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A decadal review of the CREST model family: Developments, applications, and outlook

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ABSTRACT

Hydrologic models are a powerful tool to predict water-related natural hazards. Of all hydrologic models, CREST (Coupled Routing and Excess STorage) was developed to facilitate hydrologic sciences and applications across various spatial and temporal scales. The CREST model was the earliest implementation of a quasi-global flood model integrating remote-sensing data and is the first operational deployment of a real-time model in the National Weather Service functioning at flash flood scales across a continent. Since being published in 2011, the CREST model has been evolving to empower flood predictions and to inform water resources management practices. Moreover, the CREST model is convenient to couple with other models/schemes (e.g., weather forecast model, snowmelt model, land surface model, hydrodynamic model, groundwater model, landslide model, vector-based routing) for border practices of investigating water-related natural hazards. To date its 10th anniversary, more than 80 peer-reviewed journal articles that have used the CREST model are curated and reviewed from the aspects of model development, worldwide applications, and outreach to emerging regions. Finally, the future directions for the CREST model family are outlined in the hope of stimulating new research endeavors. A digital collection of CREST model family is archived online at https://crest-family.readthedocs.io/en/latest/.

1. Introduction

Floods are one of the most devastating and deadliest natural hazards across the globe. About 1.6 billion people were affected during 2000–2019, the highest figure of all disasters (UNDRR, 2020). A growing number of people have been exposed to flood risks for the last two decades, as revealed by satellite images (Tellman et al., 2021). There was a median of 81 flood fatalities per year from 1959 to 2005 (Ashley and Ashley, 2008), and almost ten percent of the flash floods have resulted in agricultural and economic losses beyond $100,000 USD per event (Gourley et al., 2017; Li et al., 2021a). In a warmer climate, floods in the US are becoming 7.9% flashier (higher magnitude and shorter rising time), leaving less response time for people at risk (Li et al., 2022a, Li et al., 2022b).

The advent of remote sensing technology has dramatically revolutionized traditional hydrological simulation, transforming it into a scale-independent process. This technology provides comprehensive and high-resolution spatial–temporal data, including meteorological factors, soil moisture, and land-use characteristics, serving as critical inputs for hydrologic simulation models (Schmugge et al., 2002). As such, the

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reliance on in-situ data has significantly reduced. By leveraging remote sensing technology, we can now access a more holistic view of hydrological systems, enabling a shift towards more accurate, data-rich, and reliable flood forecasting models (Hong et al., 2007). In this new paradigm, the Coupled Routing and Excess STorage (CREST) model stands as a seminal innovation. The CREST developed at the University of Oklahoma (OU) and National Aeronautics and Space Administration (NASA), is a distributed hydrologic model that resolves water re-distribution across spatial and temporal scales (Wang et al., 2011; Li, 2022a). Conceived with the specific primary objective of facilitating global flood forecasting, the CREST model integrates seamlessly with remote sensing data. This paves the way for the first-ever global streamflow simulation powered by the real-time satellite precipitation product - Tropical Rainfall Measuring Mission (TRMM) operated by NASA (Wu et al., 2012). Since its success in its global application, a testament to its efficacy and robustness, CREST model was later coupled with the National Mosaic Quantitative Precipitation Estimation system in the US (now called the Multi-Radar Multi-Sensor system), achieving kilometers scale streamflow prediction across a continent. Today, the CREST model is the first real-time model operationally deployed at the National Weather Service, functioning at flash flood scales (kilometer and sub-hourly) across the continent, which includes the entire US and outer territories. It makes a significant milestone in flood prediction and management. Several capacity building projects were carried out in emerging counties in Africa for addressing their local flood risks (Clark et al., 2017). The CREST model's proven success demonstrates the transformative potential of integrating traditional hydrologic models with remote sensing in the realm of flood forecasting, paving the way for more advanced and effective flood applications globally. Additionally, CREST model has not only revolutionized flood forecasting but also stimulated the development of a multi-hazard and multi-scale framework by facilitating coupling with an array of other environmental models. These include weather forecast model, land surface model, landslide model, hydrodynamic model, groundwater model, etc (Chen et al., 2022b; Li et al., 2022a). This integration approach acknowledges the interconnectedness and cascading effects of various natural hazards, creating a comprehensive, systems-based model that accurately mirrors the complexity of real-world environmental phenomena. This approach,

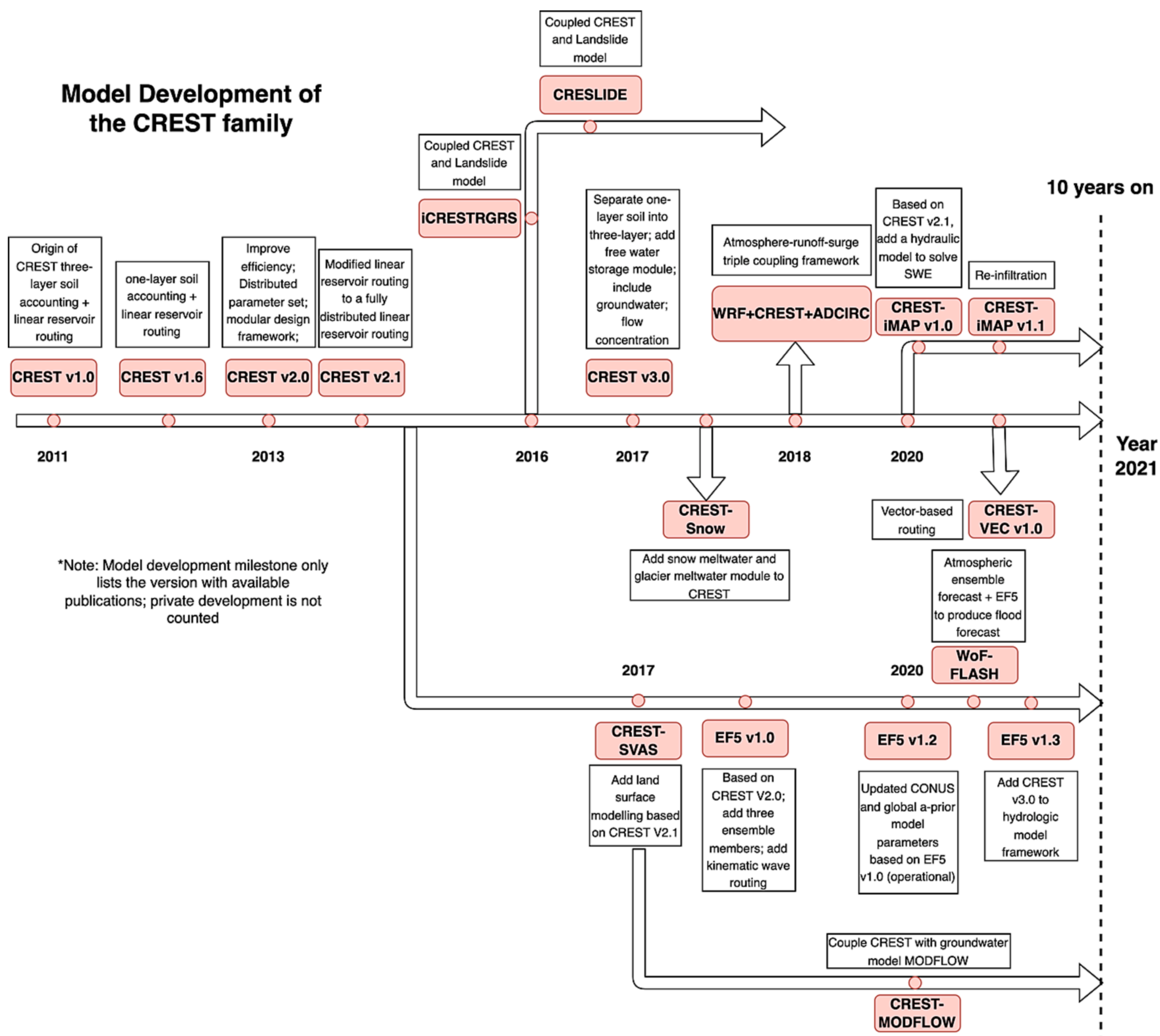

Fig. 1. Evolution of the family of CREST models.

made possible by the technological advancements embodied in the CREST model, heralds a new era in multi-hazard disaster management, moving towards a future where the devastating impacts of natural hazards can be better predicted, managed, and mitigated (Kappes et al., 2012).

As the CREST model was announced in 2011, we review the development of CREST and its applications to water-related issues over the past decade in the following sections (see Fig. 1). To date (July 2022), CREST has been widely accepted by the community, and 87 + publications have used the CREST model family for a range of applications, including 3,524 citations in total (data from Google Scholar). We collected those papers through the keyword search “CREST hydrologic model” and applied manual inspection to filter non-relevant ones. Fig. 2 highlights the time series of publications and citation numbers for the CREST model family, indicating a prevailing trend in recent years (peaking in 2017). In the following sections, we follow the chronological order and focus on the model core, which is the main package to reveal the relative changes to the source. At last, we summarize the limitations and provide outlooks for the CREST model family in terms of new components to be considered for development.

2. CREST model evolution

There have been three significant version upgrades of CREST since 2011 - CREST v1.0 (Wang et al., 2011), CREST v2.0 (Xue et al., 2013), CREST v2.1 (Shen et al., 2017), and CREST v3.0 (Kan et al., 2017). The building blocks for the mass balance component of CREST are conceptual “bucket” models at each grid cell to represent the spill-fill nature of water storage and movement (McDonnell et al., 2021). Fig. 3 depicts the evolution of the CREST model structure in these iterations. Overall, CREST v1.0 has three-layer soil and incorporated linear reservoir routing; followed by CREST v1.6, CREST v2.0 enhanced model efficiency with advanced calibration schemes; CREST v3.0 added a groundwater component to extend model capacity.

2.1. CREST version 1.x

CREST v1.x represents the major version v1 and minor versions v1.0 and v1.6. The software packages were written in FORTRAN 95 and C. It features three important characteristics: 1) distributed rainfall-runoff generation process and cell-to-cell routing, 2) coupled routing and runoff generation mechanisms, and 3) sub-grid variability of soil moisture capacity (Wang et al., 2011). CREST has featured a seamless integration of distributed rainfall and runoff process, making it unique to readily accommodate these distributed forcings. The atmospheric forcing, the deficit of rainfall and evaporation, encounters the canopy layer whose capacity (Canopy Interception Capacity - *CIC*) is parameterized as a linear function of the Leaf Area Index (*LAI*), vegetation coverage (*d*), and a coefficient of land cover (k_c) (Dickinson, 1989). The canopy layer acts as a simple excess storage reservoir that receives whatever rainfall comes through. Then the remaining water P_{soil}, if $CI > CIC$, infiltrates into soil layers along with incoming interflow (SS) from upstream cells.

$$CIC = k_c \times d \times LAI \tag{1}$$

$$P_{soil} = P - (CI - CIC) \tag{2}$$

where CI is the intercepted water in the canopy.

The Variable Infiltration Curve (VIC) describes water partitioning in soils, which is a classic method originally formulated in the Xinanjiang model (Zhao, 1992) and adopted by the University of Washington VIC model (Liang et al., 1996). In CREST v1.0, three soil layers are incorporated to characterize upper (0–0.5 m), lower (0.5–2 m), and deeper (greater than2 m) soils. The infiltration process is mathematically represented by the following equations (Eqs. 3–5).

$$i = i_m[1 - (1 - A)^{1/b_i}] \tag{3}$$

$$i_m = W_m(1 + b_i) \tag{4}$$

$$W_m = W_{m1} + W_{m2} + W_{m3} \tag{5}$$

where i is the point infiltration capacity while i_m is the maximum infiltration capacity, A is the fractional area of the cell, and b_i is the exponent of the curve. W_m is the maximum soil tension water capacity which is the sum of tension water capacity at three soil layers: W_{m1}, W_{m2}, W_{m3}. The infiltrated water (*I*) is the deficit of maximum soil water capacity (W_m) and the soil water state (*W*), if available soil water P_{soil} plus point infiltration capacity (*i*) is larger than maximum infiltration capacity (i_m). Otherwise, it follows the exponent function shown in. Eq. (6).

$$I = W_m\left[1 - \frac{i + P_{soil}}{i_m}\right]^{1+b_i}, i + P_{soil} < i_m \tag{6}$$

To be noted, since CREST v1.6, the three-layer soil columns have been reduced to one layer (see Fig. 3). The one bulk soil layer in lieu of three layers is attempting to represent soils within five meters of the surface. The rationale behind this is threefold: (1) to ease data preparation; (2) to reduce the number of model parameters, especially those that are not readily linked to observations; (3) and to speed up model implementation. The previous parameterization in the VIC model (Eqs. 3–6) has changed to Eq. (7), thereby reducing the number of parameters in the VIC model from 7 to 3.

$$i = i_{max} \times [1 - (1 - W/W_m)^{1/B}] \tag{7}$$

The runoff generation in CREST v1.x is primarily based upon excess saturation runoff in which interflow is produced from the ratio of excess rain (*R*) and soil water (P_{soil}) and soil hydraulic conductivity (*K*) (Eqs. 8–10). The overland runoff (*RS*) is the deficit of excess rain (*R*) and interflow (*SS*).

$$R = P_{soil} - I \tag{8}$$

$$SS = K\frac{R}{P_{soil}} \tag{9}$$

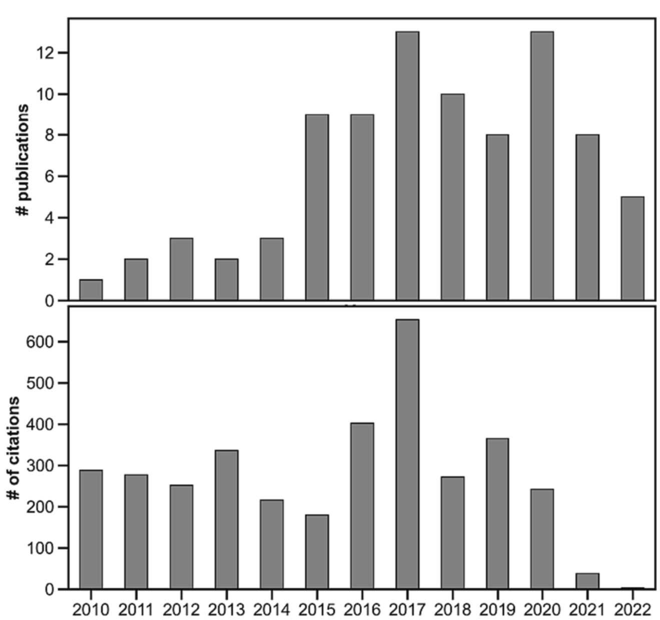

Fig. 2. Time series of the number of publications and citations. We curated papers and citations from Google Scholar, as well as manual inspection to sift through relevant ones.

