Seasonal Runoff Forecasting Using Precipitation from Meteorological Data Assimilation Systems

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ABSTRACT

In semiarid mountainous regions such as central Asia, runoff from snowmelt often represents the dominant contribution to river flow and freshwater supply during the dry season. The estimation of snow accumulation during the preceding seasons then provides a key to seasonal runoff forecasting with lead times of a few months, and it requires appropriate coverage with surface precipitation and/or snow water equivalent observations. This study tests whether the lack of conventional precipitation and snow observations can be overcome by using model-based precipitation estimates from meteorological data assimilation systems.

To this end, a detailed examination is undertaken of the ability of model-assimilated precipitation data to represent the interannual (year-to-year) variations of observed runoff in the Aral Sea basin in central Asia. Precipitation from the 15-yr Re-Analysis (ERA-15) of the European Centre for Medium-Range Weather Forecasts (ECMWF) for the period 1979–93 is compared against precipitation estimates derived from rain gauge networks, and against the observed natural runoff in the Syrdarya (166 400 km²) and Amudarya (320 520 km²) basins. It is demonstrated that the ERA-15 dataset is able—despite its low spatial resolution—to describe the seasonal cycle and the larger-scale geographical distribution of precipitation in central Asia. For the Syrdarya basin, it is found that December–April ERA-15 precipitation correlates well with observed May–September natural discharge. The correlation coefficient between the two time series amounts to $r = 0.92$. It is also demonstrated that ERA-15 precipitation is a better predictor for subsequent runoff than rain gauge–based precipitation analyses, presumably because of the poor coverage with rain gauge stations. The high correlations suggest that a reliable seasonal runoff forecasting system can be constructed from the statistical relationship between model-assimilated precipitation and subsequent runoff. Cross-validation hindcasting techniques are used to confirm this conclusion. A real runoff forecasting system would, however, require using a real-time precipitation product from an operational data assimilation system.

For the Amudarya basin, the correlation between precipitation and subsequent runoff is substantially lower, presumably because of a lower quality of ERA-15 precipitation estimates within the tropical weather system, and/or due to a lower quality of the withdrawal-corrected runoff figures.

1. Introduction and objectives

The hydrology of central Asia is dominated by the Amudarya and Syrdarya rivers. These have their source regions in the Hindukush, Pamir, and the Tian Shan Mountains and flow across the Kyzylkum and Karakum Deserts to finally feed the Aral Sea more than 1000 km downstream (see Fig. 1). The economy and ecology of the central Asian region heavily relies on the two rivers, and the exploitation of this precious but limited resource has led to the dramatic dessication of the Aral Sea (Micklin 1988; Letolle and Mainguet 1995; Glantz 1999).

Already in 1960, about 50 000 km² of agricultural land were irrigated. In a boost to support the Soviet textile industry, the irrigation area was extended by 20% between 1960 and 1980 for cotton plantations. In the same time period, the annual water withdrawal from the...
Amudarya and Syrdarya Rivers doubled from ~45 to ~90 km$^3$, leaving little water to reach the Aral Sea. The result was the “Aral Sea Disaster” (Micklin 1988). As the Aral Sea is located in a desert and has no natural outlet, its water level is governed by a delicate balance between inflow and evaporation. From 1960 to 2002, the water level has dropped by 22.2 m from an initial level at 53.4 m above sea level (numbers apply to the larger of the two remaining seas). As a result, the surface area of the shallow Aral Sea has shrunk from an initial 66 900 to 20 800 km$^2$, its salinity has increased from ~10 to ~68 g L$^{-1}$, its ecosystems with numerous indigenous species have largely been destroyed, and formerly prosperous fishing ports find themselves now in the desert, up to 80 km away from the shores. In 1987, the Aral Sea was split into two lakes, a northern part near Aralsk in Kazakhstan and a southern near Moynaq in Uzbekistan. By 2001 the formerly small Vozhodenia Island had grown to become a large peninsula that extended many hundreds of kilometers into the sea. Following the disintegration of the Soviet Union in 1991, the central Asian countries have declared independence and struggle with difficult economic circumstances that absorb most of the resources and attention of the young republics. Despite these difficult circumstances, several programs are underway—since 1993 partly supported by international bodies such as the World Bank—to improve the water situation in the Aral Sea basin. These programs address the conversion of formerly cotton-dominated plantations into a less water-demanding and more productive vegetable, fruit, and livestock-based agriculture, improvements of the irrigation systems, and the reestablishment of hydrological monitoring and forecasting that was diminished with the decay of the Soviet Union.

In a heavily overused system such as the Aral Sea basin, appropriate short-term (lead time up to a few days) and seasonal forecasting (lead time up to a few months) is particularly important to optimize the highly complex water management systems in the region. The latter include several large dams (such as the Toktogul reservoir with a capacity of ~19 km$^3$) and many artificial channels and irrigation systems. During wet spells, large amounts of river water are sometimes released into the desert and Lake Arnasai, in order to avoid flooding farther downstream. During droughts, water shortage sometimes forces the termination of irrigation prior to the end of the harvest period. In both cases, timely anticipation of these conditions can avoid wasting water resources, which are lost to both the Aral Sea and the agriculture of the region.

For the past 10 years, partly supported by Swiss projects, quantitative methods for short-term and seasonal hydrological forecasting are under development for several subcatchments of the Amudarya and Syrdarya Rivers (Baumgartner et al. 2000; Pertziger et al. 2002). Seasonal forecasting is mainly based on the concept that the melting of winter and spring snow is the source of runoff in the subsequent summer period. Currently, however, there are no quantitative approaches for the whole Amudarya and Syrdarya basins.

