Remote Sensing for Environmental Monitoring and Change Detection (Proceedings of Symposium HS3007 at IUGG2007, Perugia, July 2007). IAHS Publ. 316, 2007.

Sequential assimilation of remotely sensed water stages in flood inundation models

PATRICK MATGEN[1], GUY SCHUMANN[1,2], FLORIAN PAPPENBERGER[3] & LAURENT PFISTER[1]

1 *Public Research Centre, Gabriel Lippmann, 41 rue du Brill, L-4422 Belvaux, Luxembourg*
matgen@lippmann.lu

2 *Geography Department, Dundee University, Dundee, DD14HN, UK*

3 *European Centre for Medium-Range Weather Forecasts, Reading RG29AX, UK*

Abstract The hydrologically and hydraulically relevant variables (e.g. soil moisture, flood extent, water stage) and basin characteristics (e.g. topography, surface roughness) that can be obtained from radar remote sensing are useful for implementing, calibrating and evaluating both rainfall–runoff and flood inundation models. To achieve a time continuity that is crucial in monitoring applications but cannot be obtained by the sole use of remote sensing observations, the information extracted from the discrete Earth observation data can be used both as parametric input and as time-varying state and flux data in coupled hydrological and hydraulic models. This paper focuses on the sequential assimilation of remotely sensed water stages into a 1-D flood inundation model (HEC-RAS). Through the integration of radar imagery of flood events with high precision digital elevation models, inundation depths can be extracted from remote sensing observations. The methodology consists of adjusting simulated water surface lines by comparing modelled water stages with those that are derived from remote sensing observations, thereby increasing the overall accuracy and reliability of flood predictions at subsequent time steps. The potential of the proposed methodology is illustrated by a well-documented flood event of the Alzette River (Grand-Duchy of Luxembourg).

Key words flood inundation modelling; remote sensing; sequential data assimilation; Synthetic Aperture Radar, HEC-RAS

INTRODUCTION

Despite the physical laws that many models used in operational flood forecasting are based upon, most of these models need their parameters to be calibrated using some sort of evidence. Calibration of model parameters that are related to physically observable properties is criticized by some authors (e.g. Cunge, 2003) but continues to be common practice. In operational forecasting applications, optimization of predictions rather than consistency remains the driving force in model development. Ideally both aspects would go hand in hand, but many practical examples prove the opposite, and more consistent models are often achieved at the expense of less accurate predictions. In near real-time applications, data assimilation can be considered as an approach to obtain more accurate and more consistent models by considering various types of measurements that are available at the time of prediction. However, to date, mainly discharge measurements are routinely assimilated in hydrological models whereas other data sets very often continue to be ignored. Unlike in meteorology where assimilation techniques are very popular and have led to significant improvements in forecasting, examples of routine data assimilation techniques are rather rare in operational flood forecasting. In many basins, a wealth of additional time varying forcing and state data would be readily available and could be of use for improved forecasting. The objective of data assimilation schemes is to put the model in better agreement with observed data whenever new observations become available. If the model results match the observations, such additional data sets would nonetheless be useful to control the models and allow the user to be more confident about model predictions. Aubert *et al.* (2003), among others, showed that real-time soil moisture measurements along with discharge measurements allowed substantial improvement of runoff predictions at subsequent time steps. The present paper intends to use remote sensing observations of flooded areas as an additional data source to support flood modelling. Assimilation of remotely sensed soil moisture in hydrological models, although not yet used operationally, has provided promising results in several studies (François *et al.*, 2003; Matgen *et al.*, 2006). However, methodologies to sequentially assimilate remotely sensed water stages in flood inundation models have, to the authors' knowledge, not been presented yet. Although the frequency of image acquisition has significantly improved in recent years due to new satellite constellations and new sensors, remote sensing data will always be restricted to the acquisition of a discrete image of an area of the Earth's surface. Hence, the continuity in time that is needed in most monitoring applications requires the integration of remote sensing information with models.