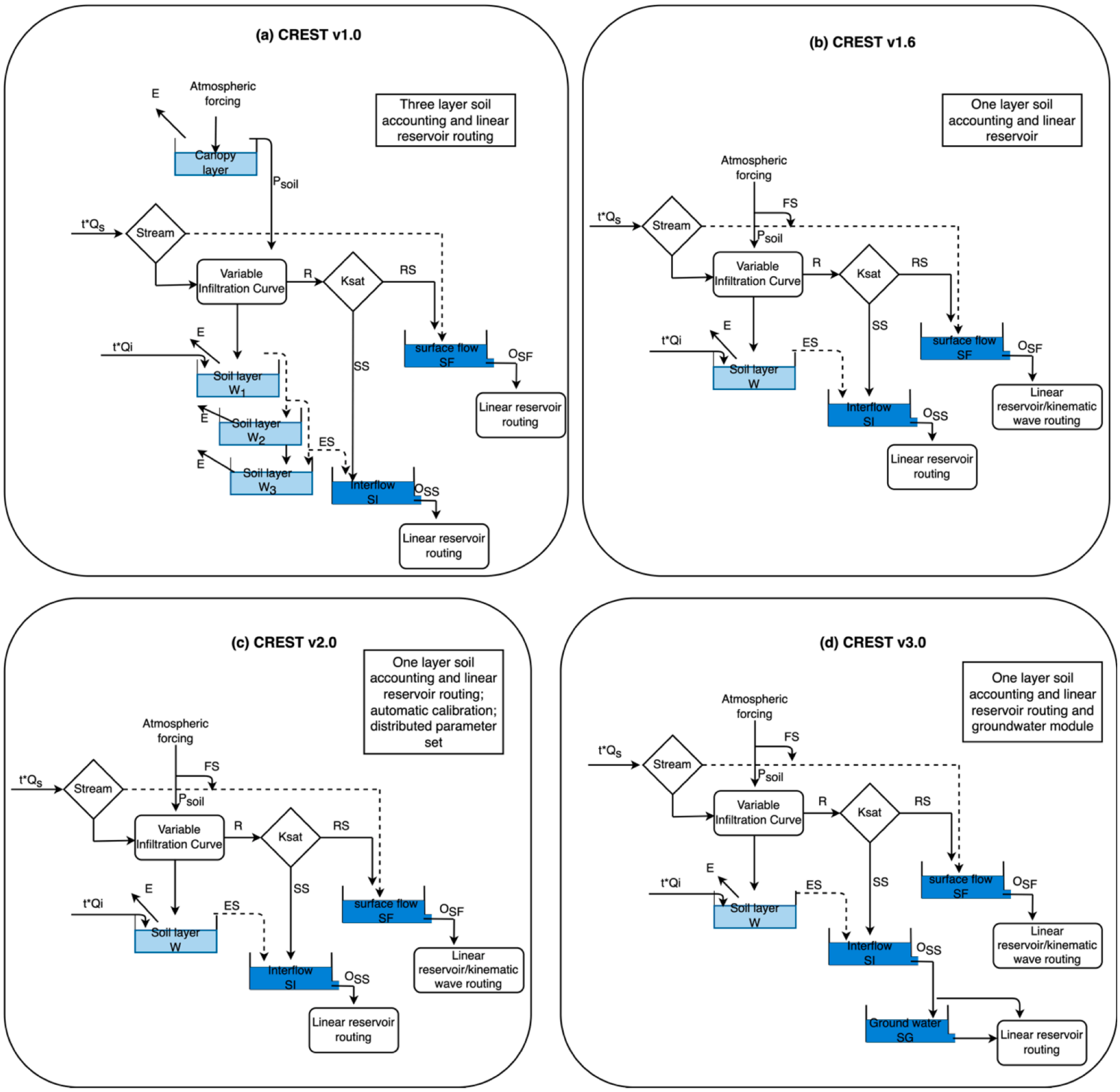

Fig. 3. Model structure of three versions of CREST model: (a) CREST v1.0, (b) CREST v1.6, (c) CREST v2.0, and (d) CREST v3.0.

$$RS = R - SS \tag{10}$$

The potential evapotranspiration (PET) value is required as a direct input to CREST v1.x, which is the maximum amount of water that can potentially be evaporated, determined by atmospheric conditions (such as temperature, wind, radiation, etc.). The actual evaporation is calculated by distributing PET in canopy and soil layers. The rule of redistribution is based on successive depletion (from canopy to soil) and water depth in each bucket. First, it assesses whether the amount of water in the canopy layer is enough for PET. If so, ET is derived entirely from canopy water through transpiration. Otherwise, soil water contributes to the remaining part via evaporation. ET in the shallow soil layer (first layer) is similar to the canopy layer based on the depletion rule (Eq. (11), as they both are open and directly connected to the air. If the first soil layer and canopy layer jointly cannot fulfil the PET demand, the second and/or third soil layers start to contribute based on an exponential separation until it is completely depleted.

$$E_p = E_r\sqrt{\frac{W}{W_m}} \tag{11}$$

where E_p is evaporation in the second or third soil layer, and E_r is the deficit of PET and canopy layer plus first soil layer evaporation.

The routing scheme in the original CREST model is based on linear reservoirs applied to surface flow and subsurface flow with different parameterizations. The linear reservoir scheme accounts for sub-grid-scale routing, meaning that the grid spacing of DEM does not impact routing results. It makes the CREST model scalable and especially suitable for global applications (Wu et al., 2012). The surface flow reservoir (SF) at time t + 1 receives upstream flow (Q_s) at time t and excess surface runoff (RS) and produces outflow (O_{SF}) for downstream routing. The interflow reservoir (SI) receives subsurface flow (SS) and deep soil spill flow (ES), if any. Equations 12–14 represent these two processes in first-order approximated Ordinary Differential Equation (ODE) which advances in time. For in-channel routing, we calculate the time of concentration at *j*th pixel (T^j) with Eq. (15), given the distance grid (l^j) and slope grid (S^j) as input and runoff velocity coefficient K_X as a parameter. From there, we can solve how many grid cells' runoff at the *j*th pixel can advance within a given time step. Finally, the discharge (Q) equals the sum of surface runoff and subsurface runoff multiplied by drainage area (A) and divided by time step (Δt) (Eq. (16).

$$\frac{dS_t}{dt} = P - E_a + \sum(Q_{O,in} - Q_{O,out}) + \sum(Q_{I,in} - Q_{I,out}) \quad (12)$$

$$SF_{t+1} = SF_t + RS_t + Q_s \times \Delta t \quad (13)$$

$$SI_{t+1} = SI_t + SS_t + ES_t \quad (14)$$

$$T^j = \frac{l^j}{K_X\sqrt{S^j}} \quad (15)$$

$$Q_{t+1} = (SF_{t+1} + SI_{t+1}) \times \frac{A}{\Delta t} \quad (16)$$

Some minor updates have been released, such as CREST v1.6, which has become more readily suited for both basin-scale (Khan et al., 2011) and global-scale applications (Wu et al., 2012). The input parameters are derived from soil survey data, land cover maps, and vegetation coverage. Notably, the CREST v1.x considers lumped parameters (Table 1) which are averaged over the study domain.

2.2. CREST version 2.x

2.2.1. CREST v2.0

Xue et al. (2013) introduced the next generation of the CREST model – CREST v2.0, written in FORTRAN and featuring more advanced options. The paradigm has been shifted thereafter towards fast implementation and is dedicated to operational flood systems. Thus, several major changes have been made to the previous generation, including: (1) model implementation with options of either spatially uniform, semi-distributed, or distributed parameter values, (2) including impervious area ratio parameter to emulate fast runoff generation, (3) including a rainfall multiplier parameter to mitigate the impact of rainfall bias on hydrologic predictions, (4) automatic calibration using the SCE-UA algorithm (Duan et al., 1992), (5) parallel computing, (6) modular design framework and enhancement of the computation capability using FORTRAN matrix operation to make the model more efficient.

Table 1
Inputs and parameters used in CREST v1.x.

Symbols	Description	Source	Unit
Model inputs			
P	Gridded rainfall data	Remote sensing, weather/climate model, and gauges	mm/ timestep
PET	Gridded potential evaporation data	Remote sensing, weather/climate model, and gauges	mm/ timestep
LAI	Leaf Area Index	Remote sensing	m^2/m^2
DEM	Digital Elevation Model	Remote sensing/ survey	M
FDIR	Flow direction	Derived from DEM	N/A
FAC	Flow Accumulation	Derived from DEM	Cells or km^2
S	Slope	Derived from DEM	Degree
l	Distance between cells	Derived from DEM	M
Model parameters			
W_{m1}	Maximum soil water capacity at soil layer 1	Soil survey	mm
W_{m2}	Maximum soil water capacity at soil layer 2	Soil survey	mm
W_{m3}	Maximum soil water capacity at soil layer 3	Soil survey	mm
b_1	Exponent parameter of the VIC model at soil layer 1	Soil survey	N/A
b_2	Exponent parameter of the VIC model at soil layer 2	Soil survey	N/A
b_3	Exponent parameter of the VIC model at soil layer 3	Soil survey	N/A
Ksat	Mean saturated hydraulic conductivity	Soil survey	mm/hr
d	Vegetation coverage	Remote sensing	N/A
coeM	The overland runoff velocity coefficient	N/A	N/A
expM	The overland flow speed exponent	N/A	N/A
coeR	The multiplier used to convert overland flow to channel flow speed	N/A	N/A
coeS	The multiplier used to convert overland flow speed to interflow speed	N/A	N/A
K_S	Surface runoff velocity coefficient	N/A	m/s
K_I	Subsurface runoff velocity coefficient	N/A	m/s

Satellite precipitation products, in particular, can exhibit bias because of systematic and random error due to instruments, infrequent sampling, and limitations of the algorithms, especially in the early stages of algorithmic development with TRMM (Li et al., 2020; Xue et al., 2013; Tang et al., 2016). To account for the systematic bias, Xue et al. (2013) introduced the *RainFact* parameter applied to remote sensing precipitation (Eq. (17). As such, it is a prerequisite to conducting a pre-analysis of the precipitation product in use to derive this parameter.

$$P_{rain} = RainFact \times P \quad (17)$$

where P_{rain} is the corrected rainfall rate at the ground.

CREST v1.x generates surface runoff based upon saturation excess runoff, which is not readily suited for an urban environment where pavement and the built-up environment can impede rainfall infiltration. On the other hand, flooding is devastating and disastrous in populated urban regions. Urbanization has proved to sharpen the response hydrograph – increasing the magnitude and reducing the flood-rising time (Smith et al., 2002; Yang et al., 2011; Zhang et al., 2018). It is of particular importance to consider such factors in an urban environment. In doing so, Xue et al. (2013) split P_{rain} into fast surface runoff (FS) and P_{soil} in Eqs. 18–19, where IM is the impervious area ratio (%). Higher IM leads to greater amounts of fast runoff.

$$FS = IM \times P_{rain} \quad (18)$$

$$P_{soil} = P_{rain} - FS \quad (19)$$

2.2.2. CREST v2.1

After CREST v2.0, Shen et al. (2017) published CREST v2.1, written in MATLAB, dedicated to improving the existing routing schemes. The proposed Fully Distributed Linear Reservoir Routing (FDLRR) scheme replaces the Quasi-Distributed Linear Reservoir Routing (QDLRR) in CREST v2.0. Specifically, the newer version addresses the underestimation of in-channel flow and discontinuous flow after storms because QDLRR only considers the donor-to-receiver relationship while ignoring water moving through the routing nodes between the donor node and receiver node. As pointed out by Shen et al. (2017), the QDLRR does not account for water continuity along river reaches, resulting in a substantial bias. Fig. 4 depicts the difference between the two schemes, where the newer version redistributes water along its pathway and thus conserves both mass and momentum. The Eq. (12) for discharge at the jth pixel has been modified to Eq. (20), where SF_{via} and SI_{via} are the surface runoff passing through node j.

$$Q^j = \frac{(SF_{out} + SI_{out})A_g + \sum SF_{via}A_g + \sum SI_{via}A_g}{\Delta t} \quad (20)$$

2.2.3. CREST version 3.x

CREST v3.0 adopted a conceptual groundwater model to further improve results, which makes it not only a flood-centric tool but also suitable for predicting water scarcity (Gao et al., 2021; Li et al., 2018).

