A Long-Term Land Surface Hydrologic Fluxes and States Dataset for China

XUE-JUN ZHANG
Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, and University of Chinese Academy of Sciences, Beijing, China

QIUHONG TANG
Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

MING PAN
Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey

YIN TANG
Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing, China

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ABSTRACT

A long-term consistent and comprehensive dataset of land surface hydrologic fluxes and states will greatly benefit the analysis of land surface variables, their changes and interactions, and the assessment of land–atmosphere parameterizations for climate models. While some offline model studies can provide balanced water and energy budgets at land surface, few of them have presented an evaluation of the long-term interaction of water balance components over China. Here, a consistent and comprehensive land surface hydrologic fluxes and states dataset for China using the Variable Infiltration Capacity (VIC) hydrologic model driven by long-term gridded observation-based meteorological forcings is developed. The hydrologic dataset covers China with a 0.25° spatial resolution and a 3-hourly time step for 1952–2012. In the dataset, the simulated streamflow matches well with the observed monthly streamflow at the large river basins in China. Given the water balance scheme in the VIC model, the overall success at runoff simulations suggests that the long-term mean evapotranspiration is also realistically estimated. The simulated soil moisture generally reproduces the seasonal variation of the observed soil moisture at the ground stations where long-term observations are available. The modeled snow cover patterns and monthly dynamics bear an overall resemblance to the Northern Hemisphere snow cover extent data from the National Snow and Ice Data Center. Compared with global product of a similar nature, the dataset can provide a more reliable estimate of land surface variables over China. The dataset, which will be publicly available via the Internet, may be useful for hydroclimatological studies in China.

1. Introduction

As the lower boundary of the land–atmosphere system, land surface is of critical importance to weather and climate systems. Several land surface variables, like soil moisture and snowpack, may have a longer memory than the fast-changing weather system and may thus influence the overlying atmosphere by changing the partitioning of water and energy fluxes between the land and atmosphere (Fan et al. 2011). Numerous studies using land–atmosphere coupled models have revealed that the precipitation and temperature forecasts are sensitive to soil moisture memory, though such sensitivities vary regionally and seasonally (e.g., Koster and Suarez 2003; Berg et al. 2005). The availability of a long-term, large-scale land surface fluxes and states dataset is essential for providing more realistic initial conditions in climate studies and for assessing the performance of land–atmosphere parameterizations.

Corresponding author address: Qiuhong Tang, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, No. 11A, Datun Road, Chaoyang District, Beijing 100101, China. E-mail: tangqh@igsnrr.ac.cn

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Although long-term observations for some variables (e.g., precipitation and runoff) can be obtained directly from ground gauge stations over many parts of the world, the problem of scale inconsistency is often inevitable when compared to model simulations (Li et al. 2013). For example, the spatial scale of station-based observations (e.g., precipitation, soil moisture, and radiation) is much smaller than model simulations (Pan et al. 2012b), and some measurements are too infrequent to capture the time evolution (e.g., soil moisture). Moreover, many land surface fields are rather difficult to measure directly on a large scale through gauging stations. For instance, evapotranspiration (ET) measurements at a flux tower are generally only locally valid because of the large spatial variability of ET (Tang et al. 2009b).

While global reanalysis products, which are produced at various forecast centers [e.g., the National Centers for Environmental Prediction (NCEP) and the European Centre for Medium-Range Weather Forecasts (ECMWF)], can provide a consistent dataset of all flux and state variables at certain spatial and temporal scales, the imbalance of the land surface water budget is still a major problem for these products because of the assimilation of surface observations (Maurer et al. 2002). Therefore, the reanalysis data are less ideal for analyzing relationships between budget components as well as their variability. In addition, satellite remote sensing has provided great potential for large-scale observations of most hydrologic fluxes and state variables (Tang et al. 2010a). Although remote sensing is promising, remote sensing alone can hardly provide hydrologically consistent observations (Tang et al. 2009a; Sheffield et al. 2009; Gao et al. 2010a).

