10

Global Flood Models

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ABSTRACT

Flooding is the most damaging natural hazard, both economically and by population affected. Flood models are important tools for evaluating the risks associated with flooding. Historically, the modeling domain has been limited in scale; however, advancements in computing power and global data sets have led to the development of global flood models (GFMs). This global modeling capability has benefited scientific studies of exposure and climate change impact, the insurance industry, and intergovernmental disaster risk reduction efforts. Global flood modeling has now progressed beyond its infancy to a point where coordinated and targeted model development can take place based on collective studies. This chapter provides a detailed summary of the current global flood modeling state-of-affairs. It begins with a summary of the history and challenges of GFM development. This is followed by a review of current GFMs and their structures, applications, and credibility. A section is also dedicated to describing global flood modeling in the context of the insurance catastrophe model, an important GFM category that is less visible due to their proprietary nature. The chapter concludes by looking to the future and highlighting how GFMs need to improve and the new data sets and methods that could contribute to their continued development.

10.1. INTRODUCTION

Global flood model (GFM) initiatives have developed rapidly over the past decade and have matured from research experiments into usable tools that are reshaping our understanding of global flood risk (Ward et al., 2015). This chapter explores how GFMs have become a recent reality and why they are important. It will also look at the different types of GFM, the differences between a GFM and more traditional flood modeling and look at some examples of how GFMs are being used, including the crossovers with insurance catastrophe models. It will finish with a look at current GFM credibility and where GFMs might develop in the future. The focus in this chapter will be mainly on models used to derive flood hazard globally, rather than those used for flood forecasting; which is a related use and many of the models discussed are used for both purposes.

While flooding is often experienced first-hand as a local impact and has traditionally been tackled at the relevant local catchment or reach scale, there is a growing understanding that many flood events are connected to, or driven by, short-term and long-term global weather systems (Fan et al., 2015; Hagos et al., 2016). In addition,

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due to our increasingly interconnected global community, flood events in all parts of the globe are now having significant economic and social impacts in all parts of the world (Trigg et al., 2013). Together with the extra challenge of addressing the effects of climate change, which are felt globally, these drivers have led to a need for assessments of flood risk at a global scale. This global need has become evident on several fronts; scientific studies to simulate the impact effects of general circulation modeling, insurance catastrophe modeling to understand risk and exposure (Bates et al., 2018), and intergovernmental efforts in disaster risk reduction (UNISDR, 2005, UNISDR, 2009, UNISDR, 2011, UNISDR, 2013, UNISDR, 2015b). This collective challenge has resulted in the formation of the Global Flood Partnership (GFP), which brings together organizations involved on all these fronts. The overall objective of the GFP is the development of flood observational and modeling infrastructure, leveraging on existing initiatives for better predicting and managing flood disaster impacts and flood risk globally (De Groeve et al., 2015).

10.1.1. The Challenges and History of GFM Development

Despite the growing need for a better understanding of global flood risk, it was not immediately evident how this could be achieved and what a resulting GFM would look like. Any GFM needs to be able to provide realistic and reliable estimates of flood hazard for a range of probabilities (return periods). For estimates of risk exposure, at a bare minimum, flood extent is required, and ideally flood depth is also needed to estimate risk from vulnerability. These outputs need to be at a sufficient resolution to be commensurate with global exposure data sets, which are also an active research field.

Traditional flood risk modeling has filled these needs at a local scale. However, this requires significant amounts of high resolution data and computation resources, as well as technical expertise to build and run the models (Table 10.1). Scaling this approach up to a global level seemed almost an impossible challenge and therefore a different approach was required. Thus, multiple parallel initiatives emerged from different sectors, leading to a rich diversity of GFM approaches, which we detail in the next section. However, despite the initial variety, there were several common primary challenges to surmount for all developers (Sampson et al., 2015) and there is therefore a common development timeline as data and methods became available (Figure 10.1).

The challenges facing developers fall into the following five categories: terrain data, channel location and size, river discharge, computational efficiency, and automation. The first challenge facing developers was the availability of global data with which to build the models. Flood models require information about the topography of the terrain that controls flooding. It was not until the advent and adoption of the Shuttle Radar Topography Mission (SRTM) digital elevation data (hereafter DEM), that data of sufficient resolution and quality were available with a near global coverage. The second challenge, correctly identifying channel location and size, is inherently linked to the first; as the channel is derived from the DEM. The HydroSHEDS hydrography data set, developed using the SRTM DEM, is essential to modeling flooding globally. The third challenge was to derive extreme flood flows at multiple locations for every river on Earth, with limited gauged data. There are two distinct approaches to solving river discharge in GFMs, regionalization growth curve methods using data from the Global Runoff Data Center (GRDC) database (Smith et al., 2015) and land surface modeling of flows from global circulation models (GCMs). The latter approach, which enables the models to produce nowcasts, forecasts, and future predictions also introduces additional uncertainties into the modeling framework. Precipitation, a major source of uncertainty in GCMs, often dominates the uncertainty of flood simulations in GCM-driven models (Chen et al., 2014). The fourth challenge was to be able to computationally model the hydraulics of the flood flows in the rivers and on the floodplains with sufficient speed to undertake this for all rivers, for multiple probability scenarios. This was achieved through simplification of the hydraulics and the development of rapid parallel computational algorithms (Bates et al., 2010) and subgrid modeling approaches to solve multiscale hydrodynamic processes in rivers and floodplains (Neal et al., 2012; Wu et al., 2014; Yamazaki et al., 2011), as well as with the help of continuous computation speed improvements. The final, not insignificant, challenge for developers was to put these data and methods into an automatic functional framework that allowed specific hazard and forecasting outputs to be generated as required and in a format and resolution that was useable.

It should also be noted here that there have been parallel efforts to develop regional flood model approaches that share similar scale challenges with GFMs but may have access to better regional data. For example, the United Kingdom has undertaken national risk assessments using simple non-hydraulic methods, due to computational cost (Hall et al., 2003), but later used two-dimensional diffusive wave hydraulic models (Bradbrook et al., 2004, 2005). In the United States, the recent focus has been on the dynamic, unsteady river routing methods for quasi-real-time, event-based flood extent mapping (Adams, 2016).

Table 10.1 Characteristics of Global Flood Models Relative to Traditional Local Flood Models

Characteristic	Global flood model	Local flood model
Digital elevation model (DEM)	Coverage is key, needs to be global. Potentially can be composite from different sources but difficulties in merging different data sources seamlessly	Best available, typically three-dimensional laser scanning (LiDAR)
Geographical coverage	Global	Typically up to tens of kilometers
Floodplain hydraulics	Limited equation base, sacrificing accuracy for speed, knowing that errors due to neglecting, e.g., advection terms are small compared to errors from lower quality DEM. Also related to resolution, as larger model cells make some terms less significant (see Hunter et al., 2007)	Typically full shallow water
Channel hydraulics	Sometimes ignored completely; allowance for channel capacity made by, e.g., removing bankfull discharge from flow estimate; or simple representation in DEM or submodel grid.	Full representation in two-dimensional or as one-dimensional submodel from bespoke topographical survey
Outputs	Typically extent only, vertical errors in DEM can prevent useful depth prediction	Extent–depth–velocity–duration
Hydrology	Regional growth-curve methods or large-scale landsurface runoff modeling	Led by hydrologist, making best use of local data
Defenses	Generally undefended scenarios only, except where simple relationship used (e.g., GDP to defended probability)	Defended/undefended/breaching
Build and run process	Fully automated	Manual, requiring experienced modelers
Hardware	Supercomputer, cluster, and cloud	Desktop computer
Flood sources	Mostly only fluvial, some now include coastal and surface water	Fluvial, coastal, surface water; sometimes dam break, groundwater, natural flood management, urban drainage systems
Resolution	1 km to ~90 m for two-dimensional models. 5–50 km and postprocess downscaling for one-dimensioal models.	~5 m or less
Catchment size	All large rivers. Smallest scale dependent on model, i.e., 50–5000 km^2	Down to ~1 km^2 for fluvial, smaller catchments in surface water models
Dynamics	Steady state or partially dynamic, but increasingly fully dynamic	Fully dynamic

Once a GFM is functioning, there may be a number of other secondary follow on challenges that require development, depending upon the use intended. Many of these are active research areas in themselves and specific approaches are outlined in the model detail section. For example, most current GFMs do not include infrastructure that may locally affect flood hazards, e.g., bridges, dams, flood defenses, and urban drainage networks. They often do not yet include other, maybe only locally important, sources of flood hazard other than fluvial (river source), such as pluvial, coastal, or groundwater.