The conceptual groundwater model inherits the classic fill-spill strategy, which is the current implementation in the US National Water Model (NWM) v2.1, as shwon in Fig. 5 (Towler et al., 2022). The

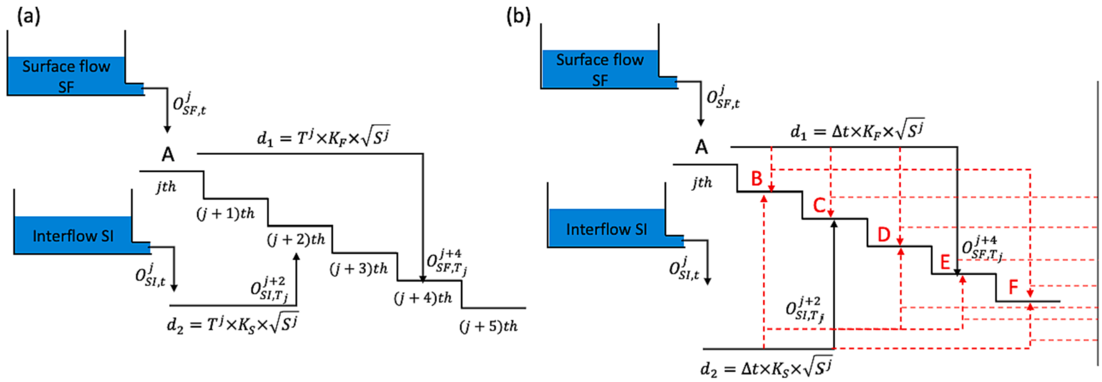

Fig. 4. Illustration of routing scheme in CREST v1.x/v2.0 (a) and v2.1 (b) with differences highlighted in red arrows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

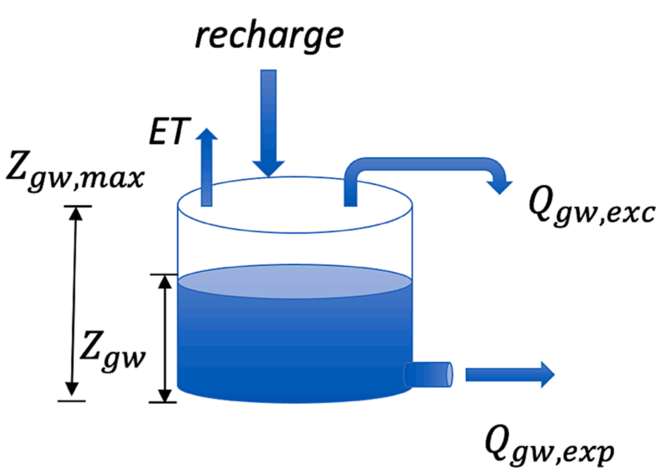

Fig. 5. A conceptual groundwater model used in CREST v3.0.

groundwater bucket receives recharge from the upper layer soil or vadose zone, while water simultaneously evaporates. The spill scheme generates lateral groundwater flow when the groundwater level (Z_{gw}) reaches its maximum level ($Z_{gw,max}$) in Eq. (21). The opening at the bottom of the bucket generates slow and continuous flow with Eq. (22), where parameter *GWC* is a multiplier, and *GWE* is an exponent factor. Compared to CREST v2.x, we added three parameters $Z_{gw,max}$, *GWC*, and *GWE*, which are inferred from aquifer depth or groundwater table data, if available.

$$Q_{gw,exc} = recharge + Z_{gw} - Z_{gw,max} \tag{21}$$

$$Q_{gw,exp} = GWC\left(\frac{Z_{gw}}{Z_{gw,max}} - 1\right)^{GWE} \tag{22}$$

Although there are several publications indicating the development of CREST v3.0 and its applications (Kan et al., 2017; Li et al., 2018), source code (developed by using C++) was not yet available for open access. This is because the version 3.0 model is still under development, and more modules such as soil water transport (by solving the Richards' equation numerically using the finite difference method), water-energy balance, and hydrodynamic routing (by solving the full dynamic wave-based Saint-Venant equations and shallow water equation numerically using the Godunov-type finite volume method) are continuously developed. This means that the further objective of v3.0 development is to improve the physical basis of the distributed hydrologic model.

3. Ensemble framework for flash flood forecasting (EF5)

Motivated by the efficiency, accuracy, and spatially distributed nature of the CREST model developments at a quasi-global scale, EF5 has been developed since 2012 as a joint effort by OU and NOAA/National Severe Storms Laboratory (NSSL) to supply meaningful forecasts of flash flooding at every pixel location in the US and outer territories. Since then, EF5 has become operational in the National Weather Service (NWS) in the US and has rapidly evolved tools and services for flash flood warnings issued by local NWS forecast offices (Clark et al., 2017; Gourley et al., 2017; Vergara et al., 2016). The code is written in C++ and works across common platforms, including Windows, Linux, and OS X/macOS (Flamig et al., 2020). The current version of EF5 (v1.3) supports nine different model configurations to adapt to a broader working environment, starting from the snowmelt model, to the water balance model, to the inundation scheme, as shown in Fig. 6.

The EF5 framework adopts a snow accumulation and ablation model (Snow-17) to parameterize the snow processes (Anderson, 1976, 2006). The Snow-17 model takes air temperature and precipitation as inputs to calculate energy and water exchange. The accumulation in snow cover happens when precipitation falls, and the air temperature drops below the freezing threshold. The energy exchange occurs between the snow-air interface to determine the melted water mass contributing to the runoff. Outflow from snowmelt is computed along with rain-on-snow.

The water balance modules in the EF5 framework include – CREST v2.0 (Xue et al., 2013), CREST v3.0, SAC-SMA (Koren et al., 2004), and a hydrophobic model to generate ensemble predictions. SAC-SMA is a classic hydrologic model used by the US NWS, which has been modified in EF5 to run in a spatially distributed mode. Readers are referred to Koren et al. (2004) and Yilmaz et al. (2008) for a detailed description of the SAC-SMA model. The hydrophobic model is the simplest model in EF5 that requires no land surface parameters, treating the surface as completely impervious. The essence of the hydrophobic model is to provide a "worst-case" scenario. Forecasters have also found it to be useful to define the upper envelope in ensemble hydrologic forecasts and to account for situations with biased rainfall forcing and highly impervious land covers such as burn scars.

EF5 includes two routing options: (1) linear reservoir routing and (2) kinematic wave routing. The kinematic wave model is a physically-based representation of the horizontal surface water movement over hillslopes and channels, which solves the Saint-Venant Equations of mass conservation and momentum conservation in Eqs.23–24.

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = 0 \tag{23}$$

$$\frac{1}{A}\frac{\partial Q}{\partial t} + \frac{1}{A}\frac{\partial}{\partial x}\frac{Q^2}{A} + g\frac{\partial y}{\partial x} - gS_0 + gS_f = 0 \tag{24}$$

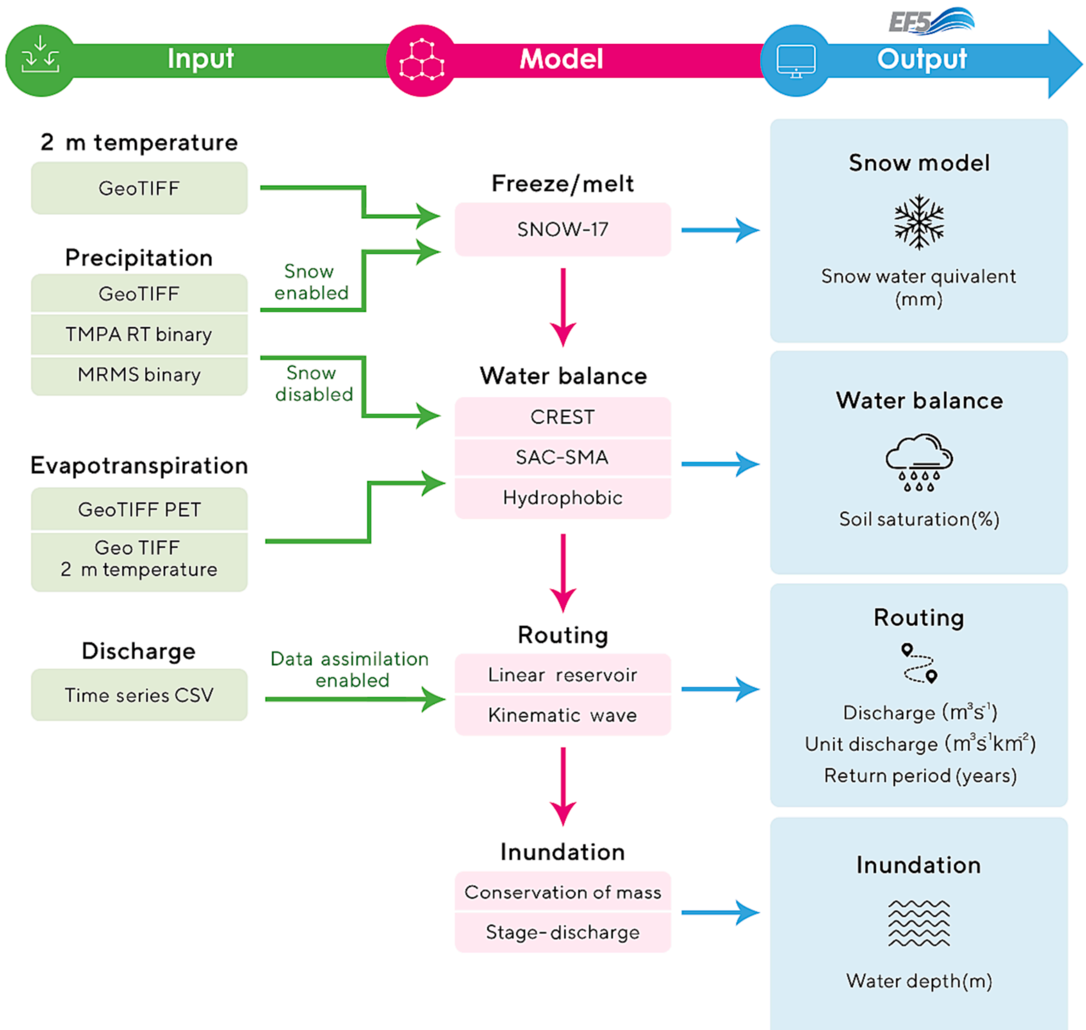

Fig. 6. Schematic view of the EF5 framework. It is adapted from Flamig et al. (2020) under the copyright Creative Common Attribution 4.0 License held by Copernicus Publications.

where Q is the volumetric flow, A is the cross-sectional area, x is longitudinal distance, y is the water depth, S_0 is the bottom slope, and S_f is the friction slope. The terms on the left-hand side of Eq. (24) represent local acceleration, convective acceleration, pressure force, gravity force, and friction force, respectively. Solving Eq. (24) in full constitutes the dynamic wave model for 1-D open channel flow. The kinematic wave model approximates the full solution neglecting the acceleration and forcing terms, leaving the gravity force and friction force to be balanced, to seek faster computational speed. Because it is assumed that flow is uniform and steady, Eq. (24) is finally simplified to Eq. (25), where the flow is dependent on cross-sectional area alone with parameters α and β. Substituting into Eq. (23), we arrive at the final form (Eq. (26) for the kinematic wave model used in EF5. The solution for Eq. (26) in EF5 is obtained through a non-linear finite-differences implicit scheme and Newton's numerical method (Chow et al., 1988): we used an iterative method to solve flow Q by substituting it repeatedly until it converges within a threshold.

$$Q = \alpha A^{\beta} \tag{25}$$

$$\frac{\partial Q}{\partial x} + \alpha\beta Q^{\beta-1}\frac{\partial Q}{\partial t} = inflow \tag{26}$$

To enhance flood hazard forecast capacity, two simple inundation mapping schemes were incorporated into EF5 – mass-conserving and stage-discharge model. The mass-conservation model utilizes the flow output and calculates the total river volume at a given time step for basins of interest. Then, the exact amount of water is redistributed by pouring it into the basin based on the DEM data. The stage-discharge model is dependent upon a rating curve that relates discharge to the river stage at the channel pixel using an exponential function. The river stage indicates the elevation in the DEM that is then compared to neighboring elevations to compute the spatial inundation map. The latter method, called Height Above Nearest Drainage (HAND; Nobre et al. 2011) is also adopted by the operational National Water Model v2.1 for generating flood inundation at large scales.

In addition to model structural developments, EF5 integrates several utilities to facilitate and improve simulation results. First, model calibration is a central component for hydrologic models, especially in cases where *a-priori* estimates of model parameters are not available for the study area. The Differential Evolution Adaptive Metropolis (DREAM) algorithm by Vrugt et al. (2008) was adopted in lieu of the SCE-UA algorithm used in CREST. The DREAM algorithm is an adaptive Markov Chain Monte Carlo (MCMC) algorithm that runs several chains in parallel to search for optimal parameter space. Second, a simple data assimilation module enables direct insertion of observed streamflow at a gauge location (i.e., nudging), serving as a boundary condition for hydrologic simulations.

4. Coupling with other models

4.1. Weather forecast model

Flash floods, a subtype of floods, are largely driven by rainfall from storms organized at mesoscale or storm scales (Merz et al., 2021; Ning et al., 2019). As such, coupling weather forecast models with hydrologic models hold great promise in predicting flood risks and protecting human lives and assets. A community model - Weather Research Forecast (WRF) - has been widely applied for short-term meteorological simulations. WRF is configurable with multiple physics, dynamics, and parameterizations to be applied under varying atmospheric conditions. It has served as the backbone for several US operational weather forecasts, such as the High-Resolution Rapid Refresh (HRRR) and Rapid Refresh (Dowell et al., 2022).