It has been demonstrated that the offline land surface hydrologic model simulation, when forced with quality-controlled surface observations, can often provide a better reference for surface hydrology than reanalysis and remote sensing because of its inclusion of more surface observations (Maurer et al. 2002; Sheffield et al. 2006; Tang et al. 2007, 2008). To date, a number of such studies have developed large-scale, long-term datasets globally (e.g., Nijssen et al. 2001; Adam and Lettenmaier 2003; Adam et al. 2006; Rodell et al. 2004; Sheffield et al. 2006; Sheffield and Wood 2007; Pan et al. 2012a) or regionally (e.g., Maurer et al. 2002; Zhu and Lettenmaier 2007; Livneh et al. 2013).

The global products may cover China’s domain (Nijssen et al. 2001; Adam and Lettenmaier 2003; Adam et al. 2006; Rodell et al. 2004; Sheffield et al. 2006; Sheffield and Wood 2007; Pan et al. 2012a) and may thus provide valuable references for hydrological studies in China (e.g., Wang et al. 2011; Tang et al. 2013). However, many ground-based Chinese hydrological and meteorological observations that were made available by the Bureau of Hydrology (BoH) and the Chinese Meteorological Administration (CMA) are not used in global products. The precipitation analyses over China in global products are generally based on gauge observations from a few international exchanging meteorological stations (P. Xie et al. 2007). There are only a few stations with available data before the 1980s in the Global Runoff Data Centre (GRDC), which is a main streamflow data source for the global products. Furthermore, naturalized flow in China (i.e., streamflow with water management effects removed), which is important for model calibration and validation, is absent in global runoff datasets. Consequently, there is a need to develop an improved hydrologic fluxes and states dataset over China that takes advantage of much more abundant and more reliable ground observations available in China. Such a dataset may be used for hydroclimatological studies in China and can also serve as a reasonable reference for comparison with global datasets. While some offline studies have been conducted in China (e.g., Z. Xie et al. 2007; Wu et al. 2011; Wang et al. 2012), few of them have presented an evaluation of the long-term interaction of water balance components. More importantly, there are few gridded Chinese hydrological datasets made available to the public in the research community.

In this paper, we developed a consistent and comprehensive land surface dataset of China using the Variable Infiltration Capacity (VIC) hydrologic model driven by observation-based surface forcings from CMA, which covers the China domain at a 3-hourly time step and a spatial resolution of 0.25°. The dataset spans from 1952 to 2012 and will continue to be updated following the update of CMA meteorological observations. It includes both consistent observation-based meteorological forcings and derived land surface water and energy flux variables. Compared with global products of a similar nature (e.g., Nijssen et al. 2001; Adam and Lettenmaier 2003; Adam et al. 2006; Rodell et al. 2004; Sheffield et al. 2006; Sheffield and Wood 2007; Pan et al. 2012a), this derived dataset is based on more meteorological stations for model inputs from CMA and better hydrologic data from BoH for model calibration over China. The dataset provides a current state-of-the-art estimate of land surface water and energy budgets, which may be useful for evaluating the long-term trend and interaction of water balance components over China.

2. Model description

The VIC model (Liang et al. 1994, 1996) is used in this study. It is a macroscale, semidistributed land surface hydrologic model, which shares several basic features
with other land surface models (LSMs). One of the most distinguishing features of the VIC model is that both water and surface energy budgets are resolved within each grid cell at each time step. The runoff generation scheme in VIC represents both saturation and infiltration excess runoff processes dynamically in a model grid cell through a statistical parameterization of subgrid heterogeneity (e.g., local water holding capacity). The model is also featured with a nonlinear ARNO model (Todini 1996) for base flow. A separate routing model is coupled with the VIC model to simulate streamflow (Lohmann et al. 1996), where the runoff generated in each grid cell is routed to selected points through the channel network. The VIC model has been successfully applied in a number of large river basins across the globe (Nijssen et al. 2001; Z. Xie et al. 2007; Sheffield and Wood 2007; Shi et al. 2008; Pan and Wood 2009; Gao et al. 2010b; Tang et al. 2010b, 2012; Wang et al. 2012; Pan et al. 2012a).

In this study, we used a relatively newer version of VIC (version 4.1.2.a) for the offline simulation. There are some comparable global datasets, such as the updated version of the Princeton University (PU) global terrestrial water budget product (Sheffield and Wood 2007; Pan et al. 2012a), which was also generated using a VIC offline simulation. The PU data were produced using a relatively older version of VIC (version 4.0.5) forced with PU global forcings (Sheffield et al. 2006) and calibrated against streamflow data at 25 global major river basins with only 3 (Yangtze River, Yellow River, and Pearl River) in China (Pan et al. 2012a). The VIC simulation in this study [referred as Institute of Geographic Sciences and Natural Resources Research (IGSNRR) dataset hereafter] incorporated much more grounded hydrological and meteorological observations in China. The model inputs of the IGSNRR dataset are described in detail in the next section.