The main challenge to seasonal forecasting in central Asia is the estimation of winter and spring snow accumulation. During the time of the Soviet Union, an extensive monitoring program was in place, partly based upon snow surveys by helicopter. Following the decay of the Soviet Union, these activities have largely been discontinued, and the number of snow-measuring stations in the river basins of Kazakhstan, Kirghizstan, Tajikistan, and Uzbekistan has decreased from 257 in 1985 to 30 in 1995—in an area of approximately 500 000 km$^2$ covered by highly complex mountainous terrain (Borovikova
1997). This station density is far too low to support a reliable estimation of snow water equivalent in the whole of the runoff formation region. Despite substantial efforts, it is unlikely that the coverage with surface stations will soon become sufficient for this task. In an attempt to circumvent these limitations, satellite data are operationally used to provide snow-cover maps (Kobilov et al. 2001). While such techniques yield precise information on the spatial and temporal extent of the snow cover (e.g., Carroll et al. 1999), it appears difficult to derive sufficiently reliable quantitative estimates of snow water equivalent from satellite data in complex terrain.

In the current study an attempt is undertaken to forecast summer runoff in central Asia based on winter and spring precipitation estimates from meteorological data assimilation systems. Such precipitation estimates are available irrespective of local precipitation observations. In essence, modern data assimilation systems are able to exploit the space–time continuity of weather systems. Meteorological observations essentially determine—with some time delay—the atmospheric conditions in some area downstream of the observation. In this regard, central Asia is ideally located, as typical atmospheric disturbances in this area arrive from the Atlantic, such that they propagate through a dense observational network in Europe, the Middle East, the Black Sea, and/or the Caspian Sea regions. Regarding the resulting precipitation estimates in central Asia, it is important to realize that these are entirely model generated and may be expected to have the quality of typical 1–2-day precipitation forecasts. To assess the ability of such precipitation estimates to capture the runoff variability in the region, estimates of accumulated winter and spring precipitation in the period 1979–93 will be compared against the observed summertime runoff of the Syrdarya and Amudarya Rivers. It will be demonstrated that—in spite of the low spatial resolution of the employed data assimilation system—it is able to capture the year-to-year variability in the Syrdarya basin with notable accuracy.

The hydrology of central Asia is special in the sense that most of the precipitation takes place in the winter and spring seasons, while most of the runoff is in the summer season (Chub 2000). In the more general case, where some fraction of the discharge derives from immediately preceding rainfall, seasonal runoff prediction requires forecasting atmospheric circulation and precipitation anomalies, using coupled atmosphere–ocean general circulation models (see, e.g., Stockdale et al. 1998; Shukla et al. 2000; Goddard et al. 2001). Such methods also appear promising in central and southwest Asia (Tippett et al. 2004, manuscript submitted to J. Climate; Barlow et al. 2002). The optimal long-term strategy toward seasonal runoff forecasting in central Asia should thus take into consideration both sources of information, that is, the initial state of the snow cover as well as forecasts of coupled models. However, as summer runoff in central Asia primarily derives from snowmelt, seasonal precipitation forecasts may be of secondary importance. Quite generally, the persistence of soil moisture and snow-cover anomalies represents a crucial factor in seasonal runoff forecasting, in particular in the mid- and high latitudes, where the seasonal predictability of atmospheric anomalies is much smaller than in the Tropics (Maurer and Lettenmaier 2003).

The structure of the paper is as follows: Section 2 contains brief descriptions of the datasets employed. In section 3 we compare precipitation estimates from the European Centre for Medium-Range Weather Forecasts (ECMWF) 15-yr Re-Analysis (ERA-15) against rain gauge–based precipitation analyses and against the observed natural discharge of the Syrdarya and Amudarya Rivers. In section 4, a simple statistical model is developed to test a pilot forecasting system. Section 5 concludes the study and provides a brief outlook.

2. Datasets
a. Precipitation data from meteorological data assimilation

Today’s operational numerical weather prediction (NWP) models consider the three-dimensional dynamics of the atmosphere, as well as a wide range of physical processes including solar and infrared radiation, cloud and precipitation formation, boundary layer processes, and others. An important key to a successful forecast is the evaluation of appropriate initial conditions. These are obtained from meteorological data collected by national meteorological and hydrological services and distributed by the World Meteorological Organization (WMO). Examples of the respective data coverage in Europe and Asia are shown in Fig. 2. The collection of these data on a three-dimensional grid in a spatially and temporally coherent fashion is referred to as meteorological data assimilation. Modern data assimilation systems are able to profitably ingest a wide range of data types (including satellite and other nonconventional data) and are almost free of spinup effects (caused by physical inconsistencies) that have seriously affected the quality of data assimilation products in the past.

An up-to-date description of data assimilation techniques can be found in Boultier and Courtier (1999). Atmospheric data assimilation systems make use of a short-term forecast (typically a 6- or 12-h forecast), and the resulting data fields thus represent a mixture of observed and forecasted data. In this way, it becomes feasible to provide a realistic analysis of the atmospheric state even in areas with few observations. As the assimilation technique is based on a full numerical model containing most relevant physical processes, it is able to output variables that are not directly observed, or whose observations do not enter the assimilation cycle. Currently most atmospheric data assimilation systems do not ingest data from conventional precipitation gauges, but they can nevertheless provide quantitative pre-
cipitation estimates, even in remote areas without precipitation observations. Such data are used in the current study.