Blanton et al. (2020), for the first time, coupled WRF with CREST and the ADvanced CIRCulation (ADCIRC) storm surge, tide, and wind-wave model to generate ensemble predictions of winds, streamflow and inundation during Hurricane Isabel. The imperfect knowledge of model physics and parameterization schemes yields diverging results in precipitation and land surface components. In this study, they perturbed the model settings based on different initial conditions and physics schemes to output a series of streamflow values. It was found that the 6-day forecast generally captures the streamflow trends and peaks.

The NOAA Warn-on-Forecast (WoF)-FLASH program initiated an integrated framework to couple storm-scale numerical weather forecasts with the EF5 framework to generate probabilistic short-term flash flood predictions over the contiguous US in real-time (Yussouf et al., 2020). The experimental WoF uses 36 ensemble members with boundary conditions generated by the HRRR ensemble (HRRRE) at every hour and re-initializes the system to run every 15 mins. The WoF system assimilates readily available data such as the MRMS (Multi-Radar Multi-Sensor) radar reflectivity, radial velocity, cloud water path, and other meteorological observations (Jones et al., 2016). These probabilistic flash flood forecast products embrace the uncertain nature of weather forecasts and enable earlier detection of damaging flash floods in a systematic way.

4.2. Snowmelt model

The original implementation of snow processes in the CREST model is rather simplified, limiting its application in high-mountain regions such as the Rockies in the US and the third pole – Tibetan Plateau. Chen et al. (2017) introduced the snow-resolving version of the CREST model (CREST-Snow) that readily fills the gap. In the first stage, the total precipitation is separated into solid and liquid phases using a temperature threshold. Snowpack and glaciers accumulate with an increase in solid precipitation. The land surface receives melted water from the snowpack and glaciers in addition to the rainfall-runoff process.

As the hydrologic process becomes complex, more inputs and parameters are assigned therein. CREST-snow requires 19 parameters, nine of which are for the snowmelt and glacier melt process. In addition to precipitation data, CREST-snow necessitates remotely sensed air temperature for determining the precipitation phase and snow/glacier melting rates. It can be envisioned that model calibration is becoming challenging with many newly added parameters. Chen et al. (2017) proposed a two-stage calibration strategy: the snow parameters are calibrated in the first stage and then the others (e.g., Ksat and WM) in the second stage. The rationale behind this is that the snowmelt process is relatively independent of the rainfall-runoff process, and more importantly, there are intermediate observational states available for model calibration. For instance, the Snow Cover Area (SCA) and Snow Water Equivalent (SWE) can be retrieved from MODIS (Moderate Resolution Imaging Spectroradiometer) because of the high reflectance of snow. In doing so, the calibration burden is much alleviated.

4.3. Land surface model

One of the limitations of the CREST model, as compared to other land surface models such as Noah and Noah-MP models, is the simplified representation of land surface processes, especially for snow- and forest-covered regions where runoff generation mechanisms are more complex. Motivated by these challenges, Shen & Anagnostou (2017) introduced a framework to solve the full cycle of the Soil-Vegetation-Atmosphere-Snow process, named CREST-SVAS. CREST-SVAS generates runoff by solving coupled water and energy balances in a closed form. Correspondingly, more model inputs are required, such as radiation, temperature, wind, etc. In fact, CREST-SVAS pushed the envelope making the CREST model adaptable in different environments, including cold climates.

4.4. Hydrodynamic model

Although a simple inundation module based on water balance or HAND exists in the current CREST/EF5 framework, the flood dynamics are not adequately simulated because the module does not consider unsteady conditions. A coupling framework between the hydrologic model and hydrodynamic model (H&H model) has been promising for simulating complex flood dynamics and risk assessments (Sampson et al., 2015). On the one hand, hydrologic models provide accurate water balance over the land surface, which is compromised in traditional hydrodynamic models. On the other hand, the physically-based 2D or 3D routing in the hydrodynamic model readily resolves water distribution over land and channels, which overshadows the simplified routing process in hydrologic models (Teng et al., 2017). Li et al. (2021b) and Chen et al. (2021) promoted an H&H framework, termed CREST-iMAP (CREST inundation MApping and Prediction), by coupling the CREST model with the Anuga hydrodynamic model. Different from common one-way and offline coupling, the CREST-iMAP seamlessly integrates hydrologic and hydrodynamic simulations into a fully coupled mode. The most computationally demanding part (finite volume solver in Anuga) was written in C language, and the model interface including CREST was written in Python interface for readability and accessibility. The CREST-iMAP framework has been successfully demonstrated in the Houston region during Hurricane Harvey by comparing simulated streamflow, inundation extent, and water depth with USGS stream gauges, SAR-derived flood area, and USGS High Water Marks (Chen et al., 2021, Chen et al., 2022a; Li et al., 2021b; Sun et al., 2023). It is found that CREST-iMAP outperforms the CREST model regarding streamflow simulation, as kinematic wave routing in CREST typically encounters problems in flatter terrain (Flamig et al., 2020). It was also coupled with Quantitative Precipitation Forecast (QPF) data to hindcast Hurricane Harvey (Chen et al., 2022b). Similar to CREST-iMAP v1.0, the recent development of CREST-iMAP v1.1 renders two-way coupling, allowing re-infiltration or run-on infiltration processes to be activated in flood simulation (Li et al., 2022c). Such a process is corroborated to be nontrivial even in extreme flood cases such as Hurricane Harvey. Furthermore, the coupling of the water balance model with a hydrodynamic model was shown to improve the accuracy of inundation extent as compared to the simpler, DEM-based inundation models, sometimes referred to as "bathtub models".

4.5. Groundwater model

The simple conceptual groundwater (GW) module in the CREST model is subject to uncertainties in parameterizations, boundary conditions, and hydrologic stresses. In contrast, physical GW models offer more realistic simulations by solving physical governing equations. The MODFLOW (MODular 3-D finite-difference) model with NWT solver (a Newton-Raphson formulation) is promising in GW model communities, especially for its open interface to be coupled with other models. Khadim et al. (2020), for the first time, coupled the CREST model with

MODFLOW and applied it to the Blue Nile Basin in Ethiopia. The CREST model provides boundary conditions of recharge rate after infiltration and streamflow to force MODFLOW. They also manifest the deviation of GW depth simulated from the physical model and global conceptual model in the same region.

4.6. Landslide model

The CREST model has been extended throughout its decade of development to be coupled with other models for predicting water-related natural hazards. He et al. (2016) published a coupled hydrological-geotechnical framework for landslide prediction, called CRESLIDE (Coupled Routing Excess Storage and Slope-Infiltration-Distributed Equilibrium). They coupled the CREST model with the SLIDE model, which computes slope stability as a factor of safety. The relatively more accurate subsurface hydrologic variables from CREST were fed to the SLIDE model in an integrated way. CRESLIDE assumes shallow depth landslide and simplifies the infinite-slope equation. Later, Wang et al. (2020) further developed an effective and computationally efficient coupling method to couple the CREST model with the SLIDE model by downscaling coarser-resolution CREST soil moisture to a finer resolution to meet the input requirements of the SLIDE model.

Unlike the simplified landslide model mentioned above, Zhang et al. (2016b) coupled the CREST model with a process-based landslide model – Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability (TRIGRS), which uses the analytical Richard's equation to solve an infinite-slope equation, termed as iCRESTRIGRS. Similar to the SLIDE model, TRIGRS only provides a simple representation of soil infiltration and runoff generation. Placing the CREST model upstream of TRIGRS can better predict landslides, as both infiltration rates and runoff are nontrivial for landslide models. Though a loose coupling, the integrated system is seamlessly executed in a distributed manner at every time step. Specifically, this system takes distributed runoff and infiltration rates from the CREST model and passes them to TRIGRS to output pore-pressure and factor of safety for each grid cell.

4.7. CREST with vector-based routing

Real-time flood forecasting entails fast and accurate streamflow prediction at a continental scale or global scale, in which flow routing is a key factor in model efficiency and accuracy. At present, most operational flood prediction systems meet such timely requirements at the expense of resolving streamflow at coarse resolutions, namely at km scales (e.g., Flamig et al., 2020; Wu et al., 2012; Yamazaki et al., 2011). Recently, the paradigm has shifted towards replacing the grid-based routing scheme with a vector-based routing scheme (David et al., 2011; Mizukami et al., 2016, 2021; Lin et al., 2019; Yang et al., 2021b). In a nutshell, the advantages of vector-based routing can be summarized as follows. First, it is more scalable and computationally efficient, regardless of grid resolutions. The advent of burgeoning continental-scale and global-scale hydrography datasets such as HydroSHEDS and NHDPlus empower the use of vector-based routing at 30 m or even 10 m (Lehner & Grill, 2013). Second, river networks, by nature, are represented in vector forms that take river topology into account, which are seamlessly integrated into vector models. In contrast, grid-based river network data fail to represent topology and thus can lead to discontinuous river discharge. In addition, the river network in a vector form is more accurate than derived from DEM, as the resampling process loses fidelity. Third, vector-based routing permits a more flexible flow direction, namely from all directions. However, conventional grid-based routing advocates the traditional eight flow direction strategy, meaning that water in the central grid can only flow through one of its neighboring grid cells, despite ongoing research to solve this issue.

In light of the advantages of vector-based routing, Li et al. (2022d) attempted to couple the core of the CREST model (water balance model) with a vector-based routing scheme (mizuRoute), termed CREST-VEC, and apply it for real-time flood prediction. Of all existing vector routing models, CREST-VEC is thus far the only one to account for not only hillslope and channel routing but also subsurface flow routing, which is essential for representing the baseflow. Building upon this, CREST-VEC also enables lake routing for natural lakes and regulated lakes. From the continental simulation for hourly streamflow, CREST-VEC can achieve over ten times speedup, as compared to the operational framework. Not only can CREST-VEC fulfil the time requirement, but it also improves streamflow simulation by increasing the Nash-Sutcliffe Efficiency coefficients by 62.5%, reducing 36.7% bias, and mitigating over 20% of the falsely alarmed floods, primarily due to the enabled lake module (Li et al., 2022d). The model efficiency opens avenues for generating an ensemble prediction given the three pivotal hydrologic uncertainties: data, parameters, and models (Beven and Freer, 2001; Ajami et al., 2007).

5. Applications and outreach

Over the past ten years, the CREST model family has been used worldwide for a range of purposes. Fig. 7 depicts the distribution of CREST model applications (from published journal articles) by country. Overall, CREST model has been applied in 29 countries for solving water-related issues. The US and China, two leading countries, have utilized the CREST model the most, reaching 33 and 30, respectively. They also have similar focuses regarding modeling purposes, with flood simulation ranked as the top concern and followed by the evaluation of hydrologic utilities of satellite precipitation products. In fact, these applications are on par with the original objectives of developing the CREST model. Due to the lack of in-situ observations, researchers have been devoted to developing strategies combining remote-sensing data and frameworks to predict streamflow or other terrestrial water components in ungauged basins. These strategies made the CREST model amendable to calibration and validation in every corner of the world. There are also some instances of the use of the CREST model in developing countries, especially in Africa, owing to the capacity-building project in cooperation with NASA. In the following sections, we break down this topic into specific applications to illustrate the capacity and popularity of the CREST model family.

5.1. Flood simulation and forecasting

Of all the applications of the CREST model, flood and flash flood simulations and prediction are regarded as the primary utility (Fig. 8). It was the first hydrologic model coupled with a global precipitation system – TRMM and implemented at a quasi-global scale for real-time flood monitoring (Wu et al., 2012). It was the first hydrologic model coupled with the National Mosaic Quantitative Precipitation Estimation system in the US for streamflow simulation (Zhang et al., 2011). It is the first model to yield distributed forecasts of flash flooding at a continental scale (Gourley et al., 2017).

The CREST model has its advantages in flood simulation. First, the CREST model considers the full scope of runoff generation schemes, including fast surface runoff caused by impervious areas in urban areas, saturation-excess runoff, and infiltration excess-runoff. Second, the rapid simulation by CREST delivers timely flood information to stakeholders, which makes it operational in several frameworks. Last, the CREST model is scalable and proven to work at spatial scales ranging from 10 m to 1000 km, which targets local flooding or pluvial flooding caused by intense rainfall and large-scale flooding or fluvial flooding.