The GFM community has succeeded in overcoming these primary challenges and in developing a range of usable flood models. The rest of the chapter focuses on describing the models and their uses in more detail, while also looking at their testing and how developers are addressing the secondary challenges that will ultimately improve their credibility and usability.

10.2. TYPES OF GFM AND SPECIFIC EXAMPLES

The palpable benefit of being able to model flood hazard anywhere in the world meant that as soon as the necessary inputs for a GFM became available, a number of different groups began developing models simultaneously. Flood modeling on such a large scale had never been undertaken before and brought with it challenges that had not previously been encountered. Each model developer approached these new challenges differently, resulting in a broad selection of GFMs with varying model structures.

This section will begin by highlighting the key differences in model configuration of six well-known GFMs, for which there is extensive documentation. These models include U-Tokyo (previously called CaMa-UT), a research model from the University of Tokyo (Yamazaki et al., 2011); Centro Internazionale in Monitoraggio

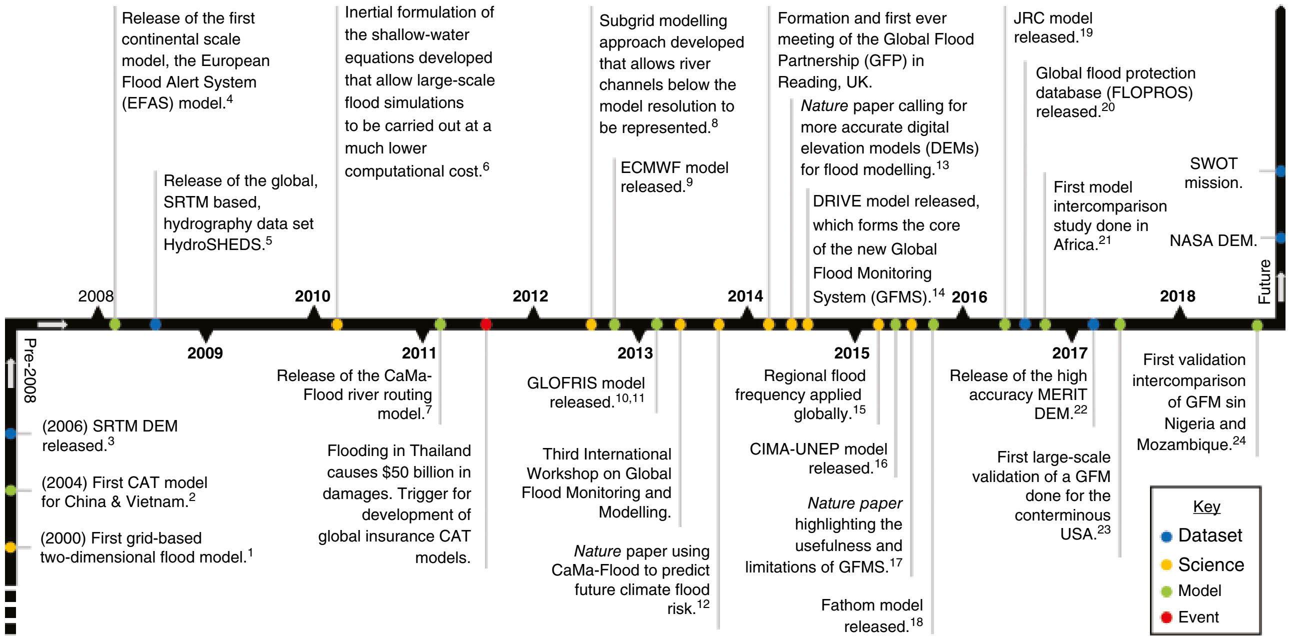


Figure 10.1 Timeline of global flood model (GFM) development highlighting key data set releases, scientific meetings and publications, model releases and testing, and flood events: 1, Bates & De Roo (2000); 2, Hall (2014); 3, Rodriguez et al. (2006); 4, Thielen et al. (2008); 5, Lehner et al. (2008); 6, Bates et al. (2010); 7, Yamazaki et al. (2011); 8, Neal et al. (2012); 9, Pappenberger et al. (2012); 10, Winsemius et al. (2013); 11, Ward et al. (2013); 12, Hirabayashi et al. (2013); 13, Schumann et al. (2014); 14, Wu et al. (2014); 15, Smith et al. (2015); 16, Rudari et al. (2015); 17, Ward et al. (2015); 18, Sampson et al. (2015); 19, Dottori et al. (2016); 20, Scussolini et al. (2016); 21, Trigg et al. (2016); 22, Yamazaki et al. (2017); 23, Wing et al. (2017); 24, Bernhofen et al. (2018).

Ambientale and United Nations Environment Program (CIMA-UNEP), a model developed for the 2015 United Nations International Strategy for Disaster Reduction (UNISDR) Global Assessment Report (GAR; Rudari et al., 2015); ECMWF, a model developed by the European Centre for Medium-Range Weather Forecasts (Pappenberger et al., 2012); GLOFRIS, a model developed by Deltares (Winsemius et al., 2013); JRC, a model developed by the Joint Research Centre in Italy (Dottori et al., 2016); and Fathom (previously called SSBN), a commercial model that arose out of research from the University of Bristol (Sampson et al., 2015).

Categorizing GFMs based on their characteristics is not a straightforward task. A previous study grouped the models into two types by extreme flow method: cascade model types and gauged flow data types (Trigg et al., 2016). A schematic of these two model groups is shown in Figure 10.2. This section will elaborate on additional model differences by looking at five different aspects: scale characteristics, model forcing, probability estimation methods, calibration, and hydraulic methods. Before highlighting the differences between the models, it should be noted that there are also many common underlying data sets, in particular, the HydroSHEDS global hydrography data set (Lehner et al., 2008) and the Shuttle Radar Topography Mission (SRTM) DEM from which it

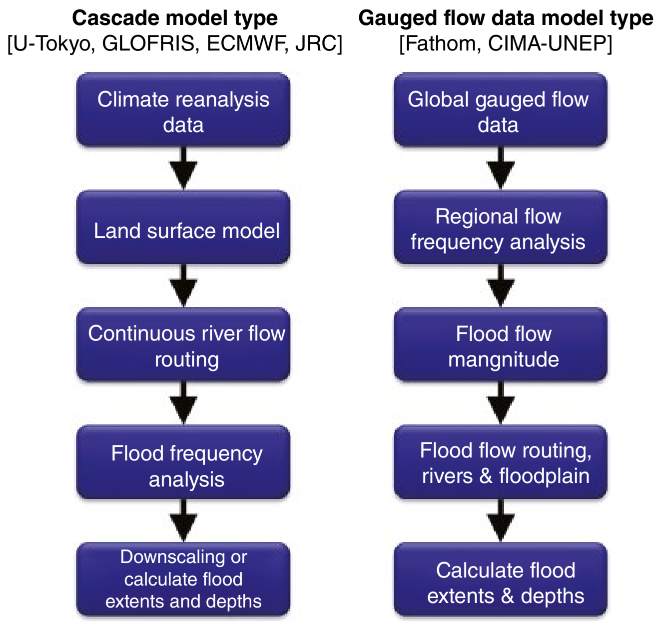


Figure 10.2 A simplified schematic of the two main model structures used by the six different global flood models (*Source:* Trigg, M. A., Birch, C. E., Neal, J. C., Bates, P. D., Smith, A., Sampson, C. C., . . . Fewtrell, T. J. (2016). The credibility challenge for global fluvial flood risk analysis. Environmental Research Letters, 11(9), 094014. Licensed under CCBY 3.0.)

is derived (Rodriguez et al., 2006). This section concludes by describing other global hydrology models that may also develop into GFMs in the future or add to process improvements in GFMs. The GFMs used for insurance purposes are described separately, partly due to the lack of published information, but also due to the very specific risk framework within which they are used.

10.2.1. Scale Characteristic

The scale of GFMs can refer to a number of things: the minimum threshold size of rivers that are represented, the resolution at which the calculations are carried out, or the resolution of the actual flood hazard output. The question of scale is something that needs to consider both the accuracy and comprehensiveness of the flood hazard output alongside the computational efficiency of the model.

Communicating the scale of river representation in GFMs is typically done in terms of upstream catchment area. The threshold river size considered by the models varies significantly, from ~50 km^2 (Fathom Global) to ~5000 km^2 (JRC). The GFM output is contingent on the input data sets, and often, global data sets are not resolved to a level where the smallest rivers can be easily represented. The coarse (~5000 km^2) upstream area threshold of the JRC's model comes as a result of using ERA-Interim climatology, where the coarse global resolution cannot accurately represent very local precipitation (Dottori et al., 2016).

