest over-estimation by TRMM occurs in July,
August and September (Figure 3a). Conversely, 0.5° TRMM April totals
underestimate gauge totals by 16%. The monthly false alarm ratio for daily
precipitation occurrence varied between 0.41 (March) and 0.67 (September).

Figure 3b shows the variability in annual gauge precipitation with 2003 having more
than twice the total of 2006. TRMM overestimates the annual total in the majority of
years, however, monthly time-series show strong correlation with the gauge at both
0.25° TRMM (r=0.86) and 0.5° TRMM (r=0.86) resolutions (Figure 4). Overall, the
correlation between monthly gauge and TRMM is strongest in February, September and November \( (r=0.94) \) and weakest in May \( (r=0.16) \) and July \( (r=0.66) \). This is explained by three significant discrepancies which occurred in May 2003, July 2006 and July 2010 when 0.5° TRMM overestimates gauge totals by 72.1%, 99.7% and 199.6% respectively. Over the course of the 13 year period, 0.25° TRMM and 0.5° TRMM over-estimate the cumulative total at Naryn by 5% and 10% respectively with the departure beginning at the May 2003 anomaly (Figures 5).

Consistent with earlier studies (Karaseva et al., 2012; Ji and Chen, 2012), TRMM over-estimates the frequency of light precipitation days, and under-estimates the occurrence of heavy precipitation (Figure 6). However, it is evident that 0.25° TRMM provides a better match to the cumulative percentile distribution than 0.5° TRMM. The correlation between daily gauge and TRMM totals is weak \( (r=0.25) \) compared with monthly totals \( (r=0.93) \) (Figure 7). This is to be expected because the bias correction procedure within TRMM scales sub-daily amounts such that their monthly aggregate converges with that of the monthly gauge total (Huffman et al., 2007).

The strength of correlation between gauge precipitation and 0.5° TRMM totals varies with distance from the meteorological station. Marginally stronger correlations are found in upwind TRMM cells for daily series (Figure 8a), and to the north and west of Naryn for monthly series (Figure 8b). These correlation surfaces show the extent to which the record at Naryn might be representative of precipitation elsewhere in the basin (assuming that TRMM values are ‘truth’).

4.2 River flow estimation

Discharge in the summer half-year (April to September) is significantly related to winter TRMM precipitation totals averaged across the Naryn basin (PA) or over the most sensitive sub-basin (PO) (Table 2). Precipitation measured at Naryn and antecedent discharge are weakly related to summer flow (but are statistically insignificant predictors since \( p>0.05 \)). Winter temperatures at Naryn and time (year) have no predictive skill over the fit period. This is consistent with the findings of Schär et al. (2004) and Schiemann et al. (2007) for the Syr Darya as a whole.
Monthly discharge typically rises from a minimum in February to maximum in June. However, peak flows are subdued during low precipitation years such as 2007 and 2008, arrive earlier in warm years (2006), or later in cold years (2009) (Figure 9). This inter-annual variability would not be captured by a ZOF based on the long-term monthly mean flow alone. Nonetheless, the ZOF still explained 81% of the variance in monthly discharge entering Toktogul and sets a challenging minimum standard for evaluating more elaborate models.

Figure 10 shows the amount of variance in monthly discharge explained by TRMM for different lag intervals (zero to three months). The cells with greatest explained variance at zero lag include eastern mountain areas with seasonal snow cover and glacier storage, as well as Song-Kul Lake (cell 41.5°N, 74.75°E) during the melt season. As the length of lag interval increases the zone producing greatest predictability migrates westwards. Even at forecast horizon t+3 the amount of variance in flows explained by TRMM still exceeds 30%.

The correlation between river flow and candidate predictors was assessed by systematically varying lead-time (t+0 to t+3 months) and averaging period (1 to 6 months) for monthly temperature and precipitation at Naryn, the TRMM basin average precipitation, and the optimum TRMM cell(s) (identified from Figure 10). The correlation coefficient for temperature is strongest with no lead-time (t+0) or smoothing (r=0.73) (Figure 11). Greater lead-times and longer averaging periods show weak but statistically significant correlations (r>0.17) that eventually become negative as the temperature and flow regimes are in anti-phase.