Most papers in recent literature, which evaluate the benefits that are to be gained from the use of remote sensing observations in support of flood modelling, focus on the extraction of flood outlines from SAR images and aerial photography. Although there is no doubt that remotely sensed flood outlines are useful for model implementation and calibration (Horritt, 2000; Romanowicz *et al.*, 2003; Matgen *et al.*, 2004) one may wonder whether remotely sensed flood stages would not provide more efficient constraints that would in turn ensure improved flood predictions. Werner *et al.* (2004) and Hostache *et al.* (2005) argue that water stages are more useful than flood outlines for model calibration. In fact, on many flood plains, beyond a certain inflow magnitude, the area of flooding does not change significantly with increasing water stages. Surprisingly few attempts have been made to estimate flood stages by combining detailed DEMs with flood outlines, among which the promising results obtained by Raclot (2006), Matgen *et al.* (2006) and Schumann *et al.* (2007) are worth mentioning.

This paper deals with the attempt to develop a framework that allows for the sequential updating of flood inundation models using distributed water stages obtained from remote sensing.

STUDY AREA AND AVAILABLE DATA

The study site on the Alzette River, Grand-Duchy of Luxembourg, is located downstream of Luxembourg City between the gauging stations at Steinsel and Mersch. The Alzette is a tributary of the Sure River, which is a tributary of the Mosel River. At the upstream boundary of the studied reach, the Alzette drains an area of 404 km^2. The river flood plain between the two gauging sites is relatively large and flat, with little villages straddling the valley floor. The presence of infrastructure such as railway lines and roads constrains the flood plain area on both sides. The reach under consideration is 10 km long with a flood plain having an average width of approximately 300 m. The reach includes four continuously recording gauging stations. Those located at the inlet and outlet of the studied reach (Steinsel and Mersch) serve as boundary conditions in the hydrodynamic model and the two intermediate ones (Hunsdorf and Lintge) enable the monitoring of the propagation of flood waves. Two well documented flood events recorded in January 2003 and March 2006, respectively, were used in this study.

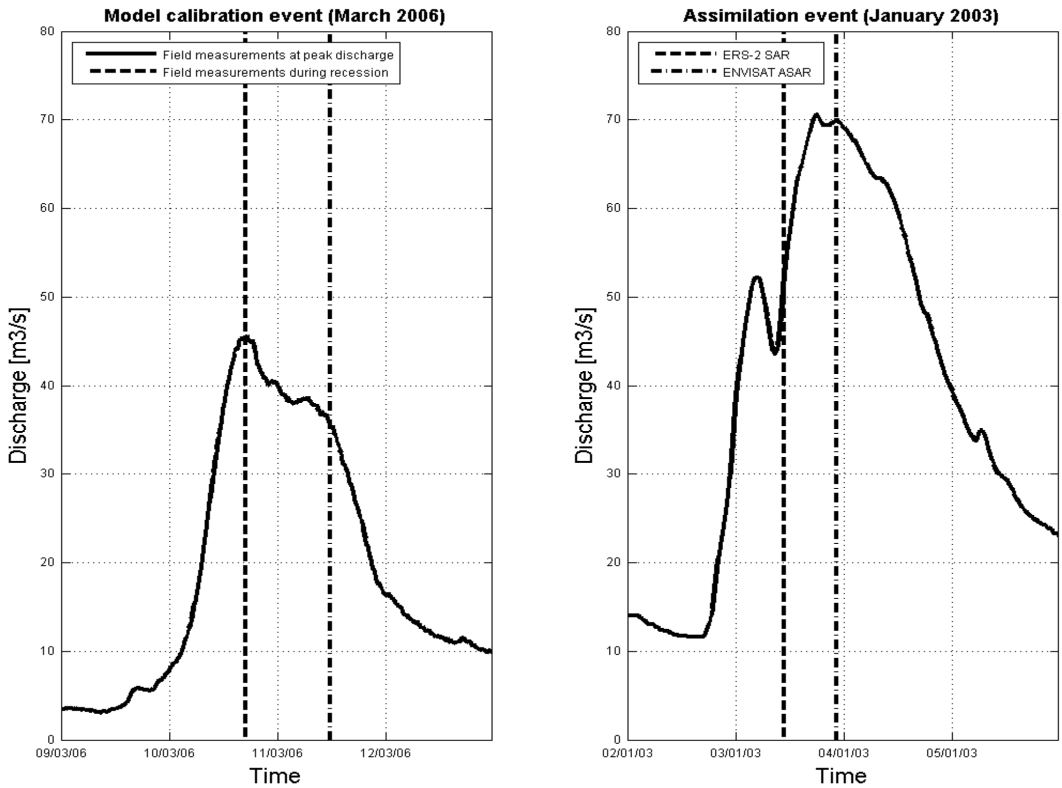

Fig. 1 Observed inflow hydrographs for the calibration and assimilation events. The figure also shows the timing of the field measurements that were used for model calibration and of the remotely sensed evaluation data, which are available to test the sequential assimilation scheme.

