Modifying the SWAT Model to Simulate Eco-Hydrological Processes in an Arid Grassland Dominated Watershed

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Grasslands are the main land cover type and one of the most important ecosystems in arid and alpine endorheic basins. The vegetation coverage of grasslands is spatially heterogeneous in arid and alpine areas and it may lead to variations in water allocation. The Soil and Water Assessment Tool (SWAT) is one of the most widely used semi-distributed catchment-scale eco-hydrological models. The leaf area index (LAI) is one of the vegetation coverage indexes and is incorporated in the SWAT model. However, in SWAT, the LAI accumulation is controlled by heat, and neglects other relevant factors such as precipitation and terrain. To address the drawbacks of the SWAT in simulating vegetation coverage and plant patterns, several studies have focused on improving LAI estimation. However, they still have been limited to arid and alpine grasslands with different vegetation coverages. In this study, we modified the SWAT model using remotely sensed LAI data with high temporal and spatial resolution. We used this to better simulate eco-hydrological processes in grassland basins with different vegetation coverages in the upper reaches of the Bayin River Basin. Results showed that for the original SWAT model, the simulated LAI was homogeneous within each land use/cover type, whereas the remotely sensed LAI was spatially heterogeneous and better captured the vegetation coverage of the entire basin. The proper estimation of the LAI was reflected in the improved simulation of the monthly streamflow and sediment yield at the basin outlet and the monthly ET. These findings indicate that the modified SWAT could better simulate hydrological processes in arid and alpine grasslands with different vegetation coverages.

Keywords: soil and water assessment tool, vegetation coverage, global land surface satellite, leaf area index, grassland

1 INTRODUCTION

Grasslands are the main land cover type and one of the most important ecosystems in arid and alpine endorheic basins (Gao et al., 2010; Zhang et al., 2020). The vegetation coverage of grasslands is spatially heterogeneous in arid and alpine areas due to the terrain and impacts of climate change and human activities (Fu et al., 2012; Sun et al., 2019). Different vegetation coverages have key impacts on eco-hydrological processes, as differences in canopy interception and transpiration ability may lead to variations in water allocation from precipitation—such as surface runoff, evaporation, and soil water storage (Yang et al., 2009; Guo et al., 2010; Feng et al., 2017). Thus, it is essential to consider
vegetation coverage when simulating eco-hydrological processes in arid and alpine grassland ecosystems.

Distributed and mechanised hydrological models are effective tools for simulating and elucidating eco-hydrological processes at different spatiotemporal scales (Gassman et al., 2007; Karlsson et al., 2016; Huang et al., 2017). The Soil and Water Assessment Tools (SWAT) is a key component of the United States Department of Agriculture Conservation Effects Assessment Program and is one of the most widely used semi-distributed catchment-scale eco-hydrological models (Parajuli et al., 2010; Wang et al., 2019; Pang et al., 2020). However, it has the following limitations in modelling plant growth in grasslands with different vegetation coverages in arid and alpine areas: 1) Land use/cover types are important input parameters for SWAT to derive its basic calculation unit—HRUs, but are generally classified without consideration of the vegetation coverage (Jin et al., 2019). 2) In SWAT, the leaf area index (LAI) is the key parameter that connects vegetation dynamics with the water cycle (Arnold et al., 2012; Alemayehu et al., 2017). It can reflect the plant growth status, plant density, and vegetation coverage (Carlson and Ripley, 1997; Ji et al., 2019). However, in SWAT, the LAI is calculated based on the average plant density in HRUs (Lai et al., 2020). Moreover, LAI accumulation is controlled by a uniform ideal leaf area development model based on heat, which neglects other relevant factors such as precipitation and terrain (Arnold et al., 2012; Ma et al., 2019).

To address these drawbacks, several studies have focused on improving LAI estimation. Strauch and Volk (2013) added a user-defined minimum LAI to the SWAT model to simulate perennial vegetation included patterns in the tropics. Alemayehu et al. (2017) incorporated a straightforward but robust soil moisture index to improve the vegetation growth module of SWAT for simulating LAI in tropical forests. Lai et al. (2020) also involved average forest density to the forest growth module of SWAT to estimate eco-hydrological processes of forests with different vegetation coverages in the Meijiang River Basin, China. These adjustments added more parameters to the plant growth module and thus improved the performance of the SWAT in modelling eco-hydrological processes under different plant densities and cover patterns. However, an increase in parameters makes the model more complex. At the regional scale, remotely sensed LAI has considerable advantages over LAI values measured in the field. Ma et al. (2019) proposed a method to enhance the modelling of vegetation dynamics in evergreen forests. This method used the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product, which increases the applicability of the SWAT in tropical or subtropical areas. Paul et al. (2021) integrated MODIS LAI data into the SWAT to improve crop yield predictions in homogenous row-crops. However, these researches has been limited to arid and alpine grasslands with different vegetation coverages.