Operating at a coarse resolution is not a detriment to these global models but rather a necessity. Many of the models run their computations at a coarser scale and then downscale these results to the output resolution. The process of downscaling makes modeling at such large scales more computationally viable (Bates et al., 2018). The Fathom model, however, no longer downscales and runs all calculations explicitly at either 30 m or 90 m resolution (depending on the DEM available). This shows how far GFMs have come in only a matter of years (Sampson et al., 2015). The principle, however, remains the same; global models cannot be run at "engineering" level resolutions (< 5 m), even if the data were available.

The scale of GFMs is likely the characteristic that will see the most improvement over the coming years. As computational capacity improves through faster processors and parallelization, so too global data sets will see advancements in terms of accuracy and resolution; making it possible to accurately model the flood hazard of even the smallest streams at some point.

10.2.2. Model Forcing

Global flood models can be most easily categorized by their method for generating extreme flood flows. Models are either forced by climate reanalysis data or by global gauge data. The two methods for forecasting extreme flows differ significantly. See Figure 10.2 for a useful visualization of this model categorization and the different stages in analysis that occur as a result of beginning with an extreme flow methodology.

Those models forced by climate data combine a climate reanalysis data set with a land surface model to predict extreme flows. Climate reanalysis data sets contain measurements of global climate data that are collected and stored at a constant time step (often 6–12 h) over an extended period (30–40 years for the GFMs in question) (Dee et al., 2016). These rainfall data, along with other relevant climate data, are input into a land surface model that simulates the land surface response to the climate forcing (Pappenberger et al., 2012) and outputs the resultant rainfall discharge and volume.

The GFMs not forced by climate data are forced instead by regionalized analysis of global gauge data. The premise for these models is that the discharges measured in well-monitored catchments can be transferred to unmonitored catchments that share similar characteristics. The GFMs use data from sources like the Global Runoff Data Centre (GRDC), which collects discharge data from 9500 stations globally. Catchments are then categorized based on their Koppen-Geiger climate classification (Kottek et al., 2006) and their rainfall characteristics. The behavior of similarly characterized gauged catchments is used to derive ungauged catchment flows so that extreme flows can then be calculated for all global catchments (Rudari et al., 2015; Smith et al., 2015).

10.2.3. Probability Estimation Methods

In order for GFMs to model flooding of a specific return period, some form of flood probability estimation needs to take place. All the models apply a Gumbel distribution (Generalized Extreme Value distribution Type I) to their forcing data to estimate the return period magnitude. The models differ, however, in the flood component that is output as a result of this probability estimation.

The JRC, Fathom, and CIMA-UNEP models return probability discharges. These discharges are then used as input for a hydraulic model, which simulates the flood extent and depth in the catchment for the given return period flow (Dottori et al., 2016; Rudari et al., 2015; Sampson et al., 2015). The ECMWF and U-Tokyo models return probability flood depths, derived from the Gumbel frequency analysis of river water storage, which is calculated by passing the climate forcing data through a river routing scheme. These probability flood depths are calculated for each river cell and are used to determine whether the surrounding cells are flooded or not (Pappenberger et al., 2012; Yamazaki et al., 2011). The GLOFRIS model operates under a similar "flooded cell" probability scheme, but uses flood volume instead of flood depth to determine the probability of cell inundation (Ward et al., 2013; Winsemius et al., 2013).

10.2.4. Calibration

A major difference between GFMs and reach-scale flood models is the level to which they are calibrated. Reach-scale flood models are often calibrated against a multitude of different measurements and observations from historical flood events, these include: gauge flow records, gauge water level measurements, flood depth, flood extent, and flood frequency (Huxley & Ryan, 2016). Data availability, in addition to the scale and global applicability of GFMs, limits the feasibility of conventional flood model calibration. Variables traditionally derived at a regional scale through calibration, such as flow roughness parameter Manning's n, are either calculated based on a relationship with streamflow (Wu et al., 2017) to account for the relationship between roughness and flooded vegetation (Soong et al., 2012), or determined based on basin characteristics (Rudari et al., 2015), previous studies (Dottori et al., 2016), or kept constant in the global domain (Winsemius et al., 2013; Yamazaki et al., 2011).

Many of the GFM input data sets have undertaken some form of correction. The forcing data sets for almost all of the models have received bias correction and the underlying SRTM-based (Rodriguez et al., 2006) HydroSHEDS DEM (Lehner et al., 2008) has in some cases received vegetation canopy and urban bias correction (Dottori et al., 2016; Sampson et al., 2015; Yamazaki et al., 2012). Bias correcting the underlying DEM is of vital importance, as these areas of vegetation and high urban concentration see consistent elevation overestimation. This incorrect terrain representation, in turn, naturally affects the accuracy of the modeled flood extent.

10.2.5. Hydraulic Method

Central to each GFM is a hydraulic model that simulates, to varying degrees of complexity, the physics of fluid flow. To operate globally, these models often need to make assumptions about flow physics that simplify the governing equations, thereby considerably reducing computation time. Information about the set-up of each model, including the most up to date hydraulic method, is provided in Table 10.2.

The CIMA-UNEP model is the only GFM that operates in one-dimension, solving Manning's equation (10.1) at regular points along the centerline of the river channel (Rudari et al., 2015):

$$Q = \frac{A}{n} R^{2/3} S^{1/2} \tag{10.1}$$

where Q is the channel flow [$L^3\ T^{-1}$], R is the hydraulic radius [L], S_o is the channel slope [L/L], A is channel cross-sectional flow area [L^2], and n is Manning's roughness coefficient [$T\ L^{1/3}$]. One-dimensional flow representation is one of the simplest forms of flood modeling, but while it is computationally efficient, it can falsely represent connectivity in floodplains and cannot model the floodplain flow well, unless it is parallel to the main river channel (Neelz & Pender, 2009). However, on the large scales of global flood models it appears to perform reasonably well considering its limitations (Bernhofen et al., 2018).

The remaining flood models all operate in two dimensions, solving some simplified form of the shallow-water equations, as the computational cost of running the full physics solvers would make modeling infeasible with such large domains. The full one-dimensional shallow-water equations for momentum and continuity are given in equations (10.2) and (10.3), respectively, below:

$$\underset{\text{[acceleration]}}{\frac{\partial Q_x}{\partial t}} + \underset{\text{[advection]}}{\frac{\partial}{\partial x}\left(\frac{Q_x^2}{A}\right)} + \underset{\text{[water slope]}}{gA\frac{\partial(h+z)}{\partial x}} + \underset{\text{[friction slope]}}{\frac{gn^2Q_x^2}{R^{4/3}A}} = 0 \tag{10.2}$$

$$\frac{\partial A}{\partial x} + \frac{\partial Q_x}{\partial x} = 0 \tag{10.3}$$

where Q_x is the flow in the x direction [$L^3\ T^{-1}$], A is the cross-sectional flow area [L^2], h is the water depth [L], z is the bed elevation [L], g is the acceleration due to gravity [$L\ T^{-2}$], n is Manning's roughness coefficient [$T\ L^{1/3}$], R is the hydraulic radius [L], t is time [T], and x is the distance in the x Cartesian direction [L].

Channel flow is calculated in the two-dimensional models using kinematic wave, diffusive wave, or inertial simplifications of the shallow-water equations. The kinematic wave simplification, which is used in the GLOFRIS model, assumes that local and convective acceleration (the first and second terms of equation 10.2) are negligible and simplifies the water-slope term (term three in equation 10.2) to consider only bed gradient (z) and not water depth (h). It retains the friction-slope term (term four in equation 10.2). The diffusive wave simplification differs from the kinematic wave simplification in that it includes water depth (h) in the water-slope term. This allows backwater effects to be simulated in models that apply the diffusive wave simplification. The inertial simplification to the shallow-water equations is an adapted form of the diffusive wave simplification that incorporates local acceleration (term one in equation 10.2) into the formulation (Bates et al., 2010). The remaining models have either updated their models to (U-Tokyo and ECMWF), or have always employed (Fathom and JRC), a form of the inertial simplifications for their hydraulic simulations.