The March 2006 data set is considered for model calibration, whereas the January 2003 flood is used to assess the potential of the proposed sequential assimilation scheme based on remote sensing. During the two events, the most upstream gauging station recorded the hydrographs shown in Fig. 1. The extent of the January 2003 flood was captured at two different times by the SAR instruments onboard the ERS-2 and ENVISAT satellites. Also, numerous GPS reference points of the maximum flood extent were collected and for both events eight evenly distributed high water marks were surveyed. More detailed information on the study area and the available data sets can be found in Pappenberger *et al.* (2006).

MODEL SET-UP AND CALIBRATION

Within the study area, one dimensional hydrodynamic codes (Matgen *et al.*, 2004; Pappenberger *et al.*, 2006) as well as quasi 2-D storage cell models (Pappenberger *et al.*, 2007) have been successfully applied for modelling flood wave routing and studying flood levels at the river reach scale. In this study, the widely used one dimensional (1-D) HEC-RAS model is used for river flow computations. HEC-RAS allows performing 1-D steady and unsteady flow calculations. As for the river reach under study the direction of flow is mainly along channel, the 2-D flow field that is typically related to riverbank overtopping can be approximated by a 1-D representation (i.e. velocity components in directions other than that of flow are not accounted for). The Unsteady Network Model UNET, which is part of HEC-RAS, solves the full 1-D St Venant equations for unsteady open channel flow. The hydraulic resistance is based on the friction slope from the empirical Manning's equation. The 1-D hydrodynamic model, contrary to the more computationally intensive storage cell models and 2-D hydrodynamic models, allows for a rapid evaluation of spatially and temporally distributed water levels and is thus well suited for operational flood forecasting applications. On the Alzette River reach, the channel and flood plain topography is represented by the geometry of 74 cross sections perpendicularly placed to the direction of flow. The calibration parameters are the flood plain and channel roughness. Various methods are available in the literature to estimate Manning's n roughness value based on field observations and measurements. However, effective parameters obtained via model calibration usually account for the heterogeneity at the model grid scale (i.e. compound effect of texture and vegetation cover between cross sections) and compensate for errors in boundary conditions and model structure, meaning that calibrated model parameters very often vary considerably from roughness values estimated from field observations. An additional problem is that channel roughness is known to vary with flow velocity. Thus, with a single set of parameters, most hydrodynamic models cannot accurately compute water surface lines over the entire reach and for every possible boundary condition.

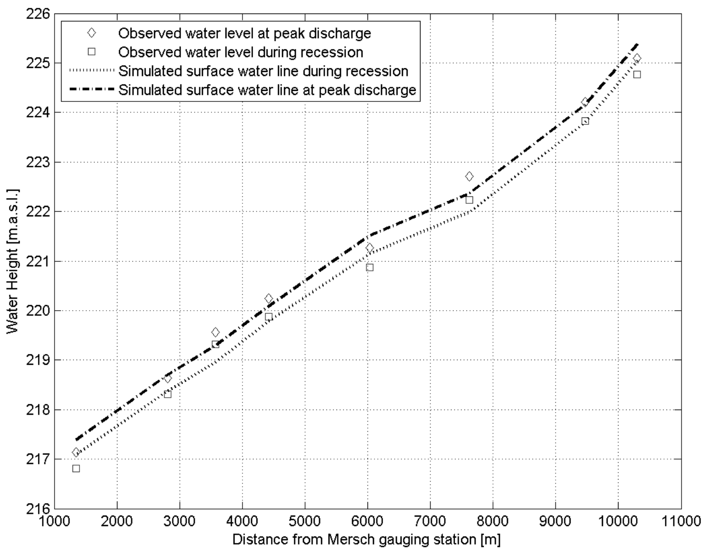

Fig. 2 Agreement of fit between the modelled and observed water stages (March 2006 flood). High water marks were surveyed at two distinct moments of the flood.