3. Model inputs

a. Land surface characteristics

The land surface characteristics required by VIC model include soil data, topography, and vegetation characteristics.

The soil parameters can be divided into two groups: physical characteristics (e.g., field capacity, wilting point, and saturated hydraulic conductivity) that depend on soil texture and numerical parameters that closely relate to runoff generation, including

1) the shape parameter of the infiltration curve $b$, which controls the amount of rainfall infiltration and the yields of surface runoff (a higher value of $b$ gives lower infiltration and higher surface runoff);

2) the soil depth for each layer $d_i$ ($i = 1, 2, 3$), which affects the water storage available for transpiration (in general, the thicker the soil depths are, the less runoff is generated because of the increase of ET); and

3) the three parameters ($D_m$, $D_s$, and $W_s$) in the base flow scheme where $D_m$ is the maximum velocity that can occur from the lowest soil layer, $D_s$ is the fraction of $D_m$ where nonlinear base flow begins, and $W_s$ is the fraction of the maximum soil moisture of the lowest soil layer where nonlinear base flow occurs (Z. Xie et al. 2007; Shi et al. 2008).

In this study, soil texture is based on the 5-arc-min Food and Agriculture Organization of the United Nations dataset (FAO 1998). For each soil texture class, the soil physical parameters (e.g., field capacity, wilting point, and saturated hydraulic conductivity) are specified following the algorithms introduced in Maurer et al. (2002). The first soil depth $d_1$ is defined as a constant ($d_1 = 10$ cm) for all grid cells (Liang et al. 1996). The remaining numerical parameters [i.e., infiltration parameter $b$, soil depth $d_i$ ($i = 2$ and 3), and base flow parameters ($D_m$, $D_s$, and $W_s$)] are determined via runoff calibration following the method described in Shi et al. (2008).

The vegetation classification is derived from the University of Maryland global land cover classifications (Hansen et al. 2000). The source of vegetation parameters for the VIC model in this study is the same as that used in Maurer et al. (2002) and Zhu and Lettenmaier (2007).

b. Meteorological and radiative forcings

The meteorological and radiative forcings driving the VIC model include precipitation, temperature, wind, vapor pressure, downward longwave (LWD) and shortwave (SWD) radiation, and air pressure at daily or subdaily scales. Among the forcings, only three meteorological forcings, that is, precipitation, temperature, and wind, can be measured routinely from a large number of monitoring stations. The other fields, which are extremely hard to measure over a large scale, are mainly calculated by relating them to precipitation, daily mean temperature, and the daily temperature range based on VIC’s built-in empirical algorithms following Maurer et al. (2002). For example, by using the method of Kimball et al. (1997), the dewpoint temperature can be calculated from daily minimum temperature and precipitation, then the downward surface shortwave radiation can be obtained by using the daily temperature range and the dewpoint temperature based on the algorithm of Thornton and Running (1999). In this paper, VIC’s meteorological forcings were derived by interpolating gauged daily precipitation $P$, maximum $T_{\text{max}}$ and minimum $T_{\text{min}}$
temperature, and wind speed $W$ from 756 CMA stations into 0.25° based on the synergraphic mapping system (SYMAP) algorithm of Shepard (1984). The meteorological station observations have been quality controlled by CMA. The missing record accounts for about 10% of the total record over the period of 1952–2012 for all the stations. A lapse rate of 6.5°Ckm$^{-1}$ is used for elevation correction in temperature interpolation. To control the quality of input precipitation, the gridded precipitation was rescaled by adjusting the 12 monthly means (January–December) with 12 scaling factors in each grid cell to match the monthly means of the CMA precipitation product in 1962–2002 (Maurer et al. 2002; Tang et al. 2009c). The CMA precipitation product (hereafter CMA precipitation) has coverage over East Asia with a spatial resolution of 0.5°, and was produced using more than 756 precipitation gauges in China (P. Xie et al. 2007). The scaling factor was calculated as the ratio of monthly means between CMA and the gridded precipitation for each month over a 41-yr period (1962–2002). To obtain the 3-hourly land surface dataset, the gridded daily meteorological forcings were then disaggregated into 3-h time steps by VIC’s built-in functions, which had been validated to have minimal effect on the model-derived moisture and energy fluxes (Maurer et al. 2002).

