

Contrasting Local Ecosystem Water and Energy Balances with a Regional Land Surface Model in the Southeastern United States

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Abstract: Land use and land cover changes, especially urbanization, can strongly alter coupled water and energy cycles, intensifying urban heat island effects, stormwater runoff, and flood risk. Process-based land surface models provide an important tool for quantifying these interactions in heterogeneous landscapes with mixed urban, grassland, and forest cover where direct observations are limited. However, few studies have evaluated how models designed for regional-scale applications perform across scales from small watersheds to a broader urban–rural interface. Here, we diagnostically assessed the upgraded Common Land Model -Urban (CoLM-U) parameterization in the Nashville metropolitan area in the State of Tennessee, southern United States. We integrated local precipitation observations, streamflow records from five small watersheds, and remote sensing-derived evapotranspiration (ET) products from 2000 to 2020. CoLM-U reproduced the broad magnitude of annual ET and runoff but showed substantial watershed-to-watershed and seasonal discrepancies. At the monthly scale, runoff root mean square error ranged from 14.4 to 27.4 mm month⁻¹ and Nash–Sutcliffe Efficiency ranged from 0.3 to 0.6. The model generally underestimated winter runoff and overestimated summer runoff, reflecting the combined effects of precipitation forcing uncertainty, growing-season ET underestimation, and limitations in representing soil water storage and runoff generation. Long-term ET estimated by CoLM-U was broadly consistent with watershed water balance estimates, while remote sensing ET was generally over estimated ET, especially over forested areas. CoLM-U modeling results indicated that forests exhibited the highest ET and lowest sensible heat fluxes during the growing season, whereas urban cores showed lower ET and higher sensible heat. This study demonstrates what a regional land surface model can and cannot capture of ecohydrological processes at local watershed-to-regional scales. Improved local model climate input data and refined soil parameterizations are essential for accurate application in estimating the environmental effects of land cover change.

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Introduction

Land use and land cover changes (LULCCs), especially urbanization, strongly alter coupled energy and water cycles (Chen et al. 2024; Sun et al. 2026). With urban population continuing to grow globally (United Nations 2019), urbanization and climate change together have intensified urban heat island (UHI) and urban dry island effects (Zhou et al. 2015; Hao et al. 2018; Huang et al. 2022), increased energy use and heat-related human health risks,

and elevated runoff, flooding, and ecosystem degradation (Hao et al. 2015; Li et al. 2020; Chen et al. 2024). By reducing vegetation and increasing impervious surfaces, urbanization disrupts surface energy and water balances, suppresses evapotranspiration, and enhances runoff (Grimm et al. 2008; Willems et al. 2012; Fletcher et al. 2013). Forests are therefore considered an important nature-based solution (NbS) through shading, evapotranspiration cooling, and stormwater retention, yet their benefits and associated coupled energy–water processes remain insufficiently assessed at large

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scales, particularly in humid regions with heterogeneous land cover (Nowak et al. 2006; Bowler et al. 2010; Pataki et al. 2011).

Ground observations provide essential data for understanding the effects of LULCCs, but are limited in spatial and temporal coverage, making it challenging to assess local impacts accurately (Arnfield 2003; Grimmer 2006). Remote sensing offers large-scale, high-resolution surface characteristic data that are useful for parameterizing energy and water balance models, but these data are often restricted to certain variables, such as surface temperature (Voogt and Oke 2003; Weng 2009). Additionally, both types of observational data are limited to current conditions and cannot explore changes in the energy and water cycles under different environmental conditions (Solecki et al. 2005; Coutts et al. 2007).

Process-based land surface models (LSMs) address these limitations by simulating interactions between the land surface and atmosphere under varying land cover and climate conditions (Fisher and Koven 2020). The Common Land Model-Urban (CoLM-U) (Yuan et al. 2026; Dong et al. 2026) offers a framework to represent urban areas, including subgrid urban forest fractions parameterized from high-resolution tree cover data, with physical processes distinct from both impervious surfaces and natural forests. CoLM-U's offline configurations allow for long-term, large-domain simulations with lower computational cost compared to fully coupled models such as weather research and forecasting-urban canopy model (WRF-UCM) (Chen et al. 2011b), making it well suited for hydrological and climate assessments on a large scale.

Despite its potential, no prior studies have systematically evaluated the upgraded CoLM-U's performance for hydrological variables such as runoff and evapotranspiration (ET), especially at the watershed scale, where streamflow data enable robust runoff validation. Past evaluations of LSM urban modules have largely emphasized energy fluxes using eddy flux measurements (Karsisto et al. 2016). Modeling the water cycle in heterogeneous urban-rural landscapes remains challenging.

This study provides a watershed-to-regional scale diagnostic evaluation of the upgraded CoLM-U in the humid southeastern United States. Although urban-capable land surface models are increasingly used in climate and energy studies, few studies have evaluated a regional model across hydrological and energy-related processes from small watersheds to broader urban-rural landscapes in a humid, heterogeneous setting. Compared with traditional watershed models such as soil and water assessment tool (SWAT), CoLM-U additionally represents coupled water-energy exchanges and urban surface components; compared with conventional large-scale land surface model applications, this study evaluates watershed runoff, evapotranspiration, and land cover-specific energy partitioning within a single framework. Rather than presenting CoLM-U as a fully calibrated urban watershed model, this study assesses what a regional land surface model can and cannot capture at local watershed-to-regional scales. Specifically, we evaluate key water- and energy-balance components using in situ observations and remote sensing products, examine variation across major land cover types, and assess how urban forests are represented within urban grids and influence modeled water and energy partitioning.

Methodology

CoLM-U Model and Its Urban Module

The Common Land Model (CoLM) (Dai et al. 2003) is a comprehensive land surface model designed to simulate the exchange of energy, water, carbon, and momentum between the land surface and the atmosphere. Its modular structure allows for flexibility in updating and modifying individual components, making it adaptable

for a wide range of research applications, including climate dynamics, hydrological cycles, and ecosystem processes. The CoLM is particularly valuable for its ability to operate across different spatial and temporal scales, providing insights into environmental changes from regional to global levels. Its compatibility with observational data and other models enhances its utility in studying land-atmosphere interactions and predicting the impacts of land use changes on climate and ecosystem functions (Li et al. 2017, 2024).

The model includes an updated urban module (CoLM-U), which adopts a three-dimensional urban building community framework instead of the traditional urban canyon assumption (Yuan et al. 2026; Dong et al. 2026). Detailed model formulation and evaluation are provided by Yuan et al. (2026), while the supporting datasets and comprehensive evaluation are described by Dong et al. (2026). This structure allows for more realistic calculation of shortwave and longwave radiation, turbulent energy exchange, and vegetation processes within urban grids. The module supports high-resolution input of urban land cover, vegetation, water bodies, and simulates anthropogenic heat fluxes, including contributions from buildings, traffic, and human metabolism. Specifically, building heat is estimated using the Building Energy Model based on the difference between indoor temperature setpoints and the simulated indoor temperature; and traffic heat and human metabolic heat are computed using the large-scale urban consumption of energy (LUCY) model approach (Allen et al. 2011), based on vehicle and population data. In CoLM-U, each urban grid cell is represented as a composition of buildings, impervious surfaces, pervious surfaces, and urban forests. Urban forests differ from natural vegetation in that their radiation and turbulent exchange processes follow the urban parameterization scheme and are influenced by urban morphology. In contrast, for vegetation-related biological and hydrological processes such as photosynthesis, canopy interception, infiltration, and subsurface flow, urban forests are treated consistently with natural vegetation and as hydrologically active surfaces.

The turbulent exchange scheme in CoLM-U is adapted from the three-dimensional vegetation canopy model (Dai et al. 2019), with modifications to account for urban morphology. The displacement height and roughness length of the urban canopy are calculated using the method of Macdonald et al. (1998). Wind speed and exchange coefficients decay exponentially within the urban canopy, following a decay function distinct from vegetation canopies (Macdonald 2000). In addition, surface water on building roofs or impervious surfaces is temporarily stored up to a maximum ponding depth, after which excess water becomes surface runoff. For pervious surfaces, the model simulates interception, infiltration, and subsurface flows. Building walls are assumed to be hydrologically inactive. Surface moisture exchange occurs only when roofs and impervious surfaces are wet; for pervious surfaces and urban forests, the model simulates interception, infiltration, and subsurface flows.

For natural vegetation, most parameters are dynamic [e.g., leaf area index (LAI) and stem area index (SAI) updated monthly, land cover types updated annually]. Other properties, such as tree height, soil, and lake depth, remain static due to data limitations. For urban areas, soil properties are obtained from the same sources as those used for natural vegetation and are treated as static over the simulation period, while land cover types and vegetation-related parameters are time-varying and updated annually or monthly depending on the dataset. Land cover is updated at the beginning of each year; if unchanged, state variables such as soil moisture and snow depth are carried over as initial conditions, while land cover changes (e.g., forest to urban) trigger re-initialization. This combination of dynamic and static data enables CoLM-U to capture seasonal and interannual variability where possible, while acknowledging that certain urban parameters remain static due to observational constraints.

Table 1. Surface datasets for natural vegetation and urban parameters used in CoLM-U, including sources, spatial/temporal resolution, and availability

Category	Parameter	Data source	Spatial resolution	Time resolution
Natural vegetation	LAI/SAI	Reprocessed MODIS (Lin et al. 2023)	500 m	2000–2020, every month
	Tree height	GLAS (Simard et al. 2011)	1 km	N/A
	Soil properties	GSDE (Shangguan et al. 2014)	1 km	N/A
	Land cover type	MODIS (Sulla-Menashe et al. 2019)	500 m	2000–2020, every year
	Lake depth	Lake-depth data set V2.0 (Kourzeneva et al. 2012)	1 km	N/A
	Soil color	NCAR (Lawrence and Chase 2007)	1 km	N/A
Urban	LAI/SAI	RF method (Dong et al. 2025)	500 m	2000–2020, every month
	Tree coverage	GFCC (Sexton et al. 2013)	30 m	2000–2015 every five years
	Tree height	ETH (Lang et al. 2023)	30 m	N/A
	Soil properties	GSDE (Shangguan et al. 2014)	1 km	N/A
	Land cover type	MODIS (Sulla-Menashe et al. 2019)	500 m	2000–2020, every year
	Water coverage	Globeland30 (Chen et al. 2015)	30 m	2000, 2010, 2020
	Population	LandScan (Dobson et al. 2000)	1 km	2000–2020, every year
	Building height	NCAR (Oleson and Feddema 2019)	Lookup table	N/A
	Building fraction			
	Canyon height-to-width			
	Pervious surface fraction			
	Thickness of roof, wall			
	Albedo of roof/wall/pervious/impervious			
	Emissivity of roof/wall/pervious/impervious			
	Heat capacity of roof/wall/impervious			
	Thermal conductivity of roof/wall/impervious			
	Heat capacity of pervious	Global Soil Data (GSDE) (Shangguan et al. 2014)	1 km	N/A
	Thermal conductivity of pervious surfaces			

Note: ETH = ETH Zurich (Swiss Federal Institute of Technology Zurich); RF = random forest; and NCAR = National Center for Atmospheric Research.

Model Input Data

The input data required by CoLM-U are divided into two categories: land surface data and atmospheric forcing data.

Land Surface Data

Land surface data provide the essential land and vegetation characteristics required by CoLM-U. These include LAI/SAI, tree height, soil properties, land cover type, lake/water coverage, and soil color for natural vegetation, primarily derived from moderate resolution imaging spectroradiometer (MODIS), global soil dataset for earth system modeling (GSDE), geoscience laser altimeter system (GLAS), and other global datasets. For urban areas, additional high-resolution data are used, including global forest cover change (GFCC) tree cover, Globeland30 water coverage, and LandScan population data, which capture the spatial heterogeneity of urban forests and human activities. Building-, impervious- and pervious-related parameters, such as building fraction, height-to-width ratio, albedo, and emissivity are specified from static lookup tables consistent with community land model version 5 (CLM5) conventions. Thermal property parameters for buildings and impervious surfaces also come from the lookup table, while parameters for pervious surfaces come from GSDE.

A summary of all input datasets, including their data sources, references, spatial/temporal resolutions, and periods of availability, is presented in Table 1, which integrates both natural and urban land surface information. This table serves as the foundation for parameterizing vegetation dynamics, soil conditions, urban morphology, and surface energy properties in CoLM-U.

Atmospheric Forcing Data

Atmospheric forcing data include essential meteorological inputs required for model operation, such as temperature, humidity, wind speed, atmospheric pressure, precipitation, and radiation. These variables are typically obtained from reanalysis datasets (Hersbach et al. 2020), which integrate historical weather observations with numerical models to produce a consistent record of the Earth's atmosphere over time. In this study, we selected ERA5-Land atmospheric forcing data (Muñoz-Sabater et al. 2021) as our input. The ERA5-Land dataset is a high-resolution reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides detailed hourly information on surface variables, spanning from 1950 to 5 days before the present date. ERA5-Land features a finer spatial resolution with approximately 9-km grid spacing, offering enhanced detail compared to its predecessor, ERA5. Numerous studies have demonstrated that ERA5-Land performs effectively as input data for numerical model simulations (Wang et al. 2022; Xu et al. 2022).

