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Hydrology and Earth System Sciences Discussions

HESS Opinions "Ensembles, uncertainty and flood prediction"

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Abstract

Ensemble predictions are being used more frequently to model the propagation of uncertainty through complex, coupled meteorological, hydrological and coastal models, with the goal of better characterising flood risk. In this paper, we consider the issues that we judge to be important when designing and evaluating ensemble predictions, and make recommendations for the guidance of future research.

1 Introduction

Many researchers are investigating the propagation of uncertainty through complex coupled meteorological, hydrological and coastal models, over a range of space and time-scales. In many cases, ensemble methods are being used to take account of this uncertainty. A workshop on ensemble prediction, sponsored by the UK NERC (Natural Environment Research Council) FREE (Flood risk from extreme events) Programme was held in Reading, UK, 23–24 September 2009. The purpose of the workshop was to disuss the common issues that must be considered when designing and evaluating ensemble prediction systems, and to make recommendations about the most important research needed over the next few years to maximize the value of such systems. Approximately 50 people attended this workshop.

In this opinion article, we first provide a short background on flooding, uncertainty and ensemble prediction, and then give summaries, identify key scientific questions and make recommendations for each of the topics discsussed at the workshop. We end with a brief conclusion. Our intention is not to provide a comprehensive review, but to point at a few key issues, and encourage debate about the most important future directions for research.

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2 Flooding, uncertainty and ensemble predictions

Storms, storm surges, floods and droughts are major and costly environmental hazards. An improved ability to forecast, quantify and manage meteorological and hydrological risks is critical for the protection of the public, property and infrastructure, and to maintain a stable economy.

While environmental models are becoming increasingly sophisticated, it will never be possible for such models to completely capture the complicated physical processes taking place in reality. In typical models, we can identify three main sources of uncertainty: errors in the inputs (initial conditions, boundary conditions and external forcings); parameter errors and model structural errors. The nature of the dynamical system, and the spatiotemporal scales that the user is interested in, will determine which source of errors may dominate. For example, the accuracy of a short-range numerical weather forecast is strongly dependent on the accuracy of the initial data (Dance, 2004); rainfall represents a major source of uncertainty for well-calibrated catchment models (Collier, 2007; Cloke and Pappenberger, 2009; Xuan et al., 2009); flood inundation modelling requires the use of poorly known friction parameters (Pappenberger et al., 2005); climate model predictions are hampered by the poorly modelled representation of clouds (Colman, 2003); the predictive skill of coastal models is limited by the accuracy of extreme wind and pressure forecasting, incomplete understanding of the air-sea momentum transfer process and highly nonlinear and turbulent nature of coastal ocean (Melville, 1996; Wolf and Flather, 2005; Zou et al., 2008; Zou and Reeve, 2009; Brown et al., 2010).

A Bayesian probabilistic representation of uncertainty allows consistent propagation of uncertainties in complex systems (e.g., Goldstein and Rougier, 2004). However, it does require the setting of prior probability distributions on the main sources of error. In practice, modelling the priors would be rather complicated (e.g., Goldstein and Rougier, 2009), and may require some compromises, for example ignoring the likely correlations between the priors over the different sources of uncertainty. Observations are vital to

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help to quantify these priors. Furthermore, probabilistic outputs require validation (or verification) against observations.

The use of an ensemble of model forecasts can help to explore these different types of uncertainties. From a theoretical viewpoint, ensemble predictions are based on Bayesian Monte Carlo ideas. To generate an ensemble, we sample from a prior probability density that encapsulates our current knowledge of the state of the system. Each ensemble member is individually propagated by the (stochastic) dynamical system that is given by our computer model, to yield an estimate of the prediction probability density. The effects of different sources of uncertainty can be (partially) captured by carrying out the sampling step in different ways e.g., by perturbing the initial state (Wei et al., 2008), boundary conditions (Bowler et al., 2008), model forcing (Pierce et al., 2005), model parameters (Murphy et al., 2004), or choice of model structure (Johnson and Swinbank, 2009).

