We are IntechOpen, the world's leading publisher of Open Access books
Built by scientists, for scientists

Chapter 4

Improved Disaster Management Using Data Assimilation

Paul R. Houser

Additional information is available at the end of the chapter

http://dx.doi.org/10.5772/55840

1. Introduction

Decision makers must have timely and actionable information to guide their response to emergency situations. For environmental problems, this information is often produced using decision support systems (DSS), which is usually a computer-based, environmental simulation and prediction model that emphasizes access and manipulation of data and algorithms. Using historical time series data, current conditions, and physically-based algorithms the DSS can predict the potential outcomes for various decision scenarios, and may also provide the decision maker with uncertainty and risk estimates. In this way, the DSS can improve decision making efficiency and accuracy, facilitate decision maker exploration and discovery, communication and information organization, and outreach and education.

An important component of advanced decision support tools is data assimilation. Data assimilation is the application of recursive Bayesian estimation to combine current and past data in an explicit dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields. Data assimilation aims to utilize both our knowledge of physical processes as embodied in a numerical process model, and information that can be gained from observations, to produce an improved, continuous system state estimate in space and time. When implemented in near-real time, data assimilation can objectively provide decision makers with the timeliest information, as well as provide superior initializations for short term scenario predictions. Data assimilation can also act as a parameter estimation method to help reduce DSS bias and uncertainty.

This chapter will provide an overview of data assimilation theory and its application to decision support tools, and then provide a review of current data assimilation applications in disaster management.

2. Background

Information about environmental conditions is of critical importance to real-world applications such as agricultural production, water resource management, flood prediction, water supply, weather and climate forecasting, and environmental preservation. Improved estimates about current environmental conditions useful for agriculture, ecology, civil engineering, water resources management, rainfall-runoff prediction, atmospheric process studies, climate and weather/climate prediction, and radiation management [1,2].

This information is usually provided to decision makers through Decision Support Systems (DSS). DSS's are generally defined as interactive software-based systems that help to assemble useful information from raw data, documents, knowledge, and models to identify and resolve problems and make decisions. A model-driven DSS emphasizes access to and operation of a statistical, financial, optimization or physical simulation model. A data-driven DSS emphasizes access to and manipulation of a time-series of data and information. Data-driven DSS's combined with analytical model processing provide the highest level of functionality and decision support that is linked to analysis of large collections of historical data.

Physically-based environmental models are often at the heart of powerful DSSs. They rely on a set of well-established physical principles to make current condition assessments and future projections. Physical model simulations are performed on powerful computer platforms, dividing the area of interest into elements in which fluxes and storages are calculated. Environmental parameters are provided by connected databases of observational and calibration data.

Observations are important components of DSSs, providing critical information that mitigates the risk of loss of life and damage to property. Environmental observations are sourced from the numerous disconnected observational networks and systems that have a wide variety of characteristics (Figure 1). Basic monthly, seasonal and annual summaries of temperature, rainfall and other climate elements provide an essential resource for planning endeavors in areas such as agriculture, water resources, emergency management, urban design, insurance, energy supply and demand management and construction.

While ground-based observational networks are improving, the only practical way to observe the environment on continental to global scales is via satellites. Remote sensing can make spatially comprehensive measurements of various components of the environment, but it cannot provide information on the entire system, and the observations represent only an instant in time. Environmental process models may be used to predict the temporal and spatial state variations, but these predictions are often poor, due to model initialization, parameter and forcing, and physics errors. Therefore, an attractive prospect is to combine the strengths of environmental models contained within DSSs and observations and minimize the weaknesses to provide a superior environmental state estimate. This is the goal of data assimilation.

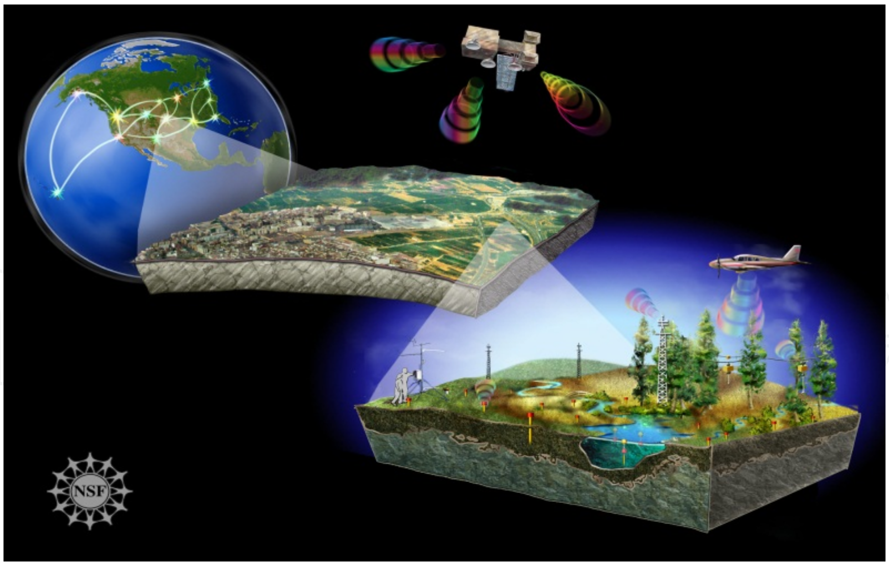

Figure 1. Illustration of an integrated environmental observation network. The network illustrated is the National Science Foundation (NSF) National Ecological Observatory Network (NEON).

Data assimilation combines observations into a dynamical model, using the model's equations to provide time continuity and coupling between the estimated fields. Data assimilation aims to utilize both our environmental process knowledge, as embodied in a numerical computer model, and information that can be gained from observations. Both model predictions and observations are imperfect and we wish to use both synergistically to obtain a more accurate result. Moreover, both contain different kinds of information, that when used together, provide an accuracy level that cannot be obtained individually.

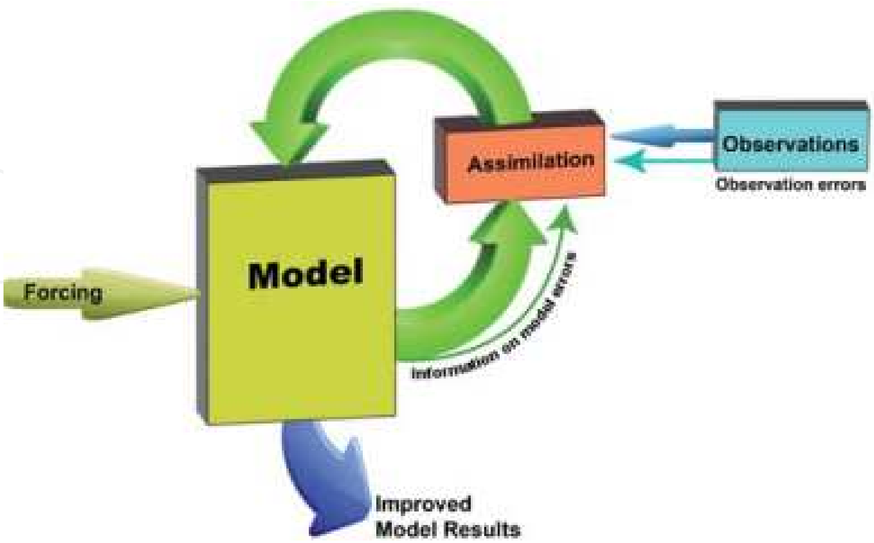

Figure 2. Numerical models contain errors that increase with time due to model imperfections and uncertainties in initial and boundary conditions. Data assimilation minimizes these errors by correcting the model stats using new observations (from http://www.hzg.de/institute/coastal_research/cosyna).