Table 10.2 Global Flood Model Details

Model	Climate forcing	Land surface model	River routing	Floodplain	Flood frequency	Downscaling	Output data resolution
GLOFRIS (Deltares, VU Amsterdam, University of Utrecht, PBL)	EU-WATCH reanalysis 1960–1999	Hydrological model PCR-GLOBWB, 0.5°	Kinematic 0.5°	30 arc s SRTM model	Flood volume Gumbel distribution for 1960–1999	Volume redistribution 30 arc s SRTM model	30 arc s ~900 m
U-Tokyo (U-Tokyo, JAMSTEC)	JRA-25 reanalysis 1979–2010 + GPCP raingauge correction	MATSIRO-GW energy and water balance (1°)	Inertia 0.25°	Subgrid topography upscaled from 3 arc s HydroSHEDS and SRTM	Water level Gumbel distribution for 1979–2010	Flood depth downscaled onto 18 arc s DEM	18 arc s ~540 m
HTESSEL + CaMa-Flood (ECMWF)	ERA-Interim reanalysis 1979–2014	HTESSEL, T255 (~80 km)	Three methods: kinematic, Inertia(×2) 0.25°	Subgrid topography upscaled from 3 arc s HydroSHEDS and SRTM	Flood depth GEV distribution for 1979–2014	Depth downscaled onto 18 arc s DEM	18 arc s ~540 m
JRC	GloFAS, ERA-Interim reanalysis 1980–2013	HTESSEL	LISFLOOD-Global (0.1°) + inertia (30 arc s)	Subgrid topography upscaled from 3 arc s HydroSHEDS and SRTM	Gumbel distribution for 1980–2013	N/A	30 arc s ~900 m
Fathom	Regional FFA from global gauge data	N/A	Inertia 1 or 3 arc s	MERIT or 1 s mixed (e.g., NED)	From FFA	N/A	3 arc s ~90 m Or 1 s (~30 m)
CIMA-UNEP, GAR2015	Regional FFA from global gauge data + ECEarth bias corrected	Continuum model to improve FFA	Manning's at multiple points	Reconditioned HydroSHEDS and SRTM	From FFA, GEV fitting	Native at 3 arc s	3 arc s ~90 m

Source: Trigg, M. A., Birch, C. E., Neal, J. C., Bates, P. D., Smith, A., Sampson, C. C., . . . Fewtrell, T. J. (2016). The credibility challenge for global fluvial flood risk analysis. Environmental Research Letters, 11(9), 094014. Licensed under CCBY 3.0.

Out of channel, or floodplain flow, in the GFMs is modeled in two dimensions; and while most solve some simplified form of the two-dimensional shallow-water equations, the GLOFRIS model represents out of bank floodplain flow using a simple water-level/volume relationship. Although floodplain flow in the GLOFRIS model is technically modeled in two dimensions, the volume distribution approach does not represent conservation of momentum. This approach is often referred to as "pseudo-two-dimensional" because it omits any flow physics in two dimensions (Evans et al., 2007; Neelz & Pender, 2009). The remaining models solve floodplain flow using the two-dimensional shallow-water equations, which take the same general form as the one-dimensional equations but in two directions, and apply the same simplifications as outlined above for one dimension.

Some of the models are also able to incorporate features below the model grid resolution into the simulation. This subgrid representation can either explicitly include channels as in the Fathom and JRC GFMs, or incorporate subgrid scale topography through parameterization (Yamazaki et al., 2011), as in the ECMWF and U-Tokyo GFMs. The ability to model subgrid processes is important in a global flood modeling context, as it allows simulations to run at a coarse, computationally efficient, resolution while still capturing the relevant floodplain connectivity and inundation dynamics.

10.2.6. Other Relevant Models

Another field that is starting to impact the GFM scene is that of global hydrology models (Schellekens et al., 2017), which have the potential, if tuned to high-flow regimes, to represent flood regimes.

One example of a global modeling framework that is similar to the models described so far is the Dominant River Tracing-Routing Integrated with VIC Environment (DRIVE) model (Wu et al., 2014). The DRIVE model applies the kinematic wave or diffusion wave equations both to dominant rivers at grid level and to tributaries at subgrid level. The DRIVE model is the core component of the Global Flood Monitoring System (GFMS, http://flood.umd.edu/). The GFMS is a NASA-funded experimental system using real-time TRMM Multi-satellite Precipitation Analysis (TMPA) and Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM (IMERG) precipitation maps, as input to the DRIVE model. The DRIVE model runs on a quasiglobal (50°N–50°S) grid for hydrological runoff and routing simulations. Flood detection and intensity estimates are based on 15 years of retrospective model runs with TMPA input, with flood thresholds derived for each grid location using surface water storage statistics. The GFMS flood forecast range is 5 days, and the DRIVE model also includes a routine for determining forecast-based inundation extent at 1 km.

The Model for Scale Adaptive River Transport (MOSART) is also an example of a global hydrology model that has the potential to model floods and has been used to study surface water dynamics of the Amazon basin (Luo et al., 2017). The MOSART was developed as a scalable framework for representing and studying riverine dynamics of water, energy, and biogeochemistry cycles across local, regional and global scales from an integrated human–Earth system perspective (Li et al., 2013, 2015). The MOSART receives runoff inputs from the land component of an Earth system model or a land surface model, routes the runoff across hillslopes into tributary channels (within each spatial unit such as a latitude/longitude grid or subwatershed) then through river networks which connect all spatial units within a study domain. The kinematic wave method is used for the routing of runoff over hillslopes and in the channels with relatively steep topography, and a diffusion wave method is used for the channels with flat topography or those prone to inundation (Luo et al., 2017).

Finally, it is worth mentioning the risk-modeling framework developed by Arnell and Gosling (2016). These authors assessed global river flood risk under climate change (flood-prone population and flood damage) using a global hydrological model with climate scenarios derived from 21 climate models, together with projections of future population. Flood hazard was calculated considering change in the flood frequency and magnitude.

10.3. APPLICATIONS OF GLOBAL FLOOD MODELS

Global flood models are multifaceted: they have applications in many different fields related to research, planning, insurance, commercial use, and emergency support. Here we present a description of some of their main applications, which are also summarized in Table 10.3.

10.3.1. Flood Hazard Mapping

Many areas of the globe still lack reliable spatial information about the location and extent of flood-prone areas; this absence has been one of the main drivers behind the development of GFMs. The main advantage of using GFMs to characterize flood hazard is that resulting estimates are derived in a consistent way, using input data sets of the same accuracy and with the same modeling framework. This consistent approach provides a more realistic picture of exposure (Wing et al., 2018). Flood hazard evaluation is typically undertaken by deriving inundation maps for a range of return periods, although some GFMs calculate hazard from continuous climatological or meteorological information. These maps can be produced either for research (Dottori et al., 2016;

Table 10.3 Different Possible Applications of Global Flood Models with Referenced Examples

Category	Model	References
Flood hazard mapping	ECMWF	Pappenberger et al. (2012)
	JRC	Dottori et al. (2016), data.jrc.ec.europa.eu/collection/floods
	GLOFRIS	Ward et al. (2013)
	Fathom (SSBN)	Sampson et al. (2015)
Flood risk analysis (climate change)	CIMA-UNEP	UNISDR (2015)
	GLOFRIS	Ward et al. (2013) Winsemius et al. (2016)
	JRC	Alfieri et al. (2017)
	U-Tokyo	Yamazaki et al. (2011); Hirabayashi et al (2013); Tanoue et al (2016); Dottori et al., 2018
	Fathom	Sampson et al. (2015)
	CAT models	
Flood forecasting	GFMS	Wu et al. (2014)
	GloFAS	Alfieri et al. (2013)

Source: Adapted from Alfieri, L., Cohen, S., Galantowicz, J., Schumann, G. J.-P., Trigg, M. A., Zsoter, E. Salamon, P. (2018). A global network for operational flood risk reduction. Environmental Science & Policy, 84, 149–158.

Pappenberger et al., 2012; Sampson et al., 2015; Ward et al., 2013) or commercial purposes, and some models are used for both (Sampson et al., 2015).

Global flood models are now also being used at a national scale, incorporating more accurate local data into their framework. Fathom have recently released a United States model that uses national U.S. Geological Survey (USGS) elevation data along with other national data sets to produce flood hazard output at 30 m resolution (Wing et al., 2017). They used the same approach in Belize, incorporating local data into their model to produce national flood hazard maps (http://www.charim.net/; Trigg et al., 2017; Ward et al., 2015).

10.3.2. Flood Risk Analysis

A further step in the use of GFMs is using the flood hazard maps as an intermediate step to produce flood risk estimates at a global scale. Typically, risk is expressed considering expected annual economic losses and expected annual number of people potentially affected (UNISDR, 2015a). These analyses can focus on current risk, how risk has changed historically, and how risk may change as a result of future climate and socioeconomic change. Risk estimates characterizing present risk conditions often do so at country level. The CIMA-UNEP model was used to predict average annual losses at national level for the GAR 2015 report (Rudari et al., 2015). Similarly, GLOFRIS is integrated into an online tool, AQUEDUCT (http://floods.wri.org/), which allows end users to easily interact with flood hazard maps and assess impacts such as urban damage, affected GDP, and affected population at the country scale.