The correlation with Naryn precipitation is strongest for t+0 when averaged over the previous three months (r=0.74) (Figure 11). Lead-time t+1 correlations are strengthened by averaging over two months (r=0.68). The correlation is statistically significant up to t+3 months if there is no averaging (r=0.28). Lead-time correlations are strengthened (relative to Naryn) when applying basin area or optimum TRMM cells. For comparison, these predictors yield significant t+3 (no-averaging) correlations r=0.39 and r=0.43 respectively. Regardless of the averaging period, no significant correlations were found for any TRMM product (whether single cell or basin average) beyond t+3, indicating a limit to predictability from this data source.
Estimation of current flows (Q0) was improved by including antecedent discharge and TRMM precipitation from the most highly correlated cell (smoothed over four months) alongside the monthly dummy variable (Tables 3 and 4). The best predictor set for the one month ahead flow forecast model (Q1) also includes temperature (lag-1) (Tables 3 and 4). Regression fit remains superior to the ZOF fit for two (Q2) and three (Q3) month lead-times but these do not incorporate antecedent temperatures. In fact, temperature explains only 9% and 1% of the variation in flow at t+2 and t+3 months respectively. Only the optimum TRMM cell provides predictability in Q3 beyond that which can be achieved by the monthly mean flow alone (Tables 3 and 4).

Given the limited data, cross-validation was used to compare predictive skill of regression models relative to the ZOF over forecast horizons t+1 to t+3 months (Figure 12). According to the chosen performance metrics, Q1, Q2 and Q3 models are superior to ZOF for all diagnostics, except the MARE for Q3 (Table 5). Hence, regression models have lower RMSE and AIC and higher NSC than the ZOF up to Q3. Regression models also have lower errors in the estimated peak, even though these are still under-predicting by typically 20 to 30% (compared with 35% for ZOF).

The circumstances under which there are large (t+1) forecast errors were explored through closer inspection of daily series of precipitation at Naryn and daily inflow at Toktogul (Figure 13). For example, the forecasted peak monthly flow in 2002 is too low and too late (see Q1 model in Figure 12) because heavy precipitation in late June 2002 is smoothed and lagged by the model such that it impacts estimated flows in July 2002. In this case, the monthly time-step of the model is simply too coarse to resolve the observed near synchronous daily rainfall-runoff response in June. Other discrepancies may be attributed to interpolation of missing daily flows from monthly means (such as the overestimation of discharge during June to September 2007).

5 Discussion

Here we interpret our results in the context of other river flow forecast models developed for the region, and from physical reasoning about the underlying hydro-climatic processes.
5.1 Evaluation of TRMM products

The quality of TRMM products has been reviewed elsewhere from the perspective of skill linked to temporal and spatial resolution (Scheel et al., 2011) or physical environment (Berg et al., 2006); performance and corrections needed in mountainous terrain (Condom et al., 2011; Matzler and Standley, 2000; Ji and Chen, 2012); local micro-meteorological and orographic effects (Petty, 2001; Barros et al., 2004); snowfall detection and evaluation (Gebremichael et al., 2010; Ji and Yu, 2013); and utility for hydrologic prediction (Yong et al., 2012).

These studies show that assessing the quality of remotely sensed precipitation estimates is not straightforward. First, lack of ground measurements limits scope to ‘ground truth’ satellite data (Ebert et al., 2007). Some studies resort to spatial interpolation to infill between stations, but this introduces additional uncertainties (Ji and Chen, 2012). Second, interpretations are complicated when comparing point measurements from gauges with area-averages from satellites because spatial averaging can lead to over-estimation of precipitation occurrence or reduce the magnitude of extreme events relative to local observations (Scheel et al., 2011). Third, gauge data are accumulated over fixed intervals (such as 3-hourly or daily totals) whereas TRMM is a snapshot measurement (Scheel et al., 2011).

