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Opinion

Effective Transfer of Science to Operations in Hydrometeorology Considering Uncertainty

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Abstract: The ability to effectively transfer results of research in hydrometeorology to operational field applications is met with several challenges. This article exemplifies cooperative implementation that explicitly considers the flow of uncertainty from data and models to products and predictions as a means to successfully meet these challenges.

Keywords: operational hydrometeorology; forecast systems; uncertainty; technology transfer

1. Introduction

The creation of effective mechanisms for dissemination of research findings to users and the establishment of effective technology transfer mechanisms were identified in the early 1990s [1] as an important need in the context of synergist basic research and technology transfer in the university environment and in the mid-1990s [2], when a U.S. National Center for Hydrology was contemplated. About 10 years later, the then young Technology Transfer Program of the Hydrologic Research Center (HRC) provided the basis for the conclusions drawn in [3] on the challenge and recommendations of corporate technology transfer for operational hydrology. A conclusion that is relevant to the present paper was that "technology transfer in the field of hydrometeorology must accommodate large natural uncertainties, and a significant effort must be put into uncertainty modeling". This assessment was also supported in [4,5] in the context of the effective use of climate information in water resource management. A recent accounting of the multidecadal process that followed for the realization and evolution of operational flash flood guidance system applications worldwide identified important elements of making research in interdisciplinary fields useful to operations in diverse environments [6]. Characterizing uncertainty in system data input and providing products that reflect that uncertainty and as planning the associated training of users constitute two of these elements.

To set the framework for the discussion below, Figure 1 presents the components of systems for prediction and response that have been proven effective in operational implementations of research products. The Figure includes components of hydrometeorological modeling for the simulation and prediction of hydrometeorological variables, such as precipitation, soil water content, and flow; components for observational data and/or for the assimilation of forecaster adjustments; components for the estimation of the flow of uncertainty from parameters, model structure, and hydrometeorological input to the variables of interest. It also includes components associated with the decision to issue warnings or to manage water resources based on the diagnostic and prognostic variables of interest, additional external information/observations, and decision-maker preferences. Finally, the response component of these decisions is considered, as supported by the cooperation of relevant agencies and public education efforts. The prevalent role of uncertainty propagation and mapping onto hazard risks or trade-off risks is depicted in Figure 1 for emphasis.

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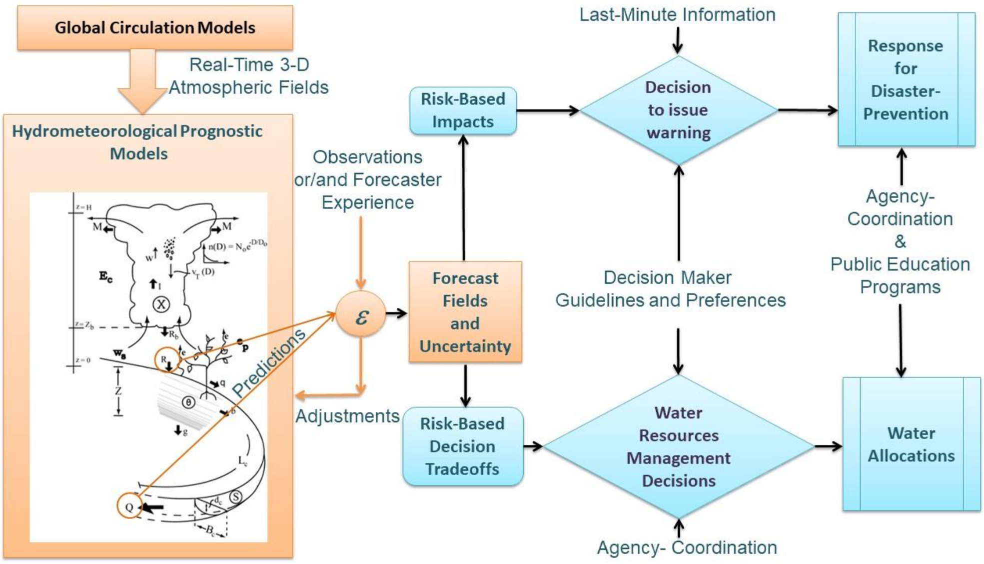

Figure 1. Components of prediction–response operational systems.