Because the CoLM-U simulations were conducted at 500-m spatial resolution, the ERA5-Land forcing fields were interpolated to the 500-m CoLM grid using the built-in CoLM preprocessing framework. This ensured consistency between the forcing data and model grid, although it did not add true fine-scale meteorological variability and thus remained a source of uncertainty in the heterogeneous urban–rural setting. The model time step was 1,800 s. Hourly ERA5-Land forcing variables were temporally interpolated within the model: air temperature, specific humidity, air pressure, wind speed (u/v), and downward longwave radiation

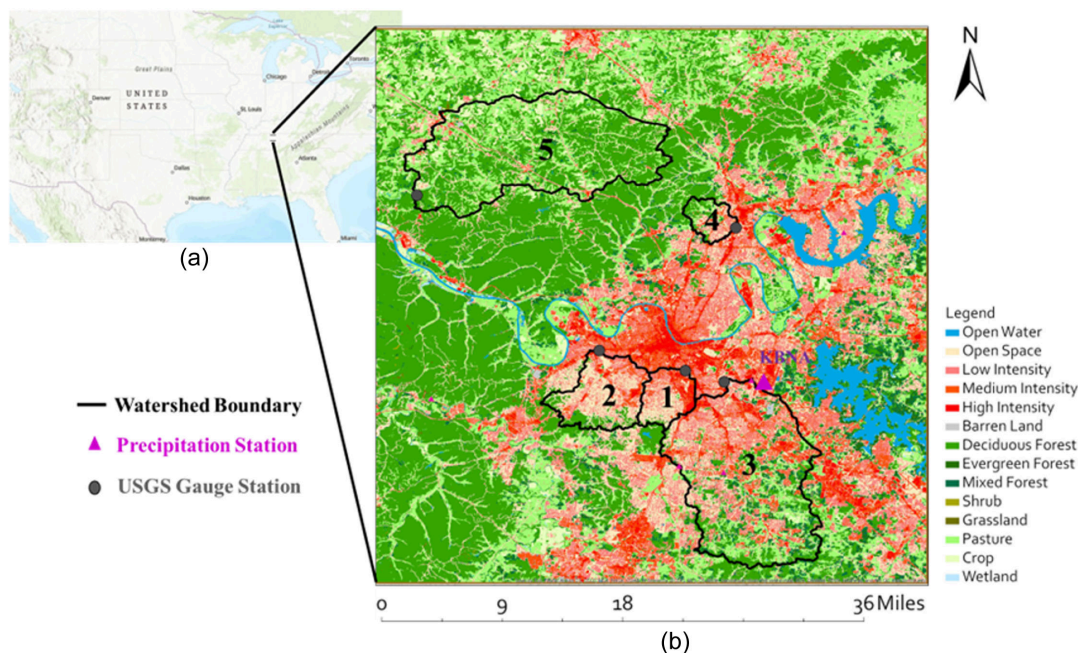


Fig. 1. The study area (primarily including Nashville city in Tennessee), showing the locations of the five watersheds used for runoff and ET validation. Numbers in the figure correspond to the watershed IDs (see Table 2). Circles represent the USGS gauge stations for the five watersheds, and the triangle represents the KBNA station used for precipitation observations. [Map (a) from ArcGIS World Topographic Map, Sources: Esri, HERE, Garmin, Intermap, INCREMENT P, GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), © OpenStreetMap contributors, and the GIS User Community; map (b) by authors using ArcGIS © Esri and land use and land cover data from the MODIS-IGBP land cover dataset (Sulla-Menashe et al. 2019), watershed boundary data from USGS (2017), and runoff observational data from USGS (2019).]

were linearly interpolated; downward shortwave radiation was interpolated using a cosine-based approach; and precipitation was applied using nearest-neighbor interpolation. No bias correction was applied to the ERA5-Land precipitation forcing in this study.

Study Area and Simulation Period

The study area is located between latitude 35.9° and 36.5° and longitude −87.1° and −86.5°, encompassing the entire city of Nashville, Tennessee, USA (Fig. 1). Nashville is situated on the Cumberland River in the north-central part of Tennessee and serves as the hub of an urbanized area that includes parts of seven surrounding counties. It is one of the fastest-growing cities in the nation. Nashville has a humid subtropical climate, characterized by hot, humid summers and generally cool winters. The annual average rainfall is approximately 1,250 mm, with precipitation typically higher during the spring (February–April) and summer (May–July) months, while autumn (August–October) tends to be the driest season.

In this study, CoLM-U was run in offline mode at a spatial resolution of 500 m from 1995 to 2020 (Fig. 2). The first five years (1995–1999) were treated as a spin-up period, and only the 2000–2020 results were used for analysis. The purpose of the spin-up was to allow the initial soil moisture and thermal states to adjust to the prescribed atmospheric forcing. A five-year spin-up was considered sufficient for stabilizing the near-surface soil moisture and thermal conditions relevant to this study, given the relatively low-latitude humid environment of the study region. Monthly outputs reported in this study were obtained by aggregating model results across all 1,800 s time steps within each month, rather than by running the model at a monthly time step.

Model Evaluation Method

Runoff

For the evaluation of the model's runoff, we selected five watersheds within the simulation area (Table 2, Fig. 1). Watershed 1 is mainly urban, while Watersheds 2, 3, and 4 are primarily grass, with Watershed 5 blending forest and grass. The land use and land cover data are derived from the moderate resolution imaging spectroradiometer–international geosphere-biosphere programme (MODIS-IGBP) land cover dataset. We extracted the model-simulated runoff based on the watershed boundaries and compared the calculated discharge data with the USGS measured runoff at the watershed gauge station. The shapefile for the watershed boundaries was obtained from the USGS StreamStats application (USGS 2017), and the runoff observational data were obtained from the USGS 2019).

ET

To evaluate simulated ET, we employed two ET datasets. The first one is the remote sensing-based SSEBop v6 [Simplified Surface Energy Balance Operational model, version 6, Senay et al. (2023)], a high-resolution global product designed to estimate actual evapotranspiration. SSEBop v6 integrates inputs from the Visible Infrared Imaging Radiometer Suite (VIIRS), enabling near-real-time data availability at a spatial resolution of approximately 1 km. By combining satellite-derived land surface temperature (LST) with simplified surface energy balance principles, the framework calculates the energy available for evaporation and transpiration from diverse land cover types (including forest, grass, and urban areas). SSEBop v6 provides daily, monthly, and annual ET estimates, making it suitable for applications in agriculture, water resource management, and climate research.

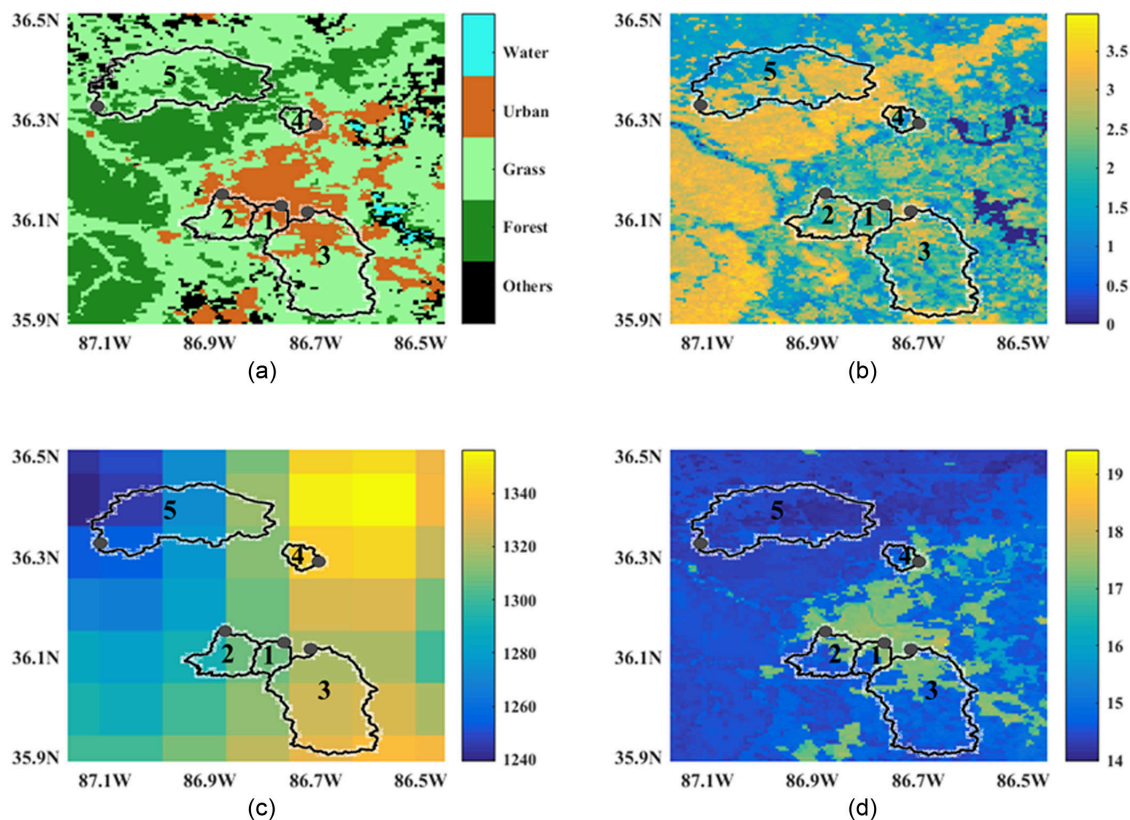


Fig. 2. (a) The 2020 land use types within the study area; (b) 2020 leaf area index within the study area; (c) the model input forcing with ERA5-Land precipitation data averaged over 2000–2020; and (d) model input forcing with ERA5-Land 2-m air temperature data averaged over 2000–2020. The outlines represent the locations of the five watersheds used for runoff and ET validation, numbers correspond to the watershed IDs (see Table 2), and the circles indicate the locations of USGS gauge stations for each watershed.

Table 2. Summary of watershed characteristics, including USGS Station ID, drainage area, dominant land use composition, and measured annual runoff and precipitation from ERA5-Land dataset

Watershed	USGS gaging station ID	Drainage area (km ²)	Forest (%)	Grass (%)	Urban (%)	Mean runoff (mm/year)	Mean precipitation (mm/year)
1	03431300	30.6	1.4	36.8	61.7	584	1,307
2	03431700	62.9	8.9	54.7	36.4	494	1,299
3	03431060	241.9	2.7	69.7	26.3	569	1,324
4	03426470	19.8	20	60.7	19.3	515	1,337
5	03431800	251.7	32.1	62.8	0	540	1,271

In addition to the SSEBop dataset, we used a watershed water balance approach to estimate annual ET in five small watersheds with long-term streamflow records (Table 1). Specifically, annual precipitation and observed runoff data were used to derive ET via the equation $ET = \text{Precipitation (P)} - \text{Runoff (R)}$. It should be noted that the watershed water balance estimate of ET ($ET = P - R$) is only applied at the long-term (multiyear) scale in this study. Changes in terrestrial water storage (ΔS), including soil moisture and shallow groundwater, can be substantial at monthly and annual timescales and cannot be reliably quantified with the available observations. As a result, the water balance approach is not suitable for validating monthly or annual ET variability. In this study, $P - R$ is therefore used solely as an approximate constraint on long-term mean ET. We then compared these water balance-based ET estimates with both the CoLM-U-simulated ET and the SSEBop-derived ET for the period in which all datasets are available. This multipronged evaluation provides a

more comprehensive assessment of the CoLM-U model's ability to capture ET processes.

Precipitation

The local weather station, KBNA (Nashville International Airport), located within the simulation domain, was selected from the Synoptic Data Repository (Synoptic Data, n.d.) to evaluate the accuracy of ERA5-Land precipitation data, which served as the forcing input for the CoLM-U model. Additionally, the KBNA precipitation data were incorporated as the precipitation component in the water balance approach to estimate ET. The geographical location of the validation site is illustrated in Fig. 1. KBNA is the only high-quality, long-term precipitation station available within the study region for the 2000–2020 period. Therefore, it is used as a practical reference for evaluating the general consistency of ERA5-Land precipitation forcing, rather than as a complete representation of precipitation variability across the entire domain.

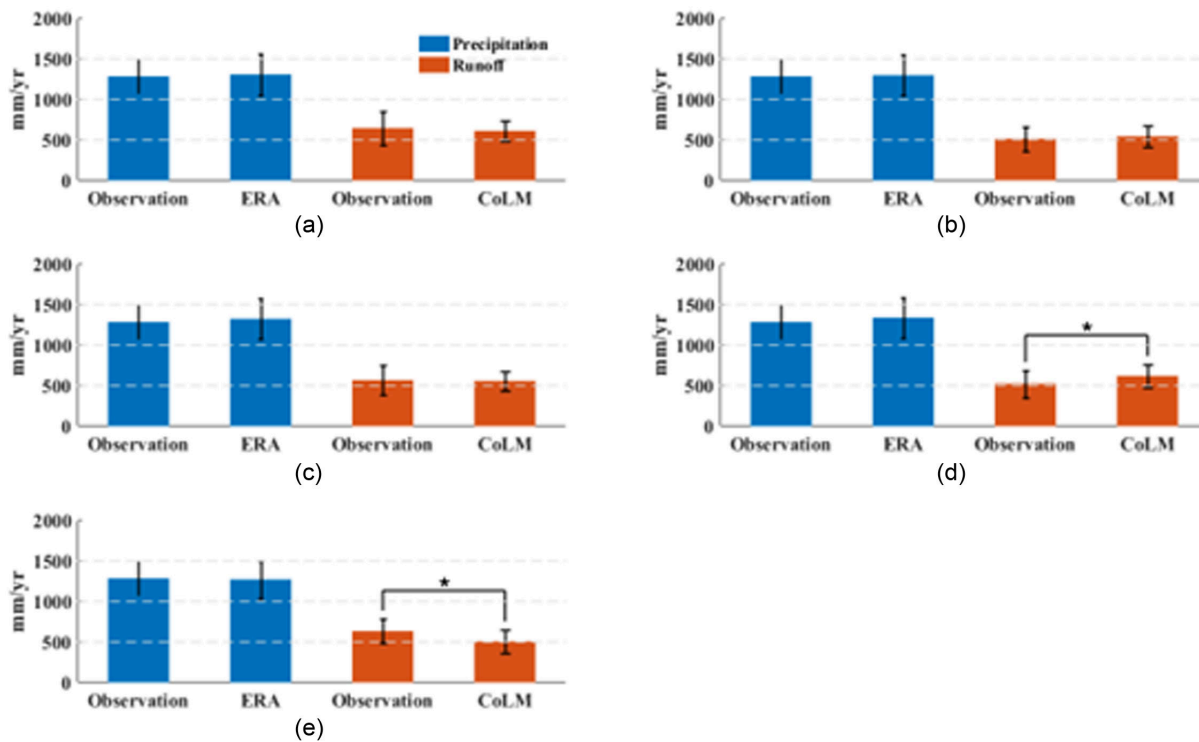


Fig. 3. Comparison of annual observed and simulated precipitation and runoff in the five small watersheds from 2000 to 2020: (a) Watershed 1; (b) Watershed 2; (c) Watershed 3; (d) Watershed 4; and (e) Watershed 5. Within each watershed, the four bars represent observed precipitation, ERA5-Land precipitation, USGS-observed runoff, and CoLM-U-simulated runoff, respectively. The bar values represent the multiyear averages, and the vertical lines indicate the standard deviations. Asterisks indicate that the differences between the two compared data groups exceed the 95% confidence interval. For Watershed 5, because observed runoff data are available only from 2013 onward, both observed and model-simulated runoff averages are calculated for 2013–2020.