From Fig. 2 it can be observed that the data coverage in central Asia is rather poor. While there is appreciable coverage by surface meteorological station data (Fig. 2a), the lack of atmospheric sounding data is of particular concern (Fig. 2b). Nevertheless, as the weather systems in midlatitudes predominantly propagate from west to east, low and high pressure systems that affect central Asia will propagate through a rather dense upper-air observational array located over Europe and the Middle East, as well as the Black and Caspian Sea regions. Thus, despite the lack of atmospheric sounding data in the region, there is the hope that the weather systems arriving in central Asia are rather accurately simulated, maybe even more accurately than the weather systems arriving in western Europe from the data-sparse Atlantic.

The assimilated precipitation datasets used in this study are summarized in Table 1. The operational ECMWF forecasting system is a temporally inhomogeneous system, as model updates and improvements are continuously implemented. For the current study we instead use the ERA-15. The latter has been obtained using a homogeneous data assimilation system throughout the period 1979–93, and inhomogeneities may only arise from changes in the observational meteorological networks. The ERA-15 dataset has also been used by Yatagai (2003) for a detailed analysis of the central Asian hydrological balance. The main objective of our study is to assess the ability of assimilated precipitation data to reproduce interannual (year-to-year) variations of precipitation in central Asia. The ability of the assimilation system to represent the underlying topography is a key to successful data assimilation in this area. At the horizontal resolution of ERA-15 (~1.125°), important topographic features such as the westernmost ranges of the Tian Shan and the Zerafshan Valley are smoothed out, and even the large-scale source regions of the Amudarya and Syrdarya Rivers are poorly represented. As a result, the effect of the respective topographic features on atmospheric flow and orographic precipitation is underestimated. This situation is calling for a statistical treatment of the data, geared toward a correction of the systematic biases.

b. Conventional precipitation data

In addition to data from meteorological assimilation systems, we use precipitation datasets that are partly or mostly derived from conventional rain gauge data. The density of such data, which is available in real time, is similar to the resolution of SYNOP stations shown in

![Fig. 2. Real-time data coverage over Eurasia for a typical 12-h time window in the operational ECMWF data assimilation system. The data categories shown are (a) conventional surface station reports (SYNOP and SHIP; plotted as circles and crosses, respectively) and (b) radiosonde upper-air reports (TEMP). Courtesy of ECMWF.](image-url)
Fig. 2a. Here we use two precipitation analyses, which—over land—draw from similar data sources (see Table 2).

The Global Precipitation Climatology Project (GPCP) combined precipitation dataset (version 2) provides monthly, global gridded fields of combined satellite- and gauge-based precipitation estimates. It covers the 21-yr period January 1979 through the delayed present (see Huffman et al. 1997). Since no single satellite data source spans the entire data record, the product draws upon many different satellite sources covering different times and regions within the data record. Over land, the estimates are mostly based on conventional rain gauge data. Details on the treatment and the analysis of rain gauge data can be found in Rudolf (1993).

The University of Delaware provides an alternative precipitation dataset with monthly resolution. For brevity, it will be referred to as UDEL. Earlier versions of this data restricted attention to climatological means (Legates and Willmott 1990), but here we use a more recent product with monthly fields. The data are currently available for the period 1950–99. Over land, it is based on essentially the same rain gauge data as GPCP, but an alternative algorithm and a substantially higher resolution are employed (see Table 2 and documentation for further information). The respective analysis procedure makes use of background climatological fields established for a fraction of the observational period.

c. River basins and runoff data

Monthly natural runoff estimates for 1979–93 over selected river basins will be used to assess the ability of the ERA-15 and other precipitation products to represent the interannual (year-to-year) variability. The catchments to be considered are (see also Fig. 1)

- the Syrdarya basin upstream of Chinaz (located near the border between Uzbekistan and Kazakhstan), including the major tributaries Naryn and the Karadarya (which merge in the Fergana Valley to become the Syrdarya), and
- the Amudarya basin upstream of Kerki (located near the border between Afghanistan and Turkmenistan), including the major tributaries Vakhsh and the Pyandzh (which merge on the Afghan-Tajik border to become the Amudarya).

These catchments cover almost the entire Pamir and Tian Shan runoff formation region of the Aral Sea watershed. The digital definition of the river basins is based on the GTOPO30 digital topography dataset (available online at http://edcdaac.usgs.gov/gtopo30)\(^1\) with a resolution of \(\sim 1\) km. When averaging the much lower resolved precipitation grids over the basins, the fractional coverage of the catchments by each grid box is used as a weighting factor. In the case of ERA-15 data, a total of 28 (Syrdarya) and 42 (Amudarya) grid points contribute.

Runoff observations over the catchments considered are heavily affected by water withdrawals, diversions, and artificial storage for irrigation, freshwater supply, and hydropower purposes. The water withdrawals are most significant for the Kerki catchment, where, for example, the Karakum channel (leading to Turkmenistan) has a capacity of 600 m\(^3\) s\(^{-1}\). The total capacity of all withdrawal channels in the Kerki catchment is as large as \(-900\) m\(^3\) s\(^{-1}\) (corresponding to 41\% of the annual mean runoff of the Rhine at Rotterdam), and this figure can be compared against the mean annual runoff at Kerki of \(-2000\) m\(^3\) s\(^{-1}\). The measured runoff at the gauging stations is thus not suited for intercomparison with accumulated catchment-averaged precipitation, but requires appropriate corrections for artificial water withdrawals and storage, as well as for drainage from irrigated areas.