4. Calibration of the simulated streamflow

The simulated runoff in each grid cell is routed (Lohmann et al. 1996) to the streamflow gauges before comparing to the streamflow observations. In this study, the channel network of the 0.25° grid cell was extracted from the 1-km digital elevation model (DEM) from the global 30-arc-s elevation (GTOPO30; Verdin and Greenlee 1996) dataset using the algorithm of O’Donnell et al. (1999).

The parameters, that is, the infiltration parameter $b$, the second and third soil layer depths ($d_2$ and $d_3$), and the three parameters in the base flow scheme ($D_m$, $D_s$, and $W_s$; Shi et al. 2008; Gao et al. 2010b), were calibrated. To find the optimal parameter set, an optimization algorithm of the multi-objective complex evolution of the University of Arizona (MOCOM-UA) from Yapo et al. (1998) was implemented, and two metrics were used as the objective function to assess the model performance: 1) Nash–Sutcliffe efficiency $E_f$ between the monthly simulated and observed streamflows, which describes the prediction skill of modeled streamflows as compared with the observations; and 2) the relative error $E_r$ (%) between the simulated and observed mean annual streamflows, which reflects the error in annual flow volume for the simulation period. The variables $E_f$ and $E_r$ (%) are calculated as

$$ E_f = 1 - \frac{\sum (Q_{i,o} - Q_{i,s})^2}{\sum (Q_{i,o} - \overline{Q}_o)^2} \tag{1} $$

and

$$ E_r(\%) = \left[ \frac{\overline{Q}_s - \overline{Q}_o}{\overline{Q}_o} \right] \times 100\%, \tag{2} $$

where $Q_{i,o}$ and $Q_{i,s}$ are the observed and simulated streamflows in month $i$ and $\overline{Q}_s$ and $\overline{Q}_o$ are the observed and simulated mean annual discharges, respectively.

We selected 15 hydrological stations where long-term monthly streamflow observations are available for model calibration. These stations are located in 11 major river basins of China across several different climate zones. The details of the gauge stations are shown in Fig. 1 and Table 1. Some streamflow gauges (e.g., Luanxian, Guantai, Lanzhou, and Lutai) have been significantly affected by water management (e.g., irrigation and reservoir regulation). The naturalized streamflow, which is the observed streamflow with water management effects removed by BoH (e.g., Li et al. 2001), is collected and used in the calibration (see Table 1). The model parameters were calibrated at the 15 streamflow gauge stations over a varying calibration period for each station (see Table 1). The model parameters of the uncalibrated watershed were set to be identical with the nearest calibrated watershed in the same major river basin.

The monthly hydrographs and average seasonal cycles of the simulated and observed streamflows at the 15 hydrological stations are shown in Figs. 2 and 3, respectively. The $E_f$ of monthly streamflow between VIC predictions and observations is at or above 0.80 at 11 of the 15 stations, suggesting that the calibrated VIC model generally does a good job in reproducing the observed streamflow. The $E_r$ of 20-yr monthly mean fluxes is less than 25% at all the stations, except for station 12 (Changdu) and station 14 (Nugesha). The two stations with large $E_r$ (i.e., Changdu and Nugesha) are located in the Tibetan Plateau, where meteorological stations are very sparse (see Fig. 1). This suggests that caution should be taken when using the data in western China, where the lack of meteorological observations may result in large uncertainties in hydrologic simulation. Furthermore, the glaciers that are not considered in the VIC model may be another source of the model bias in western China (Luo et al. 2013). At the two stations (Tangnaihai and Lanzhou) in the Yellow River basin, the simulated values tend to be smaller than the observations in the cold season, which may be partly attributed to the nature of the frozen soil algorithm in the VIC model. Although Cherka9uer and Lettenmaier (2003) have improved the representation of a spatial variation in
soil frost, which leads to the increase of base flow in winter and spring, the simulated flow in cold winter is still lower than observations. The reason for such errors needs to be studied further in the future (Su et al. 2006). While substantial biases exist at some stations in western China, the seasonal cycle of the VIC-derived streamflows agrees reasonably well with the observations over the major river basins in China.