The data assimilation challenge is to merge the spatially comprehensive observations with the dynamically complete but typically poor predictions of an environmental model to yield the best possible system state estimation (Figure 2). In this illustration, the model represents any environmental model that simulates system states. Model biases can be mitigated using a complementary calibration and parameterization process. However, model imperfections will always remain and will be exasperated by uncertain initial and boundary (forcing) conditions. Data assimilation techniques can be used to continuously partially reinitialize the model with information provided by observations. This reinitialization can be constrained by the model physics to assure that it is physically and dynamically realistic. Limited point measurements are often used to calibrate the model(s) and validate the assimilation results [3].

3. Data assimilation

Charney *et al.* (1969) first suggested combining current and past data in an explicit dynamical model, using the model's prognostic equations to provide time continuity and dynamic coupling amongst the fields [4]. This concept has evolved into a family of techniques known as data assimilation. In essence, data assimilation aims to utilize both our physical process knowledge as embodied in an environmental model, and information that can be gained from observations. Both model predictions and observations are imperfect and we wish to use both synergistically to obtain a more accurate result. Moreover, both contain different kinds of information, that when used together, provide an accuracy level that cannot be obtained when used separately.

Data assimilation techniques were established by meteorologists [5] and have been used very successfully to improve operational weather forecasts. Data assimilation has also been successfully used in oceanography[6] for improving ocean dynamics prediction. Houser et al., (2010) gave an overview of hydrological data assimilation, discussing different data assimilation methods and several case studies in hydrology [7].

Data assimilation was meant for state estimation, but in the broadest sense, data assimilation refers to any use of observational information to improve a model [8]. Basically, there are four methods for "model updating", as follows:

- *Input:* corrects model input forcing errors or replaces model-based forcing with observations, thereby improving the model's predictions;
- *State:* corrects the state or storages of the model so that it comes closer to the observations (state estimation, data assimilation in the narrow sense);
- *Parameter:* corrects or replaces model parameters with observational information (parameter estimation, calibration);
- *Error correction:* correct the model predictions or state variables by an observed time-integrated error term in order to reduce systematic model bias (*e.g.* bias correction).

http://dx.doi.org/10.5772/55840

State updating can be justified by lack of knowledge about the model's initial conditions, but with unconstrained state updating, the model logic is foregone, while this is exactly the main strength of dynamic assimilation and modelling. If an intensive update of the state is needed for good results, the model may simply not be able to produce correct state or flux values. In such cases, assimilation for parameter estimation is better advised. The static parameters obtained through off-line calibration, prior to the actual forecast simulations, may not always result in a proper model definition, because of the state and time dependency of parameters or problems in the model structure or input. Often the model validation residuals show the presence of bias, variation in error and a correlation structure.

The data assimilation challenge is: given a (noisy) model of the system dynamics, find the best estimates of system states $\hat{x}$ from (noisy) observations y. Most current approaches to this problem are derived from either the direct observer (*i.e.*, sequential filter) or dynamic observer (*i.e.*, variational through time) techniques (Figure 3).

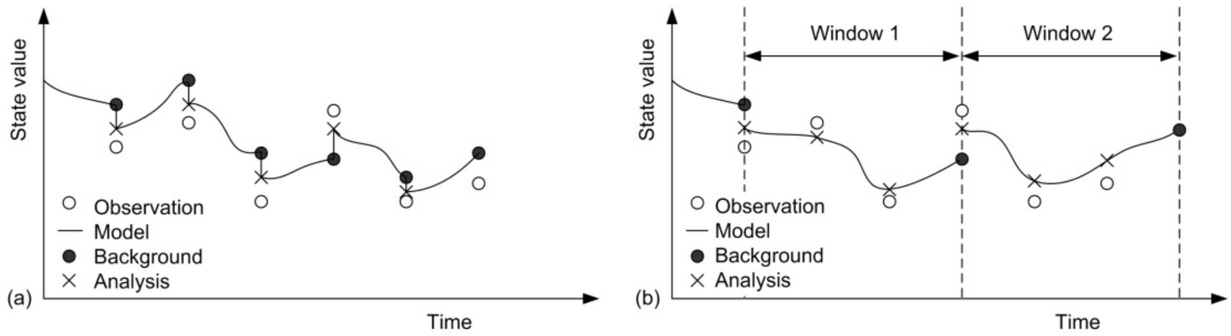

Figure 3. Schematic of the (a) direct observer and (b) dynamic observer assimilation approaches [7].

3.1. Direct observer assimilation

Direct observer techniques sequentially update the model forecast $\hat{x}_k^b$ (*a priori* simulation result), using the difference between observation y_k and model predicted observation $\hat{y}_k$, known as the "innovation", whenever observations are available. The predicted observation is calculated from the model predicted or "background" states, indicated by the superscript *b*. The correction, or analysis increment, added to the background state vector is the innovation multiplied by a weighting factor or gain **K**. The resulting estimate of the state vector is known as the "analysis", as indicated by the superscript *a*.

$$\hat{\mathbf{x}}_k^a = \hat{\mathbf{x}}_k^b + \mathbf{K}_k \left(\mathbf{y}_k - \hat{\mathbf{y}}_k \right) \tag{1}$$

The subscript *k* refers to the time of the update. For particular assimilation techniques, like the Kalman filter, the gain represents the relative uncertainty in the observation and model variances, and is a number between 0 and 1 in the scalar case. If the uncertainty of the predicted observation (as calculated from the background states and their uncertainty) is large relative to the uncertainty of the actual observation, then the analysis state vector takes on values that will closely yield the actual observation. Conversely, if the uncertainty of the predicted observation is small relative to the uncertainty of the actual observation, then the analysis state vector is unchanged from the original background value. The commonly used direct observer methods are: (i) direct insertion; (ii) statistical correction; (iii) successive correction; (iv) analysis correction; (v) nudging; (vi) optimal interpolation/statistical interpolation; (vii) 3-D variational, 3D-Var; and (viii) Kalman filter and variants [7].

While approaches like direct insertion, nudging and optimal interpolation are computationally efficient and easy to implement, the updates do not account for observation uncertainty or utilize system dynamics in estimating model background state uncertainty, and information on estimation uncertainty is limited. The Kalman filter, while computationally demanding in its pure form, can be adapted for near-real-time application and provides information on estimation uncertainty. However, it has only limited capability to deal with different types of model errors, and necessary linearization approximations can lead to unstable solutions. The Ensemble Kalman filter (EnKF), while it can be computationally demanding (depending on the size of the ensemble) is well suited for near-real-time applications without any need for linearization, is robust, very flexible and easy to use, and is able to accommodate a wide range of model error descriptions.

Direct insertion. One of the earliest and most simplistic approaches to data assimilation is direct insertion. As the name suggests, the forecast model states are directly replaced with the observations by assuming that $\mathbf{K} = \mathbf{I}$, the unity matrix. This approach makes the explicit assumption that the model is wrong (has no useful information) and that the observations are right, which both disregards important information provided by the model and preserves observational errors. The risk of this approach is that unbalanced state estimates may result, which causes model shocks: the model will attempt to restore the dynamic balance that would have existed without insertion. A further key disadvantage of this approach is that model physics are solely relied upon to propagate the information to unobserved parts of the system [9,10].

Statistical correction. A derivative of the direct insertion approach is the statistical correction approach, which adjusts the mean and variance of the model states to match those of the observations. This approach assumes the model pattern is correct but contains a non-uniform bias. First, the predicted observations are scaled by the ratio of observational field standard deviation to predicted field standard deviation. Second, the scaled predicted observational field is given a block shift by the difference between the means of the predicted observational field and the observational field [9]. This approach also relies upon the model physics to propagate the information to unobserved parts of the system.