The objective function that was used to calibrate the model was the sum of mean squared errors between modelled and observed water stages at two different instants of the March 2006 flood event. Eight evenly distributed water stages were surveyed at peak discharge and during recession. In total, 5000 model runs with randomly chosen channel and flood plain roughness coefficients were generated. The parameter set that gave the highest performance measure was retained with channel and flood plain Manning n values of 0.033 and 0.077 and a mean squared error of 0.23 m (Fig. 2).

SEQUENTIAL ASSIMILATION OF REMOTELY SENSED WATER STAGES

Remote sensing of water stages

Hydraulically relevant information needs to be extracted from satellite imagery prior to sequential updating of flow routing models. This information may then be used to evaluate and eventually improve hydrodynamic models. Therefore, a spatially distributed water surface line that may be compared to that simulated at the time of image acquisition needs to be extracted from a single remote sensing scene. To obtain inundation depth from remote sensing, a procedure outlined in Matgen *et al.* (2006) and further improved by Schumann *et al.* (2007) was adopted. The procedure is based on an integration of remotely sensed flood boundaries with high-precision topographic data. Using histogram thresholding on a geo-rectified SAR image, a distinction between flooded and non-flooded area is obtained. For each river cross-section that is defined in the hydrodynamic model, water elevation data is extracted from a LiDAR-DEM at the land-water contact zone. Water levels derived from remote sensing observations are known to be uncertain. Sources of uncertainty include geo-coding inaccuracies due to a lack of easily identifiable ground control points, a coarse image ground resolution and terrain geometry causing abrupt changes in slope at the edge of most flood plains. Moreover, flood area detection may be hampered by wind roughening the water surface, and volume scatter caused by protruding vegetation. Schumann *et al.* (2007) demonstrated that regression analysis performed on the extracted water stages provides high-resolution 3-D flood information that is useful for near-real time flood hazard management. However, it is sensible to argue that this simplified steady-state SAR-based model cannot substitute physically-based models that are based on the solution of the full St Venant equations for hydrodynamic flow. It can be expected that hydraulic model outperform simplified remote sensing-based models due to their ability to account for processes such as backwater effects that dominate flow behaviour locally (Schumann *et al.*, 2007). In an assimilation framework it would be fundamentally wrong to force complex models towards simplified linear models. Nevertheless, integrating binary flood maps extracted from remote sensing with high precision topographical information may still provide useful data for model evaluation.

Given the argument above, uncertainties of the remotely sensed water surface line need to be considered and the model should only be corrected where the simulated water stage falls outside of the uncertainty interval of the radar-derived water surface lines. Of course, using uncertain remote sensing observations, a well-calibrated physically-based model should only be corrected where there is a high probability of the model being in error. Thus, the objective is to derive an interval of likely water stages at each cross section from remote sensing imagery, rather than getting a best fit to the observed data in the sense of a least squared error. At the land–water boundary on both sides of the river channel, minimum and maximum remotely sensed water stages are determined inside a buffer encircling the intersection point between flood boundary and river cross section. The size of the buffer corresponds to three pixels (i.e. 37.5 m) to account for positioning and flood delineation uncertainties. The interval given by the minimum and maximum water stage values implicitly represents uncertainty in remotely sensed water stages (Hostache *et al.*, 2005). Further, a land cover map is used to mask out areas where accurate flood area detection may be hindered by buildings and vegetation cover.