The operational framework FLASH (https://inside.nssl.noaa.gov/flash/) demonstrates the capacity of CREST/EF5 for continental flood and flash flood simulation, driven by the highest available resolution observational radar precipitation product – MRMS at 1-km^2/2-min (Gerard et al., 2021; Gourley et al., 2017; Zhang et al., 2016a; Li et al., 2023). This operational implementation represents the first deployment of a real-time, distributed hydrologic model functioning at

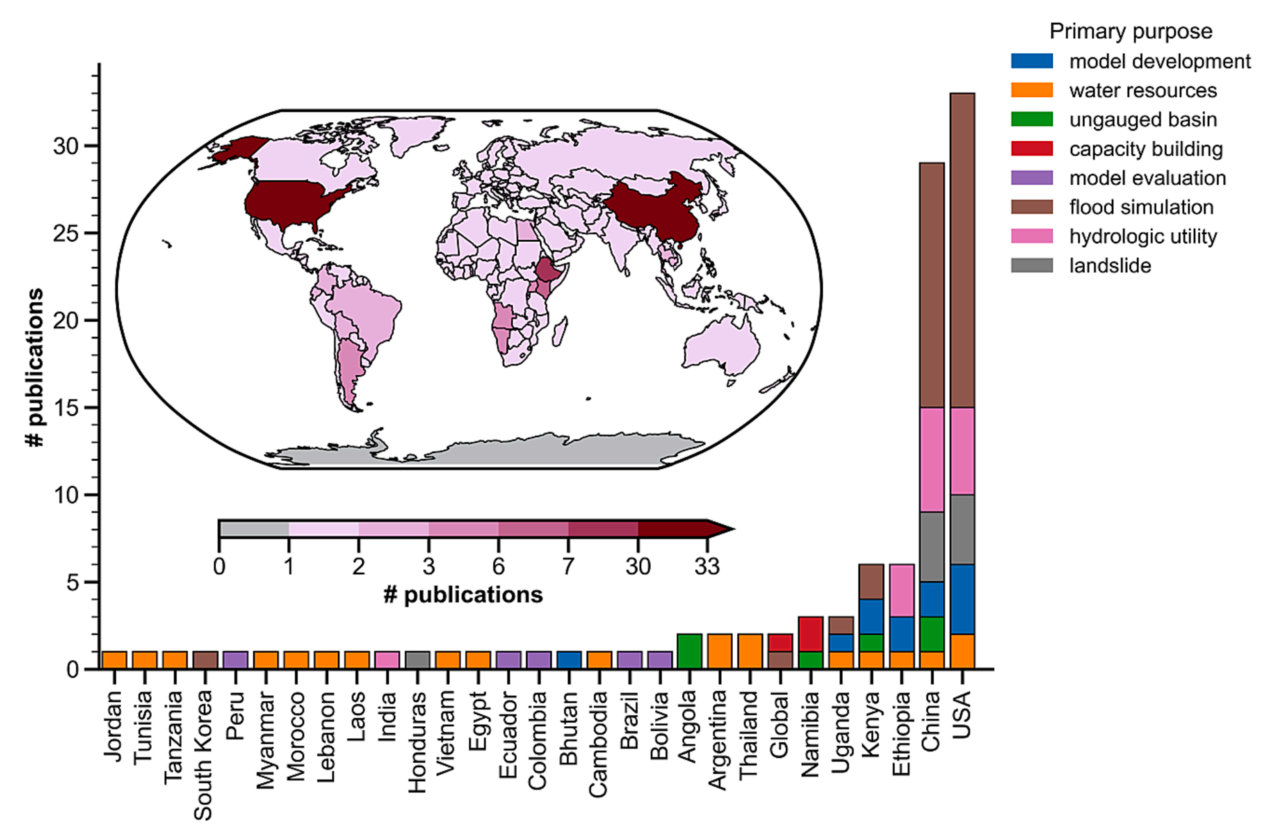

Fig. 7. Map of CREST model applications in the world, grouped by primary purposes.

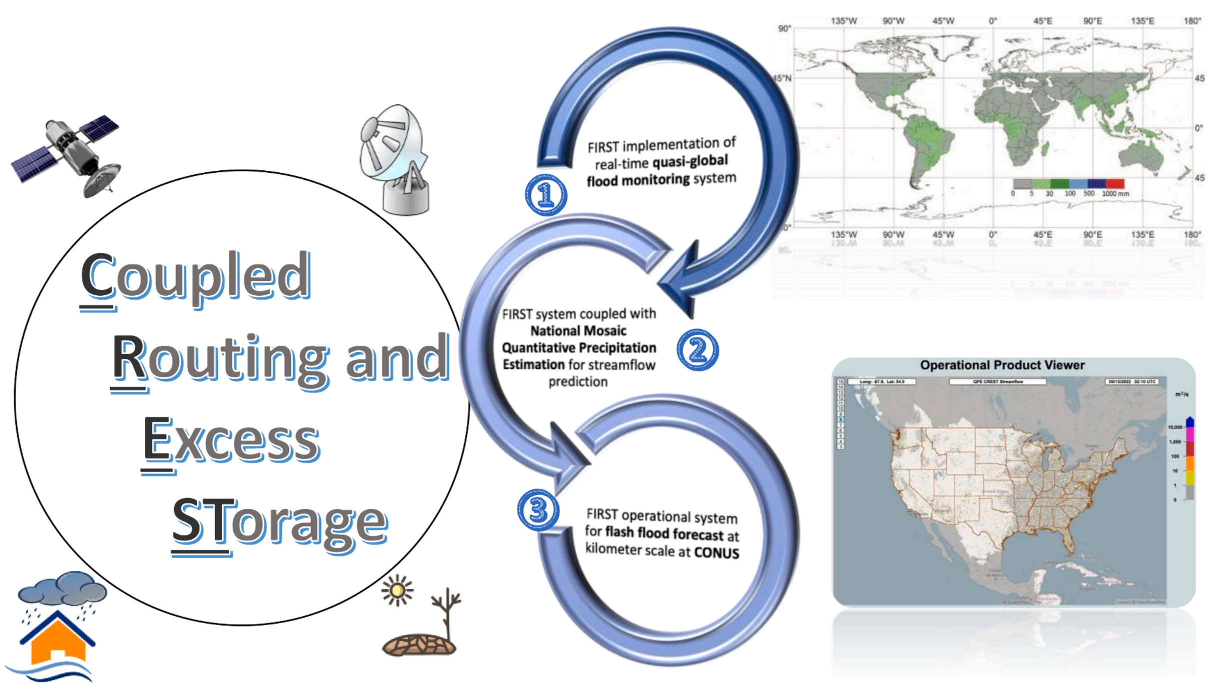

Fig. 8. An illustration of utilities of the CREST model for flood monitoring at national and global scales.

flash flood scales across a continent, which includes the entire US and outer territories. Funded by the NASA SEVIR project, CREST/EF5 has been deployed in African countries such as Namibia, Ethiopia, Kenya, Uganda, and surrounding areas to aid in local decision-making (Clark et al., 2017; Macharia et al., 2010; Yami et al., 2021). Wu et al. (2012) prototyped the Global Flood Monitoring Framework (GFMS) using TRMM-era precipitation as forcing and CREST as a hydrologic model to run at 3-hr and 0.125-deg. Taking advantage of advanced weather forecast datasets in the US, there are experiments and frameworks using quantitative precipitation forecasts (QPF) and probabilistic QPF (PQPF) data to alert local residents (Martinaitis et al., 2017; Yussouf et al., 2020). Zhang et al. (2015) evaluated the flood detectability of the Global Hydrological Prediction System (GHPS) forced by Global Forecast System (GFS) and CREST model.

Besides these real-time services worldwide, there are individual efforts to validate the efficacy of CREST simulated flood events. Khan et al. (2010) evaluated a simple inundation mapping scheme in CREST and compared it to the Earth-observing satellite – Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), providing insights into using remote sensing data to validate hydrologic simulation in ungauged basins. Similarly, Gao et al. (2017) used satellite-based precipitation products and the CREST model to develop flood frequency analysis in ungauged basins. A number of studies have used CREST model to investigate flood risks under a warmer climate. Li et al. (2022a) showed the US floods on average are becoming 7.9% flashier in a high-emissions scenario. In a follow-up study, we demonstrated that future floods are becoming more frequent, wider spread, yet less seasonal, which poses challenges to flood risk management (Li et al., 2022d).

5.2. Water resources management

Water resources management is a central component of human society. Groundwater, soil moisture, surface water, snow, and ice are the five main components of available water resources on Earth. The dynamic changes of the five states have been of considerable interest in recent years as (1) a warmer climate accelerates the terrestrial water cycle (Huntington, 2006) and (2) more regions are under water stress due to climate change and anthropogenic influences (Rodell et al., 2018). Hydrologic models such as CREST are well equipped to simulate the dynamic changes of terrestrial water storage over a long time for water resources management.

Khan et al. (2011) first applied the CREST model to inspect the hydroclimatology of Lake Victoria in Africa. From there, they not only proved that CREST simulated states agree well with observations but also analyzed the hydrologic behavior in such a region. Habib et al., (2012, July) found that reduced streamflow and groundwater by CREST simulation cannot sustain societal needs in the MENA region – Morocco, Tunisia, Egypt, Lebanon, and Jordan. Rossi & Ares (2015, 2016) applied the CREST-IRRIGATION model to improve agricultural irrigation efficiency in Argentina. Similarly, the soil moisture simulated by CREST can be used to inform crop yield (Yang et al., 2021a). Li et al. (2019) used the streamflow by CREST to examine the benefits of water sharing for the transboundary Lancang-Mekong River. Additionally, other applications sought to simulate terrestrial water components over long-term water cycles (Gathecha, 2015; Lazin et al., 2020; Ren et al., 2015; Rossi & Ares, 2016; Shen & Anagnostou, 2017).

5.3. Hydrologic simulation in ungauged basins

The Prediction of Ungauged Basins (PUB) is a long-standing challenge for the hydrologic community (Hrachowitz et al., 2013). Unfortunately, there has been a decline in hydrometric stations over recent years due to insufficient funding, inadequate institutional frameworks, criticisms of operating a network, and other factors such as wars or hazards (Mishra & Coulibaly, 2009). Under these pressures, developing new prediction methods that embrace remote sensing data is imperative. For hydrologic simulations, model calibration and validation are deemed necessary, although we hope models to be calibration-free if all physical processes are correctly represented.

The CREST model was born to integrate remote-sensing products and is ready to be calibrated or evaluated by them. Back in 2012, Khan et al. (2012) provided implications in PUB by evaluating the CREST model against AMSR-E derived inundation maps. Later, Zhang et al. (2014) extracted streamflow signals from TRMM and AMSR-E to calibrate the CREST model. Chen et al. (2017) calibrated the CREST model against SWE (first stage) and GRACE (Gravity Recovery and Climate Experiment; second stage) to ungauged basins. Han et al. (2020) used the CREST model along with satellite altimetry data to infer reservoir operation curves, filling data voids in ungauged basins, or by the reluctant data-sharing policy. The CREST-RS framework proposed by Huang et al. (2020) does not rely upon stream gauges in the calibration and validation stages. They tested two schemes: one was water level from satellite altimetry, and the other one was river width plus rating curve parameters to emulate SWOT-like (the Surface Water and Ocean Topography) data. Although not yet explored, remote-sensing soil moisture products such as SMAP (Soil Moisture Active Passive) can be used to calibrate and evaluate the model in ungauged basins as well. It is also worth mentioning the project strives to relieve heavy-lifting calibration procedures in the hydrologic framework. That is the continental- and global-scale parameter estimate by Vergara et al. (2016), which sets the foundations for the operational flash flood forecast framework (Gourley et al., 2017). It makes the CREST model easy to implement worldwide, with provided a-priori parameter sets.

5.4. Evaluating the hydrologic utility of the remote sensing precipitation products

As the original development of the CREST model was largely motivated by accommodating remote-sensing precipitation datasets across the globe, one of its principal uses is to assess and compare different precipitation products from a hydrologic perspective (Hou et al. 2014; Skofronick-Jackson et al. 2017). Conventional evaluation of satellite precipitation products was done by comparing them to more trustworthy estimates from surface instruments such as in-situ rain gauges. However, such an approach is effective only at well-instrumented locations when considering all of them across the globe only cover the size of a football field (e.g., Kirstetter, 2021; Kidd et al., 2017). Alternatively, the hydrologic utility of satellite or radar remote-sensing products offers additional insight, especially when considering the errors that propagate from precipitation to streamflow (Hong et al. 2006). Because streamflow is a basin-integrated variable, some trivial changes (including location, magnitude, and timing) among precipitation products can be accumulated and magnified in the simulated streamflow (Kirstetter, 2021).

Meng et al. (2014) provided some insights into the applicability of the TRMM Multi-satellite Precipitation Analysis (TMPA) product, concluding that the daily rainfall rates by TMPA do not have much hydrologic utility, but monthly rates agree quite well. Tang et al. (2016) assessed the hydrologic utility of the after-launch Global Precipitation Measurement (GPM) mission compared to its predecessor TRMM using the CREST model in China. They experimented with two sets of model parameters: (1) static parameter set calibrated from rain gauges and (2) dynamic parameter set that is calibrated for each GPM and TRMM dataset at their optima. The hydrologic simulation results present a clear outperformance of GPM IMERG over TRMM-based products, which is not discernable by precipitation evaluations alone. Other evaluation studies can be found in Tang et al. (2015), Lakew et al. (2017), Li et al. (2017), Jiang et al. (2017), Ma et al., (2018a,b), Sun et al. (2018), Yuan et al. (2018), Ma et al. (2019), Chen et al. (2020).

5.5. Capacity building and outreach

As mentioned above, CREST model developments and applications are funded by the NASA SERVIR program (https://www.nasa.gov/mission_pages/servir/overview.html) to help local government agencies build up their skills for model simulation and decision-making. It was in 2011 when the CREST development team delivered its first training course to the East Africa node of NASA and the U.S. Agency for International Development's (USAID) SERVIR project, covering Kenya, Tanzania, Uganda, and surrounding areas. In the consecutive year, with the release of CREST v2.0, the development team spawned a new training course, aiming to help local specialists upgrade the CREST model. Ever since, training courses and hands-on workshops have been offered annually to local specialists, although some joined the sessions from other countries or virtually (Clark et al., 2017, Yami et al., 2021). The participants from private sectors, government agencies, environmental scientists, and academics were able to foster modeling skills owing to the concise model structure, minimum parameter preparation, well-structured model interface, cross-platform functionality, and minimal computational requirements.

Beyond hands-on and in-person workshops, tutorial videos were developed that remain publicly accessible online, from basic training such as model description and simulation to more advanced training such as flood frequency analysis and inundation mapping. The upfront web interface (https://ef5.ou.edu) hosts a body of learning materials, videos, and model codes. We strongly support open-source model codes and request community efforts to extend model capacities. Upon marking the tenth-year anniversary of the CREST model family, we operate a brand-new website (https://crest-family.readthedocs.io/en/latest/) where a collection of model codes (from CREST v1.x, v2.x, and v3.0), training materials, applications, and publications are made fully online.