Successive correction. The successive corrections method (SCM) [5,11-13] is also known as observation nudging. The scheme begins with an *a priori* state estimate (background field) for an individual (scalar) variable, which is successively adjusted by nearby observations in a series of scans (iterations, n) through the data. The advantage of this method lies in its simplicity. However, in case of observational error or different sources (and accuracies) of observations, this scheme is not a good option for assimilation, since information on the observational accuracy is not accounted for. Mostly, this approach assumes that the observations are more accurate than model forecasts, with the observations fitted as closely as is consistent. Furthermore, the radii of influence are user-defined and should be determined by trial and error or more sophisticated methods that reduce the advantage of its simplicity. The weighting functions are empirically chosen and are not derived based on physical or statistical properties. Obviously, this method is not effective in data sparse regions.

Analysis correction. This is a modification to the successive correction approach that is applied consecutively to each observation [14]. In practice, the observation update is mostly neglected and further assumptions make the update equation equivalent to that for optimal interpolation [15].

Nudging. Nudging or Newtonian relaxation consists of adding a term to the prognostic model equations that causes the solution to be gradually relaxed towards the observations. Nudging is very similar to the successive corrections technique and only differs in the fact that through the numerical model the time dimension is included. Two distinct approaches have been developed [16]. In analysis nudging, the nudging term for a given variable is proportional to the difference between the model simulation at a given grid point and an "analysis" of observations (*i.e.*, processed observations) calculated at the corresponding grid point. For observation nudging, the difference between the model simulation and the observed state is calculated at the observation locations.

Optimal interpolation The optimal interpolation (OI) approach, sometimes referred to as statistical interpolation, is a minimum variance method that is closely related to kriging. OI approximates the "optimal" solution often with a "fixed" structure for all time steps, given by prescribed variances and a correlation function determined only by distance [17]. Sometimes, the variances are allowed to evolve in time, while keeping the correlation structure time-invariant.

3-D variational. This approach directly solves the iterative minimization problem given [18]. The same approximation for the background covariance matrix as in the optimal interpolation approach is typically used.

Kalman filter. The optimal analysis state estimate for linear or linearized systems (Kalman or Extended Kalman filter, EKF) can be found through a linear update equation with a Kalman gain that aims at minimizing the analysis error (co)variance of the analysis state estimate [19]. The essential feature which distinguishes the family of Kalman filter approaches from more static techniques, like optimal interpolation, is the dynamic updating of the forecast (background) error covariance through time. In the traditional Kalman filter (KF) approach this is achieved by application of standard error propagation theory, using a (tangent) linear model. (The only difference between the Kalman filter and the Extended Kalman filter is that the forecast model is linearized using a Taylor series expansion in the latter; the same forecast and update equations are used for each approach.)

A further approach to estimating the state covariance matrix is the Ensemble Kalman filter (EnKF). As the name suggests, the covariances are calculated from an ensemble of state forecasts using the Monte Carlo approach rather than a single discrete forecast of covariances [20].

3.2. Dynamic observer assimilation

The dynamic observer techniques find the best fit between the forecast model state and the observations, subject to the initial state vector uncertainty and observation uncertainty, by minimizing over space and time an objective or penalty function, including a background and observation penalty term. To minimize the objective function over time, an assimilation time "window" is defined and an "adjoint" model is typically used to find the derivatives of the objective function with respect to the initial model state vector. The adjoint is a mathematical operator that allows one to determine the sensitivity of the objective function to changes in the solution of the state equations by a single forward and backward pass over the assimilation window. While an adjoint is not strictly required (*i.e.*, a number of forward passes can be used to numerically approximate the objective function derivatives with respect to each state), it makes the problem computationally tractable. The dynamic observer techniques can be considered simply as an optimization or calibration problem, where the state vector – not the model parameters – at the beginning of each assimilation window is "calibrated" to the observations over that time period. The dynamic observer techniques can be formulated with: (i) strong constraint (variational); (ii) weak constraint (dual variational or representer methods).

Dynamic observer methods are well suited for smoothing problems, but provide information on estimation accuracy only at considerable computational cost. Moreover, adjoints are not available for many existing environmental models, and the development of robust adjoint models is difficult due to the non-linear nature of environmental processes.

4D-Var. In its pure form, the 4-D (3-D in space, 1-D in time) "variational" (otherwise known as Gauss-Markov) dynamic observer assimilation methods use an adjoint to efficiently compute the derivatives of the objective function with respect to each of the initial state vector values. Solution to the variational problem is then achieved by minimization and iteration. In practical applications the number of iterations is usually constrained to a small number.

Given a model integration with finite time interval, and assuming a perfect model, 4D-Var and the Kalman filter yield the same result at the end of the assimilation time interval. Inside the time interval, 4D-Var is more optimal, because it uses all observations at once (before and after the time step of analysis), *i.e.*, it is a smoother. A disadvantage of sequential methods is the discontinuity in the corrections, which causes model shocks. Through variational methods, there is a larger potential for dynamically based balanced analyses, which will always be situated within the model climatology. Operational 4D-Var assumes a perfect model: no model error can be included. With the inclusion of model error, coupled equations are to be solved for minimization. Through Kalman filtering it is in general simpler to account for model error.

Both the Kalman filter and 3D/4D-Var rely on the validity of the linearity assumption. Adjoints depend on this assumption and incremental 4D-Var is even more sensitive to linearity. Uncertainty estimates via the Hessian are critically dependent on a valid linearization. Furthermore, with variational assimilation it is more difficult to obtain an estimate of the quality of the analysis or of the state's uncertainty after updating. In the framework of estimation theory, the goal of variational assimilation is the estimation of the conditional mode (maximum *a posteriori* probability) estimate, while for the Kalman filter the conditional mean (minimum variance) estimate is sought.

Hybrid assimilation methods have been explored in which a sequential method is used to produce the *a priori* state error or background error covariance for variational assimilation [7].

4. Review of current data assimilation applications in disaster management

4.1. Weather forecasting

During the last three decades, data assimilation has gradually reached a mature center stage position at operational numerical weather prediction centers, and are largely responsible for the significant advances in weather forecast accuracy [21]. Improved weather forecasts are critical for better informing the public and decision makers about impending severe weather events such as tropical storms, tornados, frozen precipitation events, wind hazards, droughts, and flooding.

The basis for improved weather prediction using data assimilation is to improve the initial state, which results in an improved forecast. Initial work was based on hand interpolations that combined present and past observations with model results [22-24]. This tedious procedure was replaced by automatic objective analysis [12, 25-27].

Currently, data assimilation is available and implemented worldwide at operational numerical weather prediction centers. The impact of adopting data assimilation in numerical weather prediction was qualified as a substantial, resulting in an improvement in NWP quality and accuracy [28]. Combined with improvement in error specifications and with a large increase in a variety of observations has led to improvements in NWP accuracy [29].

The development of the global positioning system (GPS) satellites has facilitated the use of radio occultation (RO) techniques for sounding the earth's atmosphere. RO is a remote sensing technique that relies on the detection of a change or refraction in a radio signal as it passes through the atmosphere. The degree of refraction depends on the gradients of density and the water vapor. These global measurements are actually commensurable with radiosonde soundings in accuracy [30]. Assimilations of the RO retrieved data have exhibited promising impact on regional as well as global weather predictions [31,32].

The impact of GPS radio occultation data assimilation on severe weather predictions was demonstrated in East Asia [33]. These observations were assimilated in the Weather Research and Forecasting (WRF) model's using a three-dimensional variational (3DVAR) data assimilation system to improve the initial analysis of the model. The GPS RO data assimilation may improve prediction of severe weather such as typhoons. These positive impacts are seen not only in typhoon track prediction but also in prediction of local heavy rainfall associated with severe weather over Taiwan. From a successive evaluation of skill scores for real-time forecasts on frontal systems operationally conducted over a longer period and predictions of six typhoons in 2008, assimilation of GPS RO data appears to have some positive impact on regional weather predictions, on top of existent assimilation with all other observations.