Good agreement between the Naryn gauge and TRMM precipitation during the accumulation period implies that the latter is able to estimate snowfall totals well at this site (Figure 3). This is contrary to some studies that assert TRMM should not be used without calibration for snowfall (Gebremichael et al., 2010; Yong et al., 2012). It is possible that the rate applied to snowfall (0.1 mm hour\(^{-1}\)) is close to that observed at Naryn which, along with relatively low totals during winter months, results in a small absolute bias. However, it must be kept in mind that the accuracy of the gauge for snowfall is also unknown. Therefore, it is unclear whether the gauge or TRMM estimate for May 2003 is most trustworthy. TRMM gave 40 mm of precipitation on one day whilst the gauge recorded zero, followed by two days of rainfall measured by the gauge totalling 30 mm that TRMM estimated to be less than 5 mm. It is conceivable that during this time very few if any of the TMPA instruments covered the study area, thereby reducing the accuracy of the TRMM estimate (Huffman et al.,...
Alternatively, observed precipitation may have been aggregated over more than one day or entered incorrectly against these dates.

TRMM overestimated the frequency of occurrence (not shown) and total precipitation in July, August and September (Figure 3). The relatively high false alarm ratio at this time could be linked to localised heavy precipitation events under southerly monsoon airflows. Such events may be detected by the area estimates of TRMM but were missed by point measurements at the gauge (Bothe et al., 2012; Bell and Kundu, 2003; Bowman, 2004). This is supported by the fact that the highest overestimation occurred in the lower half of the 0.5° TRMM cell – the area furthest from the gauge.

The correlation surfaces (Figure 8) partly reflect the time-varying influence of neighbouring gauges within the domain. Overall, the r≥0.7 correlation field (i.e., more than 50% variance explained) for monthly amounts covers 21 out of 35 cells in the study area (Figure 8b). In other words, the Naryn record is strongly correlated with TRMM precipitation estimates over approximately 60% of the basin area. The Naryn record is least representative of TRMM values in the Fergana Range (the southwest portion of the basin, Figure 1). Karaseva et al. (2012) and the GPCC visualizer show a cluster of five gauges in this area (Figure 2) which presumably exert a stronger influence than Naryn on local TRMM estimates.

5.2 River flow estimation

A growing number of studies are exploring the application of remotely sensed information in hydrological modelling (e.g., Yilmaz et al., 2005; Artan et al., 2007; Su et al., 2008; Bookhagen and Burbank, 2010; Stisen and Sandholt, 2010; Wilby and Yu, 2013). Previous research shows that model skill can be improved by bias correcting TRMM precipitation estimates, or by blending TRMM with gauge data to simulate runoff (Yu et al., 2011; Bitew et al., 2012). Many studies have focused on large scale modelling (medium/large basins to global scale); relatively few examine the utility of satellite data for runoff simulation at smaller scales (Hong et al., 2007a; Milewski et al., 2009). It is also recognised that different satellite products can yield different river flow simulations even when passed through the same hydrological model (Chintalapudi et al., 2012). Arid and semi-arid basins can be particularly
challenging to model with satellite precipitation estimates because of localised, heavy precipitation events, coupled with strongly non-linear rainfall-runoff processes (Sagintayev et al., 2012).

Earlier research into river flows within the Naryn/Syr Darya basins examined how climate change could impact water resources with and without adaptation (e.g., Siegfried et al., 2012; Ismaiylov et al., 2007; Wilby et al., 2011). Others have used satellite precipitation estimates to calibrate models. For example, Immerzeel et al. (2012) applied a conceptual model with PERSIANN satellite precipitation inputs to assess climate change impacts on water resources. Pereira-Cardenal et al. (2011) used TRMM precipitation with radar altimetry to produce near real-time simulations of Toktogul reservoir water levels.