While ensemble techniques have been used operationally for medium-range meteorological applications since the early 1990s, there are many applications in the areas of storm, storm-surge and flood risk predictions for which the use of ensembles is in its infancy. An important question for the community is what can these fields learn from medium-range numerical weather prediction (NWP), and where are the existing techniques not sufficiently developed or simply not appropriate?

3 Uncertainty in initial conditions, boundary conditions and forcing data

Errors in initial conditions, boundary conditions and forcing data may sometimes be fairly well defined. Observational instrument manufacturers may provide an estimate of instrument precision and accuracy based on laboratory experiments, often in the form of an observation error variance. However, errors of representativity, where there is a mismatch between the scales measured by the observational instrument and the scales resolved by the numerical model are much harder to quantify. Observation pre-processing, such as cloud clearing in NWP, or data compression techniques such

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as principal component analysis, may introduce further observational error correlations (Stewart, 2010). To confound matters, the required initial, boundary or forcing data may be very high dimensional, so that prior information is needed to fill data voids.

Data assimilation techniques are often used for initial condition estimation in NWP (Kalnay, 2003). In these algorithms observational and model information are optimally blended to produce improved estimates of the current state of the atmosphere. With the arrival of distributed models in hydrology, the need for model initialization and rainfall forcing across a large domain may require the use of similar techniques. However, the assumptions of the algorithms designed for synoptic scale meteorological dynamics, may not be appropriate for the highly nonlinear, non-Gaussian, multiscale meteorological dynamics of the storms that can cause flooding (Dance, 2004; Park and Zupanski, 2003; Sun, 2005), let alone for flow of water through soil in a catchment model.

Data assimilation is computationally intensive, and provision of a posteriori error information is not feasible with the variational assimilation techniques (Nichols, 2003) used in operational NWP. There is some hope that the use of ensemble (Evensen, 2006) or hybrid ensemble-variational (Buehner et al., 2010) assimilation techniques might lead to a more seamless probabilistic prediction system. However, currently the ensembles used in ensemble forecasting systems are tuned to capture the spread of the prediction pdf at forecast verification time, whereas data assimilation ensembles are tuned for the best analysis accuracy. Furthermore, ensemble assimilation algorithms suffer from sampling problems associated with small ensemble size (Hamill et al., 2001). Since ensemble assimilation algorithms are a relatively new development, their theoretical and numerical behaviour is not yet fully understood. Although progress is being made (e.g., Furrer and Bengtsson, 2007; Livings et al., 2008), there are a number of questions yet to be addressed.

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3.1 Key scientific questions

- How can we characterize observation errors, taking into account the mismatches in resolution between models and observations, and different observation types?
- What assumptions are appropriate when designing assimilation systems for new applications such as very high resolution NWP or a hydrological catchment model?
- What is the best strategy for ensemble generation in seamless prediction, and how many ensemble members do we need?
- Are ensemble assimilation schemes theoretically and numerically stable, for non-linear problems and a finite ensemble size?

3.2 Recommendations

- Field campaigns should be carried out to quantify the full error structures associated with key observation types. These will also provide valuable data for evaluating new diagnosis techniques that use data assimilation to estimate such errors (ECMWF, 2009).
- Idealized model studies should be carried out in order to understand and develop assimilation and ensemble generation schemes for multiscale, nonlinear, non-Gaussian dynamical systems, before trialling these new techniques in applications.
- We should work closely with the mathematical sciences community to understand the analytic and numerical properties of the new algorithms.

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4 Parameter errors

In the past, model parameters have typically been determined theoretically or by adhoc calibration of the model against observations. More recently, a number of authors have been investigating parameter estimation schemes employing optimization algorithms that minimize cost functions of various forms (Hill et al., 2003; Knaapen and Hulscher, 2003; Ruessink, 2005b). Another approach is to use Bayesian ideas to take account of the uncertainty in the estimates (Beven and Binley, 1992; Ruessink, 2005a, 2006; Wüst, 2004).

However, since model forecasts also depend on their initial data which may also contain errors, in some scenarios it can make sense to perform joint estimation of both the model state and parameters simultaneously. Navon (1997) and Evensen et al. (1998) review joint state-parameter estimation in the context of four-dimensional variational data assimilation (4-D Var). Ensemble assimilation algorithms can also be adapted to perform joint estimation (Trudinger et al., 2008; Zupanski and Zupanski, 2006). Such methods are suboptimal due to the underlying assumptions of Gaussian statistics which may be violated for parameter estimation, and they typically do not take account of additional constraints on the parameters such as positivity.