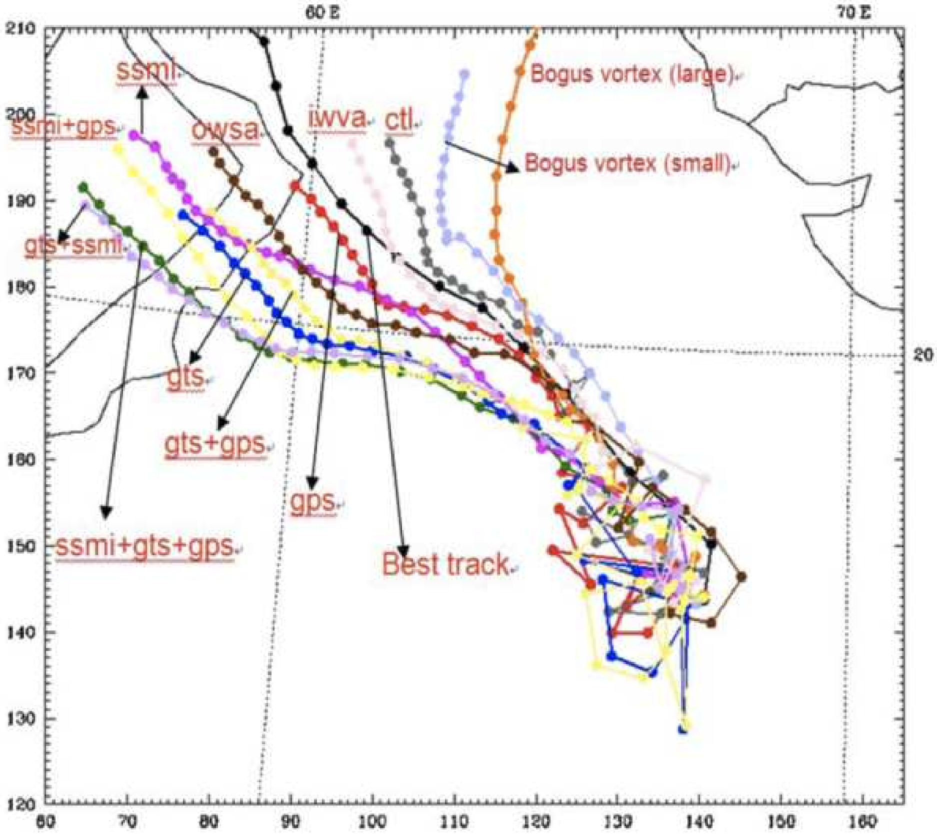

Figure 4. The best track from JTWC (black line) for Cyclone Gonu (2007) and simulated tracks for experiments CTL and GPS without and with the RO data assimilated, respectively, and other experiments with different data, GTS (radiosondes), SSMI (SSM/I retrieved oceanic near-surface wind speed OWS and integrated precipitable water PW, denoted as OWSA an IWVA, respectively), bogus vortex 1 (large vortex) and bogus vortex2 (small vortex) [33].

The impact of GPS RO assimilation on Tropical Cyclone Gonu (2007) was studied over the western Indian Ocean [33]. Gonu was one of the most intense in regional history and had asevere impact. The positive impact of GPS RO data on track prediction is clearly seen in Figure 4. It is surprisingly found that assimilations with all other data (including SSM/I, GTS and their combinations) do not outperform the run with GTS+GPS or even the run with GPS RO data only.

4.2. Flood management: early warning, monitoring, and damage assessments

Flood forecasting using numerical models and data assimilation techniques provides extended lead-time and improved accuracy for flood information useful for residents, local authorities and emergency services. The use of data assimilation in operational hydrologic forecasting predates its use in weather forecasting and oceanography. Examples include updating of snow model states and the use of observed streamflow to make short-term adjustments to the simulated streamflow. However, despite its early adoption, more advanced methods of data assimilation (i.e. Kalman filtering) has yet to take firm root in operational hydrologic forecasting.

Operational hydrologic data assimilation typically uses telemetered, near real-time measurements of river levels and flows, and raingauge or Doppler radar precipitation estimates as inputs to a computer-based flood forecasting system. Model outputs include minute to several day forecasts for river levels, river flows, and reservoir and lake levels. Forecasts can be extended further using weather forecasts, and can include snowmelt processes and river control operations.

Hydrologic rainfall-runoff models are used to estimate river flows from rainfall observations and forecasts. These models may take into account local catchment topography, soils, vegetation, temperature, river flow hydrodynamics, and structure operations and backwater effects. These models are enhanced using data assimilation methods such as error prediction, state updating, and parameter updating techniques. Forecast uncertainties can arise and propagate through the modeling network from errors in model parameters, initial conditions, boundary conditions, data inputs and model physics.

As part of the European Union near real time flood forecasting, warning and management "FloodMan" project data-assimilation techniques were developed, demonstrated and validated for integrated hydrological and hydraulic models in a pilot study of the Rhine River [34]. The model combines a hydraulic model (SOBEK) representing the Rhine River between Andernach and Düsseldorf with a hydrological model (HBV) for the Sieg tributary. To increase the accuracy of flood forecasts, data assimilation is applied, using measured water levels at Bonn and Cologne to adapt bed roughness and lateral discharges until the calculated water levels agree with the measured water levels.

The data-assimilation technique computes model corrections based on the assumption that the uncertainties in model output and observations are known and are normally distributed. The data-assimilation algorithm compares the observed value with the calculated value, and makes corrections to the parameters. The changes are made taking into consideration the uncertainty of the parameters and measured data. For example, a mean water level measurement is accurate compared to calculated water levels. Therefore the water level calculated with data-assimilation will be closer to the measured water level than the calculated without data-assimilation.

The data-assimilation algorithm is applied to the flood of December 1993 (Figure 5). The data-assimilation improves the water level forecast. The small differences between forecast and measured data are due to the perfect forecast for the input at Andernach. The adaptations by the data-assimilation on the model parameters were small indication a well calibrated hydraulic model for 1993 flood and that robust data assimilation procedure.

4.3. Drought management

Droughts are environmental disasters that occur in virtually all climates, and are generally related to reduced precipitation for an extended period of time. High temperature, high wind, low humidity; rainfall timing, intensity and duration, also play a significant role in droughts [35]. Aridity is a permanent feature of climate related to low rainfall areas [36], while drought is a temporary anomaly, lasting from months to several years. Population growth, agricultural and industrial expansion, energy demands for water, climate change, and water contamination further amplify the effects of drought and water scarcity.