During past decades, remote sensing techniques of different platforms are used to rapidly and efficiently retrieve LAI on the landscape scale, the sensors involves not only optical remote sensing, but also the active LiDAR system ranges from terrestrial, airborne, satellite based system (Zheng and Moskal, 2009; Zhao et al., 2013). Most of the researches focused on the estimation of spatial distribution of LAI in a given region with a single time based on different remote sensing techniques (Zheng and Moskal, 2009). Another important aspect of LAI estimation is the time series issue, which is important in land surface processes models (Xie et al., 2019). The passive satellite remote sensing based long time series LAI products are widely used because of the wide spatial-temporal coverage and easy to access (Fang et al., 2012; Xiao et al., 2016; Xie et al., 2019), such as MODIS (Moderate-resolution Imaging Spectroradiometer) LAI (Zhao et al., 2013), GLASS (Global LAnd Surface Satellite) LAI (Xiao et al., 2016), GLOBMAP (Long-term Global Mapping) LAI (Xie et al., 2019) etc. Among these LAI products, the GLASS LAI was proved having high accuracy in China (Xiao et al., 2016).

In this study, we aimed to improve the simulation of eco-hydrological processes in grassland basins with different vegetation coverages. We combined the GLASS based and Landsat-based LAI to obtain a LAI dataset with high spatiotemporal resolution that could fit the time step and spatial calculation units of the SWAT model. Next, we replaced the LAI calculation module and mapped the grid-based LAI to HRUs. The upper reaches of the Bayin River were selected as the study area. The catchment is a typical arid and alpine area located in the northeast of the Qaidam Basin in the Qinghai-Tibet Plateau (Jin and Jin, 2020). The majority of the catchment area is covered by grasslands with different vegetation coverages (Zhu et al., 2012). The site-based streamflow, sediment yield data and remotely sensed actual evapotranspiration (ET) data of the Bayin River were used to estimate the performance of the original and modified SWAT models.

2 METHODS
2.1 Simulation of Vegetation Dynamics in SWAT
SWAT incorporates a simplified erosion productivity impact calculator model to estimate plant growth (Neitsch et al., 2011). The plant growth module contains two parts: biomass accumulation and LAI accumulation. LAI can reflect plant growth status and plant patterns (Neitsch et al., 2011; Lai et al., 2020), and its development model is described below.

Before the LAI reaches its maximum value, the new LAI on day $i$ is calculated as follows:

$$\Delta LAI_i = \left( fr_{LAI_{max}} - fr_{LAI_{max,i-1}} \right) \times LAI_{max} \times \left\{ 1 - \exp^\left[ \frac{1}{(LAI_{i-1} - LAI_{max})} \right] \right\}$$

(1)

where $\Delta LAI_i$ is the new LAI on day $i$; $fr_{LAI_{max}}$ and $fr_{LAI_{max,i-1}}$ are the maximum LAI calculated based on heat on days $i$ and $i-1$, respectively; $LAI_{max}$ is the maximum LAI for a plant; and $LAI_{i-1}$ is the LAI on day $i-1$.

The LAI does not change after reaching its maximum value. However, after leaf senescence exceeds leaf growth, the LAI is calculated as follows:
where \( \text{LAI} \) is the LAI on a day; \( \text{LAI}_{\text{max}} \) is the maximum LAI for a plant; \( f_{\text{PHU}} \) is the accumulated potential heat unit fraction on a day; and \( f_{\text{PHU,sen}} \) is the fraction of days where leaf senescence exceeds leaf growth in the entire plant growth season.