6. Discussion and outlook

6.1. Comparisons with global hydrologic models

Hydrologic models have been catalysed to resolve global scale hydrologic states and fluxes since the remote-sensing era and empowered by high-performance computing systems. Sood & Smakhtin (2015) reviewed 12 global operational hydrologic models, including VIC, WaterGAP, PCR-GLOBWB, etc. NASA Global Land Data Assimilation System (GLDAS) operates three land surface models – VIC, Noah, and Catchment at 3-hourly and 0.25-degree resolution (Rodell et al., 2004). The Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) provides climate-scale hydrologic simulation including multiple models (e.g., VIC, H08, WaterGAP, MacPDM, WBM) at variable spatiotemporal resolutions. Similarity exists in model structure comparing CREST to those well-known global hydrologic models. One is the single soil layer used in Macro-PDM, MPI-HM, WaterGAP, and H08, etc. Such simplification enables faster computation and requires less parameters. The CREST water balance model originated from the VIC model despite that the VIC model refines soil layers to account for heterogeneity (Liang et al., 1994). These land surface models diverge for different purposes. Some model developments place primary focus on resolving complex land surface processes (Pitman, 2003). For instance, the Noah and Noah-MP models, since their inception, are designed to predict the energy, water, and carbon exchange between the land surface and atmosphere, so they are beyond the scope of flood-forecasting hydrology (Niu et al., 2011). The WaterGAP model addresses global water resources and use (Schmied et al., 2021). The CREST model, however, was developed to provide early warnings to water-related natural hazards, which requires timely and high-resolution prediction. Currently, the CREST model operates at 5 km and 30 min resolution, empowered by the GPM IMERG precipitation system. Over the CONUS, the EF5 model provides 1 km^2 and 10 min streamflow estimates at a flash flood-resolving scale (Gourley et al., 2017). These are so far, to our knowledge, the highest resolution of hydrologic simulation around the globe and CONUS.

The original CREST model development led the way for accessibility, adaptability, scalability, and efficiency. We ensure the source code of each version of the model is accessible to the public. As it evolves, it becomes easily adaptable to other environmental models beyond the scope of streamflow prediction, such as landslide model, groundwater model, weather forecast model, etc. To achieve this, we refactored the code into modular format so that not only are the codes more readable but also easier to access intermediate results to provide initial and boundary conditions for other environmental models. The CREST model becomes highly scalable because of less complexity compared to other land surface models without sacrificing its streamflow prediction performance. Reducing complexity leads to less required parameters and lower dimensions of parameter uncertainty (Merz et al., 2022). The only required inputs for global configuration include catchment topography and derivatives (DEM, Flow Direction, Flow Accumulation), precipitation, potential evapotranspiration (PET), soil properties (hydraulic conductivity, maximum soil water capacity, exponent parameter of the VIC soil model), routing parameters (channel properties alpha and beta). With the burgeoning remote sensing data, the dynamic inputs (i.e., precipitation and PET) are available at the global scale with low data latency. We also made the *a-priori* parameters available at 5 km over the globe (https://github.com/HyDROSLab/EF5-Global-Parameters) and 1 km over the CONUS (https://github.com/HyDROSLab/EF5-US-Parameters), so one can easily set up the model in any place around the world. The CREST model is one of the most efficient hydrologic systems for streamflow prediction, making it informative for water-related hazard forecasting. Efficiency is computationally achieved through vectorization and matrix operation instead of heavy-lifting for-loops in FORTRAN and MATLAB. This practical coding style offers great efficiency but has not been implemented by most ESMs. Owing to these development guidelines, the CREST model was used for three “first” systems: (1) the first quasi-global flood monitoring system, (2) the first national streamflow prediction framework coupled with national mosaic precipitation quantitative estimation, and (3) the first national flash flood forecast system.

6.2. Outlook for future development

From our past experience and lessons learned, we lay out some key aspects to advance the CREST model family:

1) Model physical structure. As shown in Fig. 3, the core physical structure of the CREST model has not been significantly updated, even though we understand its physical limitations. Taking soil moisture as an example – it underpins correct (sub)runoff and evaporation generation – the singular bulk layer soil configuration cannot well represent the soil heterogeneity and complex processes. For instance, root zone soil moisture, the layer from which vegetation can freely access water, has a different representation than deep soil moisture, where soil water interacts with groundwater (Boone et al., 1999). Even within the root zone, modern land surface models (e.g., Noah, Noah-MP, etc.) discretize several sublayers to consider different vegetation types (Niu et al., 2011). Other land surface representations could be considered, but the primary focus is tilted towards flood simulation, and more complex physical schemes may add more computational expense without a significant improvement in flood prediction accuracy.
2) A unified modeling system. Since a one-size-fits-all model structure is not feasible for hydrologic models, it is of particular interest to developing a “malleable” structure, which is adaptable to environmental conditions (Clark et al., 2015; Fenicia et al., 2011; Savenije, 2009). The key to model development is to refactor the code in a modular manner, meaning that users have the option to switch between different model physics in a configuration file. The EF5 provides a reusable framework upon which a comprehensive CREST family framework can be built. We also anticipate a unified multi-hazard and multi-scale framework that captures compound water-related natural hazards.
3) Upgrades to an operational flood monitoring system. Current continental (1 km in the US) and global flood monitoring systems (5 km) are still adopting the conventional grid-based routing, but with CREST-VEC, it is promising for channel routing to operate at 10-m scale (in the US) and 90-m scale (worldwide) for streamflow simulation. In addition to the framework change, parameters for the water balance model and routing model need to be updated accordingly. Strategies such as parameter regionalization are a

remedy to large-scale calibration (Samaniego et al., 2010). In parallel to model advancements, input rainfall data have been undergoing major revolutions throughout the years. One example is Probabilistic Quantitative Precipitation Estimation (PQPE), which explicitly includes uncertainties in precipitation forcing for ensemble hydrologic prediction. Another example is the advent of the Phased Array Radar, the next generation of weather radars can have five times finer temporal resolution than conventional radars, collecting rainfall data at a sub-minute scale (Wen et al., 2021). It has far-reaching implications for predicting flash floods, landslides, and other water-related natural hazards. Equipping our model with modern technology is a pivotal way to improve flood prediction skills and is thus informative for decision-makers.

4) Embrace open source, interoperability, and outreach. Over the ten-year development of the CREST model, our core modeling team strived to promote and advocate open-source codes and data (past model codes and documentation have been archived to https://crest-family.readthedocs.io/en/latest/). Beyond that, we encompass a wide range of tools (tutorial videos, manuals, online documentation, and test cases) to make the CREST model easy to use and easy to understand. The Graphic User Interface (GUI) and some free online computing platforms (e.g., Google Colab) facilitate potential users to run the model even without a programming background. The easy-to-integrate modular design empowers a wide range of extensions to be integrated with the CREST model. We will continue to devote time and effort to developing and improving models while bridging to end users in the future. We also encourage community contributions to the CREST model family to extend model capacity.

7. Summary

The CREST model has been a widely recognized hydrologic modeling tool over the past ten years and will continue making its contribution to our community on many fronts, with its core anchored in flood prediction. For this paper, we have reviewed over 80 + papers that have used the CREST model for their advances in hydrologic modeling, applications in solving domestic and global water security issues, and outreaches to educate and help the community to build capacity. We showed the evolution of the CREST model family from its mainstem (CREST v1, v2, and v3) to branches, featuring the coupling with weather forecast models, land surface model, hydrodynamic model, vector-based routing model, and landslide model. The flexibility owing to its modular design is highlighted and makes it amendable to coupling. Meanwhile, it is readily available to operate in real-time to address water security issues, thanks to its adaptability, scalability, and efficiency. The capacity-building and outreach work conducted over the years feature community stewardship. We further provide some insights for future model development, focusing on improving model physics, unifying multi-models, enhancing real-time flood forecast, supporting open science. These insights not only apply to CREST model development but also are adaptable to other community models.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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References

Ajami, N.K., Duan, Q., Sorooshian, S., 2007. An integrated hydrologic Bayesian multimodel combination framework: confronting input, parameter, and model structural uncertainty in hydrologic prediction. Water Resour. Res. 43, W01403. https://doi.org/10.1029/2005WR004745.

Anderson, E.A., 1976. A point energy and mass balance model of a snow cover. NOAA Technical Report, NWS 19, 1976.

Anderson, E.A., 2006. Snow accumulation and ablation model–SNOW-17. US National Weather Service, Silver Spring, MD, p. 61.

Ashley, S.T., Ashley, W.S., 2008. Flood Fatalities in the United States. J. Appl. Meteorol. Climatol. 47 (3), 805–818.

Beven, K., Freer, J., 2001. Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. J. Hydrol. 249 (1–4), 11–29.

Blanton, B., Dresback, K., Colle, B., Kolar, R., Vergara, H., Hong, Y., Leonardo, N., Davidson, R., Nozick, L., Wachtendorf, T., 2020. An integrated scenario ensemble-based framework for hurricane evacuation modeling: Part 2—hazard modeling. Risk Anal. 40 (1), 117–133.

Boone, A., Calvet, J., Noilhan, J., 1999. Inclusion of a third soil layer in a land surface scheme using the force-restore method. J. Appl. Meteorol. Climatol. 38 (11), 1611–1630.

Chen, M., Li, Z. and Gao, S. (2022b). Multisensor Remote Sensing and the Multidimensional Modeling of Extreme Flood Events. In Remote Sensing of Water-Related Hazards (eds K. Zhang, Y. Hong and A. AghaKouchak). 10.1002/9781119159131.ch5.

Chen, X., Long, D., Hong, Y., Zeng, C., Yan, D., 2017. Improved modeling of snow and glacier melting by a progressive two-stage calibration strategy with GRACE and multisource data: How snow and glacier meltwater contributes to the runoff of the Upper Brahmaputra River basin? Water Resour. Res. 53 (3), 2431–2466.

Chen, M., Nabih, S., Brauer, N.S., Gao, S., Gourley, J.J., Hong, Z., Kolar, R., Hong, Y., 2020. Can remote sensing technologies capture the extreme precipitation event and its cascading hydrological response? A case study of Hurricane Harvey using EF5 modeling framework. Remote Sense. 12 (3), 445.

Chen, M., Li, Z., Gao, S., Luo, X., Wing, O.E., Shen, X., Gourley, J., Hong, Y., 2021. A comprehensive flood inundation mapping for Hurricane Harvey using an integrated hydrological and hydraulic model. J. Hydrometeorol. 22 (7), 1713–1726.

Chen, M., Li, Z., Gao, S., Xue, M., Gourley, J.J., Kolar, R.L., Hong, Y., 2022. A flood predictability study for Hurricane Harvey with the CREST-iMAP model using high-resolution quantitative precipitation forecasts and U-Net deep learning precipitation nowcasts. J. Hydrol. 612, 128168.

Chow, V.T., Maidment, D.R., Mays, L.W., 1988. Applied hydrology. McGraw-Hill Inc.

Clark, R.A., Flamig, Z.L., Vergara, H., Hong, Y., Gourley, J.J., Mandl, D.J., Frye, S., Handy, M., Patterson, M., 2017. Hydrological modeling and capacity building in the Republic of Namibia. Bull. Amer. Meteor. 98 (8), 1697–1715.

Clark, M.P., Nijssen, B., Lundquist, J.D., Kavetski, D., Rupp, D.E., Woods, R.A., Freeer, J. E., Gutmann, E.D., Wood, A.W., Gochis, D.J., Rasmussen, R.M., Tarboton, D.G., Mahat, V., Flerchinger, G.N., Marks, D., 2015. G.: A unified approach for process-based hydrologic modeling: 1. Modeling concept. Water Resour. Philos. Phenomenol. Res. 51, 2498–2514. https://doi.org/10.1002/2015WR017198.

David, C.H., Maidment, D.R., Niu, G.Y., Yang, Z.L., Habets, F., Eijkhout, V., 2011. River network routing on the NHDPlus dataset. J. Hydrometeorol. 12 (5), 913–934.

Dickinson, R.E., 1989. A regional climate model for the western united states. Clim. Change 15 (1), 383–422.

Dowell, D.C., Alexander, C.R., James, E.P., Weygandt, S.S., Benjamin, S.G., Manikin, G. S., Blake, B.T., Brown, J.M., Olson, J.B., Hu, M., Smirnova, T.G., Ladwig, T., Kenyon, J.S., Ahmadov, R., Turner, D.D., Duda, J.D., Alcott, T.I., 2022. The high-resolution rapid refresh (HRRR): an hourly updating convection-allowing forecast model part I: motivation and system description. Weather Forecast. 37 (8), 1371–1395.

Duan, Q., Sorooshian, S., Gupta, V., 1992. Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resour. Res. 28 (4), 1015–1031.

Fenicia, F., Kavetski, D., and Savenije, H. H. G. (2011). Elements of a flexible approach for conceptual hydrological modeling: 1. Motivation and theoretical development, Water Resour. Res., 47, W11510, 10.1029/2010WR010174, 2011.

Flamig, Z.L., Vergara, H., Gourley, J.J., 2020. The Ensemble Framework For Flash Flood Forecasting (EF5) v1.2: description and case study. Geosci. Model Dev. 13, 4943–4958. https://doi.org/10.5194/gmd-13-4943-2020.

Gao, S., Chen, M., Li, Z., Cook, S., Allen, D., Neeson, T., Yang, T., Yami, T., Hong, Y., 2021. Mapping dynamic non-perennial stream networks using high-resolution distributed hydrologic simulation: a case study in the upper blue river basin. J. Hydrol. 600, 126522.

Gao, Z., Long, D., Tang, G., Zeng, C., Huang, J., Hong, Y., 2017. Assessing the potential of satellite-based precipitation estimates for flood frequency analysis in ungauged or poorly gauged tributaries of China's Yangtze River basin. J. Hydrol. 550, 478–496.

Gathecha, H.M., 2015. Reconstruction of streamflow into Lake Naivasha using crest model and remote sensed rainfall and evapotranspiration. University of Twente). Master's thesis,.