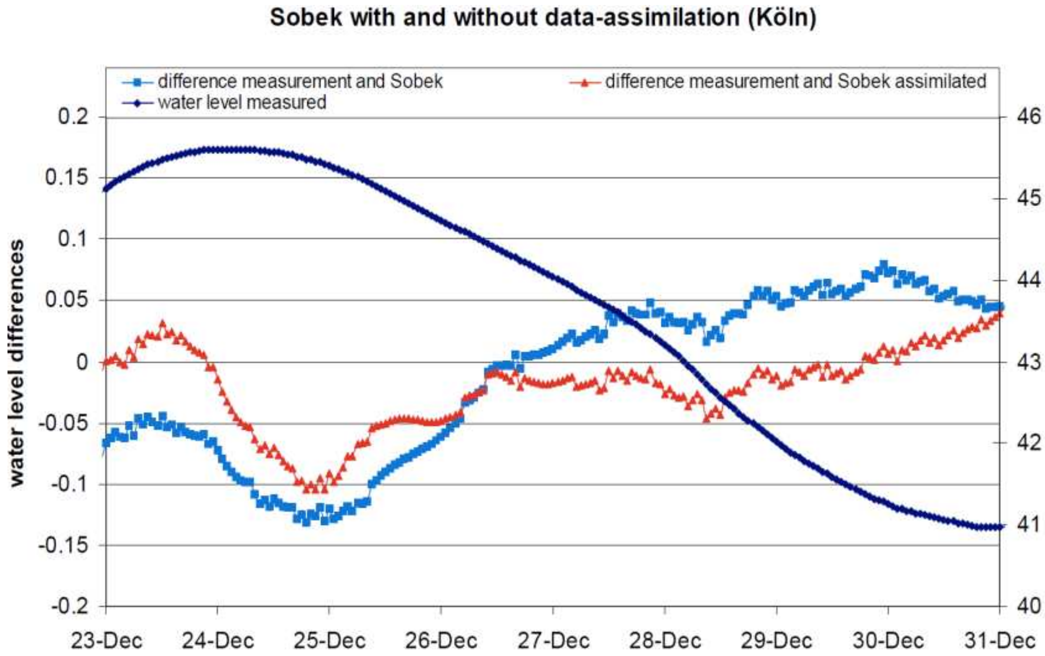

Figure 5. Streamflow forecasts using data assimilation. The blue line depicts the difference between forecast and measured water levels without data-assimilation, the red line the differences with data-assimilation [34].

Droughts impact both surface and groundwater, leading to reduced water supply and quality, crop failure, reduced livestock range, reduced power supply, disturbed riparian habitat, and deferred recreation [37]. Therefore, droughts are of great importance in the planning and management of water resources.

Droughts rank first among all natural hazards when measured in terms of the number of people affected [38]. Hazard events were ranked based on the degree of severity, the length of event, total areal extent, total loss of life, total economic loss, social effect, long-term impact, suddenness, and occurrence of associated hazards [39]. It was found that drought stood first based on most of the hazard characteristics. Other natural hazards, which followed droughts in terms of their rank, are tropical cyclones, regional floods, earthquakes, and volcanoes.

The Gravity Recovery and Climate Experiment (GRACE) satellite mission, launched in 2002 measures monthly changes in total water storage over large areas, which can help to assess change in water supply on and beneath the land surface. However, the coarse spatial and temporal resolutions of GRACE, and its lack of information on the vertical distribution of the observed mass changes limits its utility unless it is combined with other sources of information. In order to increase the resolution, eliminate the time lag, and isolate groundwater and other components from total terrestrial water storage, the GRACE data was integrated with other ground- and space-based meteorological observations (precipitation, solar radiation, etc.) within the Catchment Land Surface Model, using Ensemble Kalman smoother type data assimilation [40]. The resulting fields of soil moisture and groundwater storage variations are then used to generate drought indicators based on the cumulative distribution function of wetness conditions during 1948-2009 simulated by the Catchment model [41] (Figure 6).

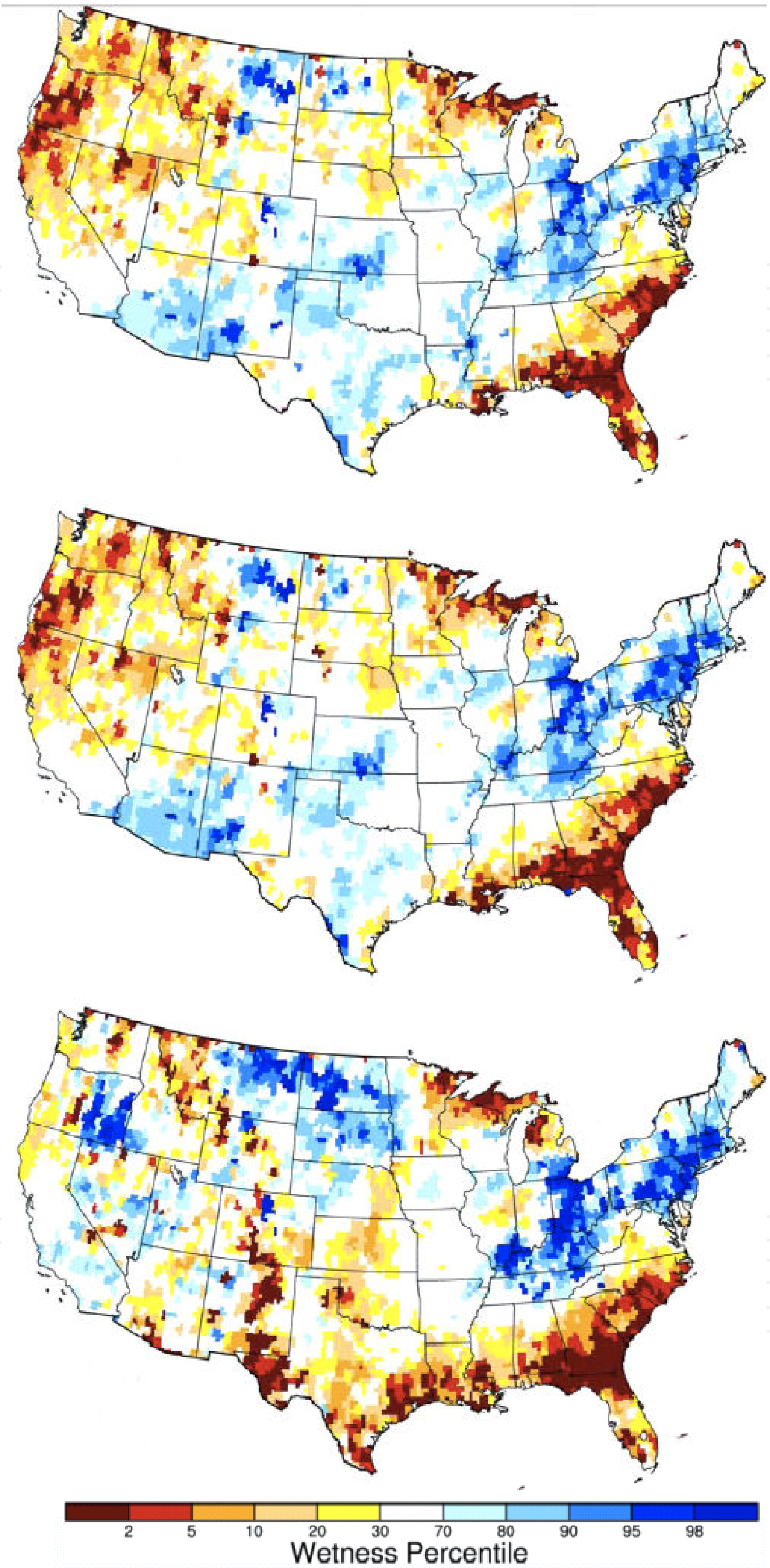

Figure 6. GRACE data assimilation based drought indicators for surface (top) and root zone (middle) soil moisture and groundwater (bottom) for 26 December 2011, expressed as percentiles relative to conditions during the 1948-2011 simulated record [41].

There are several aquifers in the U.S. that have been depleted in that way over the past century, such as the southern half of the High Plains aquifer in the central U.S. If the groundwater drought indicator map accounted for human-induced depletion, such regions would be red all the time, which would not be useful for evaluating current wetness conditions relative to previous conditions. On time scales of weeks to ten years, we expect that these maps will be reasonably well correlated with measured water table variations over spatial scales of 25 km (16 miles) or more. However, users should not assume a direct correspondence between these groundwater percentiles and measured groundwater levels over multiple decades. The color-coded maps show how much water is stored now as a probability of occurrence in the record from 1948 to the present.