The actual LAI is affected by the stress factors. The plant growth factor—defined as the fraction of actual plant growth to potential plant growth—is used to adjust the LAI calculation on each day as follows:

\[
\gamma_{\text{reg}} = 1 - \max\{\text{wstrs, tstrs, nstrs, pstrs}\} 
\]

where \( \gamma_{\text{reg}} \) is the plant growth factor (range, 0–1); \( \text{wstrs} \) is the water stress on a day; \( \text{tstrs} \) is the temperature stress on a day; \( \text{nstrs} \) is the nitrogen stress on a day; and \( \text{pstrs} \) is the phosphorus stress on a day. If one of the four stress factors exceeds 0, the LAI on day \( i \) is adjusted as follows:

\[
\Delta \text{LAI}_{\text{act},i} = \Delta \text{LAI}_{i} \times \sqrt{\gamma_{\text{reg}}} 
\]

where \( \Delta \text{LAI}_{\text{act},i} \) is the actual LAI on day \( i \); \( \gamma_{\text{reg}} \) is the plant growth factor; and \( \Delta \text{LAI}_{i} \) is the potential LAI calculated by Eqs 1, 2. Neitsch et al. (2011) contains a detailed calculation of LAI in the SWAT model. The LAI is an important parameter and influences processes such as biomass, surface runoff, and ET (Neitsch et al., 2011; Ma et al., 2019).

Figure 1 shows the plant growth module of the original SWAT model.

2.2 Modifications to the Simulation of Vegetation Dynamics in SWAT

2.2.1 Derivation of the Land Use/Cover Classification

We derived land use/cover types using Landsat Operational Land Imager images of upper reaches of the Bayin River in 2018. Using a 1:50,000 topographic map as the datum and the Albers projection, images were geometrically corrected using a quadratic polynomial model. Interpretation keys of the images were established using land use maps and observed data for the same period, including 53...
The SWAT model was run at monthly intervals for various periods from 2013 to 2018: the warm-up period (2013), the ET data, all other datasets were provided by the National Operational Simplified Surface Energy Balance model-simulated ET with a spatial resolution of 1 km (Lei et al., 2019). Apart from the ET data, all other datasets were provided by the National Tibetan Plateau/Third Pole Environment Data Centre of China (https://data.tpdc.ac.cn/en/).

The SWAT model was run at monthly intervals for various periods from 2013 to 2018: the warm-up period (2013), the ET data, all other datasets were provided by the National Tibetan Plateau/Third Pole Environment Data Centre of China (https://data.tpdc.ac.cn/en/).
calibration period (2014–2016), and the validation period (2017–2018). The model performance in fitting the observations was measured using three objective functions according to Moriasi et al. (2007): Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), percent bias (PBIAS), and coefficient of determination ($R^2$). NSE measures the “goodness of fit” with a value ranging from 0 to 1 (indicating a perfect match). PBIAS measures the average tendency of the simulated values to be larger or smaller than the observed values, and is expressed as a percentage as follows: −10% to +10% represents a very good performance rating, and −25% to +25% represents a satisfactory performance rating. $R^2$ describes the proportion of variance in the measured data that is explained by the model. $R^2$ ranges from 0 to 1, with higher values indicating lower error variance. Values greater than 0.5 are typically considered acceptable (Nash and Sutcliffe, 1970; Moriasi et al., 2007; Jin et al., 2015). NSE, PBIAS, and $R^2$ were calculated as follows:

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n} (V_{\text{obs}} - V_{\text{sim}})^2}{\sum_{i=1}^{n} (V_{\text{obs}} - V_{\text{mean}})^2}$$  \hspace{1cm} (5)$$

$$\text{PBIAS} = \frac{\sum_{i=1}^{n} (V_{\text{obs}} - V_{\text{sim}}) \times 100}{\sum_{i=1}^{n} V_{\text{obs}}^2}$$ \hspace{1cm} (6)$$

$$R^2 = \frac{\left[ \sum_{i=1}^{n} (V_{\text{sim}}^2 - V_{\text{sim}}^2) \right] \left[ \sum_{i=1}^{n} (V_{\text{obs}}^2 - V_{\text{obs}}^2) \right]}{\sum_{i=1}^{n} (V_{\text{sim}}^2 - V_{\text{sim}}^2) \sum_{i=1}^{n} (V_{\text{obs}}^2 - V_{\text{obs}}^2)}$$ \hspace{1cm} (7)$$

