Postprint: Applicability of Hydrological Models for Different Types of Watersheds in the Eastern Section of the Agro-pastoral Ecotone in Northern China

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Abstract

Water resources are fundamental to maintaining ecosystem balance and ensuring human livelihood and economic development. Simulating hydrological processes in arid and semi-arid ecosystems can promote the effective utilization of local water resources. This paper analyzes the applicability of two models—the Distributed Hydrology-Soil-Vegetation Model (DHSVM) and the Soil and Water Assessment Tool (SWAT)—in different types of watersheds in semi-arid regions. (1) Conduct sensitivity analysis and parameter calibration for both models. (2) The two models were used to simulate monthly runoff in the upper Xilamulun River basin and the upper Laoha River basin in the eastern section of the northern agro-pastoral ecotone during the growing seasons of 2011–2012 and 2017–2019. The upper Xilamulun River basin is dominated by grassland, while the upper Laoha River basin is dominated by forestland and cropland. The results show that the DHSVM model has 7 main sensitive parameters for hydrological process simulation in the upper Xilamulun River basin and 6 main sensitive parameters in the upper Laoha River basin. The SWAT model selected 11 and 12 sensitive parameters, respectively. Through calibration of sensitive parameters, in the upper Xilamulun River basin, the Nash–Sutcliffe efficiency coefficient of the DHSVM model was 0.70 in the calibration period and 0.11 in the validation period; for the SWAT model, the Nash coefficients were 0.43 and 0.04, respectively. In the upper Laoha River basin, the Nash coefficients of the DHSVM model were 0.56 and 0.70 in the calibration and validation periods, respectively; for the SWAT model, they were 0.86 and 0.54, respectively. Both models demonstrate good applicability for hydrological process simulation in the upper reaches of the Xilamulun and Laoha rivers in the northern agro-pastoral ecotone. The DHSVM model provides more accurate simulation of total runoff, while the SWAT model provides more accurate simulation of monthly runoff

peaks.

Full Text

Abstract

Water resources form the foundation for maintaining ecosystem balance and ensuring human life and economic development. Simulating hydrological processes in arid and semi-arid ecosystems promotes the effective utilization of local water resources. This paper analyzed the applicability of two models—the Distributed Hydrology Soil Vegetation Model (DHSVM) and the Soil and Water Assessment Tool (SWAT)—in different types of watersheds in semi-arid regions by performing sensitivity analysis and parameter calibration. The two models were used to simulate monthly runoff in the upper reaches of the Xar Moron River and the Laoha River in the eastern section of the agro-pastoral transitional zone in northern China during the growing seasons from 2012 to 2019. The upper reaches of the Xar Moron River are dominated by grasslands, while those of the Laoha River are dominated by forestland and farmland. The results show that DHSVM exhibits 7 primary sensitive parameters in the Xar Moron River and 6 in the Laoha River, whereas SWAT identifies 11 and 12 sensitive parameters, respectively. Following parameter calibration, in the upper reaches of the Xar Moron River the Nash-Sutcliffe efficiency coefficient for DHSVM is 0.70 during calibration and 0.11 during validation, while for SWAT it is 0.43 and 0.04, respectively. In the upper reaches of the Laoha River, the Nash-Sutcliffe efficiency coefficients for DHSVM are 0.56 and 0.70 during the two periods, compared with 0.86 and 0.54 for SWAT. The findings indicate that both models are applicable for simulating hydrological processes in the study area, with DHSVM more accurately simulating overall runoff and SWAT more accurately simulating peak monthly runoff.