4.4. Radiation guidance and monitoring

Decision makers must have the information needed to react in a rapid and appropriate manner before, during and immediately after an accidental or intentional contamination of the environment. Decision support systems are needed to estimate the likely evolution of the environmental contamination. The primary goal is to determine the area likely to be affected by a possible release and to obtain an estimate of the potential maximum environmental consequences. In the early phases of an accident the main goal is to provide a forecast of the magnitude and geographical coverage of the potential environmental consequences. It is important to know the prevailing and forecasted meteorological conditions in the local area. Also the status of the source should be known in detail. Depending on the meteorological situation and the model used, trajectories may be calculated first to give a rough estimation of the plume transport.

Dispersion models driven with weather data and best-estimate source information can be used. When results of radiological measurements are available they can be used to improve model calculations by data assimilation. Atmospheric dispersion modeling of radioactive material in radiological risk assessment and emergency response has evolved significantly over the past 50 years. The three types of dispersion models are the Gaussian plume, Lagrangian-puff and particle random walk, and computational fluid dynamic models. When data from radiological measurements are available, they should be taken into account in the consequence assessment and used to correct and update model calculation results (data assimilation). Because observations are often sparse in emergency situations, data assimilation procedures should be designed to handle cases with only a few measurements. Even simple dispersion models would benefit from data assimilation, and may also run faster to provide critical time-sensitive information to decision makers [42].

Rojas-Palma et al., (2005) describe an in-depth effort to integrate a suite of computer codes, with different degrees of complexity, into a European real-time, on-line decision support system for off-site management of nuclear emergencies (the RODOS system) [42]. The resulting modeling system describes the transport and dispersion of radionuclides in both atmospheric and aquatic systems, as well as their impact on the food chain.

RODOS predicts the values of many quantities that are likely to be of interest to decision makers after an accident (e.g. activity concentration in air, deposition, concentration in foods, external dose rates, concentrations in water bodies). The predictions will not exactly reflect the situation after an accident, as the models use a number of assumptions that are appropriate to the average situation across large areas of Europe, rather than to the particular conditions of the area affected by the accident. In the period immediately after the accident there will be a limited amount of information available from monitoring programs. To make the best use of this information, it is necessary to correct the RODOS predictions in light of the available measurements.

A 2 km RODOS test case was generated with a release point at Risø, Denmark, and 23 detector points surrounding Risø (Figure 7,8). The meteorological situation was a 7m/s westerly wind at 60 m above ground with neutral stability, and no rain.

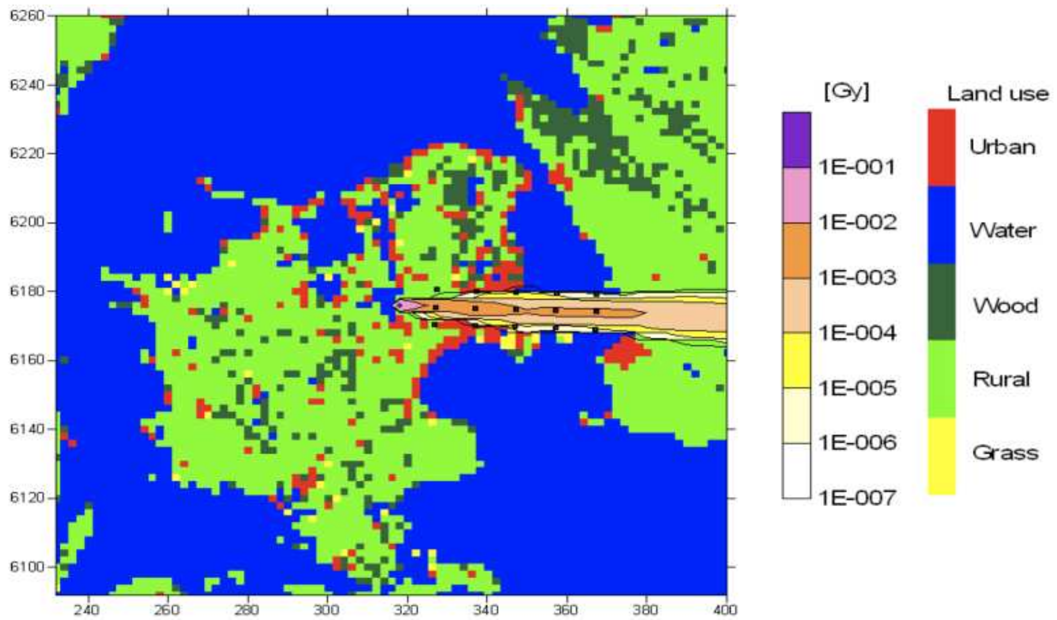

Figure 7. Gamma dose field from puffs in measurement generating run. The 15 detector points 10 to 50 km east of the release point are seen as black squares, the 8 points surrounding the release point are not marked. The background picture is the land use map [42].

In general, in off-site emergency management, data assimilation will prove useful throughout the different stages of the accident. In the assessment of the consequences during the early phase, in the improvement of prior assumptions based solely on expert judgement, and when there is a clear need for longer-term predictions to assess the radiological impact on the food chain.

4.5. Tsunami warnings and forecasts

A tsunami is a series of waves that can move on shore rapidly, but last for several hours and flood coastal communities with little warning. Tsunamis can be triggered by a variety of geological processes such as earthquakes, landslides, volcanic eruptions, or meteorite impacts. Throughout history, Tsunami's have taken many lives in coastal regions around the world. In

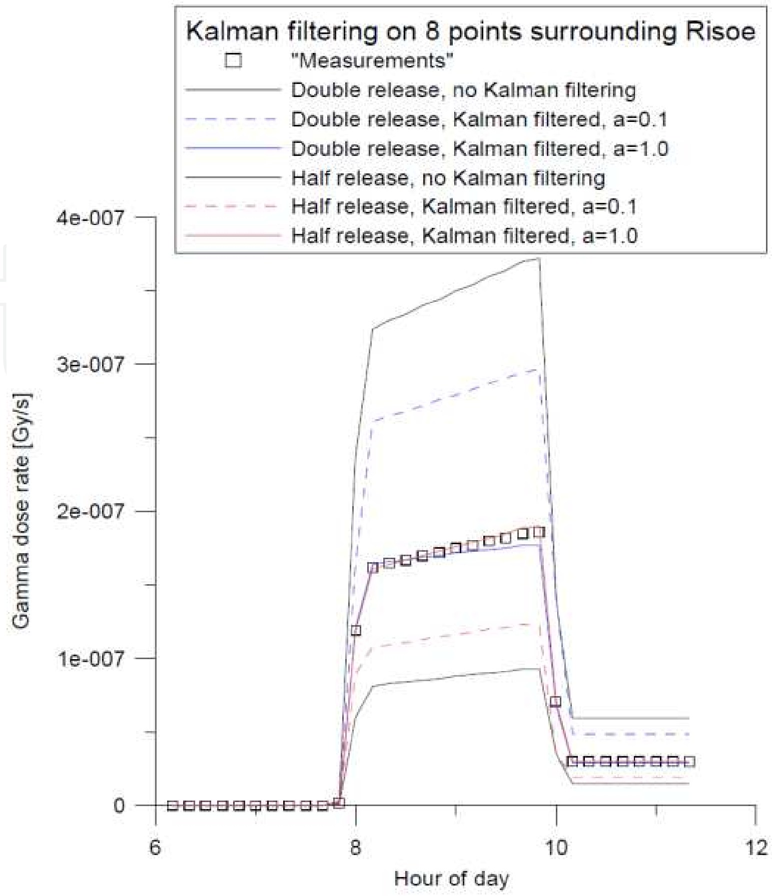

Figure 8. Gamma dose rates 50 km from the release point, right below the plume. Kalman filtering applied in runs with the release doubled and halved relative to that having generated the "measurements", and with different release rate uncertainties "a" [42].

the wake of the catastrophic 2004 Indian Ocean tsunami, which caused over 200,000 deaths and widespread destruction, many governmental organizations have increased their efforts to diminish the potential impacts of a tsunami by strengthening tsunami detection, warning, education and preparedness efforts [43].