TABLE 1. The 15 gauge stations.

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Basin</th>
<th>Location</th>
<th>Drainage area (103 km²)</th>
<th>Calibration period</th>
<th>Missing from calibration period</th>
<th>Validation period</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Changjiangtun</td>
<td>Songhua River</td>
<td>46.00</td>
<td>36</td>
<td>1965–84</td>
<td>1978</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Liaoyang</td>
<td>Liao River</td>
<td>41.27</td>
<td>8</td>
<td>1956–75</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Shigu</td>
<td>Yangtze River</td>
<td>27.03</td>
<td>233</td>
<td>1956–75</td>
<td>1966, 1969, 1970</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Boluo</td>
<td>Pearl River</td>
<td>23.18</td>
<td>25</td>
<td>1960–79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>Wuzhou</td>
<td>Pearl River</td>
<td>23.48</td>
<td>310</td>
<td>1960–79</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Nugesha</td>
<td>Brahmaputra River</td>
<td>29.33</td>
<td>110</td>
<td>1958–77</td>
<td>1966</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Yingluoxia</td>
<td>Hei River</td>
<td>38.82</td>
<td>10</td>
<td>1978–87</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5. Evaluation and analysis

To evaluate the quality and reliability of the IGSNRR dataset, analyses were conducted against several observational or observational-based data products.

a. Evaluation of the gridded precipitation

To evaluate the gridded precipitation in the IGSNRR dataset, the corresponding variable from a global daily meteorological forcing, which was derived by combining several global observation-based datasets with the NCEP–National Center for Atmospheric Research (NCAR) reanalysis by PU (hereafter PU precipitation; Sheffield et al. 2006; Pan et al. 2012a), was taken for comparison. Here, the comparison was performed at 15 river basins controlled by the stations used in model calibration (see Table 1) during the period of 1981–2000. It should be noted that IGSNRR precipitation is adjusted to match the monthly mean of CMA precipitation in 1962–2002 and is thus expected to agree with CMA precipitation better.

Figure 4 shows the seasonal cycles of IGSNRR, PU, and CMA precipitation at the 15 river basins. Both IGSNRR and PU precipitation show close agreement with CMA precipitation with the $E_f$ values at or above 0.90 at 6 of the 15 stations. At the river basins monitored by 7 stations (i.e., Tangnaihai, Lanzhou, Shigu, Wuzhou, Changdu, Jiayuqiao, and Nugesha), IGSNRR precipitation agrees better with CMA than PU precipitation. In particular, at the Tangnaihai and Lanzhou stations in the Yellow River basin, PU precipitation shows a high peak in June whereas both IGSNRR and CMA data show high precipitation from June to September. Furthermore, the relative errors of mean annual IGSNRR and PU precipitation as compared with CMA precipitation were calculated. IGSNRR is closer to CMA precipitation at 10
of 15 stations compared with PU precipitation as expected. In particular, the \( E_r \) of IGSNRR precipitation is less than 10% at Tangnaihai, Lanzhou, Changdu, Jiayuqiao, and Nugesha stations, while that of PU precipitation generally exceeds 20% at these stations. While the relative errors of IGSNRR precipitation are higher than those of PU at Changjiangtun, Guantai, and Lutai stations, their differences are generally small (∼8%) at these three stations. It should be noted that both IGSNRR and PU precipitation show high errors against the CMA precipitation at station Yingluoxia, suggesting that the sparse gauging network is still a critical problem for the hydroclimatological study of the inland area of western China.

b. Evaluation of the surface fluxes

1) SURFACE DOWNWARD RADIATION FLUXES

To evaluate the surface radiation fluxes from the IGSNRR product, the dataset developed by the Institute of Tibetan Plateau Research, Chinese Academy of Sciences (referred as ITPCAS dataset hereafter), was used for comparison. The ITPCAS radiation data have incorporated radiation observations at the available ground stations in China and have been extensively evaluated using several independent surface radiation data sources, including a quality-controlled, SWD dataset at 95 CMA radiation stations; the high-resolution data collected through Global Energy and Water Cycle Experiment (GEWEX) Asian Monsoon Experiment–Tibet (GAME–Tibet); and the data collected through the Coordinated Energy and Water Cycle Observations Project (CEOP) Asia–Australia Monsoon Project–Tibet (CAMP–Tibet; He and Yang 2011; Chen et al. 2011). Here, we compare the SWD (Fig. 5) and LWD (Fig. 6) in seasonal means from the IGSNRR and ITPCAS datasets.