### 3 RESULTS

#### 3.1 Sensitivity and Calibration of Parameters in SWAT

We built two SWAT models: the original SWAT model and the modified SWAT model based on the remotely sensed, spatiotemporally heterogenous and high-resolution LAI. Before calibrating and validating the models, we determined the most sensitive parameters—those were, key parameters and the degree of parameter precision required for calibration (Arnold et al., 2012; Jin et al., 2018). We used the monthly streamflow data from the Deingha Station (2014–2016) to conduct a sensitivity analysis of the original and modified SWAT models. Figure 5 shows results of the sensitivity analysis and lists the ten most sensitive parameters for streamflow simulation. The $t$-stat values (Figure 5) provide a measure of sensitivity (where larger absolute values indicate higher sensitivity) and the $p$-values indicate the significance of the sensitivity (where $p$-values close to zero indicate more significance). The first four parameters with highest sensitivity in the original (Figure 5A) and modified (Figure 5B) SWAT models were CN2 (initial SCS runoff curve number for moisture condition II), ALPHA_BF (base flow alpha factor), CH_K2 (effective hydraulic conductivity in the main channel alluvium), and SOL_BD (moist bulk density). The other sensitive parameters in the two models are listed Figure 5. See Arnold et al. (2011) for details regarding the parameters. These parameters were calibrated using the
sequential uncertainty fitting version 2 algorithm in the SWAT-CUP software. After the calibration of streamflow-related parameters, four more sediment-related parameters were calibrated: LAT_SED (sediment concentration in lateral and groundwater flow), USLE_P (USLE equation support practice factor), SPCON (Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing) and SPEXP (exponent parameter for calculation sediment reentrained in channel sediment routing).

3.2 Remotely Sensed and SWAT-Simulated LAI

We downscaled the GLASS LAI to fit the basic calculation units of the SWAT model. Figures 6A,B shows a comparison of the downscaled and original GLASS LAI data. Pixels of the two LAI datasets had the same spatial distribution. Moreover, the downscaled LAI had a higher spatial resolution and provided more detailed spatial information. We calculated the monthly average LAI for the entire watershed based on the downscaled and original GLASS LAI datasets. The two datasets had the same patterns of seasonal variations, where the LAI was highest in July or August and lowest in January. While for the original SWAT model, the LAI reaches the peak value in June (Figure 6C). In almost every month, the remotely sensed LAI was noticeably higher than the original SWAT simulated value. The deviation of the downscaled and original GLASS LAI was −0.005 to 0.9 but 0.1–3.3 for the original SWAT simulated LAI and the two datasets; the lowest and the highest deviation were during the winter and during the summer months, respectively. The correlation of the monthly LAI derived from the two datasets was 0.9482 (Figure 6D). In summary, the downscaled remotely sensed LAI data were reliable. We mapped the grid-based downscaled GLASS (remotely sensed) LAI to each HRU. Figure 7 shows the remotely sensed and original SWAT-simulated long-term monthly average LAI mapped to the

FIGURE 5 | The sensitive parameters for the original (A) and modified (B) Soil and Water Assessment Tool (SWAT) models.

FIGURE 6 | Comparisons of the downscaled leaf area index (LAI) and the original Global LAnd Surface Satellite (GLASS) LAI. (A) Spatial distribution of the downscaled LAI. (B) Spatial distribution of the original GLASS LAI. (C) Monthly variation of the downscaled LAI and GLASS LAI. (D) Correlation between the downscaled LAI and GLASS LAI.
HRU level. For the entire watershed, the remotely sensed LAI was heterogeneous in each month. In contrast, in the original SWAT data, the simulated LAI was homogeneous in the same land use/cover types. In every month, the original SWAT simulated LAI was 0 for the barren land, slightly higher for the grassland, and highest for the sparsely distributed forest land (Figure 2).

### 3.3 Simulations of the Streamflow

The performance of the original and modified SWAT models in simulating the monthly streamflow is shown in Figure 8 and Table 1. During the calibration and validation periods, the original SWAT model had the $R^2$ of over 0.87, the NSE over 0.85, and the PBIAS within 0–9%. For the modified SWAT, the $R^2$ was over 0.90, the NSE was over 0.89, and the PBIAS was within 0–4%. The performance of the modified SWAT to simulate the monthly streamflow was better than that of the original SWAT.