The present assessment work is anchored in the lessons learned from the aforementioned efforts of worldwide implementations and sustained use of operational hydrometeorological prediction systems. It identifies the characterization of uncertainty in data, models, and products as an important prerequisite for the transfer of science-research results to operational applications in the field of hydrometeorology. The next section identifies specific challenges and offers promising approaches for meeting these challenges. Section 3 provides two illustrative examples of operational implementation. The first is for a data-rich region, and the second is for data-sparse regions. Conclusions are presented in Section 4.

2. Elements of Effective Research-to-Operations Pathways

There are four basic challenges in the effective and sustainable transfer of research results to operations. They all concern the acceptance and use of research results by operational hydrologists, hydrometeorologists, and decision makers in real-world applications. These are: (a) large occasional errors in research output for hazardous events prevent ready acceptance of such output by operational meteorological and hydrological forecasters; (b) disruption of operationally established methodologies by new field-untested research methodologies; (c) provided research output (such as new forecasts) is not directly linked to the decision parameters used by decision makers; and (d) significant uncertainty in research output is not linked to decision parameters used by decision makers.

In addition, worldwide implementation of diagnostic and prognostic systems for operational use poses several additional challenges. Important among these for the effective transfer of research to operations are: (i) the requirement for application-specific multi- and interdisciplinary component synthesis, such as that indicated by the hydroclimatology of the application region; (ii) the necessary accommodation of any barriers that exist in some regions to local data exchanges for applications involving transboundary domains and even in national data exchanges among agencies; and (iii) the diversity in the backgrounds of operational users, who range from technicians with little experience with modern forecaster support systems to scientists with graduate degrees.

All these challenges introduce uncertainties in system implementation, from the parametrization of system components for specific applications under data uncertainty to the design of effective training programs for the operational use of the implemented systems. Multiyear experience with the research-to-operations process at HRC suggests the following useful approaches to meet the aforementioned basic challenges (a–d) and to establish effective transfer to field operations (see also Figure 1): (a) explicit uncertainty modeling and training in uncertainty concepts as related to the problem at hand; (b) maximum feasible use of existing operational methods and models, and development of hands-on demonstration projects where new research results are compared to status quo with due account of uncertainty; (c) mapping of the research information (e.g., precipitation forecasts) to impact information appropriate for decision makers for the problem at hand (e.g., irrigation scheduling), again with due account for uncertainty; and (d) providing trade-offs of the metrics familiar to the decision maker at various risk levels based on the uncertainty in the relevant research products.

Sustainability of the effective use of implemented systems is well supported by the establishment of cooperative tailoring and implementation with local agencies that will use the system products. This cooperative process involves iterations whereby initial research-output designs must be adapted to the local conditions, including available parametric and hydrometeorological input data, as well as computational resources, in order to improve the reliability of the operational, diagnostic, and prognostic products, as well as the sustainability of the operational systems. A realization of this cooperative process within the operational implementation process is depicted in Figure 2. In this figure, the cooperative process yields iterations of model component structure adjustments for system components that contribute to the initial system designs for the purpose of enhanced reliability and sustainable utility by operational agencies.