In general, the ITPCAS- and IGSNRR-derived radiations have similar spatial patterns in seasonal means. Compared to the ITPCAS dataset, IGSNRR data

![Fig. 3. Seasonal cycles of the IGSNRR VIC and observed streamflows at the hydrological stations during the calibration periods.](image-url)
FIG. 4. Seasonal cycles of CMA, IGSNRR, and PU precipitation during 1981–2000 at the river basins monitored by the hydrological stations.
overestimate SWD by about 60–80 W m$^{-2}$ in January–March (JFM) and April–June (AMJ) over most parts of China. The SWD difference is relatively small (about 20 W m$^{-2}$) in July–September (JAS) and October–December (OND). Bohn et al. (2013) had assessed the performance of the algorithms for estimating surface downward radiations and found that the estimated SWD had a negative bias at coastal sites or in the presence of snow at the continental interiors. Our results suggest a general positive bias over all the seasons in China. As for LWD that closely relates to temperature, large positive biases (40–60 W m$^{-2}$) are found in northern China and the Tibetan Plateau during the cold seasons (JFM and OND). The biases are generally small (less than 20 W m$^{-2}$) in southern China during the cold seasons and over most of the area during the warm seasons (AMJ and JAS). Bohn et al. (2013) found that the estimated LWD had large positive biases over the arid area. Our results suggest that the positive biases are concentrated in the cold area and during the cold seasons in China. While substantial differences exist, the relative difference is generally less than 12% and 5% for SWD.

![Fig. 5. SWDs from IGSNRR and ITPCAS datasets and the difference (IGSNRR – ITPCAS) in JFM, AMJ, JAS, and OND during 1979–2010.](image-url)
and LWD, respectively, in all seasons. It suggests that the IGSNRR product performs reasonably well at estimating surface downward radiation fluxes.

2) LATENT HEAT FLUX

The general success of reproducing runoff hydrographs (see the evaluation of streamflow simulation in the next section) suggests that the long-term mean ET estimate (i.e., latent heat flux) is close to the reality in order to balance the observed precipitation and runoff. In this study, a global product of ET estimates using multisensor remote sensing (RS) data (Vinukollu et al. 2011) was used for comparison with the modeled ET from the IGSNRR dataset over the period of 1984–2007. Because the remote sensing ET may not balance with precipitation, runoff, and water storage change (Gao et al. 2010a), the comparison here focuses on the spatial pattern rather than the absolute values of ET.

Figure 7 shows the spatial patterns of annual ET from IGSNRR and RS. The IGSNRR ET pattern bears some resemblance to the pattern of the remote sensing product at the large scale, that is, high values in southeastern China and low values in northwestern China. The relative difference between IGSNRR and RS ET is less than 25%
over most parts of eastern China but is large (≥ 50%) in the arid area of western China. The large relative difference in the arid area is likely related to the sparse meteorological station network, suggesting a data challenge in estimating ET in western China. The average ET over the whole China domain is 346 and 361 mm yr\(^{-1}\) for IGSNRR and RS, respectively, corresponding to a relative bias of −4%.

c. Validation and evaluation of the streamflow

The derived runoff in the IGSNRR dataset was validated against the observed streamflow during the period of 1981–2000 and compared with the PU global dataset at six stations (Luanxian, Guantai, Tangnaihai, Lanzhou, Lutai, and Changdu). It should be noted that the validation period (1981–2000) is relatively independent of the calibration period at the six stations (see Table 1).

Figure 8 shows the comparison of monthly streamflow from IGSNRR, PU, and the observations. The performance of the IGSNRR dataset is satisfactory, with \(E_f\) values at or above 0.67 at all the six stations in the validation period (Moriasi et al. 2007). The \(E_f\) values of the PU dataset fall into the satisfactory catalog (i.e., \(E_f > 0.67\)).
The $E_f$ values of the IGSNRR dataset are higher than those of the PU dataset at all six stations. Additionally, IGSNRR streamflow is closer to the observations than that from PU global product at Luanxian, Tangnaihai, and Lanzhou stations, where the $E_r$ of IGSNRR precipitation is also lower than PU precipitation as compared to the CMA precipitation. The results are likely because the IGSNRR dataset has benefited from more ground hydrological and meteorological observations from BoH and CMA than the global dataset.