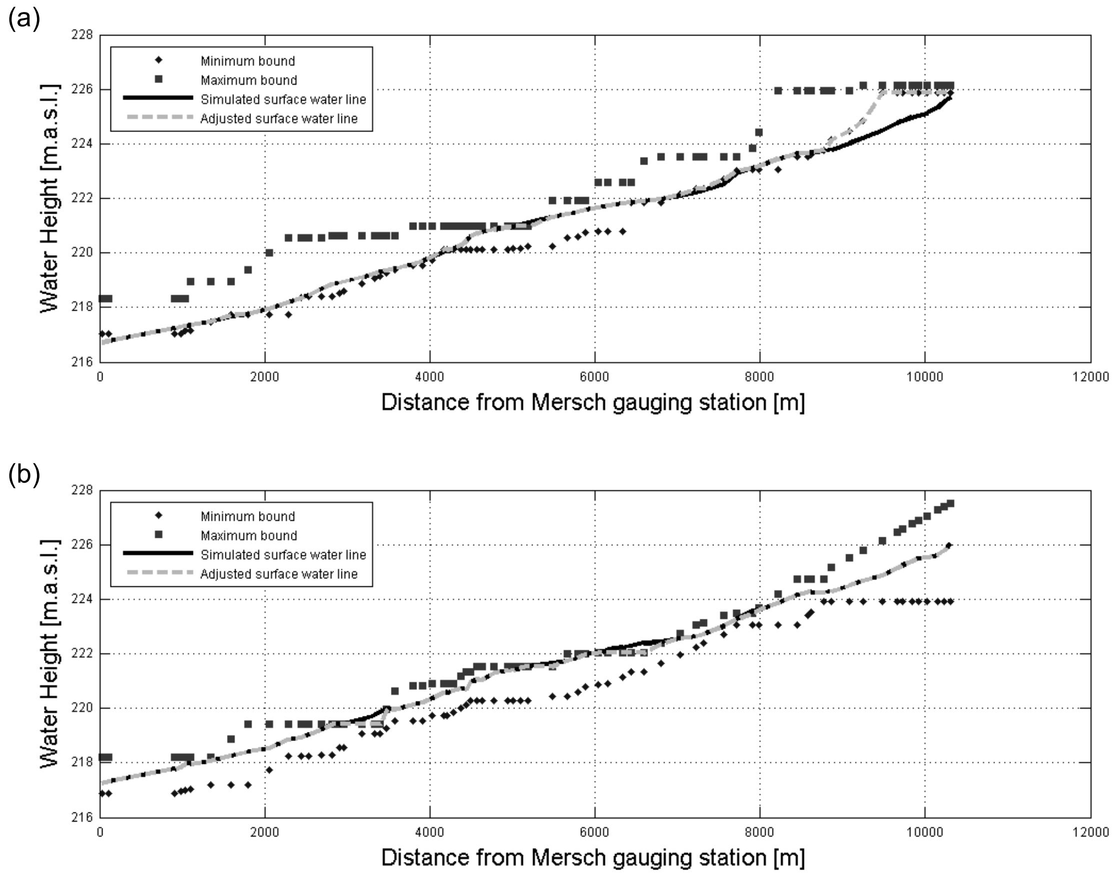

Fig. 3 Maximum and minimum water stages derived from ERS SAR (a) and ENVISAT ASAR (b) images acquired at two distinct moments of the January 2003 flood. The initial estimate of the water stages and the subsequently adjusted water surface line are also depicted.

Wide bands of uncertainty probably bracket model predictions at any time and at any place, meaning that no correction or additional information can be obtained from remote sensing. To render remote sensing observations useful for integration with hydraulic models, reduction of remote sensing uncertainty is of paramount importance. A significant reduction of uncertainties is achieved through verification of hydraulically coherent water flow (i.e. water height should decrease in a downward direction). An iterative algorithm (Raclot, 2006) that adjusts hydraulically incoherent water stages is therefore applied on the initial water stage values to guarantee a consistent downward trend of the water surface line. In a 1-D modelling approach, the preferential flow direction is along the stream centreline. The method is applied to the ENVISAT ASAR and ERS-2 SAR images acquired during the 2 January 2003 flood (Fig. 3). Also, improved sensors and high accuracy DEMs more readily available in the near future may considerably help further reduce remote sensing water stage uncertainties.

Sequential assimilation

There are three possible ways to integrate remote sensing observations with flood inundation modelling: (i) as parametric input data, including the geometrical description of river channels and flood plains; (ii) as evaluation data to calibrate distributed model parameters, such as channel and flood plain roughness that are difficult to measure directly; and (iii) as time varying state data, such as water storage within the channel, to improve model predictions. This paper focuses on the latter. In fact, conceptually, sequential state updating is preferable to sequential parameter updating because parameter updating would violate a basic principle of physically-based modelling, namely that the constants should stay constant while the variables vary (Kirchner, 2006). The previous section outlined a way to process radar images in such a way as to allow commonly used flood inundation models to work with the retrieved information. The state of the model that represents the storage of water in the channel and flood plain is verified and updated whenever a remote sensing-based estimate of the water surface line becomes available. The method is based on the assumption that a better simulation of the model state at time step j will improve the accuracy of the model predictions at time steps $j + 1$, $j + 2$, etc. (Aubert *et al.*, 2003). As pointed out by Walker (1999), there is the challenge to merge the high temporal resolution of—generally rather poor—model predictions with the spatially comprehensive but limited remote sensing observations to yield the best possible model predictions. The method consists in allowing the model to give a first estimate of the "true" water surface line. This model estimate is then compared to the remote sensing-based estimate. The latter is represented by an uncertainty band that should ideally bracket the "true" water surface line. At each cross section where the model estimate of the water level is located outside this uncertainty band, the modelled line is adjusted in such a way that the uncertainty interval constrains the water surface line over the entire river reach. Next, the model is re-initialized with the adjusted water surface line. After the model is conditioned on the observed data, it evolves again freely until the next observation becomes available. Since abrupt static forcing of the model may lead to numerical instabilities, only every third cross section was updated with the remotely sensed water level. This gives the model enough flexibility to adapt to the constraint. The approach was tested with the two radar images acquired during the January 2003 flood on the Alzette River.