Statistical Analysis

To quantitatively assess the agreement between observed and simulated time series of precipitation and runoff, we used three statistical metrics: the root mean square error (RMSE), the coefficient of determination (R^2), and the Nash–Sutcliffe Efficiency (NSE). The RMSE is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2} \quad (1)$$

where S_i and O_i = simulated and observed values at time step i , respectively; and n = number of valid observations. RMSE measures the average magnitude of the simulation error, with lower values indicating better performance.

The NSE is calculated as

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (O_i - S_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (2)$$

where $\bar{O}$ = mean of the observed values. NSE values range from $-\infty$ to 1, with 1 indicating a perfect match between simulations and observations, 0 indicating performance equivalent to the mean of the observations, and negative values indicating performance worse than the mean.

We also used scatterplots to compare observed and simulated values and performed linear regression analysis. The fitted regression equation and R^2 were reported to quantify the overall relationship between simulations and observations. For these regression

analyses, data from all five watersheds were pooled to provide an overall evaluation of model behavior across the full set of available validation basins, rather than to emphasize basin-specific differences. Accordingly, the sample size for each regression corresponded to the total number of annual or monthly data points included in the pooled comparison. In figures showing multiyear mean comparisons, black asterisks indicate that the difference between the two compared groups exceeds the 95% confidence interval. The confidence intervals were calculated from the interannual variability of the compared data groups, and the corresponding sample sizes are given by the number of years included in each comparison period.

Results

Runoff Simulation Evaluation

To diagnostically evaluate how the CoLM-U model represents runoff processes under real-world conditions, we conducted a comprehensive assessment of simulated runoff across five selected watersheds. Given that runoff simulations are highly sensitive to precipitation inputs, we systematically analyzed both the precipitation forcing data and the model-generated runoff estimates.

We first conducted a multiyear average comparison (Fig. 3). ERA5-Land precipitation, which serves as the precipitation input for CoLM-U, exhibits strong agreement with weather station observations on a long-term basis, indicating no substantial systematic bias. However, notable discrepancies arise in runoff simulations. While CoLM-U reproduces the broad magnitude of runoff in Watersheds 1–3, aligning more closely with USGS observations, significant biases

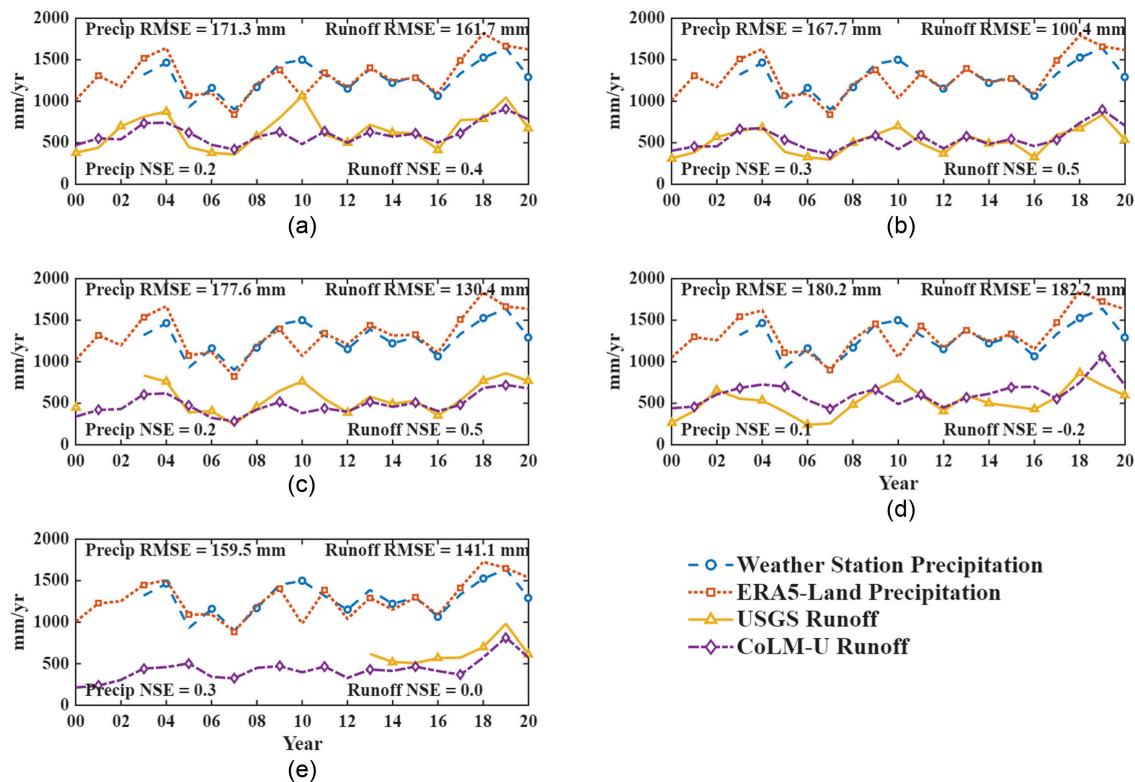


Fig. 4. Annual time series comparison of observed and simulated precipitation and runoff in five watersheds from 2000 to 2020: (a) Watershed 1; (b) Watershed 2; (c) Watershed 3; (d) Watershed 4; and (e) Watershed 5. Weather station precipitation is represented by dashed lines with circles, ERA5-Land precipitation by dotted lines with squares, USGS-observed runoff by solid lines with triangles, and CoLM-U-simulated runoff by dash-dotted lines with diamonds. Precipitation RMSE and NSE quantify the agreement between weather station and ERA5-Land precipitation, whereas runoff RMSE and NSE quantify the agreement between USGS-observed and CoLM-U-simulated runoff.

are observed in Watersheds 4 and 5. Specifically, the model overestimates runoff in Watershed 4 and underestimates it in Watershed 5.

We then carried out a temporal evaluation (Fig. 4). For precipitation, the overall trends between ERA5-Land and station observations are generally aligned, but notable deviations occur during years with extreme rainfall events. For example, in 2010, ERA5-Land significantly underestimates precipitation relative to observations, leading to a pronounced underestimation of modeled runoff. Across the five watersheds, precipitation RMSE values range from 160 mm to 180.2 mm, with corresponding NSE values between 0.1 and 0.3, indicating limitations of ERA5-Land in reproducing local precipitation variability at the watershed scale. This highlights the limitations of reanalysis datasets in capturing precipitation extremes, which can propagate into errors in simulated hydrological responses, particularly when combined with structural simplifications in urban hydrological representation. For runoff, Fig. 4 also illustrates substantial interannual variability between modeled and observed values. Runoff RMSE values span 100.4 mm to 182.2 mm, while NSE ranges from -0.2 to 0.5 , showing strong watershed-to-watershed differences in model performance. The larger runoff discrepancies observed in Watersheds 4 and 5 likely reflect watershed-specific hydrogeological and drainage network complexities that are not represented in the current model configuration.

Fig. 5 provides a regression analysis of observed versus modeled annual precipitation and runoff, serving as a diagnostic tool to characterize systematic differences between CoLM-U simulations and observations rather than as a measure of predictive capacity. Fig. 5(a) illustrates the relationship between ERA5-Land precipitation inputs and station observations. The regression equation, $y = 0.98x + 79$, suggests that ERA5-Land precipitation closely tracks observational

data, with a minor overestimation at lower precipitation values. The regression equation indicates an underestimation of high runoff but overestimation of low flows, suggesting that the model does not adequately capture annual flow in some years [Fig. 5(b)].

Fig. 6 provides a seasonal diagnostic of precipitation and runoff differences between the ERA5-Land forcing, in situ observations, and CoLM-U simulations. RMSE and NSE are reported to facilitate comparison across variables, but they are interpreted here as descriptive indicators of seasonal mismatch rather than as a strict measure of predictive performance. For precipitation, RMSE values range from 10.3 mm/month to 16.4 mm/month, with NSE values between 0.3 and 0.6, suggesting that ERA5-Land broadly captures the seasonal cycle but deviates from station observations in certain months. For runoff, RMSE values vary from 14.4 mm/month to 27.4 mm/month, and NSE ranges from 0.3 to 0.6, indicating notable seasonal discrepancies. CoLM-U tends to underestimate runoff from January to May and overestimate runoff from June to November, indicating a systematic seasonal mismatch. This suggests that precipitation forcing uncertainty is important, but not the only source of runoff error. In particular, higher ERA5-Land precipitation in winter does not necessarily lead to proportionally higher simulated runoff, because runoff is also influenced by evapotranspiration, infiltration, soil water storage, and the partitioning between surface and subsurface flow pathways.

The monthly scale analysis reveals additional discrepancies in CoLM-U's simulations (Fig. 7). The regression equation for precipitation, $y = 0.68x + 39$, indicates that ERA5-Land tends to underestimate precipitation during wetter months, particularly when precipitation levels are high. Similarly, the regression for modeled versus observed runoff, $y = 0.29x + 33$, highlights an even

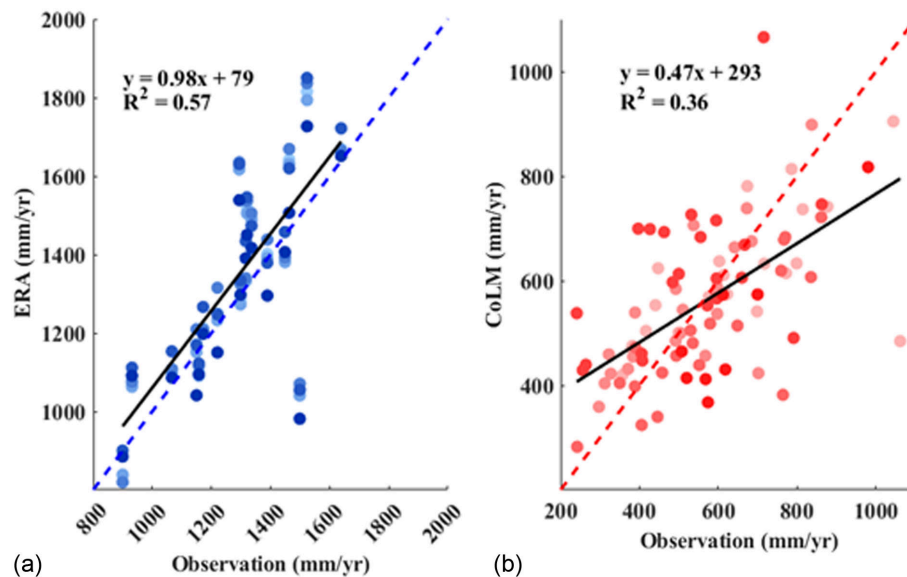


Fig. 5. Scatterplots and regression formulas of (a) annual observed versus simulated precipitation data; and (b) annual observed versus simulated runoff data. The annual values for the five watersheds are plotted on a single chart, with the shading of the scatter points representing different watersheds. Dashed lines represent the 1:1 reference line, while solid lines show linear regression fits. The fitted regression equation and R^2 are displayed in each subplot.

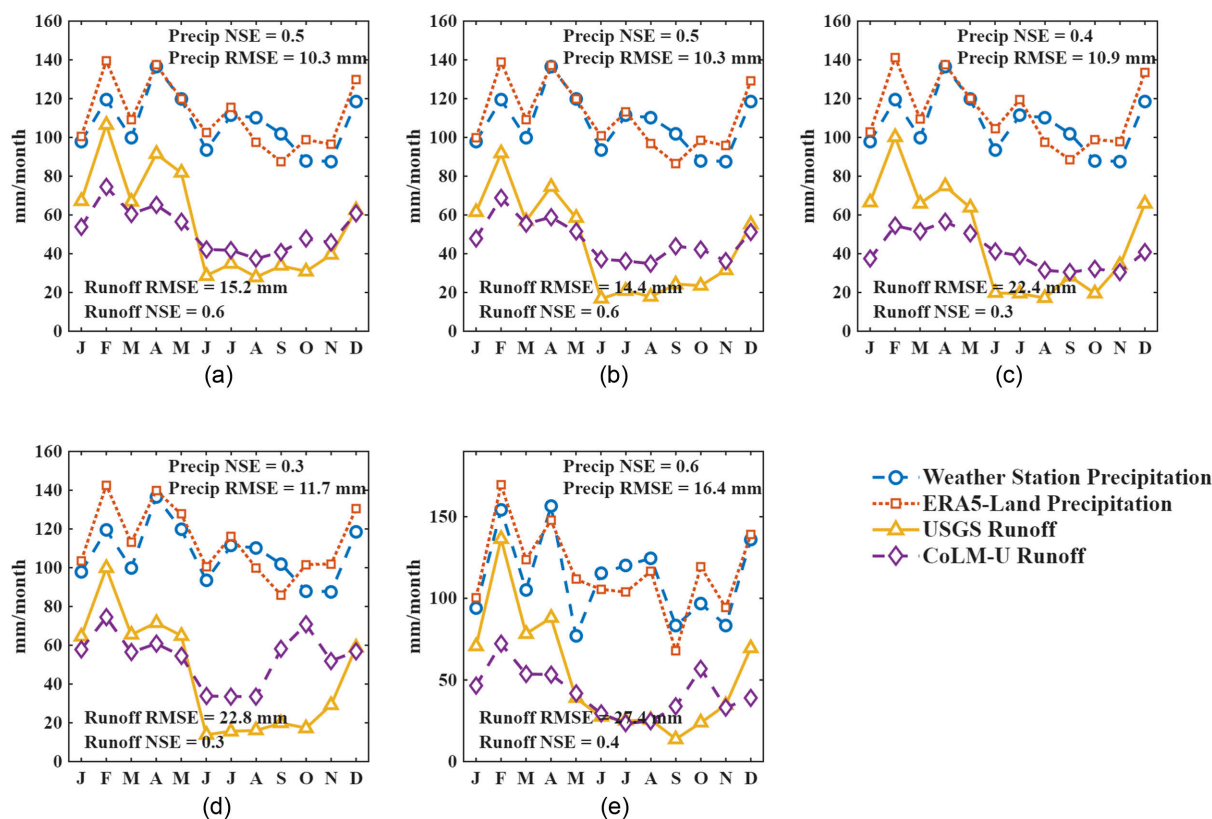


Fig. 6. Average monthly precipitation and runoff for the five watersheds: (a) Watershed 1; (b) Watershed 2; (c) Watershed 3; (d) Watershed 4; and (e) Watershed 5. Weather station precipitation is represented by dashed lines with circles, ERA5-Land precipitation by dotted lines with squares, USGS-observed runoff by solid lines with triangles, and CoLM-U-simulated runoff by dashed lines with diamonds. Precipitation RMSE and NSE quantify the agreement between weather station and ERA5-Land precipitation, whereas runoff RMSE and NSE quantify the agreement between USGS-observed and CoLM-U-simulated runoff. For Watersheds 1–4, monthly values are averaged over 2003–2020; for Watershed 5, monthly values are averaged over 2013–2020.

greater underestimation of runoff at the monthly scale, reinforcing the challenges CoLM-U faces in representing short-term hydrological dynamics. These results suggest that while CoLM-U captures general runoff trends, it underrepresents rapid runoff responses to precipitation events, likely due to limitations in soil moisture retention, infiltration processes, and evapotranspiration simulations.