Figure 9 shows the seasonal cycles of the observed, IGSNRR, and PU streamflows. The $E_f$ value of IGSNRR streamflow is at or above 0.74, suggesting that the IGSNRR dataset could reproduce the seasonal cycle of streamflow well. The $E_f$ value of PU streamflow is above 0.5 (i.e., satisfactory) at five of the six stations. It shows that the PU dataset can capture the seasonal cycle of streamflow quite well, although the performance of the PU dataset is slightly lower than the IGSNRR dataset. The better performance of the IGSNRR dataset in streamflow simulation is partly a consequence of the better agreement of IGSNRR precipitation to CMA precipitation (see Fig. 4). In the Yellow River basin (i.e., Tangnaihai and Lanzhou), the PU dataset shows that precipitation peaks in June while both IGSNRR and CMA precipitation show high precipitation from June to September. As a consequence, the streamflow estimates in PU dataset peak in June while both IGSNRR estimates and streamflow observations show high flow from June to September.

Because the IGSNRR precipitation was rescaled to match the monthly means of the CMA precipitation product in 1962–2002, it was expected that the seasonal cycle of the IGSNRR data agrees better with observations than the PU data. We tried to rescale the PU precipitation to match the monthly means of the CMA precipitation and use the rescaled PU precipitation to generate the streamflow [see also Demaria et al. (2013)]. The rescaled PU precipitation could improve the seasonal cycle of the streamflow simulation. However, rescaling the PU precipitation had little impact on the $E_f$ value of the monthly streamflow. The rescaled PU precipitation could not reproduce the monthly streamflow well because it could not capture the interannual variability of precipitation well. It suggests that the added value of the IGSNRR data against the PU dataset is not only a better seasonal...
cycle but also a better interannual variability from denser observations.

d. Comparison with the observed soil moisture

The simulated IGSNRR soil moisture was compared with soil moisture observations at 43 Chinese stations over 1981–99, which were obtained from the Global Soil Moisture Data Bank (Robock et al. 2000). The observed soil moisture is measured three times on the eighth, eighteenth, and twenty-eighth of each month and at 11 vertical layers within 1-m soil depth (i.e., 5 cm for each layer from surface down to 10 cm and 10 cm for each layer from 10 cm down to 1 m; Li et al. 2005). To take full advantage of the long-term records, eight in situ sites with high availability of observed data (~80%) within 1-m soil depth were chosen and grouped into northeastern China (hereafter NE; including stations Fuyu, Changlin, Dunhua, and Jinzhou), central China (hereafter CENT; including stations Tongwei, Nanyang, and Xuzhou), and northwestern China (hereafter NW; including station Shache; see Fig. 1). For each group, soil moisture simulations from those model grid cells covering the selected gauge sites were considered as the corresponding model predictions following Nijssen et al. (2001) and Maurer et al. (2002). For groups NE and NW, the comparison was only performed from March/April to October because of the absent observations in the frozen period. Note that the comparison here aims at reproducing the seasonal evolution and soil moisture persistence in time rather than the magnitude difference owing to the different spatial scales between the observations and modeled results.

Figures 10a–c show the seasonal cycle of observations and IGSNRR estimates within the upper 1 m of soil for the groups of NE, CENT, and NW, respectively. Although with substantial difference in absolute value, IGSNRR soil moisture generally presents a compatible seasonal cycle with observations in NE and CENT, that is, high soil moisture in summer (June–August) and low soil moisture in spring (March–May). In addition, coefficient of variation (CV) was used as a metric to measure the interannual variation of soil moisture. In Figs. 10d–f, the monthly CV of IGSNRR simulations are smaller than that of the observed soil moisture for all three groups, which indicates that IGSNRR soil moisture estimates tend to underestimate interannual variability at all months as compared to the observations. Finally, the autocorrelation of soil moisture anomalies was calculated...
to present the time persistence of soil moisture in Figs. 10g–i. The closely matched autocorrelation curves of the predicted and observed soil moisture anomalies in the NE and CENT groups suggest that the soil moisture persistence in the IGSNRR dataset is similar to that revealed by the soil moisture measurements in northeastern and central China. The IGSNRR soil moisture simulation is relatively poor in northwestern China, where considerable biases in precipitation (Fig. 4), ET (Fig. 7), and runoff (Figs. 8 and 9) simulations are also found. That may be attributed to the few meteorological and hydrological observations in the inland area of western China.