Gerard, A., Martinaitis, S.M., Gourley, J.J., Howard, K.W., Zhang, J., 2021. An overview of the performance and operational applications of the MRMS and FLASH systems in recent significant urban flash flood events. Bull. Amer. Meteor. 1–29.

Gourley, J.J., Flamig, Z.L., Vergara, H., Kirstetter, P.E., Clark, R.A., Argyle, E., Arthur, A., Martinaitis, S., Terti, G., Erlings, J., Hong, Y., Howard, K.W., 2017. The FLASH project: Improving the tools for flash flood monitoring and prediction across the United States. Bull. Amer. Meteor. 98 (2), 361–372.

Habib, S., Kfouri, C., and Peters, M. (2012, July). Water information system platforms addressing critical societal needs in the MENA region. IEEE Geosci. Remote. Sens. Lett., 2767-2770.
Han, Z., Long, D., Huang, Q., Li, X., Zhao, F., Wang, J., 2020. Improving reservoir outflow estimation for ungauged basins using satellite observations and a hydrological model. Water Resour. Res. 56 (9).
He, X., Hong, Y., Vergara, H., Zhang, K., Kirstetter, P.E., Gourley, J.J., Zhang, Y., Qiao, G., Liu, C., 2016. Development of a coupled hydrological-geotechnical framework for rainfall-induced landslides prediction. J. Hydrol. 543, 395–405.
Hong, Y., Hsu, K.L., Moradkhani, H., Sorooshian, S., 2006. Uncertainty quantification of satellite precipitation estimation and Monte Carlo assessment of the error propagation into hydrologic response. Water Resour. Res. 42 (8).
Hong, Y., Adler, R.F., Hossain, F., Curtis, S., Huffman, G.J., 2007. A first approach to global runoff simulation using satellite rainfall estimation. Water Resour. Res. 43, W08502. https://doi.org/10.1029/2006WR005739.
Hrachowitz, M., Savenije, H.H.G., Blöschl, G., McDonnell, J.J., Sivapalan, M., Pomeroy, J.W., Arheimer, B., Blume, T., Clark, M.P., Ehret, U., Fenicia, F., Freer, J.E., Gelfan, A., Gupta, H.V., Hughes, D.A., Hut, R.W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P.A., Uhlenbrook, S., Wagener, T., Winsemius, H.C., Woods, R.A., Zehe, E., Cudennec, C., 2013. A decade of Predictions in Ungauged Basins (PUB)—a review. Hydrol. Sci. J. 58 (6), 1198–1255.
Huang, Q., Long, D., Du, M., Han, Z., Han, P., 2020. Daily continuous river discharge estimation for ungauged basins using a hydrologic model calibrated by satellite altimetry: Implications for the SWOT mission. Water Resour. Res. 56 (7).
Huntington, T.G., 2006. Evidence for intensification of the global water cycle: Review and synthesis. J. Hydrol. 319 (1–4), 83–95.
Jiang, S., Zhang, Z., Huang, Y., Chen, X.i., Chen, S., 2017. Evaluating the TRMM multisatellite precipitation analysis for extreme precipitation and streamflow in Ganjiang River basin. Adv. Meteorol. 2017, 1–11.
Jones, T.A., Knopfmeier, K., Wheatley, D., Creager, G., Minnis, P., Palikonda, R., 2016. Storm-scale data assimilation and ensemble forecasting with the NSSL experimental Warn-on-Forecast system. Part II: Combined radar and satellite data experiments. Weather Forecast. 31 (1), 297–327.
Kan, G., Tang, G., Yang, Y., Hong, Y., Li, J., Ding, L., He, X., Liang, K., He, L., Li, Z., Hu, Y., Cui, Y., 2017. An improved coupled routing and excess storage (CREST) distributed hydrological model and its verification in Ganjiang River Basin. China. Water 9 (11), 904.
Kappes, M.S., Keiler, M., von Elverfeldt, K., Glade, T., 2012. Challenges of analyzing multi-hazard risk: a review. Nat. Hazards 64, 1925–1958. https://doi.org/10.1007/s11069-012-0294-2.
Khadim, F.K., Dokou, Z., Lazin, R., Moges, S., Bagtzoglou, A.C., Anagnostou, E., 2020. Groundwater modeling in data scarce aquifers: the case of Gilgel-Abay, Upper Blue Nile. Ethiopia. J. Hydrol. 590, 125214.
Khan, S.I., Hong, Y., Wang, J., Yilmaz, K.K., Gourley, J.J., Adler, R.F., Brakenridge, G.R., Policelli, F., Habib, S., Irwin, D., 2010. Satellite remote sensing and hydrologic modeling for flood inundation mapping in Lake Victoria basin: implications for hydrologic prediction in ungauged basins. IEEE Trans. Geosci. Remote Sens. 49 (1), 85–95.
Khan, S.I., Adhikari, P., Hong, Y., Vergara, H., F Adler, R., Policelli, F., Irwin, D., Korme, T., Okello, L., 2011. Hydroclimatology of Lake Victoria region using hydrologic model and satellite remote sensing data. Hydrol, Earth Syst. Sci. 15 (1), 107–117.
Khan, S.I., Hong, Y., Vergara, H.J., Gourley, J.J., Brakenridge, G.R., De Groeve, T., Flamig, Z., Pollicelli, F., Yong, B., 2012. Microwave satellite data for hydrologic modeling in ungauged basins. IEEE Geosci. Remote Sens. Lett. 9 (4), 663–667.
Kidd, C., Becker, A., Huffman, G.J., Muller, C.L., Joe, P., Skofronick-Jackson, G., Kirschbaum, D.B., 2017. So, how much of the Earth's surface is covered by rain gauges? Bull. Amer. Meteor. Soc. 98 (1), 69–78.
Kirstetter, P.E., (2021). Validating the intrinsic uncertainty: Implications for hydrologic applications, in The Joint IPWG/GEWEX Precipitation Assessment (ed. R. Roca), WCRP Report 2/2021, World Climate Research Programme (WCRP), Geneva, Switzerland. 10.13021/gewex.precip.1.2 (http://hdl.handle.net/1920/11985).
Koren, V., Reed, S., Smith, M., Zhang, Z., Seo, D.J., 2004. Hydrology laboratory research modeling system (HL-RMS) of the US national weather service. J. Hydrol. 291 (3–4), 297–318.
Lakew, H.B., Moges, S.A., Asfaw, D.H., 2017. Hydrological evaluation of satellite and reanalysis precipitation products in the Upper Blue Nile Basin: A case study of Gilgel Abbay. Hydrol. 4 (3), 39.
Lazin, R., Shen, X., Koukoula, M., Anagnostou, E., 2020. Evaluation of the hyper-resolution model-derived water cycle components over the upper Blue Nile Basin. J. Hydrol. 590, 125231.
Lehner, B., Grill, G., 2013. Global river hydrography and network routing: baseline data and new approaches to study the world's large river systems. Hydrol. Process. 27, 2171–2186. https://doi.org/10.1002/hyp.9740.
Li, N., Tang, G., Zhao, P., Hong, Y., Gou, Y., Yang, K., 2017. Statistical assessment and hydrological utility of the latest multi-satellite precipitation analysis IMERG in Ganjiang River basin. Atmos. Res. 183, 212–223.
Li, Z., Yang, Y., Kan, G., Hong, Y., 2018. Study on the applicability of the Hargreaves potential evapotranspiration estimation method in CREST distributed hydrological model (version 3.0) applications. Water 10 (12), 1882.
Li, Z., Chen, M., Gao, S., Hong, Z., Tang, G., Wen, Y., Gourley, J.J., Hong, Y., 2020. Cross-examination of similarity, difference and deficiency of gauge, radar and satellite precipitation measuring uncertainties for extreme events using conventional metrics and multiplicative triple collocation. Remote Sens. 12, 1258. https://doi.org/10.3390/rs12081258.
Li, Z., Chen, M., Gao, S., Gourley, J.J., Yang, T., Shen, X., Kolar, R., Hong, Y., 2021. A multi-source 120-year US flood database with a unified common format and public access. Earth Syst. Sci. Data 13 (8), 3755–3766.
Li, Z., Chen, M., Gao, S., Luo, X., Gourley, J.J., Kirstetter, P., Yang, T., Kolar, R., McGovern, A., Wen, Y., Rao, B.o., Yami, T., Hong, Y., 2021. CREST-iMAP v1. 0: A fully coupled hydrologic-hydraulic modeling framework dedicated to flood inundation mapping and prediction. Environ Model Softw. 141, 105051.
Li, Z., Gao, S., Chen, M., Gourley, J.J., Liu, C., Prein, A.F., Hong, Y., 2022. The conterminous United States are projected to become more prone to flash floods in a high-end emissions scenario. Commun. Earth Environ. 3 (1), 1–9.
Li, Z., Chen, M., Gao, S., Wen, Y., Gourley, J.J., Yang, T., Kolar, R., Hong, Y., 2022. Can re-infiltration process be ignored for flood inundation mapping and prediction during extreme storms? A case study in Texas Gulf Coast region. Environ Model Softw. 155, 105450.
Li, Z., Gao, S., Chen, M., Gourley, J., Mizukami, N., Hong, Y., 2022. CREST-VEC: a framework towards more accurate and realistic flood simulation across scales. Geosci. Model Dev. 15, 6181–6196. https://doi.org/10.5194/gmd-15-6181-2022.
Li, Z., Gao, S., Chen, M., Gourley, J.J., Hong, Y., 2022. Spatiotemporal characteristics of US floods: current status and forecast under a future warmer climate. Earth. Future 10. https://doi.org/10.1029/2022EF002700.
Li, D., Zhao, J., Govindaraju, R.S., 2019. Water benefits sharing under transboundary cooperation in the Lancang-Mekong River Basin. J. Hydrol. 577, 123989.
Li, Z. (2022a). Decadal development of CREST hydrological model family: review, improvements, applications, and outlook, [Doctoral dissertation, University of Oklahoma]. SHAREOK Dissertations Publishing, https://hdl.handle.net/11244/335976.
Li, Z., Gao, S., Chen, M., Zhang, J., Gourley, J., Wen, Y., Yang, T., Hong, Y., 2023. Introducing Flashiness-Intensity-Duration-Frequency (F-IDF): A New Metric to Quantify Flash Flood Intensity. Authorea. https://doi.org/10.22541/essoar.168748464.41784321/v1.
Liang, X., Lettenmaier, D.P., Wood, E.F., Burges, S.J., 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. J. Geophys. Res. 99 (D7), 14415–14428. https://doi.org/10.1029/94JD00483.
Liang, X., Lettenmaier, D.P., Wood, E.F., 1996. One-dimensional statistical dynamic representation of subgrid spatial variability of precipitation in the two-layer variable infiltration capacity model. J. Geophys. Res. 101 (D16), 21403–21422.
Lin, P., Pan, M., Beck, H.E., Yang, Y., Yamazaki, D., Frasson, R., David, C.H., Durand, M., Pavelsky, T.M., Allen, G.H., Gleason, C.J., Wood, E.F., 2019. Global reconstruction of naturalized river flows at 2.94 million reaches. Water Resour. Res. 55 (8), 6499–6516.
Ma, Z., Tan, X., Yang, Y., Chen, X., Kan, G., Ji, X., Lu, H., Long, J., Cui, Y., Hong, Y., 2018. The first comparisons of IMERG and the downscaled results based on IMERG in hydrological utility over the ganjiang river basin. Water 10, 1392. https://doi.org/10.3390/w10101392.
Ma, Q., Xiong, L., Liu, D., Xu, C.Y., Guo, S., 2018. Evaluating the temporal dynamics of uncertainty contribution from satellite precipitation input in rainfall-runoff modeling using the variance decomposition method. Remote Sens. 10 (12), 1876.
Ma, Q., Xiong, L., Xia, J., Xiong, B., Yang, H., Xu, C.Y., 2019. A censored shifted mixture distribution mapping method to correct the bias of daily IMERG satellite precipitation estimates. Remote Sens. 11 (11), 1345.
Macharia, D., Korme, T., Policelli, F., Irwin, D., Adler, B., and Hong, Y. (2010, October). SERVIR-Africa: Developing an integrated platform for floods disaster management in Africa. In 8th International Conference African Association of Remote Sensing of the Environment (AARSE) (No. M10-1035).
Martinaitis, S.M., Gourley, J.J., Flamig, Z.L., Argyle, E.M., Clark III, R.A., Arthur, A., Smith, B.R., Erlingis, J.M., Perfater, S., Albright, B., 2017. The HMT multi-radar multi-sensor hydro experiment. Bull. Amer. Meteor. Soc. 98 (2), 347–359.
McDonnell, J.J., Spence, C., Karran, D.J., van Meerveld, H.J., Harman, C.J., 2021. Fill-and-spill: a process description of runoff generation at the scale of the beholder. Water Resour. Res. 57 https://doi.org/10.1029/2020WR027514.
Meng, J., Li, L., Hao, Z., Wang, J., Shao, Q., 2014. Suitability of TRMM satellite rainfall in driving a distributed hydrological model in the source region of Yellow River. J. Hydrol. 509, 320–332.
Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J.C.J.H., Bates, P., Bertola, M., Kemter, M., Kreibich, H., Lall, U., Macdonald, E., 2021. Causes, impacts and patterns of disastrous river floods. Nat. Rev, Earth Environ. 2 (9), 592–609.
Merz, R., Miniussi, A., Basso, S., Petersen, K., Tarasova, L., 2022. More complex is not necessarily better in large-scale hydrological modeling: a model complexity experiment across the contiguous United States. Bull. Amer. Meteor. Soc. 103 (8), E1947–E1967.
Mishra, A.K., Coulibaly, P., 2009. Developments in hydrometric network design: a review. Rev. Geophys. 47 (2).
Mizukami, N., Clark, M.P., Sampson, K., Nijssen, B., Mao, Y., McMillan, H., Viger, R.J., Markstrom, S.L., Hay, L.E., Woods, R., Arnold, J.R., Brekke, L.D., 2016. mizuRoute version 1: a river network routing tool for a continental domain water resources applications. Geosci. Model Dev. 9, 2223–2238. https://doi.org/10.5194/gmd-9-2223-2016.
Mizukami, N., Clark, M.P., Gharari, S., Kluzek, E., Pan, M., Lin, P., Beck, H.E., Yamazaki, D., 2021. A vector-based river routing model for Earth System Models: parallelization and global applications. J. Adv. Model. Earth Syst. 13, e2020MS002434 https://doi.org/10.1029/2020MS002434.
Ning, L., Zhan, C., Luo, Y., Wang, Y., Liu, L., 2019. A review of fully coupled atmosphere-hydrology simulations. J. Geog. Sci. 29 (3), 465–479.
Niu, G.-Y., Yang, Z., Mitchell, K.E., Chen, F., Ek, M.B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., Xia, Y., 2011. The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model