In contrast to forecasting other natural hazards such as hurricanes or floods, near-real-time tsunami forecast models must produce predictions after a seismic event has been detected, but before the event arrive at the coast. These forecasts provide emergency managers near-realtime information about the time of first impact as well as the sizes and duration of the tsunami waves, and give an estimate of the area of inundation. The entire forecasting process has to be completed very quickly, to allow time for evacuation efforts. The entire forecast, including data acquisition, data assimilation and inundation projections, must take place within a few hours [44].

Titov et al., (2003) presented a method for tsunami forecasting that combining real-time data from tsunameters with numerical model estimates to provide site- and event-specific forecasts for tsunamis in real time [45]. Observational networks will never be sufficiently dense because the ocean is vast. Establishing and maintaining monitoring stations is costly and difficult, especially in deep water. Numerical model accuracy is inherently limited by errors in bathymetry and topography and uncertainties in the generating mechanism. But combined, these techniques can provide reliable tsunami forecasts, as is demonstrated in the Short-term Inundation Forecasting (SIFT) system. The Method of Splitting Tsunamis (MOST) numerical model is run in two steps or modes. In the data assimilation mode, the model is adjusted "on-the-fly" by a real-time data stream to provide the best fit to the data. In the forecast mode, the model uses the simulation scenario obtained in the first step and extends the simulation to locations where measured data is not available, providing the forecast. An effective implementation of the inversion is achieved by using a discrete set of Green's functions to form a model source. The algorithm chooses the best fit to a given tsunameter data among a limited number of unit solution combinations by direct sorting, using a choice of misfit functions (Figure 9).

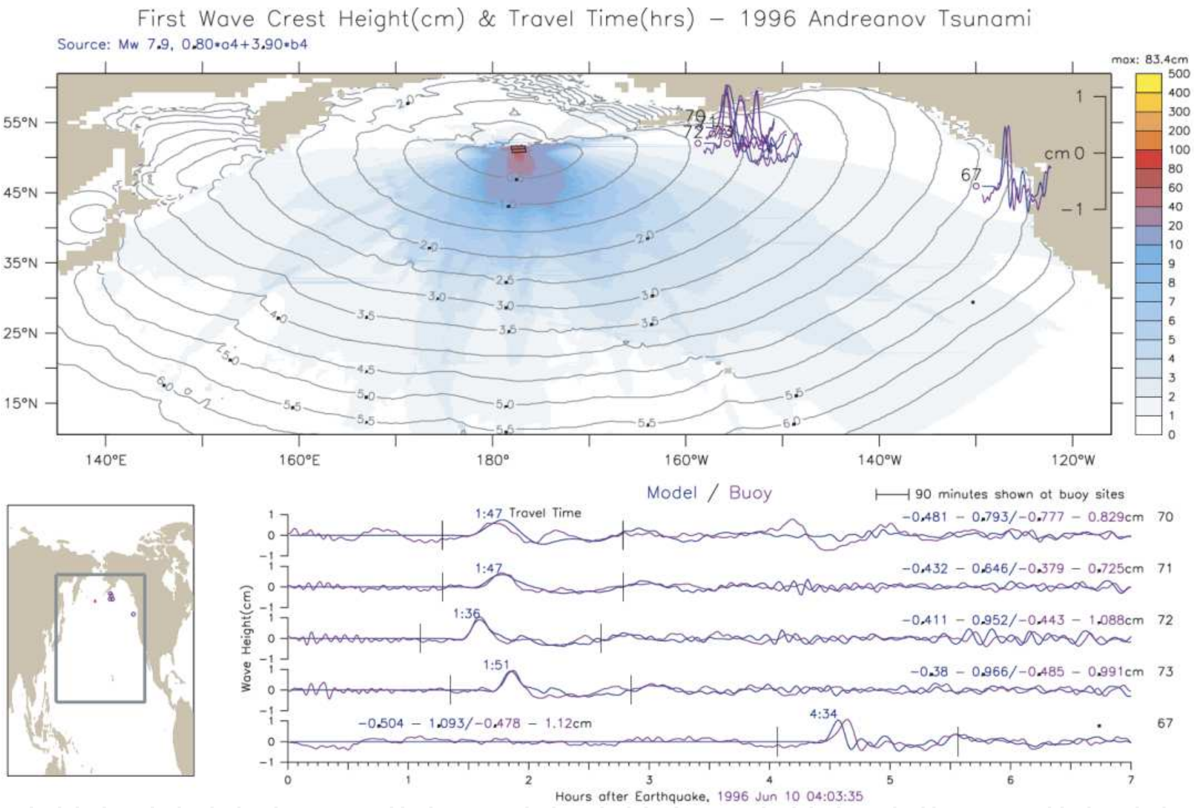

Figure 9. Results of MOST data assimilation for 1996 Anderanov Island tsunami [45]. Top frame shows the source inferred by the data assimilation (black rectangles show unit sources' fault plains), maximum computed amplitudes of tsunami from this source (filled colored contours), travel time contours in hours after earthquake (solid lines), and locations of the bottom pressure recorders. Bottom frame shows a reference map (left) and comparison of the model (blue) and bottom pressure recorder data (magenta).

5. Conclusions

This chapter provided an overview of data assimilation theory and its application to decision support tools, and provided 5 examples of operational data assimilation applications in disaster management. These included tsunami warning, radiation guidance and monitoring, flood and drought management, and weather forecasting.

Information about environmental conditions is of critical importance to real-world applications disaster management in areas such as agricultural production, water resource management, flood prediction, water supply, weather and climate forecasting, and environmental preservation. This information is usually provided to decision makers through Decision Support Systems (DSS). Observations are important components of DSSs, providing critical information that mitigate the risk of loss of life and damage to property. Environmental process models are used in DSSs to predict the temporal and spatial state variations, but these predictions are often poor, due to model initialization, parameter and forcing, and physics errors. Therefore, we must combine the strengths of environmental models contained within DSSs and observations and minimize the weaknesses to provide a superior environmental state estimate – data assimilation.

Data assimilation merges the spatially comprehensive observations with the dynamically complete but typically poor predictions of an environmental model to yield the best possible system state estimation. Data assimilation aims to utilize both our knowledge of physical processes as embodied in a numerical process model, and information that can be gained from observations, to produce an improved, continuous system state estimate in space and time. When implemented in near-real time, data assimilation can objectively provide decision makers with the timeliest information, as well as provide superior initializations for short term scenario predictions. Data assimilation can also act as a parameter estimation method to help reduce DSS bias and uncertainty.

Author details

Paul R. Houser*

Address all correspondence to: phouser@gmu.edu

George Mason University, Fairfax, VA, USA

References

[1] Houser, P. (2002). Air and Water Monitoring for Homeland Security, Earth Observation Magazine, , 11(8), 33-36.

[2] Houser, P, Hutchinson, M. F, & Viterbo, P. Hervé Douville, J., and Running, S. W. (2004). Terrestrial data assimilation, Chapter C.4 in Vegetation, Water, Humans and the Climate. Global Change- The IGB Series. Kabat, P. et al. (eds). Springer, Berlin.

[3] Walker, J. P, & Houser, P. R. (2005). Hydrologic Data Assimilation, In: A. Aswathanarayana (Ed.), Advances in Water Science Methodologies, A.A. Balkema, TheNetherlands, 230pp.

[4] Charney, J. G, Halem, M, & Jastrow, R. (1969). Use of incomplete historical data to infer the present state of the atmosphere. J. Atmos. Sci., , 26, 1160-1163.

[5] Daley, R. (1991). Atmospheric data analysis. Cambridge University Press, 460 pp.

[6] Bennett, A. F. (1992). Inverse methods in physical oceanography. Cambridge University Press, 346 pp.