Savoskul et al. (2003) observed that a substantial fraction of winter precipitation contributes to runoff with delay due to seasonal and perennial storage of precipitation in snow and ice. Onset of snowmelt occurs later in the year at higher elevations so these regions might be expected to contribute at longer lag intervals. This is indeed the case, with strongest correlations for delayed runoff from the mountain ranges in the north and southwest of the basin. A further factor is the spatial variation in magnitude of the spring peak in precipitation. Aizen et al. (1996; 1997) report that areas below 2,500 m have two maxima with the main occurring between March-May; whereas areas above 2,500 m have a single maximum between May-July. They also noted that the proportion of annual precipitation occurring during spring varies from 35-45 % in areas below 2,500 m compared to 45-55 % above 2,500 m.

Schär et al. (2004) assumed that accumulated runoff for the Syr Darya in summer (May to September) is a linear function of accumulated precipitation in the preceding winter and spring (December to February, March and April). Temperature potentially influences contributions from glacier melt, timing of melt season onset and proportion of total precipitation in liquid state. However, their stepwise regression model of summer runoff omitted all temperature variables, depending instead on precipitation during winter (December to February), March and April alone despite a high degree of glaciation of the test basin.
Predictability of summer flows into Toktogul appears to be maximised by using TRMM precipitation estimates for the cell over Song-Kul Lake (Figure 1). The TRMM basin average for winter also surpassed observed precipitation at Naryn as a predictor. This suggests that seasonal inflows to Toktogul may be routinely forecasted using publicly available satellite products and regression models akin to those shown in Table 2. As more satellite and river flow data become available it will be possible to re-evaluate the stationarity of model parameters, and to discern possible long-term augmentation of summer flow by glacier wastage (Kriegel et al., 2013).

In the meantime, temperature was found to be a statistically insignificant predictor of summer discharge and was retained in only one of the four monthly models developed for the Naryn (Tables 3 and 4). Once the seasonal snow and ice melt regime is captured by the monthly dummy variable, the remaining temperature effect is negative: months preceded by higher air temperatures typically have lower than average runoff. This could be interpreted as earlier onset of melting, greater evaporative losses at lower elevations, or as reflecting the weak negative correlation (r=-0.27) between summer temperature and precipitation. A negative (but statistically non-significant) regression parameter between air temperature and summer runoff has also been reported for the Syr Darya to Chinaz (Schiemann et al., 2007). More generally, positive temperature anomalies and suppressed summer convective precipitation over Central Asia are associated with strong Indian summer monsoons (Schiemann et al., 2007).

6 Conclusions

The purpose of this paper was to explore the feasibility of forecasting monthly and seasonal reservoir inflows given minimal surface data and remotely sensed (TRMM) precipitation estimates. Toktogul reservoir was chosen to test the approach because of the economic significance of the structure, and importance to the region's highly complex water management system (Karaev, 2005; Kraak, 2012b). Previous studies have evaluated aspects of TRMM for Kyrgyzstan and the wider region; others have investigated the potential for seasonal forecasting of runoff for large basins in Central
Asia. We refined these analyses by showing how predictive skill might be maximised through judicious selection of TRMM cell(s), averaging and lag intervals.

Despite the simplicity of the models and limited data requirements over 80% of the variance in monthly inflows is explained with three month lead, and up to 65% for summer half-year flows based on TRMM estimates of winter precipitation. In line with earlier research, temperature was found to have limited predictive skill at monthly scales, and no skill for seasonal forecasting Naryn flows. The sub-basin feeding the major tributary below Song Kol Lake was shown to have significant influence on inflows during the melt season and is a priority location for long-term monitoring. Indeed, any remaining meteorological stations in the vicinity (41° 50’N, 75° 10’E) should be protected from closure, and the area prioritised for network expansion.

Despite the parsimony of the regression models there may be good reasons for parallel development of non-linear statistical or deterministic algorithms (such as the Snowmelt Runoff Model (SRM) which has already been implemented for the Naryn basin) (Wilby et al., 2011). These models could assimilate remotely sensed snow cover for initialising forecasts of runoff over days to weeks ahead, driven by numerical weather predictions of precipitation and temperature. In this way, probabilistic forecasts of extreme inflows could be issued by deploying ensemble predictions of inputs and SRM parameter sets. Snow and ice budgeting can also be used to carry-over mass balance changes between successive melt seasons and to investigate the observed long-term deglacierization of the Naryn due to prolongation of the melt season (Kriegel et al., 2013).