Historical data sets can be incorporated into flood risk analysis to evaluate changes in vulnerability and risk over time. Databases such as the History Database of the Global Environment (HYDE) provide gridded time series of population and land use changes. Combining these time series with flood hazard maps reveal historical trends in flood risk exposure (Jongman et al., 2012; Tanoue et al., 2016).

Those models forced by climate data (as outlined in the previous section) benefit from the fact that future climate scenarios can be easily simulated within the model framework. Studies investigating future flood risk also incorporate socioeconomic and demographic changes into their analyses, as these are seen as equally contributory to future risk. The JRC, GLOFRIS, and U-Tokyo models have all been integral to high impact research studies predicting future flood risk under various climatic, demographic, and socioeconomic projections (Alfieri et al., 2017; Dottori et al., 2018; Hirabayashi et al., 2013; Winsemius et al., 2016).

The flexible, semiautomatic framework of GFMs also lends them useful to flood management scenario modeling. The models can be run under different defense scenarios and coupled with exposure data sets to provide a cost-benefit analysis of various management schemes (Ward et al., 2017).

10.3.3. Flood Forecasting

Given the computational burden of deriving inundation maps, GFMs are currently not applied for real-time flood forecasting. The GFMS is a flood forecasting model that shares a similar framework to GFMs. However, instead of being forced by historical climate or gauge data, it is forced instead by real-time satellite-based precipitation data (Wu et al., 2014). The previously described global flood hazard models can quasiforecast flooding by producing and using static inundation maps as reference scenarios to evaluate potential flood-prone areas and flood impacts according to forecasts. The GFM modeling frameworks are already automated and built for speed, in the future we will likely see these frameworks used in forecasting over large scales. This potential use presents one the most promising GFM development areas in the near future.

10.3.4. Insurance Exposure

A key application for GFMs is in modeling insurance exposure. Some of the GFMs we have covered already, such as those developed by Fathom, are being used to inform insurance companies about the exposure of their portfolio. The bulk of this insurance exposure analysis is undertaken within specialized insurance catastrophe model frameworks. The commercial nature of these models means that there is little published literature about their development and structure. The next section provides a summary of the current "public" state of knowledge for these commercial examples of GFMs.

10.4. INSURANCE CATASTROPHE MODELS

The insurance and reinsurance industry started considering natural catastrophe (CAT) models in the late 1980s at a time when modeling companies first appeared. The use of CAT models by property (re)insurers has grown since then. They are now commonly used for portfolio management (e.g., accumulation control, analysis of the key risk drivers) and risk transfer (e.g., structuring and pricing of risk transfer through reinsurance or alternative solutions). Property (re)insurers are also expected by regulators to use CAT models in their risk management processes.

The CAT models are designed to quantify the financial impact of catastrophic scenarios for the risk carrier. Both the frequency and the severity of the scenario (also called "event") are estimated. One of the specificities of CAT models is that they adopt different financial perspectives for the loss computation: economic losses but also insured losses or reinsured losses, depending on the interest of the risk carrier. The structure of CAT models can be described in four main modules.

1. The hazard module: this is the core of CAT models and it contains information specific to the peril.

2. The exposure module: all relevant information from the (re)insurance portfolio is captured. This includes the location of the properties; but also the occupancy, building type, and sums insured.

3. The vulnerability module: hazard intensities are translated into potential damages based on the local hazard, the physical characteristics of the properties at risk, and the values insured by coverage (e.g., building, content, or business interruption). Vulnerability functions are one of the main sources of uncertainty in flood risk models (Metin et al., 2018) because of the large variabilities in damages. Vulnerability functions are therefore typically described with an uncertainty distribution around the mean damages.

4. The financial module: insured and reinsured losses are computed based on the (re)insurance terms and conditions. All the CAT model vendors have developed their proprietary CAT modeling platforms that include a financial module. Model users run the set of stochastic events on their portfolio of policies and obtain from the platform the list of losses for different financial perspectives and by stochastic event. In the past few years, a new initiative largely driven by the (re)insurance industry has developed an open source loss modeling platform: OASIS (https://oasislmf.org/) Loss Modeling Framework (LMF). The main objectives of the OASIS initiative are to improve risk assessment through more models by providing the modeling platform, more transparency, and innovation.

There are three main categories of companies developing CAT models: the modeling companies that license their products to insurers, reinsurers, and reinsurance brokers; the reinsurance brokers that provide their CAT models as part of their service to their clients (insurance companies) or license them; and some large insurance and reinsurance companies that use their CAT models internally.

Flood events in a CAT model stochastic event set are defined as flood footprints. The local hazard intensity of those footprints is generally the flood depth. Other indicators are usually not modeled. Three main components are necessary to build those stochastic footprints: flood hazard maps, stochastic precipitation and discharge scenarios, and flood defense information. The final footprints run in the CAT models are a combination of these three components. The flood hazard maps are used to translate the precipitation and discharge scenarios into flood footprints by taking into account the local flood defense systems.

10.4.1. Flood Hazard Mapping

The objective with flood hazard mapping in the context of financial loss assessment is to have comprehensive and detailed flood hazard maps for different return periods, typically six return periods between 20 years and 1000 years. However, the challenges when mapping flood hazard are the resolution required and the spatial coverage. In fact, local topography conditions can significantly influence the damages sustained in the properties. Furthermore, it is estimated that around 30% of the

National Flood Insurance Program (NFIP) claims in the United States are located outside of the 100-year flood zones (Wojtkiewicz et al., 2013). A standard flood mapping strategy has been adopted to overcome these two difficulties.

Detailed topography data are used as topography is one of the main drivers for accurate flood mapping (Bhuyian & Kalyanapu, 2018). The nationally complete digital elevation data range in resolution from 5 m (e.g., in the United Kingdom) or 10 m (e.g., in the United States) to 90 m in other countries (e.g., in Asia). The resolution of the digital elevation data is, however, limited by the availability and cost of high-resolution topography data at very large scales, and by the run time cost of the hydraulic model. Developers of GFMs will often vary the digital elevation data used from country to country depending on the quality of data available at a national level.

The flows are propagated along the river network in order to obtain the extent and depth of the flooding by using hydraulic models solving the shallow-water equations. Different modeling solutions have been chosen: one-dimensional or two-dimensional hydraulic models, or a combination of both types of hydraulic model.

The flood frequency analysis approach is often applied to derive design discharges at all river locations for a set of return periods. Alternative techniques can also be used because of the global scale of some of the modeling. The rationale behind those alternative approaches is to make use of precipitation data, as they are common and more comprehensive than discharge data in some parts of the world.

The analysis of historical insurance claims data from floods shows that a significant proportion of those claims come from outside of the large river floodplains. Consequently, both fluvial flooding and surface water flooding are modeled, and the fluvial flood maps cover the large and the small rivers draining a few square kilometers.

Some companies have developed global flood hazard map products based on the specifications and approaches described above. Those companies use approaches that they can apply anywhere, paralleling the GFMs described in the rest of the chapter.

10.4.2. Stochastic Precipitation and Discharge Scenarios

Realistic scenarios reproducing dependences across catchments are important to properly assess potential financial impacts for a (re)insurance company. These scenarios can be developed at the country or at the regional level and cover several countries.

The stochastic scenarios need to include both precipitation and river discharges in order for the CAT model to estimate claim amounts from both flood types. Precipitation modeling is the first component of the modeling chain for the stochastic scenarios in most of the models. In countries where tropical cyclones are present, precipitation is modeled as tropical cyclone induced and nontropical cyclone induced. This requires a realistic catalogue of tropical cyclones tracks.

Temperature modeling is usually carried out along with precipitation to account for snow accumulation and snowmelt in the runoff generation process for relevant regions. The precipitation and temperature simulations then drive rainfall-runoff models to compute river discharges at all river locations. The precipitation, temperature, and hydrological modeling can be carried out on a continuous basis or as event based.

A key parameter for the evaluation of financial losses under reinsurance contracts is the definition of an event. It is often found in reinsurance contracts that a natural event has a physical definition, for instance that a flood event must come from a single weather system, but also has a maximum duration. This maximum duration is called the hours clause, and current practice in the United States is for this to be 168 h; clauses of 504 h are also common in Europe. However, those clauses are not necessarily standard and can differ from one contract to another even for the same territory. This means that if the travel time of the flood wave along a river system is long enough, flooding can happen more than 168 h apart at two different locations. In that case, the flood claims would be considered as belonging to two different events. The hours clause can have an impact on the payment by the reinsurer to the insurer after an event depending on the details of the reinsurance contract. The hours clause is often taken into account in the definition of the events of the stochastic event set. Some models provide the flexibility to the CAT model users to define their own relevant hours clause.