description and evaluation with local-scale measurements. J. Geophys. Res. 116, D12109 https://doi.org/10.1029/2010JD015139.
Nobre, A.D., Cuartas, L.A., Hodnett, M., Rennó, C.D., Rodrigues, G., Silveira, A., Waterloo, M., Saleska, S., 2011. Height Above the Nearest Drainage–a hydrologically relevant new terrain model. J. Hydrol. 404 (1-2), 13–29.
Pitman, A.J., 2003. The evolution of, and revolution in, land surface schemes designed for climate models. Int. J. Climatol. 23 (5), 479–510.
Ren, G., Zhan, Y., Ren, Y., Chen, Y., Wang, T., Liu, Y., Sun, X., 2015. Spatial and temporal patterns of precipitation variability over mainland China: I: climatology. Adv. Water Sci. 26 (3), 299–310.
Rodell, M., Houser, P.R., Jambor, U., Gottschalck, J., Mitchell, K., Meng, C.-J., Arsenault, K., Cosgrove, B., Radakovich, J., Bosilovich, M., Entin, J.K., Walker, J.P., Lohmann, D., Toll, D., 2004. The global land data assimilation system. Bull. Amer. Meteor. Soc. 85 (3), 381–394.
Rodell, M., Famiglietti, J.S., Wiese, D.N., Reager, J.T., Beaudoing, H.K., Landerer, F.W., Lo, M.H., 2018. Emerging trends in global freshwater availability. Nature 557 (7707), 651–659.
Rossi, M.J., Ares, J.O., 2015. Efficiency improvement in linear-move sprinkler systems through moderate runoff–runon control. Irrig. Sci. 33 (3), 205–219.
Rossi, M.J., Ares, J.O., 2016. Overland flow from plant patches: coupled effects of preferential infiltration, surface roughness and depression storage at the semiarid Patagonian Monte. J. Hydrol. 533, 603–614.
Samaniego, L., Kumar, R., Attinger, S., 2010. Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. Water Resour. Res. 46 (W05523), 2010. https://doi.org/10.1029/2008WR007327.
Sampson, C.C., Smith, A.M., Bates, P.D., Neal, J.C., Alfieri, L., Freer, J.E., 2015. A high-resolution global flood hazard model. Water Resour. Res. 51 (9), 7358–7381.
Savenije, H.H., 2009. HESS Opinions“ The art of hydrology”. Hydrol. Earth Syst. Sci. 13 (2), 157–161.
Schmied, H.M., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Peiris, T.A., Popat, E., Portmann, F.T., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C.-E., Trautmann, T., Döll, P., 2021. The global water resources and use model WaterGAP v2.2d: model description and evaluation. Geosci. Model Dev. 14, 1037–1079. https://doi.org/10.5194/gmd-14-1037-2021.
Schmugge, T.J., Kustats, W.P., Ritchie, J.C., Jackson, T.J., Rango, A., 2002. Remote senisng in hydrology. Adv. Water Resour. 25, 1367–1385.
Shen, X., Anagnostou, E.N., 2017. A framework to improve hyper-resolution hydrological simulation in snow-affected regions. J. Hydrol. 552, 1–12.
Shen, X., Hong, Y., Zhang, K., Hao, Z., 2017. Refining a distributed linear reservoir routing method to improve performance of the CREST model. J. Hydrol. Eng. 22 (3), 04016061.
Smith, J.A., Baeck, M.L., Morrison, J.E., Sturdevant-Rees, P., Turner-Gillespie, D.F., Bates, P.D., 2002. The regional hydrology of extreme floods in an urbanizing drainage basin. J. Hydrometeorol. 3 (3), 267–282.
Sood, A., Smakhtin, V., 2015. Global hydrological models: a review. Hydrol. Sci. J. 60 (4), 549–565. https://doi.org/10.1080/02626667.2014.950580.
Sun, A.Y., Li, Z., Lee, W., Huang, Q., Scanlon, B.R., Dawson, C., 2023. Rapid Flood Inundation Forecast Using Fourier Neural Operator. ArXiv. /abs/2307.16090.
Sun, W., Ma, J., Yang, G., Li, W., 2018. Statistical and hydrological evaluations of multi-satellite precipitation products over Fujiang river basin in humid southeast China. Remote Sens. 10 (12), 1898.
Tang, G., Li, Z., Xue, X., Hu, Q., Yong, B., Hong, Y., 2015. A study of substitutability of TRMM remote sensing precipitation for gauge-based observation in Ganjiang River basin. Adv. Water Sci. 26 (3), 340–346.
Tang, G., Zeng, Z., Long, D., Guo, X., Yong, B., Zhang, W., Hong, Y., 2016. Statistical and hydrological comparisons between TRMM and GPM level-3 products over a midlatitude basin: Is day-1 IMERG a good successor for TMPA 3B42V7? J. Hydrometeorol. 17 (1), 121–137.
Tellman, B., Sullivan, J.A., Kuhn, C., Kettner, A.J., Doyle, C.S., Brakenridge, G.R., Erickson, T.A., Slayback, D.A., 2021. Satellite imaging reveals increased proportion of population exposed to floods. Nature 596 (7870), 80–86.
Teng, J., Jakeman, A.J., Vaze, J., Croke, B.F., Dutta, D., Kim, S.J.E.M., 2017. Flood inundation modelling: a review of methods, recent advances and uncertainty analysis. Environ Model Softw. 90, 201–216.
Towler, E., Foks, S.S., Dugger, A.L., Dickinson, J.E., Essaid, H.I., Gochis, D., Viger, R.J., Zhang, Y., 2022. Benchmarking high-resolution, hydrologic performance of long-term retrospectives in the United States. Hydrol. Earth Syst. Sci. Discuss. [preprint], DOI: 10.5194/hess-2022-276, in review.
UNDRR, 2020. Human Cost of Disasters. An Overview of the last 20 years: 2000–2019. https://reliefweb.int/report/world/human-cost-disasters-overview-last-20-years-2000-2019.
Vergara, H., Kirstetter, P.E., Gourley, J.J., Flamig, Z.L., Hong, Y., Arthur, A., Kolar, R., 2016. Estimating a-priori kinematic wave model parameters based on regionalization for flash flood forecasting in the Conterminous United States. J. Hydrol. 541, 421–433.
Vrugt, J.A., Clark, M.P., Hyman, J.M., Robinson, B.A., 2008. Treatment of input uncertainty in hydrologic modeling: Doing hydrology backward with Markov chain Monte Carlo simulation. Water Resour. Res 44 (12). https://doi.org/10.1029/2007WR006720.
Wang, J., Hong, Y., Li, L., Gourley, J.J., Khan, S.I., Yilmaz, K.K., Adler, R.F., Policelli, F. S., Habib, S., Irwin, D., Limaye, A.S., Korme, T., Okello, L., 2011. The coupled routing and excess storage (CREST) distributed hydrological model. Hydrol. Sci. J. 56 (1), 84–98.
Wang, S., Zhang, K.e., van Beek, L.P.H., Tian, X., Bogaard, T.A., 2020. Physically-based landslide prediction over a large region: Scaling low-resolution hydrological model results for high-resolution slope stability assessment. Environ Model Softw. 124, 104607.
Wen, Y., Schuur, T., Vergara, H., Kuster, C., 2021. Effect of Precipitation Sampling Error on Flash Flood Monitoring and Prediction: Anticipating Operational Rapid-Update Polarimetric Weather Radars. J. Hydrometeorl. 22 (7), 1913–1929. https://doi.org/10.1175/JHM-D-19-0286.1.
Wu, H., Adler, R.F., Hong, Y., Tian, Y., Policelli, F., 2012. Evaluation of global flood detection using satellite-based rainfall and a hydrologic model. J. Hydrometeorol. 13 (4), 1268–1284.
Xue, X., Hong, Y., Limaye, A.S., Gourley, J.J., Huffman, G.J., Khan, S.I., Dorji, C., Chen, S., 2013. Statistical and hydrological evaluation of TRMM-based Multi-satellite Precipitation Analysis over the Wangchu Basin of Bhutan: Are the latest satellite precipitation products 3B42V7 ready for use in ungauged basins? J. Hydrol. 499, 91–99.
Yamazaki, D., Kanae, S., Kim, H., Oki, T., 2011. A physically based description of floodplain inundation dynamics in a global river routing model. Water Resour. Res 47 (4). https://doi.org/10.1029/2010WR009726.
Yami, T.L., Gao, S., Chen, M., Li, Z., Labriola, L., Wara, C., Beshah, F.Z., Hong, Y., 2021. CREST/EF5 capacity building to enhance resilience to hydrodynamic disasters in emerging regions. Afr. J. Environ. Sci. Technol. 15 (6), 230–242.
Yang, G., Bowling, L.C., Cherkauer, K.A., Pijanowski, B.C., 2011. The impact of urban development on hydrologic regime from catchment to basin scales. Landsc. Urban Plan. 103 (2), 237–247.
Yang, Y., Pan, M., Lin, P., Beck, H.E., Zeng, Z., Yamazaki, D., David, C.H., Lu, H., Yang, K., Hong, Y., Wood, E.F., 2021. Global reach-level 3-hourly river flood reanalysis (1980–2019). Bull. Amer. Meteorol. Soc. 102 (11), E2086–E2105.
Yang, M., Wang, G., Lazin, R., Shen, X., Anagnostou, E., 2021. Impact of planting time soil moisture on cereal crop yield in the Upper Blue Nile Basin: a novel insight towards agricultural water management. Agric Water Manag 243, 106430.
Yilmaz, K.K., Gupta, H.V., Wagener, T., 2008. A process-based diagnostic approach to model evaluation: application to the NWS distributed hydrologic model. Water Resour. Res. 44 (9).
Yuan, F., Wang, B., Shi, C., Cui, W., Zhao, C., Liu, Y., Ren, L., Zhang, L., Zhu, Y., Chen, T., Jiang, S., Yang, X., 2018. Evaluation of hydrological utility of IMERG Final run V05 and TMPA 3B42V7 satellite precipitation products in the Yellow River source region. China. J. Hydrol. 567, 696–711.
Yussouf, N., Wilson, K.A., Martinaitis, S.M., Vergara, H., Heinselman, P.L., Gourley, J.J., 2020. The coupling of NSSL warn-on-forecast and FLASH systems for probabilistic flash flood prediction. J. Hydrometeorol. 21 (1), 123–141.
Zhang, Y., Hong, Y., Gourley, J.J., Wang, X., Brakenridge, G.R., De Groeve, T., Vergara, H., 2014. Impact of assimilating spaceborne microwave signals for improving hydrological prediction in ungauged basins. Remote Sensing of the Terrestrial Water Cycle 206, 439.
Zhang, Y., Hong, Y., Wang, X., Gourley, J.J., Xue, X., Saharia, M., Ni, G., Wang, G., Huang, Y., Chen, S., Tang, G., 2015. Hydrometeorological analysis and remote sensing of extremes: Was the July 2012 Beijing flood event detectable and predictable by global satellite observing and global weather modeling systems? J. Hydrometeorol. 16 (1), 381–395.
Zhang, J., Howard, K., Langston, C., Vasiloff, S., Kaney, B., Arthur, A., Van Cooten, S., Kelleher, K., Kitzmiller, D., Ding, F., Seo, D., Wells, E., Dempsey, C., 2011. National mosaic and multi-sensor QPE (NMQ) system: description, results, and future plans. Bull. Amer. Meteor. Soc. Soc. 92 (10), 1321–1338.
Zhang, J., Howard, K., Langston, C., Kaney, B., Qi, Y., Tang, L., Grams, H., Wang, Y., Cocks, S., Martinaitis, S., Arthur, A., Cooper, K., Brogden, J., Kitzmiller, D., 2016. Multi-radar multi-sensor (MRMS) quantitative precipitation estimation: initial operating capabilities. Bull. Amer. Meteor. Soc. Soc. 97 (4), 621–638.
Zhang, W., Villarini, G., Vecchi, G.A., Smith, J.A., 2018. Urbanization exacerbated the rainfall and flooding caused by hurricane Harvey in Houston. Nature 563 (7731), 384–388.
Zhang, K., Xue, X., Hong, Y., Gourley, J.J., Lu, N., Wan, Z., Hong, Z., Wooten, R., 2016. iCRESTRIGRS: a coupled modeling system for cascading flood–landslide disaster forecasting. Hydrol. Earth Syst. Sci. 20 (12), 5035–5048.
Zhao, R.J., 1992. The Xianjiang model applied in China. J. Hydrol. 135 (3), 371–381.