Assimilation schemes are inevitably less successful in situations where the model is relatively insensitive to a particular parameter (Smith et al., 2010). We cannot expect to be able to correct parameters that cause errors in the model solution that are smaller than can be reliably observed. This raises the issues of observability and identifiability (Navon, 1997); whether the available observations contain sufficient information for us to be able to determine the parameters of interest and whether these parameters have a unique deterministic set of values. A parameter estimation method can only be expected to work reliably when both these properties hold. When parameters are strongly correlated, it may be prudent to consider a re-parameterisation of the model equations to improve the identifiability of the parameters or even to transform the parameters to a set of uncorrelated variables (Sorooshian and Gupta, 1995).

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If we accept that our chosen parameters will always contain errors, there is then the question of how we measure the forecast uncertainty arising from parameter errors. Ensemble techniques have been used for this purpose (Murphy et al., 2004), where results from forecasts evolved using a random sampling of parameters enable an estimate of the size of the uncertainty associated with parameter error to be estimated. However, the output uncertainty is critically dependent on the prior for the parameter errors which is poorly known.

Stochastic parametrization schemes are employed in NWP ensemble predictions (Buizza et al., 1999) and these have improved the spread of the ensemble, and the skill of the probabilistic parametrization of weather parameters such as precipitation. However, with limited computational resources, it is not clear how much effort to invest in parameter perturbations as opposed to initial condition perturbations, and how might this vary with forecast lead time.

4.1 Key scientific questions

– How can we achieve observability and identifiability for parameter estimation with current and future models?

– What criteria can we use to determine the balance between computational effort invested in initial condition and parameter perturbations in a given modelling scenario?

4.2 Recommendations

– Designers of model parametrization schemes should take into account issues of identifiability and observability

– Large quantitative studies of forecast model sensitivities to initial condition and parameter perturbations should be carried out, in order to understand the characteristics of model uncertainties.

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5 Model structural errors

Model structural errors are a major concern because they affect not only the usefulness of the output of individual predictions, but also the propagation of uncertainty in an ensemble system. They are also some of the hardest errors to quantify.

Goldstein and Rougier (2009) have proposed an approach known as reification for determining model error pdfs, using an emulator. More often in the NWP and ocean forecasting community, discrepancies between model predictions and observations are computed, often in a data assimilation algorithm, in order to learn something about model errors, although it is difficult to disentangle these errors from those from other sources (Bell et al., 2004; Dee, 2005; Griffith and Nichols, 2000; Trémolet, 2007; Zupanski and Zupanski, 2006).

Despite a lack of quantitative knowledge of model structural errors, multi-model ensembles (Johnson and Swinbank, 2009) can provide some information about likely modelling uncertainties. Of course, such techniques cannot account for structural errors when all the models in the ensemble are wrong in the same sort of way. However they can provide additional confidence in predictions if models with differing structures give similar results.

5.1 Key scientific questions

– How can we estimate model structural errors?

– How can we represent information about model structural uncertainties in data assimilation and ensemble prediction?

5.2 Recommendations

– When developing models, mechanisms for managing the uncertainties in these models should be put in place. This might mean providing an assessment of the

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uncertainties and a mechanism by which they could be included. For example, a model for the model error should be built alongside the model.

– Model building should be a joint activity between scientists from different disciplines, including the physical sciences, mathematics and statistics.

– Operational multimodel ensemble NWP data such as TIGGE (Richardson et al., 2005) should be used to drive multi-model ensembles of river flood and storm surge models.

6 Sampling

For many environmental models, there is a large state space, and the computational expense of running the model means that only a relatively small ensemble size is feasible. Ensemble generation techniques are often physically motivated, with different ensemble members created by choosing dynamically inspired perturbations of initial conditions, boundary conditions, model parameters and sub-grid-scale parameterizations. The statistical interpretation of such sampling techniques is unclear. For example, are all the initial perturbations equally likely, or should we weight the resulting ensemble members differently? (Johnson and Swinbank, 2009). Furthermore, from a statistical viewpoint, there may be more efficient ways to explore phase space (Conti and O'Hagan, 2010).