### 3.4 Simulations of the Sediment Yield

The performance of the original and modified SWAT models in simulating the monthly sediment yield is shown in Figure 9 and
Table 2. During the calibration and validation periods, the original SWAT model had the $R^2$ of over 0.85, the NSE over 0.79, and the PBIAS within 15–28%. For the modified SWAT, the $R^2$ was over 0.87, the NSE was over 0.86, and the PBIAS was within −15 to 25%. The performance of the modified SWAT to simulate the monthly sediment yield was obviously better than that of the original SWAT.

### 3.5 Simulations of the ET

The spatial resolution of the remotely sensed ET data was relatively high (1 km). Therefore, we analysed the performance of the original and modified SWAT models to simulate the monthly ET at subbasin level (Figure 10). The results demonstrated that in most subbasins, the $R^2$ and NSE values of the modified SWAT were higher than those of the original SWAT. Moreover, the absolute value of PBIAS was lower for the modified SWAT than for the original SWAT in most subbasins: During the calibration and validation periods, 82 and 83% of the subbasins for the modified SWAT had higher $R^2$ and NSE values than that for the original SWAT. For the modified and original SWAT, there were 62 and 55% of the subbasins had the PBIAS values in −25 to 25%, respectively, during both of the calibration and validation period. Therefore, the modified SWAT showed better performance than the original SWAT in simulating the monthly ET.

### 4 DISCUSSION

The simulated LAI was homogeneous within a land use/cover type for the original SWAT, whereas the remotely sensed LAI was spatially heterogeneous and could better capture the vegetation coverage of the entire basin. The LAI calculated by the original SWAT was primarily affected by land use/cover types, water stress, temperature stress, nitrogen stress, and phosphorus stress (Arnold et al., 2012; Alemayehu et al., 2017). Only one meteorological station exist in the Bayin River Basin, and all of the vegetation is natural and without fertilisation. Therefore, in the original SWAT model, the spatial heterogeneity of LAI in Bayin River Basin was only determined by the land use/cover types (Figures 2, 7). The second-level classification of grassland (Figure 4) could reflect vegetation coverage (Jia et al., 2018). However, these land cover types are not included in the plant and land cover database of the SWAT (Arnold et al., 2012). Therefore, the original SWAT simulated LAI values were the same for one land cover type. This does not conform to the spatial heterogeneity of vegetation coverage especially within grassland (Figure 4) in Bayin River Basin (Wang et al., 2014; Yang et al., 2018). The downscaled remotely sensed LAI data in this study was reliable, because: 1) Most remotely sensed LAI products have gaps and missing values, and either underestimate or overestimate the LAI in many areas (Fensholt et al., 2004; Sun et al., 2014; Li et al., 2018), while the GLASS-based LAI used in this study was spatially and temporally continuous with no gaps and missing values and had high quality and accuracy in China (Zhao et al., 2013; Li et al., 2018; Xie et al., 2019). 2) The GLASS LAI was downscaled, and higher resolution LAI data would reduce the mismatch boundary of HRUs in SWAT models (Ma et al., 2019). The modified SWAT incorporated the downscaled remotely sensed LAI which could better reflect the spatiotemporal heterogeneity of the LAI and thus overcome the limitation of the original SWAT.

SWAT models are commonly calibrated and validated with streamflow and sediment yield data at the outlet of a watershed, which improves the reliability of the model simulations (Gassman et al., 2007; Jin et al., 2015; Yang et al., 2020). The improved LAI can improve the simulation results of the canopy interception loss, soil water content, runoff and further, the whole water budget in SWAT (Jaromir and Karsten, 2010; Zheng et al., 2018; Ma et al., 2019). Moreover, the erosion process would be improved because the SWAT model compute erosion caused by rainfall and runoff with the Modified Universal Soil Loss Equation (MULSE). In MUSLE, the average annual gross erosion

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**TABLE 1** | The performance of the original and modified Soil and Water Assessment Tool (SWAT) models in simulating the monthly streamflow.

| Metric  | Modified SWAT | Original SWAT |
|---------|---------------|---------------|
| $R^2$   | Calibration period | 0.9 | 0.87 |
|         | Validation period | 0.95 | 0.90 |
| NSE     | Calibration period | 0.89 | 0.84 |
|         | Validation period | 0.94 | 0.89 |
| PBIAS (%) | Calibration period | 3.3 | 8.1 |
|         | Validation period | 3.7 | 14.6 |