Modeled ET Evaluation

To assess CoLM-U's ability to simulate ET, we compared model-simulated ET against two independent ET estimates: SSEBop-derived ET and a long-term water balance constraint. Here, the water balance estimate follows $ET = P - R - \Delta S$; because ΔS (changes in soil and groundwater storage) cannot be quantified reliably at subannual timescales with the available data, we only use multiyear means where ΔS can be reasonably assumed to approach zero, such that $P - R$ provides an approximate constraint on mean ET. Fig. 8 compares multiyear mean ET across the five watersheds and shows that CoLM-U and the long-term water balance constraint are broadly consistent in magnitude, whereas SSEBop yields higher ET in several watersheds, especially over forested areas. This comparison is designed as a diagnostic consistency check among methods, not as a strict validation against a single *ground truth* ET product. The differences reflect methodological assumptions and structural uncertainties inherent in each approach. In all five watersheds, both datasets show a similar seasonal pattern, with higher ET in summer and lower ET in winter, while SSEBop remains consistently higher than CoLM-U, especially during the growing season (Fig. 9).

At the regional scale, we further compared SSEBop ET with CoLM-U-simulated ET across the entire simulation area. Temporal trends in ET further illustrate model discrepancies. For annual average ET values [Fig. 10(a)], SSEBop estimates are significantly higher than CoLM-U simulations. Over the multiyear average from 2013 to 2020, the mean ET in the simulation area is 927 mm year^{-1} for SSEBop and 715 mm year^{-1} for CoLM-U. At the monthly scale [Fig. 10(b)], CoLM-U and SSEBop ET estimates follow a similar seasonal pattern, peaking in summer, but SSEBop remains consistently higher, with the largest differences occurring during the

growing season. Differences across land cover types are also evident [Fig. 10(c)]: the ET difference is largest for forest land cover (SSEBop mean: $1.021 \text{ mm year}^{-1}$; CoLM-U mean: 789 mm year^{-1}), followed by grassland (933 versus 714 mm year^{-1}), and smallest for urban land cover (739 versus 600 mm year^{-1}). Here, SSEBop is not treated as a ground truth ET product, but as a spatially continuous reference that enables diagnosis of systematic differences in ET magnitude and seasonality between satellite-based and process-based approaches.

Spatial variability in ET estimates is further analyzed in Fig. 11, which compares the spatial distribution of annual ET from SSEBop and CoLM-U. It is clear that SSEBop produces higher values compared to CoLM-U. Since CoLM-U is based on land use types, the simulation results can clearly distinguish between forests, grasslands, and urban areas. Moreover, two rivers are clearly visible, exhibiting the highest ET values. On the other hand, SSEBop is based on remote sensing observations and does not show distinct differences between forest and grassland land use types, nor does it highlight the high ET values along the two rivers. However, it does clearly show very low ET values in urban areas. The watershed-scale ET comparisons presented above are primarily intended for model evaluation using available observational constraints, whereas the influence of land cover type on water and energy partitioning is examined more explicitly at the broader simulation-domain scale in the section "Simulated Energy and Water Cycles for Different Land Use and Land Cover Types."

Simulated Energy and Water Cycles for Different Land Use and Land Cover Types

Because independent observations of energy fluxes are not available, this section is not intended as an independent validation of modeled energy balance components. Instead, it provides a diagnostic comparison of how CoLM-U partitions energy (Fig. 12) and water (Fig. 13) balance components across forest, grassland, and urban land cover types over the broader simulation domain. For forest and grassland land use and land cover types, the energy balance equation is $\text{Net Radiation} = \text{Latent Heat} + \text{Sensible Heat} + \text{Heat}$

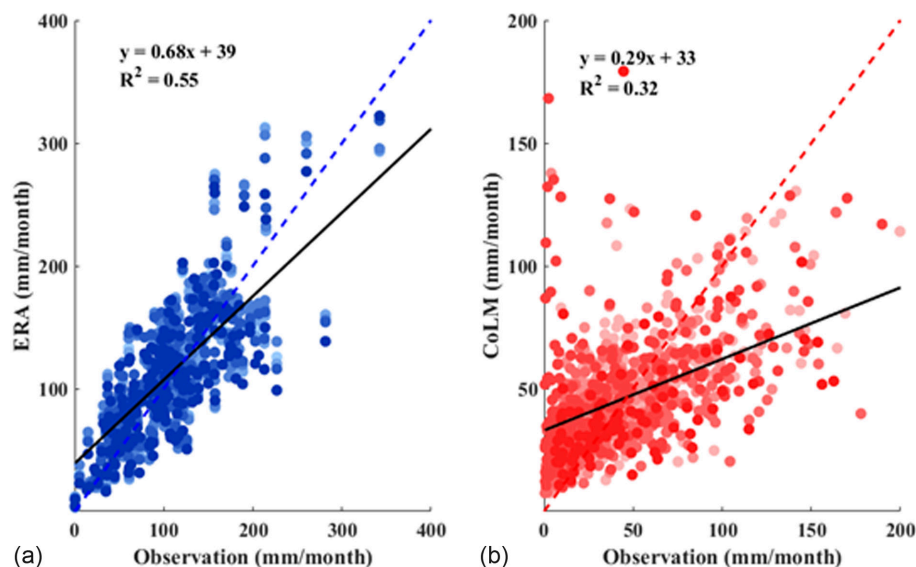


Fig. 7. Scatterplots and regression formula of (a) monthly observed versus simulated precipitation data; and (b) monthly observed versus simulated runoff data. The monthly values for the five watersheds are plotted on a single chart, with the shading of the scatter points representing different watersheds. Dashed lines represent the 1:1 reference line, while solid lines show linear regression fits. The fitted regression equation and R^2 are displayed in each subplot.

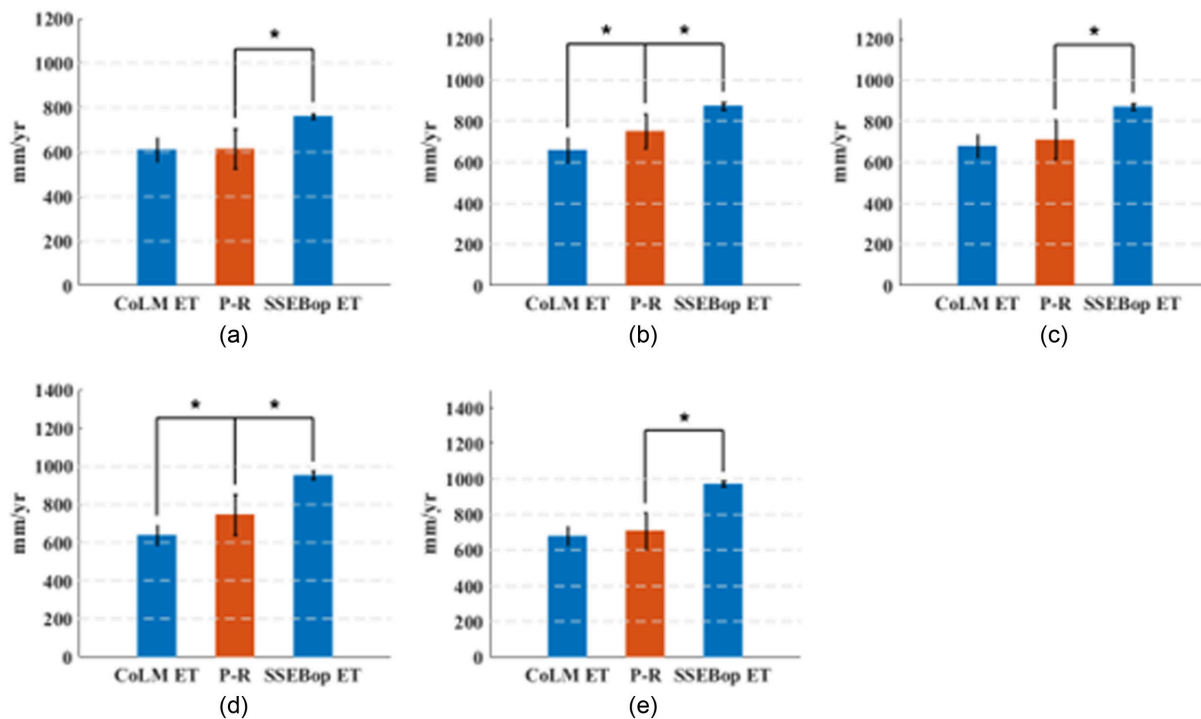


Fig. 8. Comparison of annual average ET estimated using three different methods across the five small watersheds: (a) Watershed 1; (b) Watershed 2; (c) Watershed 3; (d) Watershed 4; and (e) Watershed 5. Within each watershed, the three bars represent CoLM-U-simulated ET, water balance ET estimated as observed precipitation minus observed runoff ($P - R$), and SSEBop ET, respectively. Asterisks indicate that the differences between the two compared data groups exceed the 95% confidence interval.

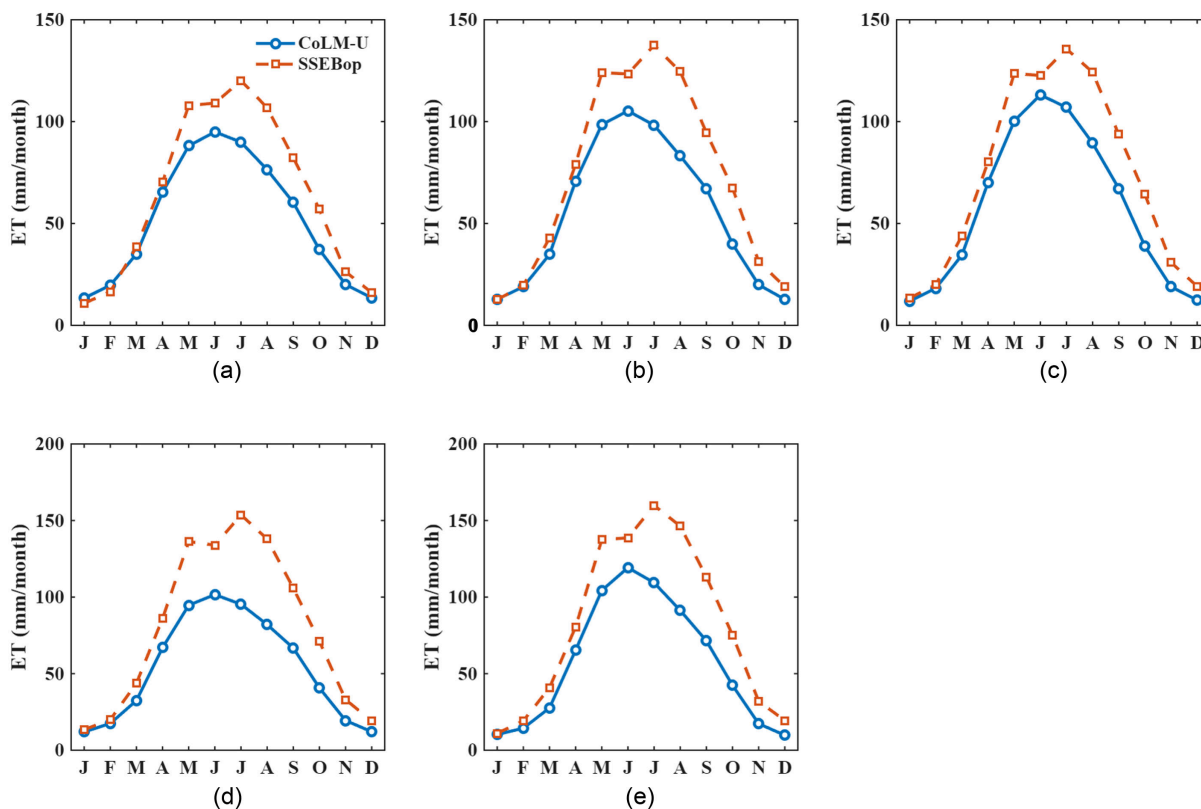


Fig. 9. Average monthly variation in evapotranspiration (ET) estimated by CoLM-U and SSEBop for the five watersheds: (a) Watershed 1; (b) Watershed 2; (c) Watershed 3; (d) Watershed 4; and (e) Watershed 5. CoLM-U ET is represented by solid lines with circles, and SSEBop ET is represented by dashed lines with squares.