Here we use the “natural runoff” figures that are operationally compiled by the Hydrometeorological Survey of Uzbekistan (Uzgidromet, Tashkent), using data from numerous runoff gauges in central Asia, as well as withdrawal figures from the Uzbek Ministry of Water Management and the central Asian interstate agencies for water management issues (so-called BVOs) in the Syrdarya and Amudarya catchments. The latter organizations exchange in near–real time the data from

| Table 2. Characteristics of the precipitation analyses from GPCP and UDEL. |
|------------------------|------------------------|------------------------|
|                        | GPCP                   | UDEL                   |
|                        | Version 2              | Version 1.02            |
| Description            | Precipitation analysis based on comprehensive rain gauge and remote sensing data | Precipitation analysis based on comprehensive rain gauge archive |
| Horizontal resolution  | 2.5°                   | 0.5°                   |
| Analysis technique     | Combined rain-gauge- and satellite-based analysis | Climatologically aided interpolation of rain gauge data |

\(^1\) The GTOPO30 database was complied in a collaborative effort led by the U.S. Geological Survey.
a large number of flow measurements in artificial channels and drainage systems. The figures are used to correct the observed runoff for withdrawals and diversions.

More specifically, the corrections involve the following steps:

- For the Syrdarya basin upstream of Chinaz, the natural runoff is estimated from the runoff of the contributing reservoirs together with the runoff measurement at Chinaz. The inflow into the Toktogul water reservoir in Kyrgyzstan (measured upstream of the reservoir) is considered unaffected. The Karadarya above the junction with the Naryn River is corrected for the Andijan water reservoir and withdrawals in the Fergana Valley (actually, this correction is accounted for as a diversion farther downstream). In the Fergana Valley between the junction Karadarya–Naryn and the Karakum water reservoir, the runoff is estimated from that of all tributaries of the upper Syrdarya, as based on runoff gauges located in runoff formation area and corrections for withdrawals upstream. Between the Kayakum reservoir and Chinaz, the same procedure is applied. Here the most important contributaries are those of the Chirichik (measured upstream of the Charvak reservoir and corrected for the diversion to the Tashkent oasis) and the Ohangaron.

- The situation of the Amudarya upstream of Kerki is simpler, as there are fewer (though sizable) withdrawals, in particular the Karakum channel mentioned above. Human interference in the Pyandzh basin is small and can thus safely be neglected. The corrected runoff figures are here based on the Kerki gauge (which was continuously in operation) and adjusted for all known withdrawals in the catchment. Changes in the water balance of the Nurek reservoir of the Vakhsh (changes in volume) are also accounted for.

The standard methodology used by the Hydrometeorological Survey of Uzbekistan was maintained throughout the ERA-15 period (1979–93) until today. However, two changes have affected the homogeneity of the series. First, in 1988 the office started to use a substantially increased set of data (most of the additional data are from drainage channels that collect runoff from irrigated areas). The use of these data in correcting the observed runoff appears to notably affect the homogeneity of the Syrdarya series, and a correction (a flat increase by 14%) has thus been applied to the natural runoff figures for the period 1979–87. Second, the decay of the Soviet Union in 1991 has dramatically affected the number of operating runoff stations. For instance, the runoff gauge of the lower Pyandzh is out of operation since 1992. However, as this only affects the last year of the series, a detailed assessment of the respective inhomogeneity has not been conducted.

3. Results

a. Intercomparison and validation of precipitation products

We start by presenting the mean seasonal precipitation amounts 1979–93 from ERA-15 in Fig. 3. Features to note include the high winter and spring precipitation associated with extratropical cyclones passing through the region, the dryness in summer and early autumn in Uzbekistan and Turkmenistan upstream of the central Asian topography, the intense summer precipitation at the southern slopes of the Himalayan Mountains associated with monsoonal precipitation, and the dry conditions throughout the year in Takla Makan Desert in eastern China.

Figure 4 shows the same fields for the rain gauge–based analysis from the UDEL dataset. Comparison against Fig. 3 demonstrates that the ERA-15 dataset captures the larger-scale seasonal precipitation variations with reasonable accuracy. As to be expected, however, the UDEL analysis shows a substantially higher level of spatial variability, which is due to complex topographic features that cannot be represented at the low resolution of the ERA-15 assimilation model. The low resolution of ERA-15 implies an underestimation of orographic precipitation and shadowing effects. For instance, the Fergana Valley (to the east of Uzbekistan; see Fig. 1b) is characterized by a comparatively dry climate even during the wet seasons, which is partly captured by UDEL but missed by ERA-15.

In Fig. 5 a validation of the mean seasonal precipitation cycle is presented, based on rain gauge data from four stations (see Fig. 1a for the locations of the four stations). For this purpose, the ERA-15 precipitation is bilinearly interpolated between the neighboring four grid points. Figures 5a and 5c evaluate the performance of ERA-15 at locations some distance upstream of the major topographic features of central Asia. The comparison against the station data demonstrates a remarkably high quality of the assimilation systems, which well captures the rainy and the dry seasons. Figures 5b and 5d relate to stations in the foothills of the Tian Shan and the Pamir, at locations where the ERA-15 system misrepresents the local topography. As a result, there are systematic biases in seasonal ERA-15 precipitation. Tashkent (Fig. 5b) is located near the entrance of the Fergana Valley, which is entirely missing in the ERA-15 topography. Kerki (Fig. 5d) is shielded to the west by a southward extending range of the Pamir, and the absence of this range in the ERA-15 system is consistent with a substantial overestimation of the local precipitation amounts.

A comparison of area-mean precipitation over the Syrdarya and Amudarya catchments for the three different datasets (ERA-15, GPCP, and UDEL) and the period 1979–93 is shown in Fig. 6. In comparison, GPCP has the lowest precipitation estimate, and ERA-15 the highest. In the yearly mean, the differences...
amount to 31% and 33% for the Syrdarya and Amudarya catchments, respectively. The UDEL estimate is very similar to GPCP for the Syrdarya, and roughly in between the two other estimates for the Amudarya. These differences do likely imply an overestimation of precipitation by ERA-15, but they might also be related to the poor coverage with rain gauges (in particular in the mountains) and/or to systematic rain gauge biases (wind losses during snowfall). The latter factor would be consistent with the result that the differences between ERA-15 and the rain gauge analyses are particularly pronounced in winter and spring.