We demonstrated the possibility of forecasting reservoir inflows using TRMM precipitation estimates but the approach remains the same regardless of the satellite products employed. Key steps include evaluating precipitation estimates against available surface data at various time and space scales, then selecting those parts of the river basin that yield greatest predictability for specified forecast horizons. Credibility of the statistical model(s) is strengthened where physically sensible explanations can be given for the prediction skill, and when stationarity of model parameters has been tested through cross-validation techniques. Although the TRMM satellite is expected to cease operating in February 2016 the successor
and/or other precipitation estimates could be calibrated then used in operational flow forecasts for strategically important water infrastructure in Central Asia.

Finally, beyond river flow, other environmental hazards affecting reservoir operations may be predictable from satellite products. For instance, peak occurrence for landslides and mudflows tends to be associated with rising temperatures and heavy rainfall in spring. This opens the potential for predicting rainfall-triggered landslides (including mud and debris flows) from real-time satellite imagery (as in Hong et al., 2006; 2007b; 2007c). The Goddard Space Flight Center already provides global maps of potential landslide areas based on rainfall estimates with 1, 3 and 7 day lead time\(^3\). Potential contingency measures that could be taken at individual hydropower plants include draw down of reservoir level to increase freeboard for flood waves induced by channel blockage or debris slides.

Acknowledgements

Observed rainfall and river flow data were provided by the Kyrgyzstan Ministry of Water Resources and Tajik Hydromet through the Pilot Programme for Climate Resilience (PPCR) with the support of the European Bank for Reconstruction and Development (EBRD). The authors are grateful for the insightful suggestions made by Nasridin Minikulov and two anonymous referees.

\(^3\) [http://trmm.gsfc.nasa.gov/publications_dir/potential_landslide.html](http://trmm.gsfc.nasa.gov/publications_dir/potential_landslide.html)


<table>
<thead>
<tr>
<th>Page 21 of 44</th>
<th>Hydrological Sciences Journal</th>
</tr>
</thead>
<tbody>
<tr>
<td>615</td>
<td>ISSN- 0144-7815.</td>
</tr>
</tbody>
</table>

URL: http://mc.manuscriptcentral.com/hsj


Table 1 Variables used in regression models

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{t,n}$</td>
<td>Naryn meteorological station precipitation</td>
</tr>
<tr>
<td>$PA_{t,n}$</td>
<td>0.5° TRMM area average precipitation estimate</td>
</tr>
<tr>
<td>$PO_{t,n}$</td>
<td>0.5° TRMM optimum cell precipitation estimate</td>
</tr>
<tr>
<td>$T_{t,n}$</td>
<td>Naryn meteorological station temperature</td>
</tr>
<tr>
<td>$Q_{t,n}$</td>
<td>Discharge at Toktogul</td>
</tr>
<tr>
<td>$t$</td>
<td>Variable lag interval ($t$ months)</td>
</tr>
<tr>
<td>$n$</td>
<td>Variable averaging period ($n$ months)</td>
</tr>
<tr>
<td>$M$</td>
<td>Dummy variable for each calendar month (0 or 1)</td>
</tr>
</tbody>
</table>