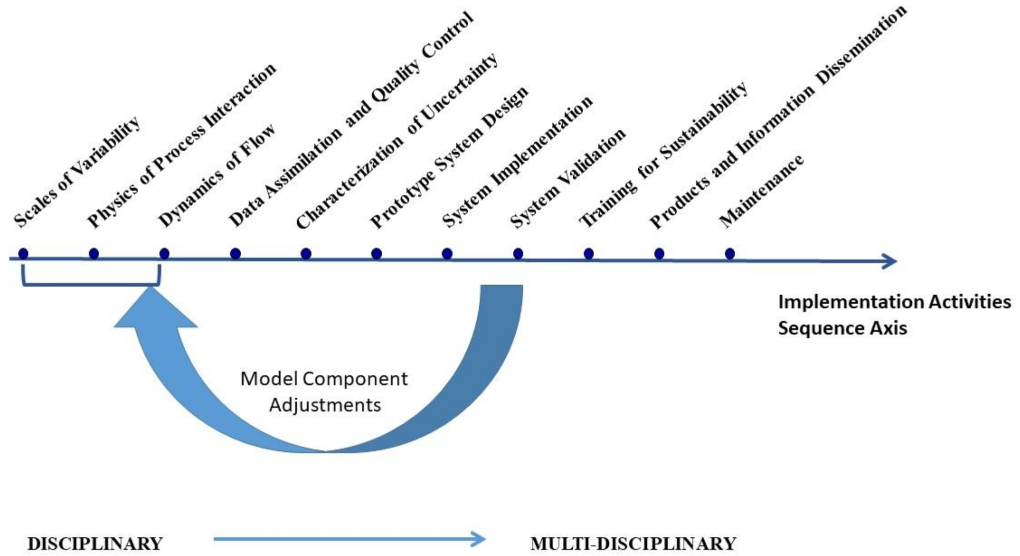

Figure 2. Schematic of the sequence of the themes of implementation activities of effective operational systems with the model-component adjustment process depicted explicitly.

It is noted that the feedback loop shown in Figure 2 in typical applications does not involve feedback loops inside it. Experience shows that adjusting the model-component structures judiciously in each application based on available supporting data or foreseeable future available data (e.g., new radars) and then following the process shown from left to right to a new system-validation step provides (a) improved reliability in operations and (b) sustainability in both operations and in future training efforts.

It is also noted that, implicitly, the transition from characterization of uncertainty to data assimilation and quality control involves a transition from the stochastic-dynamical equations of the characterization of uncertainty step to a stochastic process formalism that informs the data assimilation and quality control steps in Figure 2.

This cooperative process (research→operations→research→ . . .) requires support by extensive hands-on training for: (a) the forecast staff on the physics of the natural processes and the uncertainties of the input and parametric data; (b) the decision making staff (disaster prevention agencies and water resource management agencies) on the properties of the system products under local data conditions; and (c) the information technology (IT) staff associated with the local host of the implemented system on computer hardware and software maintenance, as well as data management for sustainability. When complexity and innovative enhancements are essential to the sustainability of the system, as mentioned earlier, a demonstration phase has proven to be a good investment prior to operational implementation.

A promising approach for system longevity is to implement systems that are flexible and modular to allow for component enhancements and uncertainty estimate updates over time when new types of data become available and to incorporate system components for secure data exchanges. Continuing periodic training of users is also important in such cases. In addition, the greatest benefits of the implementation and effective-use process for the user agencies is found in situations when the field staff involved in the training and use of the system are provided with incentives by their user agency to expend effort to understand and use the advanced science and technology implementations and to be involved in system enhancement and reliability improvement over time. For improved utility in several cases, existing operational protocols of user agencies have been adjusted for most effective product use (e.g., incorporating flash flood warning protocols within a pre-existing flood warning protocol).

3. Examples of Transferring Research Output and Associated Uncertainty to Operations for Effective Decision Support

3.1. Short-Term Operational Precipitation and Flow Prediction in a Data-Rich Environment

Research on the development of coupled meteorological–hydrological model components for operational hydrologic applications over a single hydrologic basin was initiated in the early 1980s with simplified precipitation prediction components, spatially-lumped conceptual hydrologic and channel-routing models, and with explicit account of the propagation and update of uncertainty (first and second moment) based on available real-time observations of precipitation and flow [7,8]. Performance of the operational systems was good for good-quality precipitation and flow data and for sustainable operations. The uncertainty component was a stable extended Kalman filter, suitable for continuous model dynamics, which was later implemented as part of the operational system in the US [3,9].

Along those lines, one of the first operational implementations of such a system was for the 3300 km^2 mountainous Panama Canal Watershed, the waters of which are used to facilitate Panama Canal shipping (Figure 3). Toward this end, distributed precipitation predictions and quasi-distributed land-surface models were used with state estimation [10]. The tributaries that feed the Panama Canal drain small basins that range in size from less than 100 km^2 to approximately 700 km^2. Precipitation over the Watershed is measured by an S-band radar and a dense network of automated rain gauges. The gauge data were used to bias adjust the radar data and, in the absence of radar observations, to provide estimates of the mean areal precipitation (MAP) and its uncertainty (kriging method was used) over the basins. The flow in each of the significant tributaries is measured by automated gauges at sites that have frequent updates in rating curves. Predictions are useful for a range of lead times from 1 h to 24 h.

Under this rather observation-rich environment and with rather short useful lead times, characterizing the uncertainty in flows using automated state estimators is beneficial, and statistical errors were kept significantly below the climatological error bounds due to frequent state estimator updates. Over time, the model components of this system have been upgraded, and because of the continuing hands-on training of the operational hydrologists and meteorologists of the ACP, the system remains operational, providing information useful for the management of the Panama Canal ([11–13]).