There are also question marks over the use of ensembles to predict extreme events. Extreme events, defined as events with long return periods, may have a high probability in short-term forecast ensembles, where assimilation of a recent observation may have ensured that the forecast ensemble occupies an appropriate neighbourhood of phase space. In contrast, for ensemble predictions over climate timescales, an extreme event may lie in the tails of the climatological probability density we are trying to capture. In this case, it is unclear how to design our ensembles to capture these events.

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6.1 Key scientific questions

- How can we marry dynamically inspired perturbations with statistical sampling theories?
- How can we design climate ensembles to capture extreme events?

6.2 Recommendations

- Dynamicists and statisticians should work together to close the gap between sampling based on dynamical ideas and sampling based on statistical ideas.
- Research should be carried out into developing new ensemble techniques for sampling extremes, with a focus on the tails of the climatological distribution of events.

7 Ensemble validation or verification

The skill of model forecasts are often measured by comparing them with observations. It is important that there are sufficient observations available for this purpose and this is not the case for elements of the flood forecasting chain. For example, in urban flood modelling, only recently has it been possible to obtain time series of flood extent data using remote sensing (Mason et al., 2009).

Forecast skill is routinely calculated in NWP and evaluated under a number of measures (Jolliffe and Stephenson, 2003). Many of these measures have been chosen to evaluate the accuracy of the forecast for the benefit of end users such as civil aviation. For fluvial and pluvial flood forecasting, precipitation is a key meteorological variable. Precipitation has a patchy, intermittent character, which means that many of the better established skill scores designed for smoothly varying fields are unsuitable for use. A number of new skill scores for precipitation have been proposed recently

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(e.g., Roberts and Lean, 2008), but greater cooperation between meteorologists and hydrologists is still needed to ensure that the new skill scores are fit for purpose. Similar statements could be made about the low level winds needed for wave and surge forecasting.

Most existing skill scores routinely calculated in NWP are usually designed for single deterministic forecasts, and do not take account of observation errors in the observations. Ensemble verification measures evaluate the skill of a probabilistic forecast, and include the rank histogram (Hamill, 2000) and reliability diagram (Wilkes, 1995), however there are few measures that can enable predicted probabilities for extreme events to be validated. Furthermore, knowledge of the properties of existing skill scores used routinely in NWP is not yet widespread in the flood prediction community.

7.1 Key scientific questions

- What kind of an observing network do we need to enable verification of flood models?
- What skill scores should we use to verify weather forecasts of parameters important for flood prediction?
- How can we validate probability forecasts of extreme events?

7.2 Recommendations

- The meteorology and flood forecasting communities should collaborate to design a structured field campaign and new skill scores for verification of end-to-end “clouds to catchments to coasts” ensemble flood forecasts.
- The meteorology and flood forecasting communities should work together to exchange knowledge about validation and verification methods used in each community.

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8 Propagation of uncertainty between models

In flood risk prediction applications, it is becoming increasingly common to chain or couple together model predictions. The coupling is usually one-way. For example, NWP may provide rainfall forecasts for a hydrological catchment model (e.g., Roberts et al., 2009); or winds and pressures for a storm-surge inundation model (e.g., Flowerdew et al., 2009; Wolf and Flather, 2005), but the descendant hydrological or coastal model does not feed-back information to the NWP model. In this case, one way to provide estimates of the uncertainty in the overall model chain is to take account of the uncertainty in the antecedent outputs that drive the inputs to the following models. Two-way model coupling has also been employed, for example, Janssen (2004) demonstrated the benefits of using a two-way coupled wave-atmosphere model for global modelling of wind and waves. In this case, modelling the propagation of uncertainty between the models is even more complex.