10.4.3. Flood Defenses

Flood defense systems can have a significant impact on flooding. Developers of CAT models collect flood defense information from authorities and incorporate them into their models. However, this information is often incomplete and assumptions need to be made for places where no information exists or is not available. Flood defense data are another significant source of uncertainty in flood risk models (Metin et al., 2018).

10.5. GFM CREDIBILITY

10.5.1. The Importance of Model Credibility

Since the beginnings of the development and use of numerical models, there has always been an acknowledgment that models need to be applied carefully, lest their limitations lead users astray. As the famous quote from George

Box states, "All models are wrong, but some are useful." This is no different for GFMs and it could be argued that it is even more pertinent, as in reality GFMs consist of a chain of models. Addressing aspects of model error and uncertainty has become a specific, and important, research field in the past few decades (Beven, 2006; Beven & Freer, 2001; Chatfield, 2006). Despite model uncertainty being a complex area of study in its own right, at its core has been the traditional process of model calibration and validation. Calibration is the tuning of model parameters to ensure model outputs match real-world observations as closely as is reasonably practicable. Validation is the testing of a calibrated model's outputs against observations to see how well they match noncalibration events. In essence, calibration and validation allow us to test the models to see how useful they are, and they form an integral part of the scientific process (Klemeš, 1986).

Given that the ambitious aim of GFMs is to provide a quantification of flood hazard for all rivers through the application of a single consistent methodology, and that their outputs are being used by an increasing range of practitioners (Ward et al., 2015), ensuring they are fit for purpose is crucial. The very different scale and ambition of GFMs, as well as the difference of approach to traditional flood modeling, makes testing them a particularly challenging process, and therefore this is still a developing, but very important, research field.

As the improvements in data resolution and increasing computation abilities enable GFMs to move towards ever higher resolutions, there is a tendency for users' expectations to increase in line with this. This expectation is particularly prevalent where there is an existing lack of national-scale or reach-scale flood hazard information with which to compare. The expectation can lead to an unrealistic view that a GFM can replace engineering-grade hydraulic modeling methods and data and be applied to purposes for which they were never intended, for example to identify risks to individual properties.

After the initial excitement of being able to generate and use flood risk analysis at a global scale for the first time fades, users are beginning to demand more information about how good the models are in particular geographical locations or for particular purposes. Model developers are very aware of the importance of communicating the limitations of their models and are therefore also keen to gain constructive feedback from users in order to focus future efforts to improve the models. This user–developer dialogue has long been a regular topic at GFP annual meetings and led directly to the first multimodel intercomparison (Trigg et al., 2016) and collective validation exercise (Bernhofen et al., 2018) for GFMs.

10.5.2. Existing Model Testing

It is ultimately the model developer's responsibility to test their models to ensure they are fit for purpose, particularly where their results have been made openly accessible. There are plenty of studies showing that developers do take this responsibility seriously (Dottori et al., 2016; Pappenberger et al., 2012; Rudari et al., 2015; Sampson et al., 2015; Wing et al., 2017; Winsemius et al., 2013; Wu et al., 2014; Yamazaki et al., 2011, 2012, 2013; Yamazaki, O'loughlin, et al., 2014), although not all to the same extent, possibly due to resource limitations, data availability, and/or project funding challenges.

Model outputs typically consist of flood extents and depths for multiple probabilities (or return periods). While methods of remote sensing of flooding have advanced significantly (Schumann & Neal, 2021), it is not possible to observe the full range of event probabilities for all rivers and therefore definitively validate all models for all locations, as these events will not necessarily have occurred in the limited time we have been observing the whole globe. Add to this the fact that the larger the river system scale, the less likely the same probability event will occur everywhere, ensuring that a definitive calibration and validation for GFMs will remain elusive.

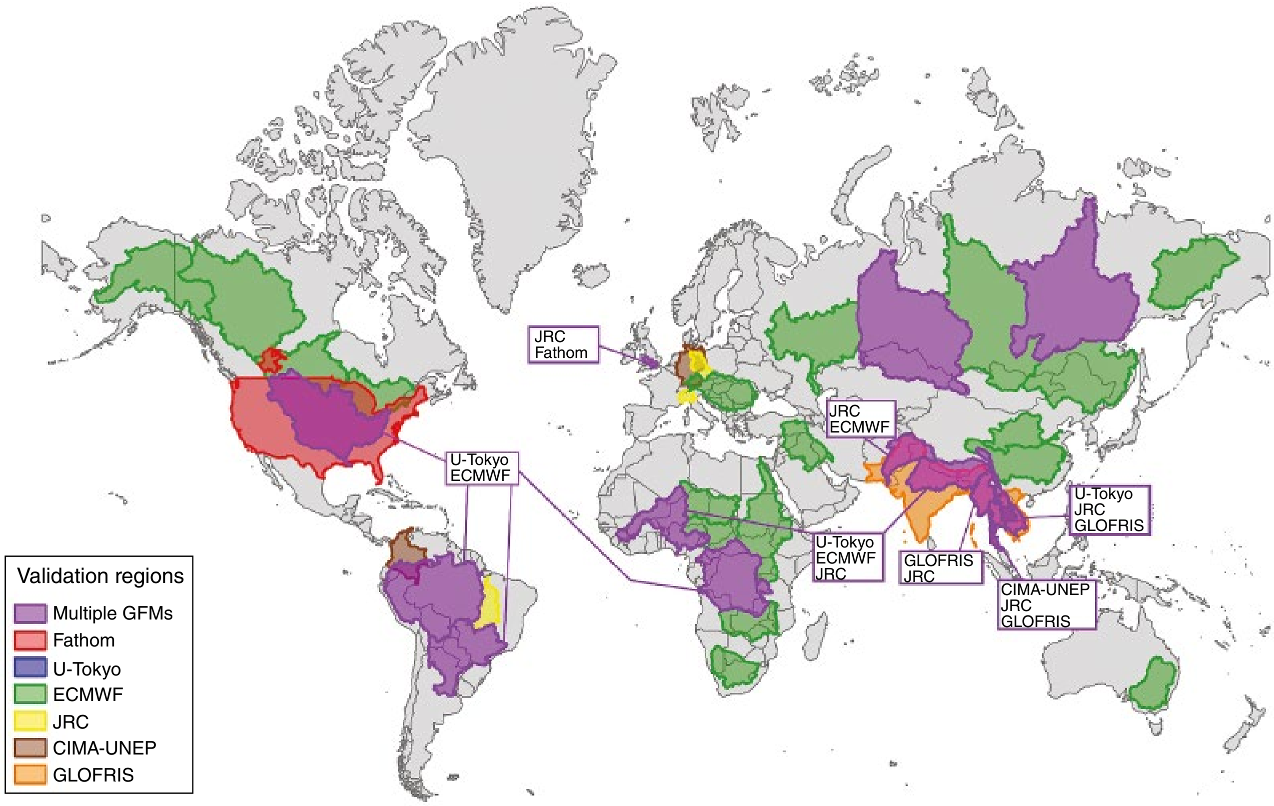
Due to the scale and complexity of GFMs and commensurate observational data challenges, GFMs do not necessarily have a full calibration of all components. Their hyperdistributed form, with multiple parameters and components ensure that model equifinality (Beven, 2006; Beven & Freer, 2001) is a serious challenge for any attempt at overall model calibration. However, developers often undertake a form of calibration and validation for subcomponents of the model, where observations are available. An example of this would be the testing of extreme flows for regionalized flow methods (Smith et al., 2015) or bias corrections for models that rely on precipitation inputs (Huffman et al., 2009). Where the GFM framework is sufficiently flexible to allow adjustment to locally available data sets, some GFMs have been applied at a national scale, such as the Fathom model in Belize, where locally gauged rainfall and river flows were used to further regionalize the global method (Ward et al., 2015).

Hoch and Trigg (2019) provide a metastudy summary of GFM validations performed to date. They show that there has been a wide range in validation (also referred to as benchmarking) data sets used, maybe partly as a result of what data were available at the time of model development. Most GFMs are validated against some inundation extent in some basins, and only a few compare simulated discharge and water surface elevation with observations. The specific river systems used for model validation differ between models as well as the number of studies documenting the model development over time (Figure 10.3; Hoch & Trigg, 2019).