Overall the above results indicate that the ERA-15 system is able to credibly represent the larger-scale variations of the seasonal cycle, while it probably overestimates catchment-averaged precipitation and misses smaller-scale features associated with the complex structure of the topography (see also Schär et al. 2002). To
counteract the systematic biases, our study employs two principles. First, precipitation from the ERA-15 system is only utilized in terms of large-scale averages over the source regions of the Amudarya and Syrdarya Rivers. Second, when establishing a relationship between precipitation and subsequent runoff, we employ linear statistical relationships that imply an implicit correction—in an approximate linear fashion—for the systematic biases of the assimilated precipitation products.

b. Catchment-integrated seasonal cycle

The mean seasonal cycle in terms of ERA-15 precipitation and observed natural runoff integrated over the two catchments under consideration is shown in Fig. 7. The display includes the mean (bold line) as well as a band spanned by the mean plus/minus one standard deviation to represent the interannual variability. Both catchments show nival/glacial characteristics, with maximum precipitation in spring and delayed maximum run-
Fig. 5. Mean seasonal cycle of precipitation 1979–93 (mm day\(^{-1}\)) at four locations according to ERA-15 data (dashed line) and conventional rain gauge observations (solid line).

Fig. 6. Mean seasonal cycle of precipitation 1979–93 (mm day\(^{-1}\)) averaged over the (a) Syrdarya and (b) Amudarya catchments. Data are shown for ERA-15, GPCP, and the UDEL datasets.

off during summer. There are some interesting differences between the catchments:

- The precipitation peak in the Amudarya basin upstream of Kerki is in March, while it is in April in the Syrdarya basin upstream of Chinaz. This behavior is consistent with the synoptic climatology of the storm track of extratropical cyclones. During winter, the storm track is located to the south of the Himalayas; that is, individual low pressure systems detour the Himalayan topography near its southward flanks. During spring, the storm track swings back to a position north of the Tibetan Plateau, leading to increased spring precipitation in central Asia (see Fig. 3). This swing of the storm track is experienced earlier in the more southerly Amudarya basin and only later in the Syrdarya basin.

- Year-to-year variations are strongest in April, in both catchments. Consideration of individual years shows that the differences between maximum and minimum ERA-15 precipitation corresponds to 6.3 mm/day\(^{-1}\) (Syrdarya upstream of Chinaz) and 4.0 mm/day\(^{-1}\) (Amudarya upstream of Kerki), respectively. Associated maximum and minimum yearly precipitation amounts differ by roughly a factor of 2 in both catchments.

The observed natural runoff in the two catchments shows a broad maximum in June to September. The peak runoff of the Amudarya is later (in July) than in the Syrdarya, which is presumably due to the higher topography and the larger fraction of glaciation in the Amudarya catchment. It is of interest to estimate the water balance in the region. For the Syrdarya and Amu-
darya basins, yearly runoff amounts to 36% and 39% of ERA-15 precipitation totals, respectively, implying that more than 60% of precipitation evaporates and does not reach the outlet of the basins. This estimate, however, is presumably affected by systematic biases of the assimilated precipitation estimates (see Fig. 6).

c. Correlation between accumulated precipitation and subsequent runoff

The seasonal prediction of river runoff is of great interest for hydropower, agricultural, and water management purposes in central Asia. The total streamflow during the flood period (spring and summer) is of particular interest because of high water demands for irrigational purposes. In this section we test the extent to which a forecast of runoff in the extended summer season can be based on estimates of preceding precipitation amounts. In particular, we test the potential of numerically assimilated precipitation totals for forecasting purposes.

1) Linear Regression

We begin by considering the linear statistical relationships between summer runoff and preceding precipitation. As the target season we choose—here and in the remainder of this paper—the accumulated runoff from the extended summer season (from May to September). Observed runoff in this season is correlated against accumulated precipitation in the preceding winter/spring season (from December to April). For the Syrdarya catchment this choice of the precipitation period yields the highest correlations. Catchment-averaged precipitation is estimated from four datasets:

- the ERA-15 assimilated precipitation
- the gridded UDEL precipitation analysis from rain gauge data (0.5° resolution)
- the gridded GPCP precipitation analysis (2.5° resolution)
- the precipitation estimated from a single rain gauge station

The first three of these datasets are available on a grid, and the respective data are spatially averaged and temporally accumulated over the catchments under consideration (see section 2c for further details). The fourth dataset may not be representative for the whole catchments, as only one single precipitation station is considered. This part of the analysis is included for comparison purposes.

Table 3 presents the resulting correlation coefficients. It also contains results for the Zerafshan catchment (see special discussion below). The highest correlations are obtained between the Syrdarya runoff at Chinaz and the assimilated ERA-15 precipitation (correlation coefficient $r = 0.907$, $r^2 = 0.823$). This high correlation significantly exceeds that obtained from the UDEL and GPCP datasets (see Table 3), presumably because of the poor coverage of central Asia with conventional rain gauge stations. In the case of the Syrdarya catchment, even a single station rain gauge record (Tashkent) correlates rather well with subsequent summer runoff.

Table 3. Correlation coefficient $r$ between natural runoff in the extended summer season (May–Sep) and accumulated catchment-averaged precipitation in the preceding months (Dec–Apr). The correlation coefficients are listed for four different precipitation datasets: the assimilation-based precipitation data of ERA-15, the rain-gauge-based precipitation grids of UDEL and GPCP, and the correlation with a single rain gauge station (Tashkent, Samarkand, and Termez, respectively).