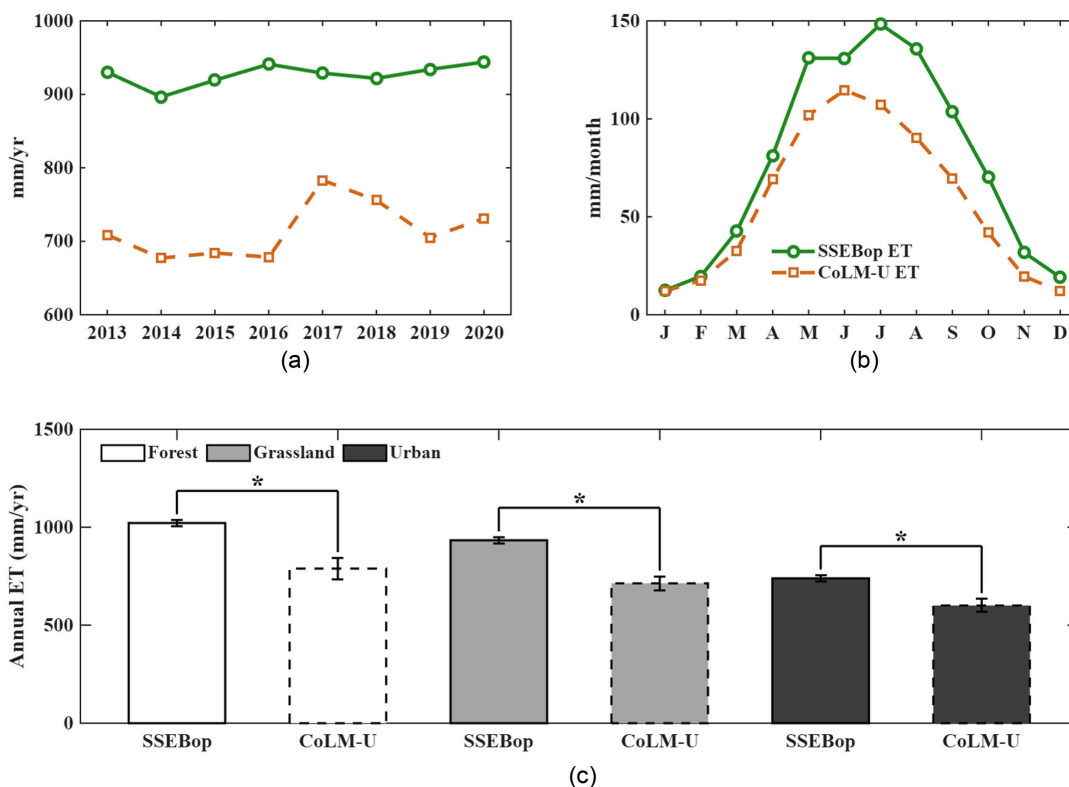


Fig. 10. Comparison of evapotranspiration (ET) estimated by SSEBop and CoLM-U across the simulation domain: (a) annual ET from 2013 to 2020; (b) average monthly ET variation; and (c) mean annual ET for different land cover types. In panels (a and b), SSEBop ET is represented by solid lines with circles and CoLM-U ET by dashed lines with squares. In panel (c), white, light-gray, and dark-gray bars represent forest, grassland, and urban land cover types, respectively; bars with solid outlines represent SSEBop and bars with dashed outlines represent CoLM-U. Error bars indicate standard deviations, and asterisks indicate that the differences between SSEBop and CoLM-U exceed the 95% confidence interval.

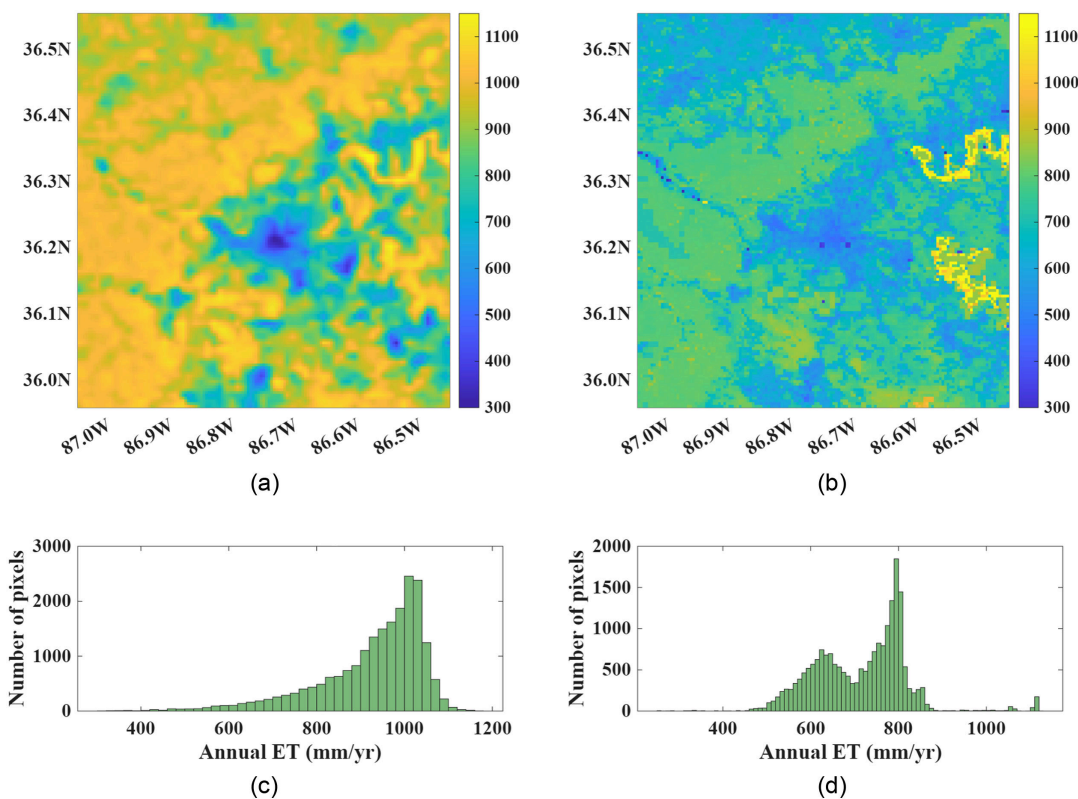


Fig. 11. (a and b) Spatial distribution maps of annual average ET values from 2013 to 2020; (c and d) number of pixels within specific ET value ranges in the two maps. Panels (a and c) are for SSEBop, and panels (b and d) are for CoLM-U.

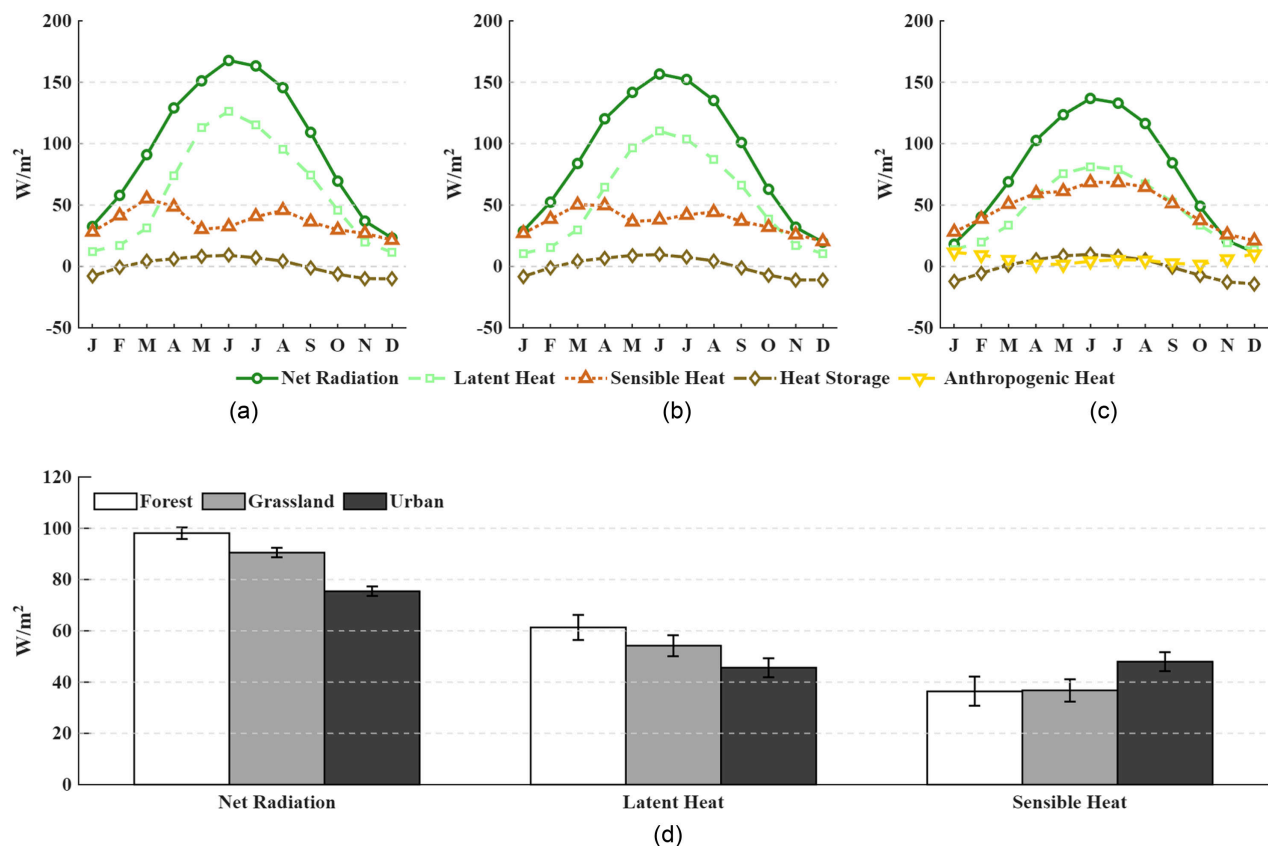


Fig. 12. Monthly variation of energy cycle variables across three land cover types from 2000 to 2020: (a) forest; (b) grassland; (c) urban; and (d) different land cover types. Net radiation, latent heat, sensible heat, and heat storage are distinguished by different line styles and markers; anthropogenic heat is additionally shown for the urban land cover type. Panel (d) compares mean net radiation, latent heat, and sensible heat among the three land cover types, with white, light-gray, and dark-gray bars representing forest, grassland, and urban, respectively. Error bars indicate standard deviations.

Storage. For urban areas, an additional term, anthropogenic heat (such as traffic heat, building heat, and others), is included, making the energy balance equation $\text{Net Radiation} + \text{Anthropogenic Heat} = \text{Latent Heat} + \text{Sensible Heat} + \text{Heat Storage}$.

In terms of net radiation, the highest values are found in forest areas, followed by grasslands, with the lowest values in urban areas. Net radiation is highest in summer and lowest in winter. For latent heat, forests have the highest values, followed by grasslands, with the lowest in urban areas. Moreover, the reduction in latent heat in urban areas is much more significant compared to grasslands and forests. This corresponds to lower ET in urban land use types compared to forests and grasslands. For sensible heat, the average values between forests, grasslands, and urban areas are not significantly different. However, both forests and grasslands show lower sensible heat in summer (June, July, and August; JJA), while urban areas experience higher sensible heat in summer and lower in winter. Regarding anthropogenic heat in urban areas, including heat from traffic and buildings, the values are higher in winter compared to summer. Moreover, the Bowen Ratio (sensible heat flux/ latent heat flux), is commonly used to describe the partitioning of energy in surface energy balance. We found that urban areas had the highest Bowen Ratio values (> 1), indicating sensible heat dominates over latent heat, with lower evaporation. Forest areas had the lowest Bowen Ratio values (< 1), indicating latent heat dominates the energy balance, accompanied by higher evaporation rates.

The water balance equation is $\text{Precipitation} = \text{ET} + \text{Runoff} + \Delta \text{ Soil water} + \Delta \text{ Groundwater}$. For the three different land use

and land cover types, the precipitation values are essentially consistent. In terms of ET, forests have the highest values, followed by grasslands, with urban areas having the lowest. Moreover, the reduction in ET for urban areas is greater than that for forests and grasslands. Runoff is highly correlated with precipitation, meaning that when precipitation is high, runoff values also increase. For runoff, due to the larger impervious surface areas in urban areas, the runoff in urban areas is higher than in forests and grasslands. Regarding soil water, its changes are inversely proportional to ET. When ET is high in the growing season, water uptake from the soil results in reduced soil moisture. Therefore, similar to ET, the seasonal variations in soil moisture are greater in forests and grasslands than in urban areas. As for groundwater, the changes across the three land use types are relatively small.