Keywords: DHSVM model; SWAT model; different types of watersheds; applicability analysis; runoff simulation

Introduction

Water scarcity poses a serious threat to human life, socio-economic sustainable development, and ecosystem evolution. Climate change and human activities are the primary drivers of water resource variations. The agro-pastoral transitional zone in northern China represents a transition from semi-humid agricultural areas to arid and semi-arid pastoral regions. Due to its inherent vulnerability and sensitivity, ecosystems in this zone respond acutely to global changes. Precipitation in this region exhibits large inter-annual variability, with an arid climate and scarce water resources that are intensively utilized, making water availability a critical constraint on socio-economic development. Since the 1980s, the Chinese government has implemented a series of major ecological projects in this region, further intensifying the conflict between water consumption for production/living and ecological restoration. Therefore, understanding watershed hydrological processes to enable rational water allocation and utilization is crucial for alleviating local water shortages and improving water use efficiency.

Hydrological modeling represents the primary method for understanding regional hydrological processes. Currently, diverse models are applied for hydrological process simulation, mainly categorized into lumped, distributed, and semi-distributed models. Research on distributed and semi-distributed watershed hydrological models represents a key focus in hydrology. In semi-distributed models, hydrological response units are typically small watersheds, whereas in distributed models the response units are grids of uniform size. Consequently, distributed hydrological models better align with refined water resource management and are more widely applied. The SWAT model is currently the most widely used distributed hydrological model, capable of simulating various hydrological physical-chemical processes including water quantity, sediment transport, and chemical migration/transformation. It has been applied across diverse geographical environments including tropical, temperate, and alpine regions. In China' s Yellow River basin, SWAT is primarily used for quantitative sediment assessment research.

The DHSVM model, as a physically based distributed hydrological model, can adapt to more geographical environments. Currently, DHSVM has been extensively applied in fields such as agriculture and future water resource prediction. However, both distributed and semi-distributed hydrological models have limitations in practical application. For instance, the coupling method employed by SWAT models neglects the dynamic feedback between socio-economic water consumption processes and natural hydrological processes. Both SWAT and DHSVM are highly sensitive to soil and vegetation parameter settings, yet these parameter configurations are extremely cumbersome. Many studies cannot collect long-term, complete observational data and mostly rely on preset values, which substantially reduces output accuracy.

While both models offer respective advantages in different geographical environments, current studies tend to select hydrological models singularly without adequately considering regional geographical characteristics. Moreover, applicability analyses of hydrological models for simulating hydrological processes in the eastern section of the agro-pastoral transitional zone remain relatively scarce. This study selected two different watershed types in the eastern section of the agro-pastoral transitional zone in northern China: a grassland-dominated watershed and a forestland/farmland-dominated watershed. DHSVM and SWAT models were applied to simulate hydrological processes in both watershed types to identify the most suitable hydrological model for the study area's geographical environment and further improve simulation accuracy. This research is significant for understanding hydrological processes in different watershed types in the eastern agro-pastoral transitional zone and rationally allocating water resources to address local water shortages.

1.1 Study Area Overview

Based on literature [?], the eastern section of the agro-pastoral transitional zone in northern China (40°-49°N, 115°-125°E) covers an area of approximately 35.24\$ $\times 10^4 km^{\{2\}, representingatransitionfromsemi-humidtoarid/semi-aridregions.Usingthe400mmisohyetastheboundary, th}$
[Figure 1: see original paper].

1.2 Data Sources

Both models require underlying surface data (land use, soil type) and meteorological data. Land use data for 2020 were obtained from the Chinese Land Cover Dataset on the Geospatial Data Cloud platform with 30 m spatial resolution. This study represents the 2020 land use distribution in the study area. Soil type data (1:1,000,000) were sourced from the Harmonized World Soil Database (HWSD) V1.2 dataset provided by the National Tibetan Plateau Data Center with 250 m spatial resolution. The main soil types in the Xar Moron River upper reaches are loam, sandy loam, sand, and silty loam, while loam and sandy loam dominate the Laoha River upper reaches.