<table>
<thead>
<tr>
<th>Catchment</th>
<th>Area (km²)</th>
<th>ERA-15</th>
<th>UDEL</th>
<th>GPCP</th>
<th>Single station</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chinaz (Syrdarya)</td>
<td>166 400</td>
<td>0.907</td>
<td>0.845</td>
<td>0.828</td>
<td>0.638</td>
</tr>
<tr>
<td>Dupuli (Zerafshan)</td>
<td>10 200</td>
<td>0.587</td>
<td>0.613</td>
<td>0.711</td>
<td>0.594</td>
</tr>
<tr>
<td>Kerki (Amudarya)</td>
<td>320 500</td>
<td>0.512</td>
<td>0.499</td>
<td>0.663</td>
<td>0.238</td>
</tr>
</tbody>
</table>
For the Amudarya catchment the correlations are not as high for all datasets considered. The GPCP rain gauge–based precipitation estimate yields a higher value than ERA-15. There are several reasons that could explain the poorer correlations in the Amudarya (in comparison to the Syrdarya) catchment: (a) larger uncertainties in the natural runoff estimation, (b) higher contributions of glacier melt due to larger extent of glaciation, (c) larger fraction of rainfall at the expense of snow due to higher spring temperatures, and (d) lower quality of ERA-15 assimilated precipitation due to stronger influence of tropical precipitation systems.

It will be the aim future work to thoroughly assess the relative role of these error contributions, but some hints may be derived from a corresponding analysis in the Zerashan catchment upstream of Dubuli. This basin is much smaller (10 200 km²) than the other two considered, located between the Syrdarya to the north and the Amudarya to the south (almost entirely within Tajikistan; see Fig. 1), associated with steep and high topography and a high degree of glaciation and characterized by a climate that is more comparable to the upper Syrdarya catchment as it is shielded toward the south. Despite the the high degree of glaciation of the Zerashan catchment, the resulting correlations between summer runoff and preceding precipitation are larger than those for the Amudarya catchment (see Table 3). This suggests that factor (b) listed above is an unlikely explanation for the differences. Furthermore, statistical modeling that includes surface temperature as a predictor (see below) suggests that the role of factor (c) is small, in all of the catchments considered. As a result, we believe that factors (a) and (d) are the dominant error contributions in the Amudarya catchment.

In the following, we focus attention on the upper Syrdarya basin using ERA-15 assimilated precipitation data. The motivation for restricting attention to ERA-15 is the real-time availability of assimilated precipitation data, which would allow for the implementation of a real-time seasonal runoff forecasting system. Similar multilinear regressions have also been performed for the Amudarya catchment, but the poor correlations seen in the simple analysis above are only marginally improved. In presenting the results, we thus restrict attention to the Syrdarya basin.

2) Multilinear Regression

As a next and more sophisticated step, consider a model based on a multilinear regression of runoff \( R \) in the extended summer season (i.e., May to September) in which monthly (rather than seasonal) precipitation and 2-m temperature estimates from ERA-15 are used as independent explanatory variables. Figure 5 suggests that runoff may be particularly sensitive to precipitation in March and April (when precipitation variability is highest). We also test the hypothesis that fluctuations of mean monthly temperature \( T \) in October–November and March–April (i.e., at the transition to/from freezing temperatures) may have an influence on the phase of the precipitation (solid or liquid) and thus on instantaneous and delayed runoff formation.

A stepwise backward algorithm (e.g., Cox and Snell 1981) has been used to determine the most accurate multilinear regression model for summer runoff \( R \) of the type

\[
R_t = \beta_0 + \sum_m \beta_m^o P_{t,m} + \sum_m \beta_m^T T_{t,m} + E_t. \tag{1}
\]

Here the variables \( R \) and \( P \) represent runoff and precipitation amounts (millimeters) averaged over the catchment and accumulated over the periods under consideration; \( T \) represents mean monthly temperature averaged over the catchment; the subscripts \( t \) and \( m \), respectively, denote the year (1979–93) and the month (November–April); and \( E \), represents inherent random variations (assumed to be Gaussian distributed with standard deviation \( \sigma \)). All nonsignificant factors (at the \( p = 0.10 \) level) are then iteratively eliminated (one at a time, in reversed order of statistical significance) to augment the stability of the statistical model. During this process the remaining coefficients \( \beta \) are recomputed after each omission. The \( p \) value for each explanatory variable is based on a \( t \) test that verifies whether the variable can be omitted in the regression model (i.e., \( \beta = 0 \) as null hypothesis).

The aforementioned procedure leads in turn to the elimination of all temperature factors. In addition, precipitation during the winter months [December–February (DJF)] is statistically significant only when combined into one single explanatory variable, referred to as accumulated winter precipitation \( P_{t,\text{DJF}} \). The resulting statistical estimation of extended summer runoff is then given by

\[
\hat{R}_t = \beta^o + \beta^o_{\text{DJF}} P_{t,\text{DJF}} + \beta^o_{\text{Mar}} P_{t,\text{Mar}} + \beta^o_{\text{Apr}} P_{t,\text{Apr}}, \tag{2}
\]

where the ’ symbol is used to denote statistical estimates. To verify the assumption that \( E \) is indeed Gaussian distributed, Dirren (2003) conducted a detailed residual analysis by using normal plot, Tukey–Anscombe plot, and Cook distances. He also showed that a robust parameter estimation technique yields essentially identical results as the least squares approach presented in this paper.

