MULTI-MISSION REMOTE SENSING OBSERVATIONS FOR OPTIMIZING HYDROLOGICAL HAZARD PREDICTIONS

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ABSTRACT

Satellite remote sensing observations offer unique possibilities to monitor, understand and predict hydrological hazards, particularly in ungauged catchments. In this study, we use state-of-the-art multi-mission remote sensing observations to update a hydrological model of the poorly instrumented Ogooué river in Gabon. We use a conceptual rainfall-runoff model forced with satellite-based climate observations; and calibrate the model parameters using an aggregated objective function including Sentinel-3 satellite altimetry and GRACE/GRACE-FO total water storage. The model is used to evaluate flood risk in combination with Sentinel-1 water surface extent and flood occurrence maps and to simulate the potential impact of climate change on the rainfall-runoff processes in the catchment.

Index Terms— *Flood, catchment hydrology, surface water extent, water surface elevation, altimetry*

1. INTRODUCTION

Rivers are at the source of significant hazard records, including floods, which can have detrimental human and material consequences [1]. Climate change is further altering flood patterns globally [2]–[4][4]. Thus, accurate representation of river dynamics is of paramount importance to hydrological hazard predictions. Numerical models are highly useful tools to support better understanding of land-surface processes as well as informed decision-making. They are a key step in forecasting and predicting vulnerability to change. However, hydrological models require significant data volumes to ensure the natural system is adequately represented. In many river catchments, monitoring is insufficient [5]. In those cases, remote sensing observations are playing an increasingly important role both – both as a supplement to in-situ observations and in some cases, the only alternative.

Several components of the water balance can now be directly observed or derived from space observations: evapotranspiration, soil moisture, total water storage change and water levels are available from e.g. optical and radar imagery, gravimetry and altimetry [6], [7]. Several of these can be integrated in hydrological models and used to improve state or parameter estimates. The uptake of publicly available remote sensing observations into model frameworks is in many cases a significant step in achieving accurate simulations. The volume and accuracy of remote sensing observations is ever increasing, offering new possibilities for improving and extending existing uptake frameworks.

In this study, we demonstrate how multi-mission remote sensing observations can be used to optimize hydrological hazard predictions. We update an existing rainfall-runoff model of the Ogooué river using Sentinel-3 WSE and GRACE/GRACE-FO total water storage. The model is then forced using climate factors to simulate expected climate change impact on the runoff generation in the basin. By correlating flood maps and model simulations, a better understanding of hazard risk in the catchment is expected.

2. STUDY AREA

The Ogooué river in Gabon is used as the case study. The Ogooué is the fourth largest river in Africa by discharge volume, however only limited historic precipitation and discharge observations are available [8]. Due to its lack of in-situ observation networks, the river is a good study area for using remote sensing observations in hydrological monitoring and modelling. Furthermore, the river is a good satellite altimetry target, with previous studies showing good results comparing in-situ and satellite-based WSE [9].

The Ogooué is prone to floods, largely driven by precipitation [10], which have caused significant damage in fall 2019 in the Moyen Ogooué and in November 2020, gravely hitting the town of Lambaréné. Hydraulic constructions are considered to mitigate the impact of floods on local populations (channeling or damming the river), but also as part of national development plans. The discontinuation of hydrological monitoring programs since the 1980s constrain the understanding of change impacts on the basin [10].

Remote sensing observations can play an important role on several fronts: simulating future predicted discharge, 2) evaluating the impact of dam building on natural floods and 3) better understanding of floods through altimetry and satellite images, potentially supporting flood forecasting and response.

3. DATA AND METHODS

3.1. Sentinel-3 altimetry

We derive Water Surface Elevation (WSE) from Sentinel-3A and Sentinel-3B radar altimetry processed on the ESA Grid Processing on Demand (GPOD, https://gpod.eo.esa.int/) using the Samosa+ retracker [11]. The processing follows the workflow described in [12]. The dataset is referenced to the EGM2008 geoid, and therefore the long-term mean must be subtracted before comparison to the simulated channel depth.

3.2. GRACE/GRACE-FO Total Water Storage (TWS)

Monthly total water storage anomaly observations are obtained from the JPL mascon (mass concentration blocks) surface mass change solution. The Ogooué is covered by two mascons. The JPL RL06M Version 2.0 dataset used in this study [13]–[16] combines observations from GRACE (April 2002-June 2017) and GRACE-FO (June 2018-present). Time series are produced for the Eastern and Western part of the Ogooué following the mascon frontier [8]. The GRACE/GRACE-FO Mascon data are available at http://grace.jpl.nasa.gov.