Discussion

Diagnostic Assessment of Runoff Simulation and Model Applicability

Our results provide a diagnostic assessment of how CoLM-U represents annual runoff across multiple watersheds, with clear watershed-to-watershed differences that reflect both forcing uncertainties and structural limitations when applying a regional land surface model at small watershed scales. The simulations capture the broad magnitude in some watersheds, but exhibit pronounced seasonal biases, systematically underestimating winter runoff and

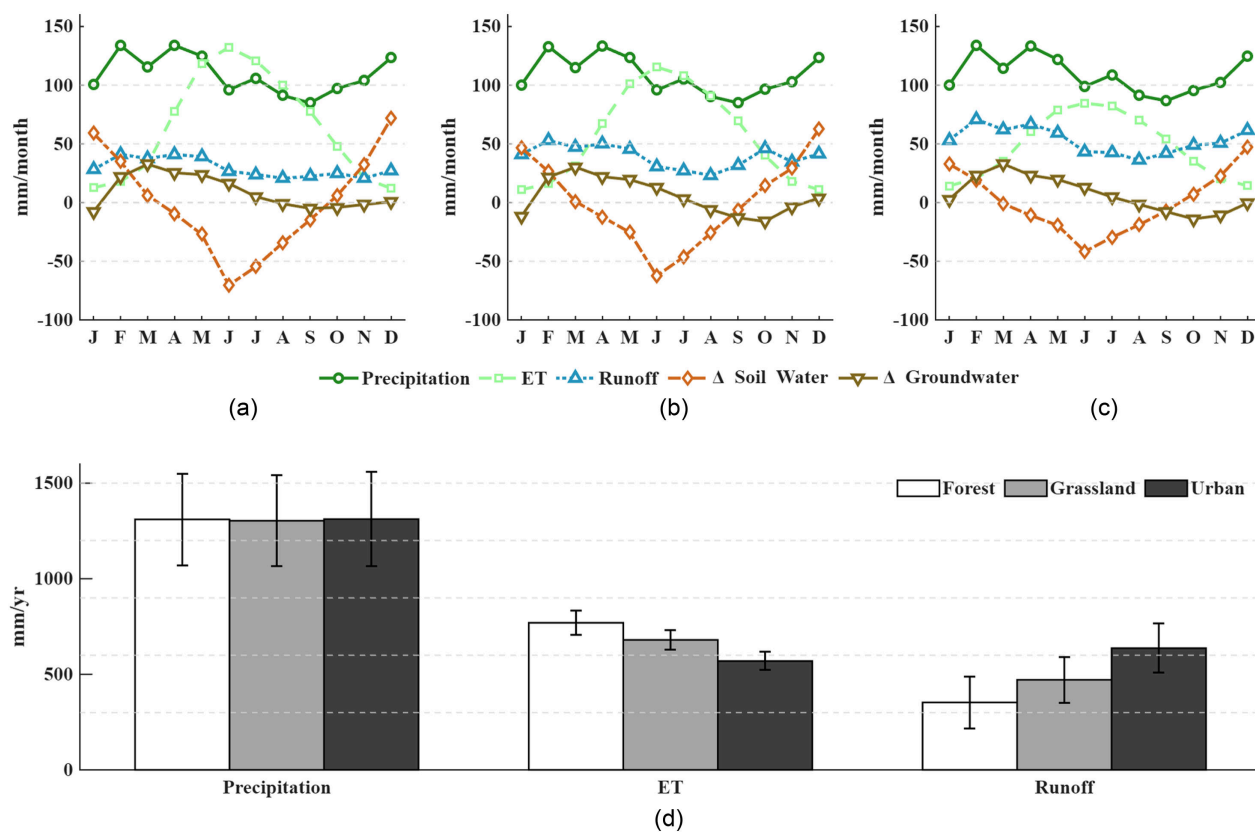


Fig. 13. Monthly variation of water cycle variables across three land cover types from 2000 to 2020: (a) forest; (b) grassland; (c) urban; and (d) different land cover types. Precipitation, evapotranspiration (ET), runoff, changes in soil water, and changes in groundwater are distinguished by different line styles and markers. Panel (d) compares annual mean precipitation, ET, and runoff among the three land cover types, with white, light-gray, and dark-gray bars representing forest, grassland, and urban, respectively. Error bars indicate standard deviations.

overestimating summer runoff. For winter runoff simulation uncertainties, since winter ET values are relatively low, the primary cause of these discrepancies is likely due to inaccuracies in the impervious surfaces and the simulation of soil water storage (Brocca et al. 2008; Chen et al. 2011a). In CoLM-U, the current threshold-based ponding approach for impervious grids may fail to represent delayed drainage or snowmelt contributions, further amplifying winter runoff errors.

Conversely, summer runoff overestimation may stem from underestimations of ET, implying a need for improved parameterization of vegetation dynamics under high-temperature conditions (Allen et al. 1998; Du et al. 2017). Given that ET is relatively high in summer, inaccuracies in runoff simulations are likely due to a combination of errors in ET modeling and the representation of impervious surfaces and soil water storage (Li and Bou-Zeid 2014; Yang et al. 2015).

Extreme precipitation events pose an additional challenge for CoLM-U, as evidenced by its inability to capture the 2010 flood event in Nashville. This limitation highlights the sensitivity of land surface models to reanalysis-based precipitation inputs, which often underestimate extreme rainfall intensities (Huffman et al. 2007). Our findings suggest that such errors propagate strongly into urban runoff estimates due to the rapid hydrological response of impervious surfaces. Notably, two watersheds (Watersheds 4 and 5) exhibit persistently larger runoff discrepancies that cannot be fully explained by precipitation forcing uncertainty alone. These watersheds are characterized by hydrogeological and hydraulic conditions, such as karst drainage and downstream backwater effects that are not explicitly represented in a general regional land surface model.

Consequently, the runoff behavior in these watersheds is interpreted as reflecting limitations in model applicability under complex local conditions, rather than as evidence of overall model failure.

In addition, several urban-specific model limitations are critical for advancing urban land surface modeling: (1) The lack of explicit urban drainage systems in CoLM-U-U likely contributes to excessive surface runoff during storms. Current runoff treatment assumes simplified threshold-based surface storage without engineered drainage representation. (2) Urban vegetation (e.g., street trees, lawns, green roofs) is treated in a highly simplified manner, potentially underestimating local ET and evaporative cooling in semi-pervious grids. (3) Anthropogenic heat fluxes are parameterized using globally uniform values. Incorporating region-specific data (e.g., local energy consumption, traffic intensity) could improve energy flux simulations in urban areas.

Importantly, our methodology that integrates in situ runoff data and satellite-based ET estimates at the small watershed scale demonstrates how multisource validation can uncover model weaknesses that are often obscured in large-scale, energy-only assessments. These insights point toward specific model development needs and can guide future efforts to enhance urban hydrology modeling in process-based LSMs.

This study also represents one of the first systematic hydrological evaluations of the recently updated CoLM-U model, complementing recent model development and comprehensive evaluation studies (Yuan et al. 2026; Dong et al. 2026). While previous evaluations of LSM urban modules have focused predominantly on energy-related variables due to the scarcity of long-term hydrological observations in urban areas, our work explicitly incorporates in

situ runoff measurements from five small watersheds in the humid southeastern United States. This multiscale validation framework, from watershed-to-regional scale, provides unique insights into how a regional-scale land surface model performs at fine hydrological scales. The primary objective of this evaluation was not to maximize statistical performance, but to conduct a diagnostic assessment under real-world urban–rural transitional conditions, thereby identifying process-level strengths and weaknesses. By revealing process-level biases and their potential causes, this evaluation offers both empirical benchmarks for future CoLM-U development and a foundation for scenario-based studies of urban hydrology and climate adaptation.

Comparison of ET Estimates at the Regional Scale: CoLM-U versus SSEBop

Our comparison of CoLM-U-simulated ET with SSEBop-derived ET reveals systematic differences between these two approaches. These differences may be linked to assumptions embedded in the remote sensing retrieval (e.g., reliance on potential ET and surface temperature) and to structural choices in the process-based model (e.g., soil moisture and canopy interception representation), as well as differences in spatial resolution (CoLM-U ~ 500 m versus SSEBop ~ 1 km) in heterogeneous urban–rural landscapes. Importantly, SSEBop is not treated here as an objective ground truth; rather, it is used as a widely adopted, spatially continuous reference that enables diagnosis of systematic discrepancies in ET magnitude and seasonality between satellite-based and process-based approaches.

Differences in spatial resolution, CoLM-U (~ 500 m) versus SSEBop (~ 1 km), may also contribute to discrepancies, especially in heterogeneous urban–rural transitional areas (Fisher et al. 2020). Prior studies have emphasized that finer resolutions improve the ability to capture localized ET variations, particularly where mixed land covers exist (Zhu et al. 2022). Our results suggest that CoLM-U better resolves land use–specific ET differences, further supporting the utility of high-resolution, process-based models for urban climate applications.

Nevertheless, spatial biases remain in the CoLM-U-simulated ET, especially in urban areas where LULCC input resolution and representation of urban vegetation are critical. These limitations underscore the importance of using more detailed land cover datasets and dynamic vegetation modeling to improve ET spatial estimates. Future research could explore hybrid approaches that integrate remote sensing products with physically based models, particularly in complex urban environments where microclimatic effects are pronounced (Jalilvand et al. 2019; Wu et al. 2020).

Energy and Water Balance Variations across Land Cover Types

The analysis of energy and water balances across forests, grasslands, and urban areas highlights distinct land cover–driven differences. Forests exhibit the highest net radiation and latent heat fluxes, leading to enhanced ET and lower surface temperatures. In contrast, urban areas, with impervious surfaces and reduced vegetation cover, experience suppressed latent heat fluxes and elevated sensible heat, contributing to the UHI effect (Li et al. 2019). These results align with prior studies on urban climate dynamics but further quantify the extent of these differences using process-based modeling (Zhao et al. 2021; Liu et al. 2025).

Our findings are consistent with studies conducted in other humid regions. Studies in the southeastern US show that urban areas consistently exhibit higher surface temperatures and reduced

ET and higher runoff (Boggs and Sun 2011; Li et al. 2020) due to extensive impervious surfaces (Niyogi et al. 2017; Diem et al. 2018, 2021, 2023). Similarly, studies in southeastern China cities reveal that forests and urban green spaces significantly mitigate heat accumulation and improve moisture retention (Wu et al. 2024; Zhang et al. 2024). These parallels reinforce the importance of vegetation in regulating urban climates under humid conditions.

Our study results show that runoff dynamics exhibit strong land cover dependencies in addition to climate. Urban areas generate significantly more runoff than other land uses due to reduced ET and infiltration, whereas forests promote ET, infiltration, and groundwater recharge. Our simulations show urbanized basins have both higher runoff ratios and flashier hydrographs. Studies in humid coastal cities, such as Shanghai, southern China, highlight the role of urbanization in exacerbating stormwater runoff, particularly during extreme precipitation events (Wang et al. 2012). Additionally, research has shown that urban forests can significantly reduce stormwater runoff and delay peak flows (Kuehler et al. 2017; Downton et al. 2023) by enhancing infiltration. Our simulation study also suggests that vegetation ET is important in affecting water balances at both monthly and annual scales.

Model Uncertainties and Future Improvements

One important source of uncertainty in our CoLM-U simulations lies in the quality and resolution of the atmospheric forcing data. Among the available products, ERA5-Land stands out as the most suitable option, providing relatively high spatial resolution (~ 9 km), hourly temporal coverage, and extensive validation across diverse climates (Dee et al. 2011; Muñoz-Sabater et al. 2021). However, the spatial resolution of ERA5-Land is still insufficient to fully resolve fine-scale landscape heterogeneity in urban areas, especially in regions with a mix of impervious surfaces and urban vegetation. This limitation likely contributes to some of the mismatches we observed between modeled and observed runoff and evapotranspiration, particularly at the watershed scale. Future improvements could involve bias-correcting ERA5-Land data using local weather station observations.

In addition to atmospheric forcing, land cover representation remains a critical challenge. This study relies on MODIS-IGBP land cover data with 500-m resolution, which are widely used but may not adequately resolve urban spatial heterogeneity such as small green patches, narrow water channels, or mixed surface types (Weng 2012). Employing higher-resolution land use products (e.g., Landsat-derived or local cadastral data) and incorporating urban vegetation structures, such as distinguishing between trees, shrubs, lawns, and green roofs, could improve the realism of CoLM-U's surface characterization (Chen et al. 2018).

Uncertainties arise from the model structure itself, especially in representing hydrological and energy exchange processes. While CoLM-U provides a comprehensive framework, several key urban-specific processes are simplified or omitted. One notable limitation is that CoLM-U does not explicitly simulate urban drainage infrastructure, such as stormwater pipes, retention ponds, or combined sewer systems. Instead, it assumes a uniform maximum water ponding depth (1 kg/m^2) for impervious surfaces, beyond which excess water becomes immediate surface runoff. This simplification likely leads to overestimation of runoff timing and magnitude, especially during short-duration high-intensity storms. This perhaps explains some of the runoff biases observed in urbanized watersheds when compared with USGS streamflow data. Incorporating simplified urban drainage schemes could improve model realism.

Additionally, CoLM-U assumes homogeneous impervious surface properties within urban grids, neglecting the diversity of

infiltration capacities and thermal behaviors across different surface materials. The anthropogenic heat flux parameterization also uses generalized global values and does not account for region-specific energy use or urban morphology, which can substantially alter the local energy balance. Refining these structural elements, particularly for urban land surface processes, is essential for improving CoLM-U's application in urban climate and hydrology studies (Fletcher et al. 2013).

Uncertainties in model parameters present a significant challenge. The sensitivity of CoLM-U to key hydrological and thermal parameters, such as soil hydraulic conductivity, canopy resistance, and land surface albedo, influences simulation accuracy. Variations in soil infiltration rates and plant transpiration coefficients can lead to discrepancies in simulated runoff and evapotranspiration. Future work should include parameter calibration and sensitivity analysis to better constrain key hydrological and thermal parameters (Wang et al. 2014, 2016, 2020, 2021).

Implications for Water Management and Climate Adaptation and Research Limitations

This study provides new insights into how land cover types, particularly urban vegetation and impervious surfaces, affect the spatial and temporal dynamics of water and energy balances. Our findings highlight the importance of urban forests as green infrastructure in mitigating UHI effects and improving stormwater management. These results reinforce the value of integrating NbS into urban planning to enhance sustainability and resilience in the city (Roy et al. 2012; Di Leo et al. 2016).

This study demonstrates that land surface models such as CoLM-U can be useful tools for simulating the hydrological and thermal impacts of urbanization. By validating CoLM-U against both in situ runoff observations and remote sensing-based ET estimates, we show that process-based models can capture key urban hydroclimatic dynamics even though model performance is strongly influenced by data resolution and structural assumptions, especially in highly developed or semipervious urban areas.

In the context of environmental adaptation to land use change, our approach also provides a modeling framework that can support scenario-based assessments of future urban growth, land use transitions, and changing climatic conditions (Mees et al. 2012). For example, simulations that test varying levels of urban vegetation, impervious surfaces, or anthropogenic heat emissions can inform design thresholds and infrastructure priorities under climate stress. Future work could couple CoLM-U with urban growth and climate scenarios to evaluate adaptation strategies.