A complete summary of the statistical model in terms of its \( \beta \) coefficients is provided in Table 4. It reveals that a multilinear model based on March, April, and DJF assimilated precipitation yields better results than

<table>
<thead>
<tr>
<th>( \beta )</th>
<th>CI (( \beta ))</th>
<th>( p ) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \beta^o )</td>
<td>34.00 mm</td>
<td>11.80 mm</td>
</tr>
<tr>
<td>( \beta^o_{\text{Mar}} )</td>
<td>0.2264</td>
<td>0.0907</td>
</tr>
<tr>
<td>( \beta^o_{\text{Apr}} )</td>
<td>0.3834</td>
<td>0.0811</td>
</tr>
<tr>
<td>( \beta^o_{\text{Apr}} )</td>
<td>0.2392</td>
<td>0.0565</td>
</tr>
</tbody>
</table>

TABLE 4. Statistical estimates of the coefficients of the multilinear regression model (2), along with the 90% confidence interval and \( p \) values. Note that all precipitations and runoffs used in the model represent amounts in mm, averaged over the catchment and accumulated over the periods under consideration.
the linear analysis presented above. Assimilated precipitation is able to explain $r^2 = 85\%$ of the variability in summer runoff (correlation coefficient $r = 0.92$), leaving an unexplained residual error variance of $\hat{\sigma}^2 = 81.9$ mm$^2$, corresponding to a mean monthly uncertainty of $\bar{\sigma} = 0.06$ mm day$^{-1}$. This estimation is based on the variance of the residuals between observed and fitted values $\hat{\sigma}^2 = (n - 4)^{-1} \sum (R - \hat{R})^2$, with $n = 15$ denoting the number of years considered. The table also lists the 90% confidence interval of the estimates.

Figure 8 depicts time series of observed and fitted discharge in the Syrdarya basin upstream of Chinaz as obtained with the statistical model (2). The comparison between the two curves shows that model-assimilated precipitation data can capture the observed year-to-year runoff variability with notable accuracy, even without explicit treatment of the snowmelt–runoff processes.

The different terms of the multilinear regression equation (2) can readily be interpreted in a physical manner, but the interpretation may suffer from systematic biases in the data. For the following interpretations we thus assume that these biases are not dominant: First, the $\hat{\beta}^o$ terms represent the fraction of precipitation of the respective month (or season) that runs off during the extended summer season (May–September). Table 4 shows that this fraction decreases from March to April (unlike the difference between $\hat{\beta}^o_{\text{spr}}$ and $\hat{\beta}^o_{\text{spr}}$, this decrease is statistically significant). More specific, 38% of March precipitation runs off during the summer season, while the fraction is down to 24% in April. The substantially lower April value is plausible and likely due to the seasonal temperature increase (and the increasing fraction of rain at the expense of snow). Based on the mean temperature in Tashkent, much of the snow storage between the time of precipitation (April) and runoff (summer) will take place at high altitudes only, above 2000 m. Second, the term $\hat{\beta}^o$ represents runoff contributions that originate from precipitation in other months than considered explicitly in the statistical model (2). It amounts to a mean daily runoff of 0.23 mm day$^{-1}$, corresponding to $\sim 34\%$ of the runoff in summer (cf. Fig. 8). The runoff component $\hat{\beta}^o$ amounts to 21% of the assimilated mean summer precipitation (cf. Fig. 7), and this is consistent with the assumption that it primarily derives from summer precipitation, and to a lesser extent from the melting of old snow and ice. Third, as noted previously, the contributions of the temperature factors $T$ are not significant at the $p = 10\%$ level, and temperature has thus been removed from the list of explanatory variables in (2). This result is consistent with the rapid warming during spring (the basin-mean warming from March to April amounts to $\sim 9^\circ$C) in comparison with the standard deviation of monthly mean temperatures ($\sim 1.5^\circ$C in April). Likewise, the omission of November precipitation from the model indicates that runoff from this month takes place to a substantial fraction in the fall and early spring seasons.

Spring precipitation is the most important input into the statistical model, consistent with the large precipitation intensity and variability in spring (see Fig. 5). This property is also signaled by the extremely high statistical significance during spring (see the $p$ values in Table 4), and it contrasts with the concept that the melting of winter snow is the main source of runoff in the subsequent summer period.

4. A pilot forecasting system

The high correlations between runoff and preceding ERA-15 precipitation as revealed in section 3 suggest a potential for discharge predictions based on multilinear regression models. This potential can be assessed by a cross-validation analysis (e.g., Mosteller and Tukey 1977). It involves a multilinear regression between the
datasets amputated by one observation, an independent prediction of this observed value, and finally repeating the same procedure for each observation.

To make such predictions more meaningful, they will need to be supplemented with a prediction interval representing the uncertainty of the underlying statistics. Consider for convenience a linear statistical model of the form

\[ \hat{R}_t = \hat{\beta}_0 + \hat{\beta} P_t. \]  

(3)

For a particular year \( \tau \), the \( p = 10\% \) prediction interval is determined by

\[ \hat{R}_\tau = \hat{\beta}_0 + \hat{\beta} P_\tau \pm q_{0.95} \sqrt{1 + \frac{1}{n} + \frac{(P_\tau - \bar{P})^2}{\sum_{t=1}^{n} (P_t - \bar{P})^2}}, \]

(4)

where \( n = 14 \) denotes the number of years considered for the calibration of the model (all years except \( \tau \), \( \bar{P} \) is the precipitation mean over these years, and \( q_{0.95} \) is the 0.95 quantile of the \( t \) distribution with \( n - 2 \) degrees of freedom. The prediction interval for the more general multilinear interval is essentially identical.