Figure 3. Controlled Lake Gatun within the Panama Canal Watershed. Lake levels regulate Panama Canal shipping and are impacted by quick flash floods from the main tributaries.

The stochastic–dynamic formulations that are involved in this type of implementation are at an advanced level that requires graduate-level background in uncertain dynamical systems; that is, background that is rarely available in the operational environment outside of focused graduate school study. The viable option for sustainability and utility in that situation was to focus the training on the interpretation of the uncertainty output of the operational system and on providing a prerequisite basic statistics course for operational hydrologists and meteorologists [11,12]. In addition and importantly, the state estimator formulations in the operational system needed to be adjusted so that real-time configuration changes in the observed data sources could be handled in a reliable manner. Three illustrations of this are discussed below.

First, in several cases, the radar data was not available in real time, and there were changes in the configuration of the rainfall-observing gauge network, as some of the sensors did not report for some of the time. In these cases, a first- and second-moment adjustment of the sub-basin MAP was made to correctly account for the time-varying reporting network and provide the forecasters with consistent uncertainty information. *Second*, if the real-time flow observations were not available for a particular time, the state estimator simply did not proceed with the update of the second-moment properties across an observation for the state vector. After some time had passed (e.g., 6 h), a state estimator was used to estimate the state again, with new predict–update cycles starting from some time in the past (several days ago). In many cases, the flow observations were available after the fact; therefore, a better and more stable estimate of the states and their uncertainty was obtained through this continuous data-reprocessing approach. *Third*, the potential incidents of system "crash" also needed to be handled in such a way that the operational forecasters could make the system operational quickly. After several configuration adjustments, the one that was found most useful for the rather small basins and response times was to estimate the steady-state limit of the second moments of the state variables for each month and keep this exported. After such a crash, these limits were used to expeditiously reinstate the real-time system operations, without the need to run the system again from the beginning of the rainy season, as would otherwise be required because of the soil water content memory. With hourly updates, the states were found to quickly adjust to the real-time data.

The information from this hydrometeorological forecast system (both the mean and the variance of the products) was used operationally by the Panama Canal Authority to determine timely actions in the case of predicted flooding in tributary streams. For the Panama Canal operations, this included extracting staff to safe ground, as well as the equipment that guides ships during Canal passage, and making decisions as to the safe operation of the Canal for shipping.

3.2. Flash-Flood Operational Prediction in a Data-Sparse Environment

The characterization of uncertainty in flow products through automated means based on automated observations, as discussed in Section 3.1, is not feasible in large areas of the world because of a lack of such observations. In particular, when the focus is on flash flooding over large regions (sometimes encompassing several countries) with high resolution, this automated state-estimation method of uncertainty characterization is not applicable. In fact, the prediction of uncertainty is valid through state estimation or through ensemble prediction [14], but the updating of uncertainty across observations through state estimators cannot be used in such data-sparse areas.

This situation is prevalent in the implementation of flash flood guidance systems (FFGSs) worldwide [6,15]. This operational system for flash flood assessment and occurrence prediction serves more than 64 countries worldwide. It is based on meteorological and hydrological models and on remotely-sensed multispectral satellite and local data (radar and on-site precipitation gauge data). The first consideration for such a system was to use coupled meteorological and hydrological models, e.g., [8,16], to produce assessments and predictions of flash flood occurrence. Real-time applications indicated that low-quality data significantly impact the performance of such operational systems [17].

Flash floods typically have short durations (<6 h) and small spatial scales (<200 km^2) and are the result of rainfall, land-surface cover, and soil water saturation conditions [18] (Figure 4). In lieu of on-site radar and rain gauge observations from dense networks, rainfall observations from satellites carry significant errors in such small scales; thus, it is important that real-time updates are engaged to best approximate the actual land-surface conditions in regions of flash flood occurrence. Additionally, typical in these implementations is the sparsity of land-surface data, including flash flood occurrence data and streamflow data. Therefore, although the lead times are rather short and the initial conditions significantly influence the prediction (in spite of large forcing uncertainty), the benefit of having automated systems to update the land-surface states (soil water content and snow water equivalent) from observations on small flash-flood scales is not realizable. A new approach was necessary.