Successful coupling of models requires spatiotemporal compatibility outputs from the antecedent model with the inputs required in the following model. This is certainly the case when coupling the latest NWP models (resolution ~1 km) with hydrological flow routing models, including distributed grid based models. However, finer spatial and temporal scale rainfall data are needed for urban applications: nowcasting ensembles (e.g., Pierce et al., 2005) may be more appropriate for these applications. For coupling of climate (resolution ~25 km, hourly rainfall accumulations) and distributed hydrological models (~1 km, 15 min accumulations), downscaling is required. There are several different types of downscaling scheme, and the hydrological results may vary widely, depending on this choice. For coastal flood predictions, the NWP or climate model will drive nested wave, tide, surge and surf zone models at resolutions from 100 km to 20 cm. Thus at ocean basin scales, the driving atmospheric model is sufficiently well resolved, however even finer detail could be used by the nearshore and surf-zone models. Downscaling from ocean to coastal to surf zone models introduces significant uncertainty.

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It is an open question as to whether an NWP/climate ensemble provides sufficient variability to drive an acceptable ensemble spread in the descendant model. For example, it may be necessary to increase the size of the ensemble in the descendant model using parameter perturbations (such as ocean friction factors). Furthermore, since uncertainty in the driving model outputs play a large role in the uncertainties in the descendant model predictions, it becomes important to have mechanisms for updating the descendant model variables using recent observations. This requires data assimilation methods suited to the descendant model.

8.1 Key scientific questions

- Do we need to add extra variability at model interfaces?
- Are the same types of ensemble perturbations appropriate for each model in the chain?
- Are there governing principles that should guide our approach when coupling models together?

8.2 Recommendations

- NWP/climate ensembles need to be carefully designed and calibrated to give correct probabilistic forecasts of appropriate variables (precipitation, wind, pressure) at the appropriate spatial scales for resolving important processes. It is important to capture the tails of the climatological distribution in order to properly predict extreme events.
- Use model chains (e.g., atmosphere to ocean/hydrology to impact model) to help assess the ensemble NWP. This could include both one-way and two way coupling.

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– Develop appropriate observing networks and assimilation methods for model chain impact modelling.

9 Communicating uncertainty to users

The users of ensemble predictions are a diverse community, with a range of levels of understanding of modelling methodology and the interpretation of uncertainty. Such users may include scientists, operational weather and flood forecasting centres, insurance and finance companies, engineering professionals, decision makers, policy makers, and the general public. The information desired by each of these groups of users is equally diverse. For example, the time-scales requested may range from nowcasting to a 5-day forecast to climate change predictions. Some users require no information on uncertainty. Guidelines, say in engineering, pre-specify safety buffers, so an engineer is required to follow engineering guidelines and will not include any additional probablistic information. Some users require the most likely outcome; others look for the "worst" events in either that particular forecast or relative to climatology; and some require knowledge of all possible outcomes. Quantitative probabilistic information is important to some users, who wish to use this information in conjunction with their own cost/loss ratio (Altalo and Smith, 2004).

A continuing dialogue is needed between researchers, forecast providers and users, both to educate the users (in terms of the availability of probabilistic data products, the benefits of using uncertainty information, and appropriate interpretation of the data) and stimulate research and development into the types of forecast products needed by users (Demeritt et al., 2007). However, it is still unclear how to go about this. It may take many years to communicate clearly and effectively to all users, but change needs to happen to erradicate confusion.

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9.1 Key questions

- How can we best present and visualize uncertain information?
- How can we balance the need for efficient research, development, production and communication of probabilistic information products, while responding appropriately to the diverse needs of individual users?

9.2 Recommendations

- Carry out research into the visualization of information and human behaviour in both interpreting and responding to probability forecasts.
- Undertake research amongst the different users to identify a common language and preferred ways of presenting probabilistic information. Draw up a set of standards or guidelines to follow so that we all communicate with the same terminology.
- Collate time series of data and user-case-studies to provide evidence to users of the benefits and to develop trust in predictions. False alarm case studies should be included.

10 Conclusions

In this article, we have summarized discussions from the NERC FREE workshop on ensemble prediction. We have presented the issues that we judge to be important when designing and evaluating ensemble flood predictions, and made recommendations for the guidance of future research. We now invite the reader to respond with their own views and comments in the journal discussion forum.

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Ensembles, uncertainty and flooding

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