Table 2 Statistical estimates of the intercepts ($\alpha$) and parameters ($\beta$) of simple linear regression models, along with the amount of explained variance ($R^2_{adj}$), standard error (SE) of the summer (April to September) runoff estimate (m$^3$s$^{-1}$) and model significance level ($p$). All predictors except for time are for the winter half-year (October to March).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$\alpha$ (m$^3$s$^{-1}$)</th>
<th>$\beta$</th>
<th>$R^2_{adj}$ (%)</th>
<th>SE (m$^3$s$^{-1}$)</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (year)</td>
<td>22993</td>
<td>-11.14</td>
<td>0</td>
<td>123</td>
<td>0.437</td>
</tr>
<tr>
<td>T</td>
<td>525</td>
<td>-28.83</td>
<td>0</td>
<td>123</td>
<td>0.418</td>
</tr>
<tr>
<td>P</td>
<td>473</td>
<td>12.67</td>
<td>22</td>
<td>107</td>
<td>0.096</td>
</tr>
<tr>
<td>PA</td>
<td>197</td>
<td>16.81</td>
<td>50</td>
<td>86</td>
<td>0.013</td>
</tr>
<tr>
<td>PO</td>
<td>247</td>
<td>17.85</td>
<td>65</td>
<td>71</td>
<td>0.003</td>
</tr>
<tr>
<td>Q</td>
<td>151</td>
<td>2.44</td>
<td>18</td>
<td>110</td>
<td>0.123</td>
</tr>
</tbody>
</table>
Table 3  Summary of regression model predictor variables, explained variance ($R^2_{adj}$) and standard errors (SE) by forecast horizon (t+0 to t+3 months). In each case, the final predictor set is shown in bold italics. See Table 1 for notations.

<table>
<thead>
<tr>
<th>Model</th>
<th>Predictors</th>
<th>$R^2_{adj}$ (%)</th>
<th>SE (m³s⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZOF</td>
<td>$M$</td>
<td>81</td>
<td>147</td>
</tr>
<tr>
<td>Q0 (t+0)</td>
<td>PA₀,₄</td>
<td>42</td>
<td>258</td>
</tr>
<tr>
<td></td>
<td>$T_{0,1}$</td>
<td>53</td>
<td>232</td>
</tr>
<tr>
<td></td>
<td>$P_{0,3}$</td>
<td>54</td>
<td>228</td>
</tr>
<tr>
<td></td>
<td>$Q_{1,1}$</td>
<td>59</td>
<td>217</td>
</tr>
<tr>
<td></td>
<td>PO₀,₄</td>
<td>73</td>
<td>174</td>
</tr>
<tr>
<td></td>
<td>$Q_{1,1}$, PO₀,₄</td>
<td>81</td>
<td>145</td>
</tr>
<tr>
<td></td>
<td>$Q_{1,1}$, PO₀,₄, $T_{0,1}$</td>
<td>84</td>
<td>137</td>
</tr>
<tr>
<td></td>
<td>$M$, $Q_{1,1}$, PO₀,₄, $T_{0,1}$</td>
<td>90</td>
<td>109</td>
</tr>
<tr>
<td></td>
<td>$M$, $Q_{1,1}$, PO₀,₄*</td>
<td>90</td>
<td>109</td>
</tr>
<tr>
<td>Q1 (t+1)</td>
<td>$T_{1,1}$</td>
<td>35</td>
<td>273</td>
</tr>
<tr>
<td></td>
<td>$P_{1,1}$</td>
<td>37</td>
<td>268</td>
</tr>
<tr>
<td></td>
<td>$P_{1,2}$</td>
<td>44</td>
<td>252</td>
</tr>
<tr>
<td></td>
<td>PA₁,₂</td>
<td>51</td>
<td>235</td>
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<tr>
<td></td>
<td>PO₁,₃</td>
<td>64</td>
<td>203</td>
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<tr>
<td></td>
<td>$Q_{1,1}$, PO₁,₃</td>
<td>70</td>
<td>185</td>
</tr>
<tr>
<td></td>
<td>$Q_{1,1}$, PO₁,₃, $T_{1,1}$</td>
<td>71</td>
<td>183</td>
</tr>
<tr>
<td></td>
<td>$M$, $Q_{1,1}$, PO₁,₃</td>
<td>89</td>
<td>111</td>
</tr>
<tr>
<td></td>
<td>$M$, $Q_{1,1}$, PO₁,₃*, $T_{1,1}$</td>
<td>89</td>
<td>110</td>
</tr>
<tr>
<td>Q2 (t+2)</td>
<td>$T_{2,1}$</td>
<td>9</td>
<td>322</td>
</tr>
<tr>
<td></td>
<td>$Q_{2,1}$</td>
<td>10</td>
<td>319</td>
</tr>
<tr>
<td></td>
<td>$P_{2,1}$</td>
<td>30</td>
<td>283</td>
</tr>
<tr>
<td></td>
<td>PA₂,₁</td>
<td>43</td>
<td>254</td>
</tr>
<tr>
<td></td>
<td>PO₂,₁</td>
<td>48</td>
<td>242</td>
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<tr>
<td></td>
<td>$Q_{2,1}$, PO₂,₁, $T_{2,1}$</td>
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<td>239</td>
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<tr>
<td></td>
<td>$Q_{2,1}$, PO₂,₁</td>
<td>49</td>
<td>240</td>
</tr>
<tr>
<td></td>
<td>$M$, $Q_{2,1}$, PO₂,₁*</td>
<td>85</td>
<td>132</td>
</tr>
<tr>
<td>Q3 (t+3)</td>
<td>$T_{3,1}$</td>
<td>1</td>
<td>336</td>
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<tr>
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<td>$Q_{3,1}$</td>
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<td>336</td>
</tr>
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<td></td>
<td>$P_{3,1}$</td>
<td>7</td>
<td>325</td>
</tr>
<tr>
<td></td>
<td>PA₃,₁</td>
<td>14</td>
<td>313</td>
</tr>
<tr>
<td></td>
<td>PO₃,₁</td>
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<td>282</td>
</tr>
<tr>
<td></td>
<td>$M$, PO₃,₁**</td>
<td>84</td>
<td>136</td>
</tr>
</tbody>
</table>