Meteorological data include daily average temperature, wind speed, relative humidity, shortwave radiation, longwave radiation, and precipitation. Shortwave radiation was calculated using the Angstrom-Prescott equation [?]. Meteorological data (maximum temperature, minimum temperature, precipitation, wind speed, relative humidity, and sunshine hours) were obtained from the China Surface Climate Data Daily Value Dataset (V3.0). The DHSVM model requires Leaf Area Index (LAI) and albedo data, sourced from the Global Land Surface Satellite (GLASS) dataset with 500 m spatial resolution. Runoff data from the Balin Bridge and Dianzi hydrological stations in the Hydrological Yearbook served as validation data .

1.3.1 Distributed Hydrology Soil Vegetation Model (DHSVM)

DHSVM is a physically based distributed hydrological model that simplifies actual watersheds into regular computational grids. Each grid cell is assigned specific vegetation and soil properties, enabling simulation of spatially heterogeneous hydrological indices. At each time step, the model solves the energy balance and water balance equations simultaneously for each grid cell. Water exchange between grids occurs through surface runoff and interflow [?].

DHSVM requires watershed, river network, soil depth, land use, and soil type data as underlying surface inputs. The ArcGIS hydrological analysis tool was used to process DEM data to obtain watershed boundaries and aspect data. The model' s meteorological data input format was used to organize meteorological data and establish a weather generator.

Shortwave radiation calculation: ($ws \times sin \times sin\ 0 = 118.08 cos \times cos \times sin = 1 + 0.033 \times cos = 0.409 \times sin\ ws = cos - tan \times tan = 24 \times$

Where: RS is incoming shortwave radiation ($MJ \cdot m^{-2} \cdot d^{-1}$); RS_0 is extraterrestrial shortwave radiation ($MJ \cdot m^{-2} \cdot d^{-1}$); as is diffuse shortwave radiation coefficient (under average climate conditions); bs is direct shortwave radiation coefficient (under average climate conditions); n is sunshine hours; N is maximum possible sunshine hours; dr is Earth-Sun relative distance; ws is sunset hour angle; Ø is latitude (positive in Northern Hemisphere, negative in Southern Hemisphere); δ is solar declination; j is day number (starting from January 1).

Longwave radiation is calculated from shortwave radiation using: $= 5.67 \times 10$ $Ea = 1 - 1 + 46.5 \times +237.3 + 237.3$

Where: RL is incoming longwave radiation ($MJ \cdot m^{-2} \cdot d^{-1}$); Ea is clear-sky transmissivity; f is clear-sky percentage; vp is actual vapor pressure; T is daily average temperature (°C); T_{max} is daily maximum temperature (°C); T_{min} is daily minimum temperature (°C);   is relative humidity.

1.3.2 Soil and Water Assessment Tool (SWAT)

SWAT is a distributed watershed hydrological model based on GIS with daily time steps. The model first divides the watershed into sub-basins, then further subdivides them into hydrological response units (HRUs) based on land use and soil type. Thus, HRUs serve as the smallest simulation units.

SWAT comprises two phases: the land phase of the hydrological cycle and the routing phase. The former controls water, sediment, nutrients, and chemical inputs to the main channel in each sub-basin, while the latter determines the transport of these materials through the river network to the watershed outlet [**?**]. The water cycle is based on the water balance equation:

$0 + \sum iSWt = Rday - Qsurf -$

Where: SWt is final soil water content (mm); SW_0 is initial soil water content (mm); t is time (days); Rday is precipitation on day i (mm); Qsurf is surface runoff on day i (mm); Ea is evapotranspiration on day i (mm); Wseep is water entering the vadose zone from the soil profile on day i (mm); Qgw is return flow on day i (mm).

SWAT requires DEM, land use, and soil type data as underlying surface inputs. Soil type data were reclassified to reduce soil categories. The SPAW calculator was used to compute corresponding data and establish a soil database. Each underlying surface dataset was analyzed individually according to SWAT requirements. Required meteorological data include maximum temperature, minimum temperature, precipitation, relative humidity, solar radiation, and wind speed, organized according to SWAT input formats.