While this study offers valuable contributions, several research limitations remain. First, our simulations are limited to the Nashville region, which may limit generalizability to other climatic or geographic contexts. Second, although the study covers a 21-year period (2000–2020), longer-term simulations incorporating future climate scenarios would be beneficial for adaptation planning (IPCC 2021). Third, while this study focuses on CoLM-U and validates ET against SSEBop, comparative evaluations with other urban-capable models (e.g., WRF-Urban, Noah-MP) would provide a more comprehensive understanding of model uncertainties and performance differences (Li et al. 2013). Expanding such inter-model comparisons is an important direction for future research.

Finally, the limitations identified in this study, particularly the lack of explicit urban drainage modeling and simplified representation of urban vegetation, offer clear directions for future model development. Improving the representation of these processes and integrating locally calibrated anthropogenic heat and land cover inputs could substantially enhance the usefulness of land surface models for urban sustainability applications.

Conclusions

This study conducted a diagnostic and applicability assessment of the regional land surface model CoLM-U in representing local energy and water balance dynamics across different land cover types in a humid southeastern region of the United States. The model reproduced the broad magnitude and spatial contrasts of ET, runoff, and energy fluxes. However, important seasonal mismatches and watershed-to-watershed modeling bias revealed both atmospheric forcing uncertainties and structural limitations when a regional land surface model is applied at small watershed scales. Our study suggests that forests can reduce stormwater runoff and sensible heat through elevated ET and infiltration in the growing season compared to grass and urban land uses. By contrast, urban land covers dominated by impervious surfaces with sparse vegetation led to lower ET and higher sensible heat, exacerbating UHI effects.

This study suggests that land surface models like CoLM-U could be valuable tools for understanding water and energy balances in a mixed land use setting and thus provide useful information guiding future climate-resilient urban planning. However, further model development, such as integrating high-resolution data and improving representations of extreme events and urban vegetation covers, is needed to enhance predictive accuracy and applicability. Implementing these improvements will enable CoLM-U to more reliably capture urban water and energy balance processes, thereby strengthening its role in supporting sustainable urban planning and effective climate adaptation strategies.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Author Contributions

Chen Wang: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing – original draft. Yujuan Chen: Conceptualization; Data curation; Funding acquisition; Investigation; Project administration; Resources; Supervision; Writing – review and editing. Steven G. McNulty: Funding acquisition; Supervision; Writing – review and editing. De'Etra Young: Data curation; Supervision; Writing – review and editing. Marcus Williams: Conceptualization; Methodology; Supervision; Writing – review and editing. Thomas Byl: Methodology; Supervision; Writing – review and editing. Anjin Chang: Data curation; Investigation; Methodology; Supervision; Writing – review and editing. Wenzong Dong: Investigation; Methodology; Software; Writing – review and editing. Hua Yuan: Investigation; Methodology; Software; Writing – review and editing. Ge Sun: Conceptualization; Formal analysis; Investigation; Project administration; Resources; Supervision; Validation; Writing – review and editing.

References

- Allen, L., F. Lindberg, and C. S. B. Grimmond. 2011. "Global to city scale urban anthropogenic heat flux: Model and variability." *Int. J. Climatol.* 31 (13): 1990–2005. <https://doi.org/10.1002/joc.2210>.
- Allen, R. G., L. S. Pereira, D. Raes, and M. Smith. 1998. *Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56*. Rome: Food and Agriculture Organization.
- Arnfield, A. J. 2003. "Two decades of urban climate research: A review of turbulence, exchanges of energy and water, and the urban heat island." *Int. J. Climatol.* 23 (1): 1–26. <https://doi.org/10.1002/joc.859>.
- Boggs, J. L., and G. Sun. 2011. "Urbanization alters watershed hydrology in the Piedmont of North Carolina." *Ecohydrology* 4 (2): 256–264. <https://doi.org/10.1002/eco.198>.
- Bowler, D. E., L. Buyung-Ali, T. M. Knight, and A. S. Pullin. 2010. "Urban greening to cool towns and cities: A systematic review of the empirical evidence." *Landscape Urban Plann.* 97 (3): 147–155. <https://doi.org/10.1016/j.landurbplan.2010.05.006>.
- Brocca, L., F. Melone, and T. Moramarco. 2008. "On the estimation of antecedent wetness conditions in rainfall-runoff modeling." *Hydrol. Processes: Int. J.* 22 (5): 629–642. <https://doi.org/10.1002/hyp.6629>.
- Chen, D., N. Liu, G. Gan, Y. Liu, M. Qin, Q. Zheng, G. Sun, and L. Hao. 2024. "Combined effects of urbanization and climate variability on water and carbon balances in a rice paddy-dominated basin in southern China." *Environ. Res. Lett.* 19 (12): 124042. <https://doi.org/10.1088/1748-9326/ad8a73>.
- Chen, F., W. T. Crow, P. J. Starks, and D. N. Moriasi. 2011a. "Improving hydrologic predictions of a catchment model via assimilation of surface soil moisture." *Adv. Water Resour.* 34 (4): 526–536. <https://doi.org/10.1016/j.advwatres.2011.01.011>.
- Chen, F., et al. 2011b. "The integrated WRF/urban modelling system: Development, evaluation, and applications to urban environmental problems." *Int. J. Climatol.* 31 (2): 273–288. <https://doi.org/10.1002/joc.2158>.
- Chen, J., et al. 2015. "Global land cover mapping at 30 m resolution: A POK-based operational approach." *ISPRS J. Photogramm. Remote Sens.* 103 (May): 7–27. <https://doi.org/10.1016/j.isprsjprs.2014.09.002>.
- Chen, Y., D. Lu, L. Luo, Y. Pokhrel, K. Deb, J. Huang, and Y. Ran. 2018. "Detecting irrigation extent, frequency, and timing in a heterogeneous arid agricultural region using MODIS time series, Landsat imagery, and ancillary data." *Remote Sens. Environ.* 204 (Jan): 197–211. <https://doi.org/10.1016/j.rse.2017.10.030>.
- Coutts, A. M., J. Beringer, and N. J. Tapper. 2007. "Impact of increasing urban density on local climate: Spatial and temporal variations in the surface energy balance in Melbourne, Australia." *J. Appl. Meteorol. Climatol.* 46 (4): 477–493. <https://doi.org/10.1175/JAM2462.1>.
- Dai, Y., H. Yuan, Q. Xin, D. Wang, W. Shanguan, S. Zhang, S. Liu, and N. Wei. 2019. "Different representations of canopy structure—A large source of uncertainty in global land surface modeling." *Agric. For. Meteorol.* 269 (May): 119–135. <https://doi.org/10.1016/j.agrformet.2019.02.006>.
- Dai, Y., et al. 2003. "The common land model." *Bull. Am. Meteorol. Soc.* 84 (8): 1013–1024. <https://doi.org/10.1175/BAMS-84-8-1013>.
- Dee, D. P., et al. 2011. "The ERA-Interim reanalysis: Configuration and performance of the data assimilation system." *Q. J. R. Meteorolog. Soc.* 137 (656): 553–597. <https://doi.org/10.1002/qj.828>.
- Di Leo, N., F. J. Escobedo, and M. Dubbeling. 2016. "The role of urban green infrastructure in mitigating land surface temperature in Bobo-Dioulasso, Burkina Faso." *Environ. Dev. Sustainability* 28 (1): 373–392. <https://doi.org/10.1007/s10668-015-9653-y>.
- Diem, J. E., D. K. Carlton, and L. A. Pangle. 2023. "Evapotranspiration from developed land and urban watersheds in a humid subtropical climate." *Water Resour. Res.* 59 (10): e2023WR035276. <https://doi.org/10.1029/2023WR035276>.
- Diem, J. E., T. C. Hill, and R. A. Milligan. 2018. "Diverse multi-decadal changes in streamflow within a rapidly urbanizing region." *J. Hydrol.* 556 (Jan): 61–71. <https://doi.org/10.1016/j.jhydrol.2017.10.026>.
- Diem, J. E., L. A. Pangle, R. A. Milligan, and E. A. Adams. 2021. "Intra-annual variability of urban effects on streamflow." *Hydrol. Process.* 35 (9): e14371. <https://doi.org/10.1002/hyp.14371>.
- Dobson, J. E., E. A. Bright, P. R. Coleman, R. C. Durfee, and B. A. Worley. 2000. "LandScan: A global population database for estimating populations at risk." *Photogramm. Eng. Remote Sens.* 66 (7): 849–857.
- Dong, W., et al. 2026. "A new 3D urban building community model for earth system modeling: Data and comprehensive evaluation." *ESS Open Archive*. Preprint, submitted February 6, 2026. <https://doi.org/10.22541/essoar.177038857.72796534/v>.
- Dong, W., H. Yuan, W. Lin, Z. Liu, J. Xiang, Z. Wei, L. Li, Q. Li, and Y. Dai. 2025. "A global urban tree leaf area index dataset for urban climate modeling." *Sci. Data* 12 (1): 426. <https://doi.org/10.1038/s41597-025-04729-y>.
- Dowtin, A. L., B. C. Cregg, D. J. Nowak, and D. F. Levia. 2023. "Towards optimized runoff reduction by urban tree cover: A review of key physical tree traits, site conditions, and management strategies." *Landscape Urban Plann.* 239 (Nov): 104849. <https://doi.org/10.1016/j.landurbplan.2023.104849>.
- Du, J., J. S. Kimball, L. A. Jones, Y. Kim, J. Glassy, and J. D. Watts. 2017. "A global satellite environmental data record derived from AMSR-E and AMSR2 microwave earth observations." *Earth Syst. Sci. Data* 9 (2): 791–808. <https://doi.org/10.5194/essd-9-791-2017>.
- Fisher, J. B., et al. 2020. "ECOSTRESS: NASA's next generation mission to measure evapotranspiration from the international space station." *Water Resour. Res.* 56 (4): e2019WR026058. <https://doi.org/10.1029/2019WR026058>.
- Fisher, R. A., and C. D. Koven. 2020. "Perspectives on the future of land surface models and the challenges of representing complex terrestrial systems." *J. Adv. Model. Earth Syst.* 12 (4): e2018MS001453. <https://doi.org/10.1029/2018MS001453>.
- Fletcher, T. D., H. Andrieu, and P. Hamel. 2013. "Understanding, management and modelling of urban hydrology and its consequences for receiving waters: A state of the art." *Adv. Water Resour.* 51 (Jan): 261–279. <https://doi.org/10.1016/j.advwatres.2012.09.001>.
- Grimm, N. B., S. H. Faeth, N. E. Golubiewski, C. L. Redman, J. Wu, X. Bai, and J. M. Briggs. 2008. "Global change and the ecology of cities." *Science* 319 (5864): 756–760. <https://doi.org/10.1126/science.1150195>.
- Grimmond, C. S. B. 2006. "Progress in measuring and observing the urban atmosphere." *Theor. Appl. Climatol.* 84 (1): 3–22. <https://doi.org/10.1007/s00704-005-0140-5>.
- Hao, L., et al. 2015. "Urbanization dramatically altered the water balances of a paddy field-dominated basin in southern China." *Hydrol. Earth Syst. Sci.* 19 (7): 3319–3331. <https://doi.org/10.5194/hess-19-3319-2015>.
- Hao, L., X. Huang, M. Qin, Y. Liu, W. Li, and G. Sun. 2018. "Ecohydrological processes explain urban dry island effects in a wet region, southern China." *Water Resour. Res.* 54 (9): 6757–6771. <https://doi.org/10.1029/2018WR023002>.
- Hersbach, H., et al. 2020. "The ERA5 global reanalysis." *Q. J. R. Meteorolog. Soc.* 146 (730): 1999–2049. <https://doi.org/10.1002/qj.3803>.
- Huang, X., L. Hao, G. Sun, Z. L. Yang, W. Li, and D. Chen. 2022. "Urbanization aggravates effects of global warming on local atmospheric drying." *Geophys. Res. Lett.* 49 (2): e2021GL095709. <https://doi.org/10.1029/2021GL095709>.
- Huffman, G. J., D. T. Bolvin, E. J. Nelkin, D. B. Wolff, R. F. Adler, G. Gu, Y. Hong, K. P. Bowman, and E. F. Stocker. 2007. "The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales." *J. Hydrometeorol.* 8 (1): 38–55. <https://doi.org/10.1175/JHM560.1>.
- IPCC (Intergovernmental Panel on Climate Change). 2021. "Climate change 2021: The physical science basis." In *Proc., Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva: IPCC.
- Jalilvand, E., M. Tajrishy, S. A. G. Z. Hashemi, and L. Brocca. 2019. "Quantification of irrigation water using remote sensing of soil moisture in a semi-arid region." *Remote Sens. Environ.* 231 (Sep): 111226. <https://doi.org/10.1016/j.rse.2019.111226>.