Key: * cell 42°N 73.25°E; ** cell 41°N 73.25°E
Table 4 Predictor variables and regression model parameters for monthly flow forecast models Q0, Q1, Q2 and Q3 based on available data (May 1999 to July 2010). Model parameters shown in **bold** are statistically significant (p<0.05). Note that the value of the dummy variable depends on prevailing month and may be interpreted as the flow anomaly with respect to December (value zero).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Q0</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-121.93</td>
<td>-69.29</td>
<td>-39.78</td>
<td>149.75</td>
</tr>
<tr>
<td>Jan</td>
<td>-1.26</td>
<td>-114.16</td>
<td>22.63</td>
<td>-134.57</td>
</tr>
<tr>
<td>Feb</td>
<td>32.71</td>
<td>-119.44</td>
<td>53.88</td>
<td>-129.37</td>
</tr>
<tr>
<td>Mar</td>
<td>64.44</td>
<td>-20.24</td>
<td>109.82</td>
<td>-79.16</td>
</tr>
<tr>
<td>Apr</td>
<td>147.01</td>
<td>214.50</td>
<td>272.65</td>
<td>86.94</td>
</tr>
<tr>
<td>May</td>
<td>348.53</td>
<td>546.26</td>
<td>580.59</td>
<td>460.67</td>
</tr>
<tr>
<td>Jun</td>
<td>455.48</td>
<td>659.18</td>
<td>771.21</td>
<td>728.37</td>
</tr>
<tr>
<td>Jul</td>
<td>185.64</td>
<td>399.02</td>
<td>477.50</td>
<td>530.45</td>
</tr>
<tr>
<td>Aug</td>
<td>62.43</td>
<td>263.15</td>
<td>218.87</td>
<td>284.05</td>
</tr>
<tr>
<td>Sep</td>
<td>16.53</td>
<td>215.15</td>
<td>31.27</td>
<td>147.83</td>
</tr>
<tr>
<td>Oct</td>
<td>15.35</td>
<td>198.81</td>
<td>40.84</td>
<td>73.41</td>
</tr>
<tr>
<td>Nov</td>
<td>15.86</td>
<td>109.27</td>
<td>57.99</td>
<td>56.92</td>
</tr>
<tr>
<td>Q1,1</td>
<td>0.48</td>
<td>0.50</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Q2,1</td>
<td>-</td>
<td>-</td>
<td>0.35</td>
<td>-</td>
</tr>
<tr>
<td>PO0,4</td>
<td>4.06</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PO1,3</td>
<td>-</td>
<td>2.54</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>PO2,1</td>
<td>-</td>
<td>-</td>
<td>1.95</td>
<td>-</td>
</tr>
<tr>
<td>PO3,1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2.31</td>
</tr>
<tr>
<td>T1,1</td>
<td>-</td>
<td>-10.90</td>
<td>-</td>
<td>-</td>
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</table>
Table 5 Cross-validation results for ZOF, Q1, Q2 and Q3 models