1.3.3 Parameter Calibration and Operation

DHSVM parameters are categorized into global parameters, vegetation parameters, and soil parameters. Vegetation parameters (e.g., minimum stomatal resistance, vegetation height) and soil parameters (e.g., porosity, lateral saturated hydraulic conductivity, exponential decay rate) are particularly sensitive for hydrological process simulation [?]. This study employed the Extended Fourier Amplitude Sensitivity Test (EFAST) for sensitivity analysis [?]. EFAST is a variance-based global method that integrates advantages of the Sobol method [?] [Figure 2: see original paper].

SWAT contains numerous uncertain parameters, primarily calibrated automatically using SUFI-2. The algorithm offers five options: Particle Swarm Optimization (PSO), Sequential Uncertainty Fitting (SUFI-2), Generalized Likelihood Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Markov Chain Monte Carlo (MCMC). This study used the ParaSol algorithm, which employs Latin hypercube sampling to obtain parameter values for model simulation. Its sensitivity analysis is implemented through the SUFI-2 algorithm [?].

Model performance was evaluated using the Nash-Sutcliffe efficiency coefficient (NSE) for simulated monthly runoff. NSE ranges from $-\infty$ to 1, with values closer to 1 indicating better fit between simulated and observed monthly runoff (i.e., model predictions match observations). Conversely, lower values indicate poorer fit [?]. The formula is:

$= 1-$

Where: qobs is observed value; qsim is simulated value; qmean is mean observed value.

2.1.1 DHSVM Parameter Sensitivity Analysis

Using 0.05 as the sensitivity threshold, parameters with values greater than 0.05 are considered sensitive, while those below are insensitive. In the Xar Moron River upper reaches, 7 primary sensitive parameters were identified: minimum stomatal resistance, bulk density, decay coefficient, soil bubbling pressure, lateral saturated hydraulic conductivity, leaf area index, and field capacity. Among these, bulk density, decay coefficient, soil bubbling pressure, lateral saturated hydraulic conductivity, and field capacity are soil parameters, while minimum stomatal resistance and leaf area index are vegetation parameters. In the Laoha River upper reaches, 6 sensitive parameters were identified: minimum stomatal resistance, soil thermal conductivity, lateral saturated hydraulic conductivity, decay coefficient, field capacity, and leaf area index. Soil thermal conductivity, lateral saturated hydraulic conductivity, decay coefficient, and field capacity are soil parameters, while minimum stomatal resistance and leaf area index are vegetation parameters .

2.1.2 SWAT Parameter Sensitivity Analysis

The SUFI-2 algorithm was used for iterative sensitivity analysis of SWAT parameters including soil parameters, land use parameters, groundwater flow parameters, snowmelt parameters, and surface characteristic parameters. This study set the model run count to 500 and iteration count to 10. Sensitive parameters for both watersheds were selected from 26 base parameters. The Xar Moron River upper reaches selected 11 sensitive parameters, while the Laoha River upper reaches selected 12 sensitive parameters for automatic calibration . Lateral saturated hydraulic conductivity, field capacity, and bulk density were calculated using soil pedotransfer functions, while other sensitive parameters referenced DHSVM model presets [Figure 3: see original paper].

2.2 Model Calibration and Validation

Rivers in the eastern agro-pastoral transitional zone of northern China experience flow interruption. To improve simulation accuracy, the growing season (May–September) was selected as the study period. Monthly observed runoff data from 2012–2019 were collected from the Hydrological Yearbook for the Balin Bridge and Dianzi stations. The period 2012–2014 served as the warm-up period, 2015–2017 as the calibration period, and 2018–2019 as the validation period.