Research was performed on the impact of errors in small-basin, real-time estimation of precipitation for basins with radar coverage and good operational density of on-site rain gauges, also considering errors in the parameters of the land-surface components. This research indicated that the uncertainty in the simulation of flow increases linearly as the logarithm of the basin area decreases, with precipitation input contributing the largest portion of flow uncertainty [19,20]. The flow simulation errors are about 30% for 1000 km^2 basins and increase to about 90% for 100 km^2 basins. Flow prediction, rather than simulation, errors are expected to be much higher in smaller basins, especially for forecast lead times longer than a few hours.

Fortunately, with respect to precipitation errors, operational meteorologists and hydrologists have significant experience with specific observation networks and with predictive high-resolution mesoscale models for certain areas. This experience could be used to make adjustments in real time to precipitation observations and/or predictions if the operational diagnostic and prognostic flash flood system were designed to allow for this. This was taken into consideration in the design and subsequent enhancements of the FFGS operational system.

Figure 4. Typical site of flash flood risk in a small mountainous stream.

The approach followed was to decouple of the meteorological and hydrological component models but in a way that allows for assessments of the risk of flash flooding. Toward this goal, an early warning index was determined to be the bankfull flow of the streams at the outlets of the identified small flash-flood-prone basins. Then, a link was made between the bankfull flow and the amount and duration of certain rainfall over the catchment that could cause this bankfull flow [21,22]. Consequently, actual or forecast mean areal rainfall of a given duration (1 h, 3 h, or 6 h) that is greater than this certain rainfall of the same duration and over the same basin would yield exceedance of the bankfull flow at the small basin and indicates likelihood of flash flooding. This certain rainfall is termed the flash flood guidance of the given duration.

In this manner, the observed or forecast rainfall becomes a product of the system, allowing for forecaster adjustments, the impact of which on the exceedance of the flash flood guidance may be directly identified by forecasters. Appropriate interactive interfaces were designed to facilitate this process. Such interfaces provided separate information for observed and forecast precipitation, surface soil water saturation, and flash flood guidance of various durations. Through these interactive interfaces, the forecaster can look at several scenarios using precipitation bounds or, in some cases, even use the interface to make several adjustments directly to precipitation and produce adjusted products so that a final adjusted product may be selected for the final prediction of flash flood occurrence. Naturally, training of operational forecasters on the basis of the system model components and the effective use of the interfaces is a critical component for sustainability, and a significant hands-on training program has been developed to support forecasters.

Forecaster adjustments to the observed rainfall are warranted based on up-to-the-minute information (observer reports, video feeds, and local gauges) not included in the current cycle of system computations and/or on the forecaster's experience with the local reliability of gauge-corrected satellite information. These adjustments yield more accurate simulations and better initial conditions for the next forecast.

Forecaster adjustments to future rainfall are based on prior numerical weather prediction-model validation studies and the experience of forecasters with the forecasts of specific numerical weather prediction models for specific seasons and regions within their country. They tend to reduce the forecast model biases, providing better overall assessment for the likelihood of future flash flood occurrence. In some of the current implementations of this approach, the systems have been made flexible to receive input from more than one numerical weather prediction model and to show the products for each of these models separately. This allows forecasters to make a single model selection in real time or consult more than one model to make their final adjustments.

Evaluations of this forecaster-centric approach that decouples the precipitation and land-surface response components in regions with very sparse data and for trained forecasters indicates that the forecaster adjustments made in real time provide significant skill (reduction in assessment uncertainty) for the identification of flash flood events in small basins [23]. It also allows for implementations under a variety of available data and forecasts.

4. Conclusions

Cooperative implementation with a focus on the reduction in observational and forecast uncertainty is the key to obtaining successful and sustainable products of advanced operational hydrometeorological systems. Examples from data-rich and data-sparse regions have been discussed. In almost all cases, the initial research-based theoretical models required adjustments (or further research) before reliable and sustained operational use by forecasters was attained. The process was one of reciprocal education: for the scientists, the realities and challenges of the evolving operational environment in terms of available data and operational-forecaster response time constraints in real time; and for the operational forecasters, the conceptual basis of the model components and their uncertainties demonstrated under a variety of situations expressed through products and hands-on exercises using the system interfaces. This reciprocal education process contributed to flexible and useable operational systems that can be adapted to various field conditions.

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