<table>
<thead>
<tr>
<th>Metric</th>
<th>ZOF</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Root Mean Squared Error (RMSE) (m$^3$s$^{-1}$)</td>
<td>151</td>
<td>118</td>
<td>139</td>
<td>144</td>
</tr>
<tr>
<td>A Information Criteria (AIC)</td>
<td>702</td>
<td>673</td>
<td>694</td>
<td>697</td>
</tr>
<tr>
<td>Nash-Sutcliffe Coefficient (NSC)</td>
<td>0.797</td>
<td>0.878</td>
<td>0.829</td>
<td>0.818</td>
</tr>
<tr>
<td>Percentage Error in Peak (PEP) (%)</td>
<td>-34.8</td>
<td>-21.4</td>
<td>-31.6</td>
<td>-27.7</td>
</tr>
<tr>
<td>Mean Absolute Relative Error (MARE) (%)</td>
<td>18.6</td>
<td>17.5</td>
<td>19.6</td>
<td>21.6</td>
</tr>
</tbody>
</table>
Figure 1 a) Location of the River Naryn basin and Toktogul reservoir within Kyrgyzstan; b) an elevation map of Kyrgyzstan.
Figure 2 Number of GPCC gauges used by TRMM across the study area for selected years. The location of the gauge at Naryn is shown by the red point.
Figure 3  Gauge versus 0.5° TRMM for a) monthly mean and b) annual precipitation totals at Naryn 1998-2012.

a)

b)
Figure 4 Monthly total precipitation recorded by the gauge at Naryn compared with the nearest a) 0.5° TRMM and b) 0.25° TRMM cell.

a)

b)
**Figure 5** Cumulative monthly precipitation totals for Naryn meteorological station, coincident 0.5° TRMM and 0.25° TRMM cells 1998-2010.
Figure 6 Cumulative percentile distributions of gauged, 0.5° TRMM and 0.25° TRMM daily precipitation amounts at Naryn 1998-2012.
Figure 7 Correlation between nearest 0.5° TRMM estimates and gauge a) daily and b) monthly precipitation at Naryn 1998-2012

a) 

```
Gauge (mm)
```

```
TRMM (mm)
```

r = 0.25

b) 

```
Gauge (mm)
```

```
TRMM (mm)
```

r = 0.93
Figure 8 Correlation between a) daily and b) monthly precipitation gauge at Naryn and concurrent 0.5° TRMM estimates 1998-2012.
Figure 9  Observed annual (upper panels) and monthly (lower panels) discharge into Toktogul (left) and air temperature at Naryn (right).
Figure 10 Amount of variance in gauged monthly discharge at Toktogul explained by 0.5° TRMM with lag=0 (upper left), lag=1 (upper right), lag=2 (lower left) and lag=3 (lower right) months for the period May 1999 to July 2010 inclusive.
Figure 11 Correlation ($r$) of gauged flows with lagged predictors averaged over one to six months: temperature (T); precipitation measured at Naryn (PN); precipitation estimates from TRMM for the basin area (PA), and optimum location (PO). For $n=130$ and at $p=0.05$ significance level, $r_{crit}=0.17$. 

![Diagram of correlation with lagged predictors](image-url)
Figure 12 Cross-validated model forecasts with lead-time one (Q1), two (Q2) and three (Q3) months compared with long-term monthly mean discharge (ZOF).
Figure 13 Daily precipitation and discharge series for the River Naryn during melt seasons with large residuals in the t+1 forecast (see Q1 in Fig. 12).