Figure 3 shows that at most cross sections the model estimates of water stage are indeed inside the uncertainty interval obtained from remote sensing. One may argue that, in this particular case, deriving water stages from SAR was not worthwhile. However, the fact that model estimates mostly lay within the range of pre-defined observation uncertainties, confirm the suitability of the selected model structure and parameters. Hence the modeller can be more confident about model results. Although the modelled water surface line is satisfactory at most cross sections, there were still minor adjustments to be made at the upstream section and on two limited stretches located in the middle part on the studied river reach. Moreover, the adjustments prove to be more significant for the ERS imagery than for the ENVISAT image. Investigating the reasons why the water surface line computed by the calibrated model needed to be adjusted is highly speculative and beyond the scope of this paper.

RESULTS

In order to quantify the efficiency of the assimilation procedure, the simulated water stages at the intermediate bridges in Hunsdorf and Lintgen are compared to recorded stage hydrographs. Moreover, simulated maximum water stages are compared to the set of eight different measurements of the maximum water level. The former allows evaluating the model's ability to compute the propagation of a flood wave, whereas the latter allows assessing the model's performance in accurately computing spatially distributed water stages along the stream channel. Both performance measures are computed for the model with and without assimilation. The model is re-initialized with the remote sensing-based estimates (extracted from ERS and ENVISAT images) of water stages at the time of image acquisition. As the calibrated flood inundation model performs reasonably well even without assimilation, model improvement is bound to be minor.

Indeed the effect of the assimilation is hardly observable in absolute values and can only be evaluated by computing the error between the observed and simulated stage hydrograph (Fig. 4). The assimilation effect is very similar at both bridges, therefore only the one obtained at the bridge in Hunsdorf is depicted in Fig. 4. The integration of the water surface line that was adjusted based on the water stages derived from the ERS image reduces the difference between modelled and observed water levels by 23 cm. However, the effect of improvement fades rapidly at subsequent time steps. One, two and three hours after image acquisition, the error is reduced by 18 cm, 8 cm and 3 cm, respectively. The simulated stage hydrographs overlap again only 4.5 hours after the actual ERS image acquisition. At the time of acquisition of ENVISAT the difference between the observed stages at the two bridges and the ones those computed with the calibrated model is only 3 cm. With the integration of the adjusted water surface line this difference increases to 6 cm, meaning that the model performance is deteriorated. Again, the two lines get closer at subsequent time steps and completely overlap as soon as 2 hours after image acquisition. When compared to the surveyed high water marks, it turns out that remote sensing did not help increase model performance. The mean squared error with and without assimilation is 25 cm. The peak discharge occurred 3 hours before the acquisition of the ENVISAT image, at a time when the integration of the adjusted ERS water surface line did no longer have any impact on model results.