- Karsisto, P., C. Fortelius, M. Demuzere, C. S. B. Grimmond, K. W. Oleson, R. Kouznetsov, V. Masson, and L. Järvi. 2016. "Seasonal surface urban energy balance and wintertime stability simulated using three land-surface models in the high-latitude city Helsinki." *Q. J. R. Meteorol. Soc.* 142 (694): 401–417. <https://doi.org/10.1002/qj.2659>.
- Kourzeneva, E., H. Asensio, E. Martin, and S. Faroux. 2012. "Global gridded dataset of lake coverage and lake depth for use in numerical weather prediction and climate modeling." *Tellus A: Dyn. Meteorol. Oceanogr.* 64 (1): 15640. <https://doi.org/10.3402/tellusa.v64i0.15640>.
- Kuehler, E., J. Hathaway, and A. Tirpak. 2017. "Quantifying the benefits of urban forest systems as a component of the green infrastructure stormwater treatment network." *Ecohydrology* 10 (3): e1813. <https://doi.org/10.1002/eco.1813>.
- Lang, N., W. Jetz, K. Schindler, and J. D. Wegner. 2023. "A high-resolution canopy height model of the Earth." *Nat. Ecol. Evol.* 7 (11): 1778–1789. <https://doi.org/10.1038/s41559-023-02206-6>.
- Lawrence, P. J., and T. N. Chase. 2007. "Representing a new MODIS consistent land surface in the Community Land Model (CLM 3.0)." *J. Geophys. Res. Biogeosci.* 112 (G1): G01023. <https://doi.org/10.1029/2006JG000168>.
- Li, C., H. Lu, K. Yang, J. S. Wright, L. Yu, Y. Chen, X. Huang, and S. Xu. 2017. "Evaluation of the common land model (CoLM-U) from the perspective of water and energy budget simulation: Towards inclusion in CMIP6." *Atmosphere* 8 (8): 141. <https://doi.org/10.3390/atmos8080141>.
- Li, C., G. Sun, P. V. Caldwell, E. Cohen, Y. Fang, Y. Zhang, L. Oudin, G. M. Sanchez, and R. K. Meentemeyer. 2020. "Impacts of urbanization on watershed water balances across the conterminous United States." *Water Resour. Res.* 56 (7): e2019WR026574. <https://doi.org/10.1029/2019WR026574>.
- Li, D., and E. Bou-Zeid. 2014. "Quality and sensitivity of high-resolution numerical simulation of urban heat islands." *Environ. Res. Lett.* 9 (5): 055001. <https://doi.org/10.1088/1748-9326/9/5/055001>.
- Li, D., W. Liao, A. J. Rigden, X. Liu, D. Wang, S. Malyshev, and E. Shevliakova. 2019. "Urban heat island: Aerodynamics or imperviousness?" *Sci. Adv.* 5 (4): eaau4299. <https://doi.org/10.1126/sciadv.aau4299>.
- Li, H., M. S. Wigmosta, H. Wu, M. Huang, Y. Ke, A. M. Coleman, and L. R. Leung. 2013. "A physically based runoff routing model for land surface and earth system models." *J. Hydrometeorol.* 14 (3): 808–828. <https://doi.org/10.1175/JHM-D-12-015.1>.
- Li, Y., X. Yuan, and Q. Zhuang. 2024. "An optimal ensemble of the CoLM-U for simulating the carbon and water fluxes over typical forests in China." *J. Environ. Manage.* 356 (Apr): 120740. <https://doi.org/10.1016/j.jenvman.2024.120740>.
- Lin, W., H. Yuan, W. Dong, S. Zhang, S. Liu, N. Wei, X. Lu, Z. Wei, Y. Hu, and Y. Dai. 2023. "Reprocessed MODIS version 6.1 leaf area index dataset and its evaluation for land surface and climate modeling." *Remote Sens.* 15 (7): 1780. <https://doi.org/10.3390/rs15071780>.
- Liu, H., M. Li, C. Yang, and L. Jia. 2025. "Application of time-series analysis to urban climate change assessment." *Int. J. Environ. Sci. Technol.* 22 (12): 11037–11044. <https://doi.org/10.1007/s13762-024-05961-6>.
- Macdonald, R., R. Griffiths, and D. Hall. 1998. "An improved method for the estimation of surface roughness of obstacle arrays." *Atmos. Environ.* 32 (11): 1857–1864. [https://doi.org/10.1016/S1352-2310\(97\)00403-2](https://doi.org/10.1016/S1352-2310(97)00403-2).
- Macdonald, R. W. 2000. "Modelling the mean velocity profile in the urban canopy layer." *Boundary Layer Meteorol.* 97 (1): 25–45. <https://doi.org/10.1023/A:1002785830512>.
- Mees, H. L., P. P. Driessen, and H. A. Runhaar. 2012. "Exploring the scope of public and private responsibilities for climate adaptation." *J. Environ. Plann. Policy Manage.* 14 (3): 305–330. <https://doi.org/10.1080/1523908X.2012.707407>.
- Muñoz-Sabater, J., et al. 2021. "ERA5-Land: A state-of-the-art global reanalysis dataset for land applications." *Earth Syst. Sci. Data* 13 (9): 4349–4383. <https://doi.org/10.5194/essd-13-4349-2021>.
- Niyogi, D., M. Lei, C. Kishtawal, P. Schmid, and M. Shepherd. 2017. "Urbanization impacts on the summer heavy rainfall climatology over the eastern United States." *Earth Interact.* 21 (5): 1–17. <https://doi.org/10.1175/EI-D-15-0045.1>.
- Nowak, D. J., D. E. Crane, and J. C. Stevens. 2006. "Air pollution removal by urban trees and shrubs in the United States." *Urban For. Urban Greening* 4 (3–4): 115–123. <https://doi.org/10.1016/j.ufug.2006.01.007>.
- Oleson, K. W., and J. Feddema. 2019. "Parameterization and surface data improvements and new capabilities for the Community Land Model Urban (CLMU)." *J. Adv. Model. Earth Syst.* 12 (Oct): e2018MS001586. <https://doi.org/10.1029/2018MS001586>.
- Pataki, D. E., M. M. Carreiro, J. Cherrier, N. E. Grulke, V. Jennings, S. Pincetl, R. V. Pouyat, T. H. Whitlow, and W. C. Zipperer. 2011. "Coupling biogeochemical cycles in urban environments: Ecosystem services, green solutions, and misconceptions." *Front. Ecol. Environ.* 9 (1): 27–36. <https://doi.org/10.1890/090220>.
- Roy, S., J. Byrne, and C. Pickering. 2012. "A systematic quantitative review of urban tree benefits, costs, and assessment methods across cities in different climatic zones." *Urban For. Urban Greening* 11 (4): 351–363. <https://doi.org/10.1016/j.ufug.2012.06.006>.
- Senay, G. B., G. E. L. Parrish, M. Schauer, M. Friedrichs, K. Khand, O. Boiko, S. Kagone, R. Dittmeier, S. Arab, and L. Ji. 2023. "Improving the operational simplified surface energy balance evapotranspiration model using the forcing and normalizing operation." *Remote Sens.* 15 (1): 260. <https://doi.org/10.3390/rs15010260>.
- Sexton, J. O., et al. 2013. "Global, 30-m resolution continuous fields of tree cover: Landsat-based rescaling of MODIS vegetation continuous fields with lidar-based estimates of error." *Int. J. Digital Earth* 6 (5): 427–448. <https://doi.org/10.1080/17538947.2013.786146>.
- Shangguan, W., Y. Dai, Q. Duan, B. Liu, and H. Yuan. 2014. "A global soil data set for earth system modeling." *J. Adv. Model. Earth Syst.* 6 (1): 249–263. <https://doi.org/10.1002/2013MS000293>.
- Simard, M., N. Pinto, J. B. Fisher, and A. Baccini. 2011. "Mapping forest canopy height globally with spaceborne lidar." *J. Geophys. Res. Biogeosci.* 116 (G4): G04021. <https://doi.org/10.1029/2011JG001708>.
- Solecki, W. D., C. Rosenzweig, L. Parshall, G. Pope, M. Clark, J. Cox, and M. Wiencke. 2005. "Mitigation of the heat island effect in urban New Jersey." *Global Environ. Change Part B: Environ. Hazards* 6 (1): 39–49. <https://doi.org/10.1016/j.hazards.2004.12.002>.
- Sulla-Menashe, D., J. Gray, S. Abercrombie, and M. Friedl. 2019. "Hierarchical mapping of annual global land cover 2001 to present: The MODIS collection 6 land cover product." *Remote Sens. Environ.* 222 (Mar): 183–194. <https://doi.org/10.1016/j.rse.2018.12.013>.
- Sun, G., et al. 2026. "Large streamflow differences between forested and urbanized watersheds in the energy-limited eastern United States: The role of evapotranspiration and impervious surfaces." *Water Resour. Res.* 62 (2): e2025WR041340. <https://doi.org/10.1029/2025WR041340>.
- Synoptic Data. n.d. "Data download tool." Accessed August 30, 2026. <https://download.synopticdata.com/>.
- United Nations. 2019. "World urbanization prospects: The 2018 revision." ST/ESA/SER.A/420. New York: Dept. of Economic and Social Affairs, Population Division.
- USGS. 2017. "StreamStats." Accessed August 10, 2026. <https://streamstats.usgs.gov/ss/>.
- USGS. 2019. "National Water Information System (NWIS) Mapper." Accessed August 10, 2026. <https://maps.waterdata.usgs.gov/mapper/nwisquery.html>.
- Voogt, J. A., and T. R. Oke. 2003. "Thermal remote sensing of urban climates." *Remote Sens. Environ.* 86 (3): 370–384. [https://doi.org/10.1016/S0034-4257\(03\)00079-8](https://doi.org/10.1016/S0034-4257(03)00079-8).
- Wang, C., et al. 2020. "Assessing the sensitivity of land-atmosphere coupling strength to boundary and surface layer parameters in the WRF model over Amazon." *Atmos. Res.* 234 (Apr): 104738. <https://doi.org/10.1016/j.atmosres.2019.104738>.
- Wang, C., Q. Duan, W. Gong, A. Ye, Z. Di, and C. Miao. 2014. "An evaluation of adaptive surrogate modeling-based optimization with two benchmark problems." *Environ. Modell. Software* 60 (Oct): 167–179. <https://doi.org/10.1016/j.envsoft.2014.05.026>.
- Wang, C., Q. Duan, C. H. Tong, Z. Di, and W. Gong. 2016. "A GUI platform for uncertainty quantification of complex dynamical models." *Environ. Modell. Software* 76 (Feb): 1–12. <https://doi.org/10.1016/j.envsoft.2015.11.004>.

- Wang, C., Y. Qian, Q. Duan, M. Huang, Z. Yang, L. K. Berg, W. Gustafson, Z. Feng, J. Liu, and J. Quan. 2021. "Quantifying physical parameterization uncertainties associated with land-atmosphere interactions in the WRF model over Amazon." *Atmos. Res.* 262 (Nov): 105761. <https://doi.org/10.1016/j.atmosres.2021.105761>.
- Wang, J., W. Gao, S. Xu, and L. Yu. 2012. "Evaluation of the combined risk of sea level rise, land subsidence, and storm surges on the coastal areas of Shanghai, China." *Clim. Change* 115 (Dec): 537–558. <https://doi.org/10.1007/s10584-012-0468-7>.
- Wang, Y. R., D. O. Hessen, B. H. Samset, and F. Stordal. 2022. "Evaluating global and regional land warming trends in the past decades with both MODIS and ERA5-Land land surface temperature data." *Remote Sens. Environ.* 280 (Oct): 113181. <https://doi.org/10.1016/j.rse.2022.113181>.
- Weng, Q. 2009. "Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends." *ISPRS J. Photogramm. Remote Sens.* 64 (4): 335–344. <https://doi.org/10.1016/j.isprsjprs.2009.03.007>.
- Weng, Q. 2012. "Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends." *Remote Sens. Environ.* 117 (Feb): 34–49. <https://doi.org/10.1016/j.rse.2011.02.030>.
- Willems, P., K. Arnbjerg-Nielsen, J. Olsson, and V. T. V. Nguyen. 2012. "Climate change impact assessment on urban rainfall extremes and urban drainage: Methods and shortcomings." *Atmos. Res.* 103 (Jan): 106–118. <https://doi.org/10.1016/j.atmosres.2011.04.003>.
- Wu, B., Y. Zhang, Y. Wang, Y. He, J. Wang, Y. Wu, X. Lin, and S. Wu. 2024. "Mitigation of urban heat island in China (2000–2020) through vegetation-induced cooling." *Sustainable Cities Soc.* 112 (Oct): 105599. <https://doi.org/10.1016/j.scs.2024.105599>.
- Wu, W. Y., M. H. Lo, Y. Wada, J. S. Famiglietti, J. T. Reager, P. J. F. Yeh, A. Ducharme, and Z. L. Yang. 2020. "Divergent effects of climate change on future groundwater availability in key mid-latitude aquifers." *Nat. Commun.* 11 (1): 3710. <https://doi.org/10.1038/s41467-020-17581-y>.
- Xu, J., Z. Ma, S. Yan, and J. Peng. 2022. "Do ERA5 and ERA5-land precipitation estimates outperform satellite-based precipitation products? A comprehensive comparison between state-of-the-art model-based and satellite-based precipitation products over mainland China." *J. Hydrol.* 605 (Feb): 127353. <https://doi.org/10.1016/j.jhydrol.2021.127353>.
- Yang, J., Z. H. Wang, F. Chen, S. Miao, M. Tewari, J. A. Voogt, and S. Myint. 2015. "Enhancing hydrologic modelling in the coupled weather research and forecasting–urban modelling system." *Boundary Layer Meteorol.* 155 (Apr): 87–109. <https://doi.org/10.1007/s10546-014-9991-6>.
- Yuan, H., W. Dong, S. Liu, S. Zhang, Z. Liu, N. Wei, X. Lu, Z. Wei, X. X. Li, and Y. Dai. 2026. "A new 3D urban building community model for earth system modeling: Model formulation and evaluation." *ESS Open Archive*. Preprint, submitted February 6, 2026. <https://doi.org/10.22541/essoar.177038865.50600890/v1>.
- Zhang, H., M. Y. Kang, Z. R. Guan, R. Zhou, A. L. Zhao, W. J. Wu, and H. R. Yang. 2024. "Assessing the role of urban green infrastructure in mitigating summertime Urban Heat Island (UHI) effect in metropolitan Shanghai, China." *Sustainable Cities Soc.* 112 (Oct): 105605. <https://doi.org/10.1016/j.scs.2024.105605>.
- Zhao, L., K. Oleson, E. Bou-Zeid, E. S. Krayenhoff, A. Bray, Q. Zhu, Z. Zheng, and M. Oppenheimer. 2021. "Global multi-model projections of local urban climates." *Nat. Clim. Change* 11 (2): 152–157. <https://doi.org/10.1038/s41558-020-00958-8>.
- Zhou, D., S. Zhao, L. Zhang, G. Sun, and Y. Liu. 2015. "The footprint of urban heat island effect in China." *Sci. Rep.* 5 (1): 11160. <https://doi.org/10.1038/srep11160>.
- Zhu, Z., S. Qiu, and S. Ye. 2022. "Remote sensing of land change: A multifaceted perspective." *Remote Sens. Environ.* 282 (Dec): 113266. <https://doi.org/10.1016/j.rse.2022.113266>.