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**FIGURE 9** | The monthly sediment yield simulated by the original and modified Soil and Water Assessment Tool (SWAT) models compared to the that of observed sediment yield.
is predicted as a function of runoff factor. Therefore, the modified SWAT that incorporated the high resolution LAI corresponded to a better estimation in streamflow and sediment yield. This study used high-resolution (1 km) remotely sensed ET data (SSEBop) to validate the original and modified SWAT models at the subbasin and HRU levels, because model performance should be analysed at a more detailed scale as well, especially when testing high-resolution input data (Alemayehu et al., 2017; Paul et al., 2020). SSEBop is also known to have a higher quality than several other datasets in grass covered surface (Herman et al., 2018; Dembélé et al., 2020). LAI is a key parameter that calculate the regional ET. Thus, the modified SWAT corresponded to a better estimation in ET. In summary, streamflow, sediment yield and ET which are the vegetation coverage-affected processes (Chen et al., 2006; Wang et al., 2021) were more accurate when using the remotely sensed high temporal and spatial resolution LAI. The spatial and temporal accuracy of the LAI was confirmed as being of crucial importance for SWAT predictions.

Coupling the SWAT model with the MODIS LAI product has been used for enhanced modelling of green vegetation dynamics (in tropical or subtropical areas) and crop patterns (in semi-arid areas), and may improve the applicability of SWAT in corresponding areas (Ma et al., 2019; Paul et al., 2020). The improvement of the SWAT in these studies was catalogued by the remotely sensed LAI, which could properly capture a more realistic plant phenology and patterns at a higher resolution. In this study, the remotely sensed LAI could capture the vegetation coverage of the grassland and barren land, which are the main land cover types for the whole study area. In addition, considerable areas of barren land have been converted to grassland under the impact of climate change and artificial vegetation restoration, and the vegetation coverage of grassland has increased in the Bayin River Basin (Jin et al., 2019). These changes can be elucidated in the LAI with high spatial and temporal resolution derived in this study.

The major limitations of this study are as follows: 1) There is only one meteorological station in the study area, which presented the only set of meteorological data. Although, two parameters (PLAPS, precipitation lapse rate; TLAPS, temperature lapse rate) were used to modify the precipitation and temperature of the study area. This would still impose uncertainties in hydrological process modelling, especially in mountainous

### Table 2

|               | Modified SWAT | Original SWAT |
|---------------|---------------|---------------|
| $R^2$ Calibration period | 0.93          | 0.89          |
| $R^2$ Validation period | 0.87          | 0.82          |
| NSE Calibration period | 0.89          | 0.83          |
| NSE Validation period | 0.86          | 0.79          |
| PBIAS (%) Calibration period | 21.24         | 27.28         |
| PBIAS (%) Validation period | -15.20        | 15.60         |

### Figure 10

The performance of the original and modified Soil and Water Assessment Tool (SWAT) models in simulating the monthly evapotranspiration at the level of subbasins.
areas. 2) Piecewise linear interpolation was used to interpolate the 8 days and 30 m LAI data to the daily time interval. However, the LAI may not vary linearly, and this may cause some uncertainties.

5 CONCLUSION

Using remotely sensed LAI data with high spatiotemporal resolution, we modified the SWAT model to better simulate eco-hydrological processes in grassland basins with different vegetation coverages in the Bayin River Basin. Site-based streamflow, sediment yield data and remotely sensed ET data (at the subbasin and HRU levels) were used to estimate the performances of the original and modified SWAT models. We report two important findings. First, the simulated LAI was homogeneous within a land use/cover type for the original SWAT, whereas the remotely sensed LAI was spatially heterogeneous and could better capture the vegetation coverage of the entire basin. Second, the improved LAI may be used to simulate canopy interception loss, soil water content, and the water budget; therefore, the modified SWAT performed better than the original SWAT in simulating the hydrological processes.

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DATA AVAILABILITY STATEMENT

The original contributions presented in this study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Conceptualization, XJ; methodology, XJ; formal analysis, XJ; investigation, XJ; resources, YJ; data curation, YJ and DF; writing—original draft preparation, XJ; writing—review and editing, YJ and XM; project administration, XJ; funding acquisition, XJ. All authors have read and agreed to the published version of the manuscript.

FUNDING

This research was supported by the National Natural Science Foundation of China, No. 42161020 and grants from the Natural Science Foundation of Qinghai Province, China, grant number 2021-ZJ-705.