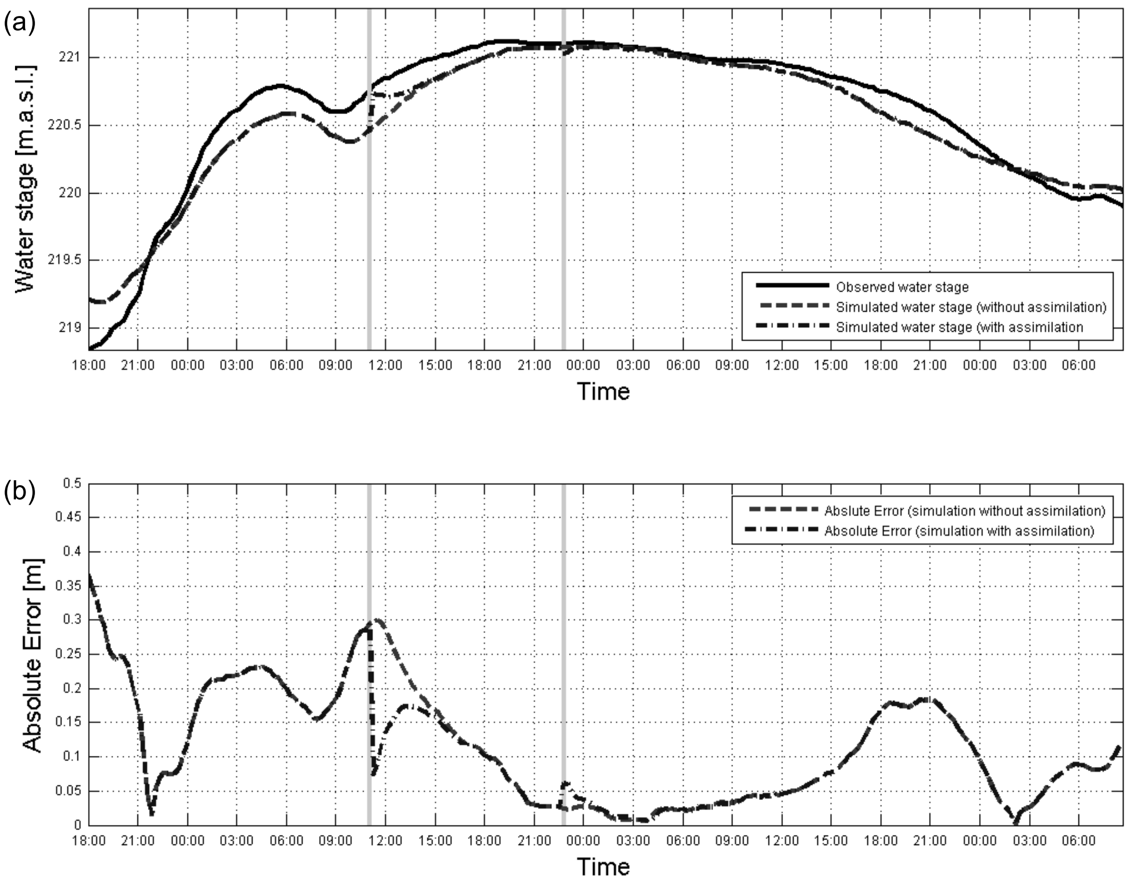

Fig. 4 (a) Simulated water stages with and without data assimilation. The vertical line depicts the timing of the remotely sensed assimilation data. (b) The figure also shows the error between simulated and observed water stages with and without data assimilation.

DISCUSSION AND CONCLUSION

The following conclusions can be drawn from the case study of the January 2003 flood on the river Alzette. First of all, it has been demonstrated that the information content of radar flood images can lead to improved flood inundation modelling in an operational flood forecasting framework. However, the value of the remote sensing information decreases rapidly. As a matter of fact, the time efficiency of data acquisition and processing determines to a large extent the usefulness of remotely sensed information. It has been shown that several hours after image acquisition the remote sensing observations did no longer provide any substantial improvement of the flood forecasting system. On larger basins, with less steep rising limbs and recessions, the information content of remote sensing observations may well be valid over longer time periods. This study also showed that there is a risk of degrading model performances by considering uncertain flood information obtained from remote sensing. Hence, continued efforts should be made to reduce uncertainties of remotely sensed flood stages. Not only does a well-calibrated model compute water surface lines that lie inside the uncertainty interval of remotely sensed water stages, thereby rendering the use of remotely sensed flood stages relatively ineffective, but also the risk of deteriorating model performances by integrating uncertain water stages would decrease. New SAR sensors with improved polarization modes, incidence angles and wavelengths better suited for flood area detection can be expected to further reduce the uncertainty of remotely sensed water stages, thereby increasing the potential use of remote sensing in operational flood forecasting. Also, highly accurate DEMs are becoming more readily available at larger scales and should allow determining water stages more accurately.