e. Evaluation of the modeled snow cover

The simulated IGSNRR snow cover was compared with the satellite-based Northern Hemisphere snow cover extent (SCE) product archived in the National Snow and Ice Data Center (NSIDC; Brodzik and Armstrong 2013). The NSIDC snow cover product was derived from the manual interpretation of Advanced Very High Resolution Radiometer (AVHRR), Geostationary Operational Environmental Satellite (GOES), and other visible-band satellite data and was provided with a spatial resolution of 25 km (Helfrich et al. 2007). For each month in the cold season (December–March), the snow cover area from the NSIDC product with >80% occurrence probability during the period of 1966–2010 and the area where the IGSNRR modeled snow water equivalent (SWE) is greater than 1 mm at >80% of the same period was compared (Fig. 11). Overall, IGSNRR snow cover shows a good consensus with NSIDC observations in terms of the spatial pattern and monthly dynamics, although the comparison varies from region to region. Both IGSNRR and NSIDC data indicate an evident presence of snow cover in northeastern and northwestern China and the southeastern Tibetan Plateau and snow reductions from January to March. As compared to the NSIDC product, IGSNRR data tend to underestimate the snow area over the entire China domain with a relative error of about 2% in winter (December–February), particularly over the mountainous regions of
northeastern China. In March, the IGSNRR snow area is much (~75%) larger than NSIDC snow over the China domain. The snow cover differences are generally found in mountainous areas. The incorrect partitioning of snowfall and rainfall due to the variable topography in mountainous regions and the prescribed SWE threshold value for snow cover may partly account for the difference between IGSNRR data and NSIDC observations (Sheffield et al. 2003; Pan et al. 2003).

Fig. 11. Comparisons of IGSNRR and NSIDC with respect to snow cover area during 1966–2010 cold seasons (December–March).
6. Discussion and conclusions

We developed a 3-hourly, 0.25°, consistent and comprehensive regional dataset of land surface fluxes and states covering China over the period of 1952–2012. In the dataset, the simulated runoff matches well with the observed seasonal hydrographs and interannual variation of streamflow at the major river basins of China. The long-term average ET estimate is reasonable at basin scale according to the VIC’s built-in water balance enforcement. As compared to a global remote sensing ET product, the annual ET estimates can capture the spatial pattern well. Compared with the seasonal radiation data from ITPCAS, the surface downward radiations (i.e., long- and shortwave radiations) show similar spatial patterns, though some substantial biases exist. The soil moisture persistence in the model is similar to that revealed by the soil moisture observations in northeastern and central China. The modeled SWE patterns and monthly evolutions generally resemble the NSIDC snow cover. Compared with the similar global products from PU, the dataset provides a more reliable estimate of land surface hydrological conditions over China, partly because of its inclusion of more surface meteorological observations as model inputs as well as better streamflow gauge data for model calibration. These evaluation and validation efforts suggest that the dataset may be useful for evaluating the long-term trends and interactions of water balance components in China. Furthermore, although the global dataset serves better for large-scale weather forecasting than the regional product, the dataset may help provide more realistic initial conditions for regional-scale weather and climate forecasting in China where precipitation is not well reproduced in reanalysis products. The dataset is made available online for hydroclimatological studies in China (see appendix).

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APPENDIX

Description of the Dataset

The forcing datasets and derived surface fluxes and state variables for China are archived in ASCII format. The 3-hourly forcing variables and VIC-derived variables, which are listed in Table A1, are available online (http://hydro.igsnrr.ac.cn). The flux variables (e.g., precipitation, ET, and runoff) are provided as the average of the preceding 3h, whereas the state variables (e.g., soil moisture and SWE) are reported at the end of each 3-h period. This dataset will be updated following the update of the CMA meteorological observations.

REFERENCES

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