So we can see that GMFs have been validated for a range of case studies and model parameters. The fact that all models are validated "successfully" for nonidentical settings may, from a model developers perspective, lead to the conclusion that the model performs well. However, it may also lead to the erroneous assumption that all models perform equally well (Hoch & Trigg, 2019). That this is not the case has been shown by grouped model intercomparison and validation studies (Bernhofen et al., 2018; Trigg et al., 2016).

10.5.3. Collective Testing

Trigg et al. (2016) performed the first intercomparison of GFMs and demonstrated that when six GFMs were compared with each other over the Continent of Africa, they only showed a 30–40% agreement in flood extent (Figure 10.4). So even at continental scales, there are significant differences in hazard magnitude and spatial



	Global flood model					
Validation type	JRC	Fathom	GLOFRIS	U-Tokyo	ECMWF	CIMA-UNEP
Discharge	✓[1]	✗	✗	✓[5,6,7,8]	✗	✗
Extent	✓[1]	✓[2,3]	✓[4]	✓[5,6]	✓[9]	✓[10]
Water surface level	✗	✗	✗	✓[6,8]	✗	✗

Figure 10.3 Map depicting the regions where each global flood model (GFM) validated model output against extents. Regions depicted in purple are locations where multiple GFMs validated, all other colors refer to specific GFMs. (Note: U-Tokyo has no unique validation locations). Table summarizing the validation methods of each GFM (Hoch & Trigg, 2019): 1, Dottori et al.(2016); 2, Sampson et al. (2015); 3, Wing et al. (2017); 4, Winsemius et al. (2013); 5, Yamazaki et al. (2012); 6, Yamazaki et al. (2013); 7, Yamazaki et al. (2011); 8, Yamazaki, O'loughlin,et al. (2014); 9, Pappenberger et al. (2012); 10, Rudari et al. (2015).

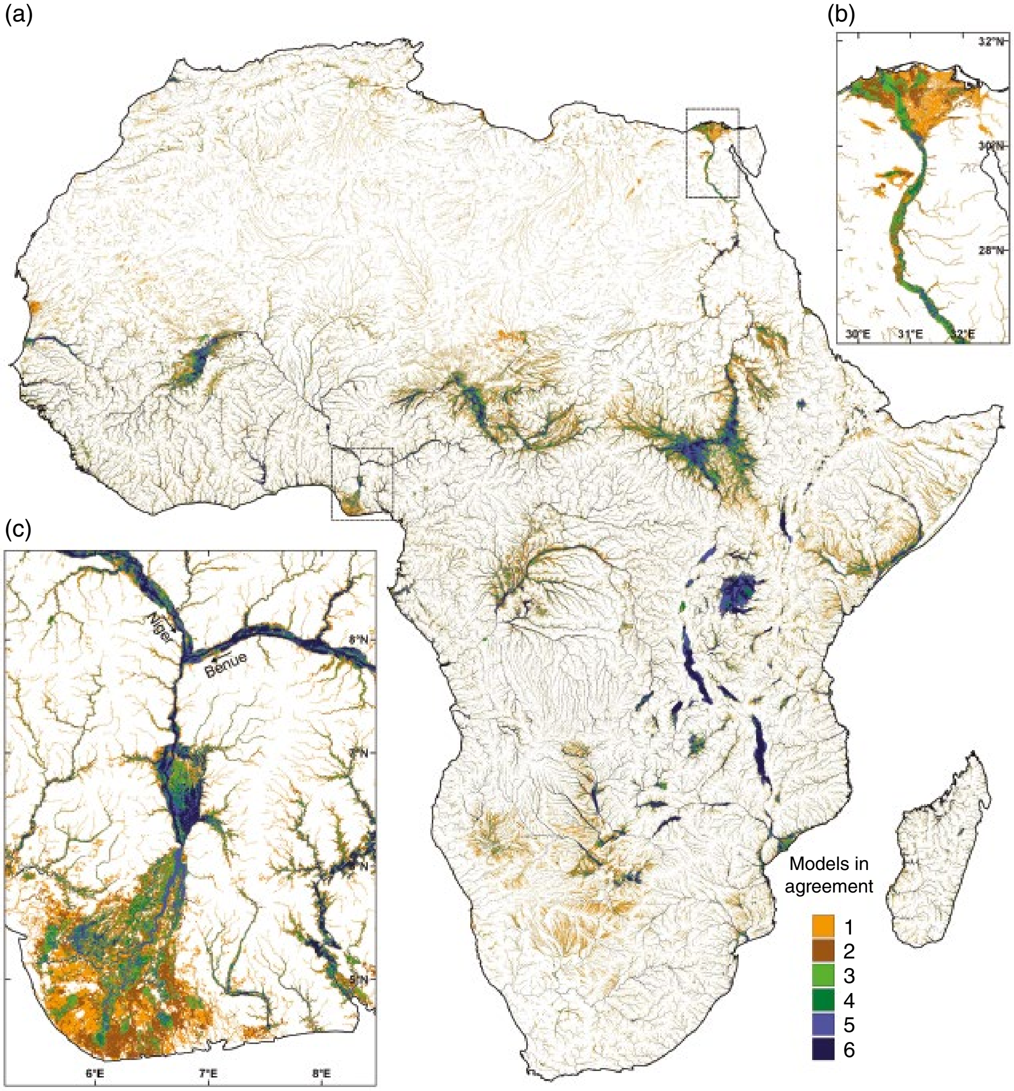


Figure 10.4 Global flood model agreement across Africa. (a) Aggregated flood results for six models for a 1-in-100 year return period fluvial flood hazard for the African continent. Color scale indicates how many models predict flooding. (b) Detail for the lower Nile. (c) Detail for the lower Niger, showing areas of strong agreement (narrow confined floodplains at the confluence of the Benue and Niger rivers) and areas of disagreement in the Niger coastal delta. (*Source:* Trigg, M. A., Birch, C. E., Neal, J. C., Bates, P. D., Smith, A., Sampson, C. C., . . . Fewtrell, T. J. (2016). The credibility challenge for global fluvial flood risk analysis. Environmental Research Letters, 11(9), 094014. Licensed under CCBY 3.0.)

pattern between models, notably in deltas, arid/semiarid zones, and wetlands (Trigg et al., 2016). Bernhofen et al. (2018) carried out the first group model validation against the same observed data for two major flood events in Africa. The flood events used were the floods of 2007 in Mozambique and of 2012 in Nigeria. These events were chosen as they were recent large-scale disasters with good observational validation data and of a scale where GFMs should perform reasonably well (Bernhofen et al., 2018). The critical success index of individual models ranged from 0.45 to 0.7 and the percentage of flood captured ranged from 52% to 97%. While this demonstrated a similar spread of model to that seen in Trigg et al. (2016), encouragingly it shows that the best individual models show an acceptable level of performance for these large rivers and demonstrates the importance of group validation.

It is encouraging to see this growing body of reports and publications recording the development and testing of GFMs, both individually and collectively, showing a growing maturity of the subject. However, there is a notable lack of record regarding one particularly important subgroup of GFMs that of the global CAT model for insurance purposes. Proprietary modeling methods with associated intellectual property rights as well as a unique application framework, make it difficult for these model groups to engage in this process in a fully open way. Nonetheless given their important application worldwide they must not be excluded from the process and no doubt benefit from the open studies reported here.

Individual model validation procedures do not contribute to a better understanding of why GMFs differ locally in their simulated inundation extent. The work of Trigg et al. (2016) and Bernhofen et al. (2018) demonstrates the value of a collective approach, but it needs to be extended and undertaken routinely rather than on an ad hoc basis. What is really needed is more insight in the relative performance of GMFs; that is, with identical boundary conditions and for the same set of validation data sets. It is only then that clearer conclusions can be drawn as to why results may differ between GFMs and where the greatest potential for improvement lies.