This research study is ongoing and will further investigate the potential use of remotely sensed water surface lines for sequential assimilation in flood inundation models. Although this seems to have been largely confirmed by the presented case study, major doubts remain about the acquisition of remote sensing imagery in near real time to be integrated with hydrodynamic models. Improved temporal sampling and, most of all, fast image acquisition and processing, are needed if SAR imagery is to be used to update flood inundation models in an operational mode. Also, special emphasis needs to be put on the constraining of uncertainties of remotely sensed water stages. Finally, the development of more sophisticated assimilation techniques may further enhance the use of Earth Observation data in operational forecasting systems.

Acknowledgements This study was part of the HYDRASENS project, financed by the National Research Fund (FNR) of the Grand Duchy of Luxembourg, and the STEREO II research programme for Earth Observation of the Belgian Federal Science Policy Office.

REFERENCES

Aubert, D., Loumagne, C. & Oudin, L. (2003) Sequential assimilation of soil moisture and streamflow data in a conceptual rainfall–runoff model. *J. Hydrol.* **280**, 145–161.

Cunge, J. A. (2003) Of data and models. *J. Hydroinformatics* **5**(2), 75–98.

Francois, C., Quesney, A. & Ottlé, C. (2003) Sequential assimilation of ERS-1 SAR data into a coupled land surface-hydrological model using an extended Kalman Filter. *J. Hydrometeorol.* **4**, 473–487.

Horritt, M. S. (2000) Calibration of a two-dimensional finite element flood flow model using satellite radar imagery. *Water Resour. Res.* **36**(11), 3279–3291.

Hostache, R., Puech, C. & Raclot, D. (2005) Caractérisation spatiale d'aléa inondation à partir d'images satellites RADAR: Cartographie et estimation de niveaux d'eau par fusion des données images avec des données topographiques. In: *Proc. Int. Conf. on Spatial Analysis and Geomatics (SAGEO)* (Avignon, France, 20–23 June), CD-Rom (in French).

Kirchner, J. W. (2006) Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology. *Water Resour. Res.* **42**, W03S04, doi:10.1029/2005WR004362.

Matgen, P., El Idrissi, A., Henry, J. B., Tholey, N., Hoffmann, L., De Fraipont, P. & Pfister, L. (2006) Patterns of remotely sensed flood plain saturation and its use in runoff predictions. *Hydrol. Processes* **20**, 1805–1825.

Matgen P., Schumann, G., Henry J. B., Hoffmann, L. & Pfister L. (2007) Integration of SAR derived river inundation areas, high-precision topographic data and flood propagation models: a step towards effective, near real-time flood management. *Int. J. Appl. Earth Observation & Geoinformation* (in press).

Matgen, P., Henry, J. B., Pappenberger, F., De Fraipont, P., Hoffmann, L. & Pfister, L. (2004) Uncertainty in calibrating flood propagation models with boundaries observed from synthetic aperture radar imagery. In: *Proc. 20th Congress of the International Society of Photogrammetry and Remote Sensing* (Istanbul, Turkey), 352–358.

Pappenberger, F., Matgen, P., Beven, K., Henry, J. -B., Pfister, L. & De Fraipont, P. (2006) Influence of uncertain boundary conditions and model structure on flood inundation predictions. *Adv. Water Resour.* **29**, 1430–1449.

Pappenberger, F., Beven, K., Frodsham, K., Romanowicz, R. & Matgen, P. (2007) Grasping the unavoidable subjectivity in calibration of flood inundation models: a vulnerability weighted approach. *J. Hydrol.* (in press).

Raclot, D. (2006) Remote sensing of water levels on flood plains: a spatial approach guided by hydraulic functioning. *Int. J. Remote Sens.* **27**(12), 2553–2574.

Romanowicz, R. & Beven, K. (2003) Estimation of flood inundation probabilities as conditioned on event inundation maps. *Water Resour. Res.* **39**(3), 1073.

Schumann, G., Hostache, R., Puech, C., Hoffmann, L., Matgen, P., Pappenberger, F. & Pfister, L. (2007) High-resolution 3D flood information from radar imagery for flood hazard management. *Trans. Geosci. & Remote Sens.* (in press).

Walker, J. P. (1999) *Estimating Soil Moisture Profile Dynamics From Near-Surface Soil Moisture Measurements and Standard Meteorological Data*. The University of Newcastle, Newcastle, Australia.

Werner, M. G. F. (2004) *Spatial Flood Extent Modelling: A Performance-Based Comparison*. Delft University Press, Delft, The Netherlands.