Observed monthly runoff data from the Balin Bridge station (Xar Moron River) and Dianzi station (Laoha River) were used to calibrate and validate both models. In the Xar Moron River upper reaches, DHSVM achieved NSE = 0.70 and $R^2 = 0.73$ during calibration, and NSE = 0.11 and $R^2 = 0.12$ during validation. SWAT achieved NSE = 0.43 and $R^2 = 0.44$ during calibration, and NSE = 0.04 and $R^2 = 0.06$ during validation. In the Laoha River upper reaches, DHSVM achieved NSE = 0.56 and $R^2 = 0.65$ during calibration, and NSE = 0.70 and $R^2 = 0.71$ during validation. SWAT achieved NSE = 0.86 and $R^2 = 0.86$ during calibration, and NSE = 0.54 and $R^2 = 0.55$ during validation .

2.3.1 Xar Moron River Upper Reaches

DHSVM simulated monthly runoff more accurately than SWAT in the Xar Moron River upper reaches. Although SWAT simulated the general trend of monthly runoff, its fit with observed flow was inferior to DHSVM. DHSVM' s simulated monthly runoff closely matched observed trends, particularly in 2015, 2016, and 2017. However, both models performed poorly in 2018 and 2019, with negative NSE values that affected overall watershed simulation results.

Both models have respective advantages in monthly runoff simulation: DHSVM better simulates baseflow, while SWAT better simulates peak flows. The average simulated peak was 624.39 $m^3 \cdot s^{-1}$ for DHSVM, close to the observed average peak of 697.45 $m^3 \cdot s^{-1}$, compared to SWAT' s average peak of 580.46 $m^3 \cdot s^{-1}$. Simulation differences may stem from the Xar Moron River' s characteristics and model parameters. From the Bacha River mouth to Balin Bridge, the channel is wide and shallow with dispersed flow. DHSVM input files contain river network descriptions, enabling more detailed watershed simulation. DHSVM' s soil parameter settings emphasize soil water regulation of river flow, resulting in better baseflow simulation. However, DHSVM' s validation period (2018–2019 growing season) showed significantly overestimated flows, with maximum differences of 377.55 $m^3 \cdot s^{-1}$, thereby reducing overall simulation accuracy [Figure 4: see original paper].

2.3.2 Laoha River Upper Reaches

Both models performed better in the Laoha River upper reaches than in the Xar Moron River. DHSVM simulated monthly runoff more accurately than SWAT during the calibration period (2015–2017 growing season), with the best results in the 2017 growing season (NSE = 0.86). Both models performed poorly during the 2018 growing season, particularly SWAT. According to precipitation data, the watershed received substantial summer precipitation with clear peaks, while observed monthly runoff data showed no obvious peaks during summer 2018. Therefore, discrepancies between simulated and observed data primarily reflect human activity impacts, such as reservoir regulation [Figure 5: see original paper].

3 Discussion

From the Xar Moron River source to the Bacha River mouth, the river is turbulent with steep slopes, primarily fed by springs and groundwater. From the Bacha River mouth to Balin Bridge, the channel is wide with dispersed flow and an unstable main current. Currently, both hydrological models primarily consider precipitation-driven recharge. DHSVM' s flexible soil parameter settings can account for soil water regulation of river flow, and its river network considerations enable more accurate baseflow simulation than SWAT. Consequently, SWAT's baseflow simulation differs substantially from observations, particularly during validation, affecting its accuracy. DHSVM' s validation results were also poor, especially during the 2018 growing season.

DHSVM simulated monthly runoff peaks in May that were not evident in observations, while SWAT' s peaks also appeared in May, whereas observed runoff peaks occurred in July. Precipitation peaks occurred in July, creating inconsistency between precipitation and runoff peaks, likely due to human activities like reservoir regulation.

Both models demonstrate applicability for hydrological process simulation in different watershed types. Previous SWAT evaluations show good performance for peak flow simulation, with peak flow errors of only 1%–18% compared to observations. DHSVM applicability analyses in different geographical environments indicate its suitability for simulating hydrological processes in mountainous forest watersheds. Consistent with these findings, our results show DHSVM simulates peak monthly runoff more accurately in both watershed types. Compared to the grassland-dominated Xar Moron River, DHSVM performed more accurately in the forestland/farmland-dominated Laoha River upper reaches, with simulated peak flows differing by only 3.6% from observed peaks.