The results for the multilinear prediction model (2) are shown in Fig. 9. In most years the model provides an excellent prediction, and only in one year (1988) is there a departure from the forecasting interval (based on a \( p = 90\% \) prediction interval, one would expect at least one miss in a 15-yr series). The model enables forecasts that represent an improvement in comparison with the climatological forecast given by the plus/minus one standard deviation from the mean (dashed lines). The forecast interval is, however, relatively broad due to the short length of this time series (\( n = 14 \) yr). According to (4), the width of the forecast interval should be reduced and the predictive power should be increased, when using more extended time series.

5. Conclusions and outlook

A detailed analysis has been undertaken of the ability of precipitation data from meteorological data assimilation systems to represent observed interannual runoff variability in central Asia. Particular consideration has been given to precipitation from the ERA-15 atmospheric reanalysis project. This precipitation product does not rely on local information from central Asia, but essentially derives from the atmospheric forecasting model of the assimilation system, in conjunction with upwind meteorological data. Despite the low resolution of this precipitation data, the results appear highly promising:

- For the Syrdarya River basin, the correlations between assimilated winter/spring precipitation totals and subsequent summer runoff are extremely high (correlation coefficients as high as \( r = 0.92 \)). For this catchment, assimilated precipitation estimates from the ERA-15 atmospheric reanalysis appear to have a higher quality (in terms of interannual variability, but not necessarily in terms of absolute amounts) than rain gauge–based precipitation analyses such GPCP and UDEL.
- Results for the Amudarya catchment are not as statistically significant, possibly because of the lower quality of the ERA-15 precipitation estimates associated with the stronger influence of tropical weather systems, and/or because of a lower quality of the natural discharge estimates.
- The gain from using assimilated surface temperature (in addition to precipitation) is not statistically significant in any of the catchments considered. This re-
sult is plausible due to the comparatively small tempera-
ture variability (in comparison with month-to-
month seasonal variations) and indicates that the de-
tails of the hydrology (such as the snowmelt–runoff
process) may be neglected in a first attempt to seasonal
runoff forecasting.

• Spring precipitation (especially during the months
of March and April) represents the most important input
of the statistical model (more important than winter
precipitation). This is due to the large amounts and
large variability of spring precipitation in central Asia.

Overall, our results suggest that a rather reliable meth-

od for seasonal runoff prediction in the whole Syrdarya
basin can be constructed from model-assimilated pre-
cipitation estimates. Such a forecasting system should
ideally provide a new forecast each month, with lead
times of 1 to 6 months. In a first step, such a forecasting
system could largely follow the pilot statistical model
presented in section 4. However, the system would need
to be based on a real-time assimilation system (such as
ECMWF). Preliminary analysis of the latter dataset sug-
gests that it should be better at representing geographical
precipitation variability because of improved horizontal
resolution, raising the hope that the methodology may
successfully be extended to smaller subcatchments.

An important precondition of the statistical approach
is to overcome the inhomogeneity between the lower-
resolution dataset (the ERA-15 reanalysis) and current
higher-resolution real-time precipitation products (e.g.,
onfigional ECMWF assimilation system). The encour-
aging statistical relations found in sections 3 and 4
should not directly be applied to precipitation data from
real-time assimilation systems, as these data may have
different systematic biases. To overcome this inho-

mogeneity gap, we intend to use the 40-yr Reanalysis
(ERA-40), which has recently become available from the
ECMWF. It will cover the 1957–2001 period (and
may possibly be extended into the future). In addition
to helping with the inhomogeneity gap, the use of a
longer calibration period (45 instead of 15 yr) might
further increase the predictive power of the statistical
model. To provide a real-time forecast, it will also be
advantageous to develop a generalized hierarchy of pre-
dictive statistical models for monthly runoffs (i.e.,
a forecast with monthly resolution rather than a forecast
for the accumulated runoff in the summer season).

In a second step, it might be advantageous to drive a
distributed hydrological runoff model with assimilated
precipitation data, rather than using a statistical ap-

roach. Such a hydrological model would continuously
be fed by accumulated precipitation from an operational
assimilation system, so as to distinguish between rain
and snowfall, and to explicitly account for the nonli-
nearities of the snow accumulation and snow melt–run-
off process. Best results may be obtained by combining
information from assimilated precipitation fields with in-
situ precipitation observations, satellite-derived snow-
cover maps, surface temperature observations, as well as
remotely sensed precipitation rate information from
satellites.

Finally, in addition to supporting forecasting, assim-
ilated meteorological datasets might also be useful in
assessing the water balance of the whole Aral Sea basin
from the 1960s up to the present and thereby support
research on the dessication of the Aral Sea.

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REFERENCES

Barlow, M., H. Cullen, and B. Lyon, 2002: Drought in central
and southwestern Asia: La Niña, the warm pool, and Indian Ocean pre-

snowmelt runoff forecasting in the central Asian mountains.
Proc. Conf. on Remote Sensing and Hydrology, Santa Fe, NM,
IAHS, IAHS Publication 267, 66–71.

Borovikova, L. N., 1997: Description of the state of the National
Hydrometeorological Surveys and concept for their future de-
velopment. Improvement of Hydrometeorological Surveys in

Bouttier, F., and P. Courtier, 1999: Data assimilation concepts and
methods. ECMWF Lecture Notes, 58 pp. [Available online at
http://www.ecmwf.int/services/training/rcourse_notes/]

Carroll, S. S., T. R. Carroll, and R. W. Poston, 1999: Spatial modeling
and prediction of snow-water equivalent using ground-based,


Dirren, S., 2003: Statistical analysis and meteorological assimilated data and observed water discharge in central Asia. Swiss Federal Institute of Technology (ETH), Postgraduate Project in Statistics, 20 pp. [Available from the authors upon request.]