Up to now, GFMs have seen a rapid increase in number, their application, and acceptance (Ward et al., 2015). However, to further extend the dissemination of GFMs and their products, the testing of GFMs should become more standardized, as is already the case in other Earth science fields such as climate research. Model intercomparison projects (MIPs) are a community-based way to compare models and their products with standardized objective functions and data sets, for instance, the Coupled Model Intercomparison Project (CMIP, 2018) or the "InterSectoral Impact Model Intercomparison Project" (ISI-MIP) (Warszawski et al., 2014). Similar to these MIPs for general circulation models, establishing a MIP for GFMs should be a next development step. With such a "Global Flood Model Intercomparison Project" (GFMIP) the uncertainties associated with model inputs, modeling cascade, parametrization, and so forth could be reduced and, consequently, the overall acceptance of models and their results would likely increase. That this is timely is shown by recent efforts benchmarking GFMs globally (Bernhofen et al., 2018; Trigg et al., 2016) or individual components such as DEMs (Hawker et al., 2018), numerical routing scheme (Hoch, Haag, et al., 2017; Hoch, Neal, et al., 2017; Zhao et al., 2017), or grid design and properties (Hoch et al., 2018; Savage et al., 2016). Besides, strong learning moments would be created which could additionally contribute to improvements of GFMs. Hoch and Trigg (2019) call for just such a project and outline how this may be achieved through a shared intercomparison framework, common forcing data, and validation data.

10.6. THE FUTURE OF GFMS

Now that GFMs have most definitely "arrived" and are demonstrating their value, what is the next stage in their development? While many GFMs derive from scientific research projects to push the bounds of what is possible, these have ultimately translated into operational tools and this drives the interest in improving the models. Users also naturally begin to expect more of GFMs as their utility is demonstrated. Future steps will depend on where priorities lie for model development groups and users and how these priorities align, with the GFP taking a central role in this dialogue. Flood is also not a standalone hazard and GFMs thus have a role as a subcomponent in integrated risk frameworks such as the upcoming UNISDR Global Risk Assessment Framework (GRAF) (Elsworth, 2018). Global flood models will certainly be around for the coming decades and development is likely to focus on three specific areas of improvement; (i) data sets, (ii) processes representation, and (iii) testing.

10.6.1. Improvements in Data Sets for Model Build and Testing

Advances in GFM will be possible through future releases of higher resolution and more accurate data sets: whether through entirely new data sets or improvements to existing ones. Elevation data, in particular, strongly influences the performance of GFMs, as it is a representation of the terrain that controls flooding (Schumann et al., 2014). For example, the most anticipated near-future DEM release is the NASADEM Global Elevation Model (Crippen et al., 2016). Here, NASA will reprocess the entire SRTM data set, which is used in all GFMs, and use new algorithms and ancillary data to produce a freely available global DEM at ~30m resolution. Other DEMs, such as those produced by the Public-Private TanDEM-X mission, are able to resolve at up to ~12m globally (Krieger et al., 2007). However, the commercial nature of the mission restricts the availability of the higher resolution data sets to paying customers and curtails their use in open GFMs. The trend is towards higher resolution DEM data sets and this will translate into better GFMs.

Derived from DEMs, hydrography data sets are a key component within GFMs, as they represent the river network. Global flood model hydrography is in urgent need of updating as all models still use the decade old HydroSHEDS data set (Lehner et al., 2008). While HydroSHEDS has been particularly important in GFMs due to its structured data properties, it suffers from significant irregularities in flat terrains and urban areas, which affects the accurate location of river channels. Future hydrography data sets should incorporate accurate vector river data from observational sources, for example Sentinel 2 or OpenStreetMap, to compliment the traditional DEM-derived river delineation.

A future mission likely to have a major impact on GFMs is the NASA Surface Water and Ocean Topography (SWOT) mission (Durand et al., 2010). Scheduled for launch in 2021 and lasting 3 years, the SWOT mission will globally monitor Earth's surface water. Data related to the height, slope, and discharge of rivers will be invaluable from a hydraulic modeling testing perspective, while topographical ocean details should also improve the climate models that force many of the GFMs.

The measurement of river discharge using satellites is an emerging field of research that will benefit from the SWOT mission and could be incorporated into GFMs in the future. The Dartmouth Flood Observatory (DFO) already runs an experimental product called the River and Reservoir Watch that estimates river discharge using satellite microwave sensors (Brakenridge et al., 2016). Although still an experimental product, its relevance to GFMs is evident: remotely sensed river flows could become another method of model forcing as well as for validation.

Data sets used to measure flood exposure are equally as important as those incorporated within the actual models. Traditionally, flood exposure has been measured using gridded data sets such as WorldPop, which represents population density within a 100 m × 100 m cell. Recently, a High Resolution Settlement Layer (HRSL) was released by Facebook in collaboration with the Center for International Earth Science Information Network (CIESIN) at Columbia University (https://www.ciesin.columbia.edu/data/hrsl/). The HRSL uses high-resolution (~0.5 m) commercial satellite data to identify individual settled cells at ~30 m resolution. Available in 22 countries, the HRSL can provide a more accurate picture of exposed population and should, in theory, result in better flood exposure estimates when used in tandem with GFMs. The limited global coverage of the HRSL warrants mentioning the Global Human Settlement Layer (GHSL), which relies on technology similar to that of the HRSL and has global coverage; though it is only available at 250 m resolution (Pesaresi et al., 2013).

Future GFM development will rely not only on new data, but also on existing data that has been adapted in a way that makes it more accessible and fit for purpose. An example of one of these "products" is the Global Flood Database being developed by Cloud to Street (http://www.cloudtostreet.info/). Satellite images of historical flood events are vital for validating GFM output. The Dartmouth Flood Observatory (DFO) has been the main source for this historical data. However, although the DFO maintains a catalogue of around 5000 flood events dating back to 1985, only around 5% of the events have been mapped and the mapping methodology for these events has not always been consistent. The Global Flood Database uses the DFO's catalogue of events to map over 3000 events since 2001 using a consistent algorithm and integrating it all within the Google Earth Engine (GEE) framework (Tellman et al., 2021). This consistent methodology as well as the accessibility provided by GEE opens the door to far more extensive future GFM validation studies.

10.6.2. Improvements in Processes Representation

In tandem with improved data sets for model build and testing, there is also a push to improve physical process representation within GFMs. Often this is through adding processes through subgrid representation, for example with improved river channel geometry (Neal et al., 2015). Further development in this area will rely on a combination of improved methods and bathymetry data, which are notoriously difficult to find. Another area that has seen improvement is the representation of river hydrography, such as the addition of bifurcating river channels (Yamazaki, Sato, et al., 2014), shown to be particularly important for flood mapping in delta regions (Trigg et al., 2016). Further developments in improving river hydrography are expected in the near future, as this is an active research area for a number of GFP groups.

One particular current weakness of GFMs is in urban areas, where understanding flood exposure is particularly important. For example, the STRM DEM has not yet been corrected for urban areas to the same level as for vegetation (Baugh et al., 2013), although some model groups do a simple correction based on GDP (Sampson et al., 2015). Large urban areas also benefit from surface water drainage systems, which are not represented at all in GFMs. Urban areas can also benefit from flood defenses and some models represent these through simple assumptions relating standards of defense linked with GDP (Sampson et al., 2015). However, there are notable efforts to build an open database of global defenses that will be important in future GFMs (Scussolini et al., 2016).

As other global modeling efforts begin to overlap with GFMs, there are possibilities to explore compound flood events, which often occur together, such as coastal (Vousdoukas et al., 2016) and fluvial flood hazard. These additional hazard components may either be included as an explicit model component such as with pluvial risk in Fathom's GFM (Sampson et al., 2015), or may be combined later in a general flood risk assessment framework.

10.6.3. Improved Model Testing

Thorough model testing and validation is key to guarantee model accuracy and as a basis for wider acceptance with end users. Currently, GFMs are validated and tested individually for different basins, with different data, and different objective functions. While this yields an estimate of how accurate a model performs in representing one or more specific flood events, it does not provide insight into its relative performance compared to other GFMs (Hoch & Trigg, 2019).

Hence, there is much potential in advancing GFMs by more thorough and streamlined validation procedures. Also needed for better testing is the integration of up-to-date observations of flood events. With remote sensing technology becoming more advanced and improved methods to account for uncertainties with such remotely sensed imagery, the overall accuracy of model testing will improve. This would not only require efforts from the GFM community, but also wider collaboration with adjacent fields such as data processing, cloud computing, and remote sensing, to provide the required cyber infrastructure.

One possible approach might be a web-based platform created to facilitate a standardized validation of GFMs. By means of the platform, the external model properties (i.e., boundary conditions and forcing data) could be provided from a central location ensuring all models are applied under comparable settings. Model results could also be uploaded to the platform where validation with observed data (which could be updated regularly) and benchmarking with other model output would be performed in an automated manner.

Regardless of the way model testing will evolve, improvement is necessary. By subjecting GFMs to stricter guidelines, all involved can benefit: the wider community, through mutual learning moments, communication, and transparent scientific discourse; the developers, as they would learn where their model excels and where adjustments are required; and the end users, as uncertainties surrounding flood maps would be reduced and quantified, leading to more actionable applications of GFMs.

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