Both models have respective advantages but also limitations. First, parameter calibration remains challenging. DHSVM parameter sensitivity analysis and calibration rely on tools with limited options (e.g., maximum simulation count and parallel simulation options), and its high data demands constrain model precision improvement. Currently, no optimal method exists for DHSVM parameter sensitivity analysis; this study employed EFAST, which may introduce errors through algorithmic iteration. DHSVM has numerous parameters (over 100), some difficult to obtain, with many values relying on empirical estimation, affecting simulation results.

Second, model representation of hydrological process influencing factors is inadequate. Human activities significantly impact simulation accuracy. SWAT includes a reservoir module, but it simplifies reservoir operation rules, representing only seasonal and interannual variations. Standard DHSVM lacks a reservoir module, though model improvements have incorporated reservoir effects, enhancing simulation accuracy. However, human impacts are diverse, extending beyond reservoirs. Therefore, simulation accuracy may be lower in watersheds with strong human activity. The Xar Moron River upper reaches experience minimal human activity, while the Laoha River upper reaches contain farmland, but this study did not consider impacts like irrigation, potentially affecting simulation accuracy.

Comparing both models, DHSVM' s applicability extends beyond runoff simulation accuracy. The region is an important agricultural and pastoral production base severely constrained by water resources, with groundwater overexploitation, dry rivers, and severe water shortages requiring comprehensive, detailed hydrological process analysis. SWAT primarily studies long-term impacts of complex soil types, land use patterns, and management practices on water, sediment, and chemicals, with HRUs as the smallest units. DHSVM uses grid cells as the smallest units, outputting multiple raster images including evapotranspiration and soil moisture, with data precision down to individual soil layers, better facilitating understanding of spatiotemporal hydrological variations and comprehensive watershed dynamics.

DHSVM has been widely applied in hydrological process studies of arid and semi-arid regions. For example, Van Wie et al. [?] estimated wheat yield by studying seasonal soil moisture changes to assess impacts of dryland agricultural practices on watershed hydrology. Ren et al. [?] monitored farmland soil moisture (0–30 cm) under four scenarios using DHSVM to analyze climate change impacts on wheat waterlogging.

4 Conclusions

This study selected the DHSVM distributed hydrological model and SWAT semi-distributed hydrological model to simulate monthly runoff during growing seasons from 2012 to 2019 in different watershed types in the eastern agro-pastoral transitional zone of northern China—the Xar Moron River and Laoha River upper reaches. The applicability of both models in different watershed types was investigated, yielding the following conclusions:

1. Both DHSVM and SWAT exhibit good applicability for hydrological process simulation in the Xar Moron River and Laoha River upper reaches, each with respective advantages. DHSVM better simulates watershed baseflow, while SWAT more accurately simulates watershed peaks. In the Xar Moron River upper reaches, DHSVM's simulated monthly runoff peak differed from the observed average peak by only 73.06 $m^3 \cdot s^{-1}$.

2. DHSVM simulated monthly runoff more accurately in both watershed types, with calibration and validation period NSE values of 0.70 and 0.11 for the Xar Moron River, respectively. In the Laoha River upper reaches, SWAT performed better during calibration (NSE = 0.86), while DHSVM performed better during validation (NSE = 0.70). Overall, DHSVM demonstrates better applicability than SWAT in both watershed types.

3. Both models performed better in the Laoha River upper reaches than in the Xar Moron River, producing more accurate simulation results. This is primarily because the Laoha River upper reaches have a single recharge source (precipitation), whereas the Xar Moron River has diverse recharge sources including springs and groundwater that are not well-represented in either model.

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Note: Figure translations are in progress. See original paper for figures.