[7] Houser, P. R, De Lannoy, G, & Walker, J. P. Land Surface Data Assimilation, pIn: Lahoz, W., Khatattov, B. and Menard, R. (Eds.), Data Assimilation: Making sense of observations, Springer, The Netherlands, (2010). pp., 549-598.

[8] WMO(1992). Simulated real-time intercomparison of hydrological models (Tech. Rep. Geneva.(38)

[9] Houser, P. R, Shuttleworth, W. J, Famiglietti, J. S, Gupta, H. V, Syed, K. H, & Goodrich, D. C. (1998). Integration of soil moisture remote sensing and hydrologic modeling using data assimilation. Water Resour. Res., , 34, 3405-3420.

[10] [10] Walker, J. P, Willgoose, G. R, & Kalma, J. D. (2001). One-dimensional soil moisture profile retrieval by assimilation of near-surface observations: A comparison of retrieval algorithms. Adv. Water Resour., , 24, 631-650.

[11] Bergthorsson, P, & Döös, B. (1955). Numerical weather map analysis. Tellus, , 7, 329-340.

[12] Cressman, G. P. (1959). An operational objective analysis system. Mon. Weather Rev., , 87, 367-374.

[13] Bratseth, A. M. (1986). Statistical interpolation by means of successive corrections. Tellus, 38A, , 439-447.

[14] Lorenc, A. C, Bell, R. S, & Macpherson, B. (1991). The Meteorological Office analysis correction data assimilation scheme. Q. J. R. Meteorol. Soc., , 117, 59-89.

[15] Nichols, N. K. (2001). State estimation using measured data in dynamic system models, Lecture notes for the Oxford/RAL Spring School in Quantitative Earth Observation.

[16] Stauffer, D. R, & Seaman, N. L. (1990). Use of four-dimensional data assimilation in a limited-area mesoscale model. Part I: Experiments with synoptic-scale data. Mon. Weather Rev., , 118, 1250-1277.

[17] Lorenc, A. (1981). A global three-dimensional multivariate statistical interpolation scheme. Mon. Weather Rev., , 109, 701-721.

[18] Parrish, D, & Derber, J. (1992). The National Meteorological Center's spectral statistical interpolation analysis system. Mon. Weather Rev., , 120, 1747-1763.

[19] Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Trans. ASME, Ser. D, J. Basic Eng., , 82, 35-45.

[20] Turner, M. R. J, Walker, J. P, & Oke, P. R. (2007). Ensemble Member Generation for Sequential Data Assimilation. Remote Sensing of Environment, 112, doi:10.1016/j.rse.2007.02.042.

[21] Navon, I. *Data assimilation for numerical weather prediction: A Review*; Springer: Berlin, Germany, (2009).

[22] Richardson, L. F. (1922). Weather prediction by numerical processes. Cambridge University Press. Reprinted by Dover (1965, New York).With a New Introduction by Sydney Chapman, xvi+236

[23] Charney, J. G, et al. (1950). Numerical integration of the barotropic vorticity equation. Tellus , 2, 237-254.

[24] Kalnay, E. (2003). Atmospheric modeling, data assimilation and predictability. Cambridge Univ Press, Cambridge, , 341.

[25] Panofsky, H. A. (1949). Objective weather-map analysis. J Appl Meteor , 6, 386-392.

[26] Gilchrist, B, & Cressman, G. P. (1954). An experiment in objective analysis. Tellus , 6, 309-318.

[27] Barnes, S. L. (1964). A technique for maximizing details in numerical weather map analysis. J Appl Meteor , 3, 395-409.

[28] Rabier, F. (2005). Overview of global data assimilation developments in numerical weather prediction centers. Q J R Meteorol Soc , 131(613), 215-3233.

[29] Simmons, A. J, & Hollingsworth, A. (2002). Some aspects of the improvement in skill of numerical weather prediction. Q J R Meteorol Soc , 128, 647-677.

[30] Kursinski, E. R, Leroy, S. S, & Herman, B. (2000). The GPS radio occultation technique. Terr. Atmos. Oceanic Sci., , 11, 53-114.

[31] Kuo, Y, Zou, H. , X, & Huang, W. (1997). The impact of GPS data on the prediction of an extratropical cyclone: An observing system simulation experiment. J. Dyn. Atmos. Ocean., , 27, 439-470.

[32] Chen, S-Y, Huang, C-Y, Kuo, Y-H, Guo, Y-R, & Sokolovskiy, S. (2009). Typhoon predictions with GPS radio occultation data assimilations by WRF-VAR using local and nonlocal operators. Terr Atmos Oceanic Sci , 20, 133-154.

[33] Huang, C, Kuo, Y. , Y. -H, Chen, S. -Y, Terng, C. -T, Chien, F. -C, Lin, P. -L, Kueh, M. -T, Chen, S. -H, Yang, M. -J, Wang, C. -J, & Rao, A. S. K. A. V. P. (2010). Impact of

GPS radio occultation data assimilation on regional weather predictions. GPS Solutions, DOI:s10291-009-0144-1., 14, 35-49.

[34] Vermeulen, C. J. M, Barneveld, H. J, Huizinga, H. J, & Havinga, F. J. (2005). Data-assimilation in flood forecasting using time series and satellite data. International conference on innovation advances and implementation of flood forecasting technology, October 2005, Tromsø, Norway, 17-19.

[35] Mishra, A. K, & Singh, V. P. (2010). A review of drought concepts. J Hydrol , 391, 202-21.

[36] Wilhite, D. A. (1992). Preparing for Drought: A Guidebook for Developing Countries, Climate Unit, United Nations Environment Program, Nairobi, Kenya.

[37] [37]Riebsame, W. E, Changnon, S. A, & Karl, T. R. (1991). Drought and Natural Resource Management in the United States: Impacts and Implications of the 1987-1989 Drought. Westview Press, Boulder, CO, , 174.

[38] Wilhite, D. A. Drought as a natural hazard: concepts and definitions. D.A. Wilhite (Ed.), Drought: A Global Assessment, New York ((2000). , 1Routledge, 1-18.

[39] Bryant, E. A. Natural Hazards, Cambridge University Press, Cambridge ((1991).

[40] Zaitchik, B. F, Rodell, M, & Reichle, R. H. (2008). Assimilation of GRACE terrestrial water storage data into a land surface model: results for the Mississippi river basin. J. Hydrometeorol. , 9, 535-548.

[41] Houborg, R, Rodell, M, Li, B, Reichle, R, & Zaitchik, B. Drought indicators based on model assimilated GRACE terrestrial water storage observations, Wat. Resour. Res., 48, W07525, doi:10.1029/2011WR011291,(2012).

[42] Rojas-palma, C. Data assimilation for off site nuclear emergency management," Tech. Rep., SCK-CEN, DAONEM final report, RODOS(RA5)-RE(04)-01, (2005).

[43] NRC(2011). Tsunami Warning and Preparedness: An Assessment of the US Tsunami Program and the Nation's Preparedness Efforts. National Academies Press, Washington, DC, 284 pp.

[44] Whitmore, P. M, Benz, H, Bolton, M, Crawford, G. L, Dengler, L, Fryer, G, Goltz, J, Hansen, R, Kryzanowski, K, Malone, S, Oppenheimer, D, Petty, E, Rogers, G, & Wilson, J. (2008). NOAA/WestCoast and Alaska Tsunami Warning Center Pacific Ocean response criteria. Science of Tsunami Hazards , 27(2), 1-21.

[45] Titov, V. V, Gonz, F. I, Alez, E. N, Bernard, M. C, Eble, H. O, Mofjeld, J. C, & Newman, A. J. Venturato ((2004). Real-time tsunami forecasting: Challenges and solutions. *Nat. Haz.*, *35*(1), 41-58.