3.3. Surface Water Extent (SWE)

Surface water extent and dynamics can be mapped and monitored using imagery acquired by spaceborne optical and Synthetic Aperture Radar (SAR) imagery. While cloud cover may impede the use of optical data (e.g., Landsat and Sentinel-2) in tropical regions and during flooding events, then SAR data (e.g. Sentinel-1) can be collected in all-weather conditions. Sentinel-1 time series are well suited for classifying and monitoring changes in surface water as the specular reflection properties of calm water surfaces will appear dark in the resulting SAR imagery, and in contrast to the land surface which has a more diffuse reflection and hence brighter appearance [17]. The SWE map is used to select Sentinel-3 altimetry observations over water.

All Sentinel-1 images over Ogooué from 2018 to 2020 will be acquired and the workflow for monitoring surface water extent dynamics (incl. flood occurrence) includes pre-processing, classification, and post-processing steps. In the pre-processing step, precise orbit vectors and range-Doppler terrain correction is applied to obtain a georeferenced SAR image. To exploit the difference in backscatter from water and non-water surfaces a trained logistic regression model will be used to convert the backscatter values into a water probability score. A thresholding approach is subsequently used to convert the probability into a binary water/not-water classification and followed by a simple sieve filtering technique to reduce some inherent speckle noise.

3.4. Rainfall-Runoff model and calibration

We use the conceptual rainfall-runoff model of the Ogooué presented in [8]. The model framework is based on the work of [18]. [8] expanded the model structure to represent tributary processes, deep groundwater, and river routing. The model is forced using remote sensing observations from ECMWF Era-Interim [19] and GPM [20]. The model parameters are calibrated using the global search algorithm Shuffled Complex Evolution University of Arizona algorithm (SCE-UA), as implemented in Python by [21].

In [8], the calibration objective aggregated performance measures for 1) discharge using the a) historical flow duration curve b) long-term average daily discharge; 2) GRACE total water storage anomaly (TWS); and 3) water level from radar altimetry using water surface elevation observations from Envisat and Jason-2. Additional data is used for model performance and data interpretation. In this study, we update the calibration strategy to include new GRACE-FO TWS observations and the denser Sentinel-3 WSE virtual station network. We use a weighted Root Mean Square Deviation (RMSD) to evaluate the TWS anomaly and WSE simulations against GRACE/GRACE-FO and Sentinel-3 respectively. Each residual is weighted by the observation uncertainty. In the case of GRACE/GRACE-FO uncertainties are included in the dataset ([13]–[16]). For the Sentinel-3 virtual stations, the along-track standard deviation is used as the observation uncertainty.

3.5. Validation

Validation is typically conducted by comparing the model predictive power to “new” observations, i.e. observations omitted in the calibration. Due to the lack of contemporary observations, and the use of long-term statistical trends in the objective function, we use a spatial split sample to assess model performance throughout the catchment. Additionally, GRACE/GRACE-FO observations from 2017-2020 are used for validation.

4. RESULTS AND DISCUSSION

Figure 1 shows the water occurrence frequency for the lower Ogooué and water surface elevation time series at two virtual stations. The WSE observations from Sentinel-3 are selected using the SWE map. Detailed water extent maps allow for better selection of suitable altimetry targets compared to standard water masks (in this case due to the higher spatial resolution). Dynamic and higher resolution surface water extent also allow for investigating model outputs (i.e. discharge simulations) relative to actual flood occurrence.

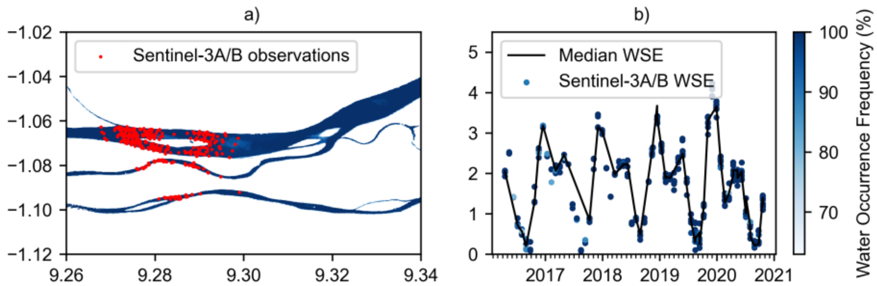

Figure 1 Surface Water Extent (SWE) frequency map for the lower Ogooué using fused Sentinel-1 and Sentinel-2 and Sentinel-3A and B Water Surface Elevation (a) and WSE time series (b).

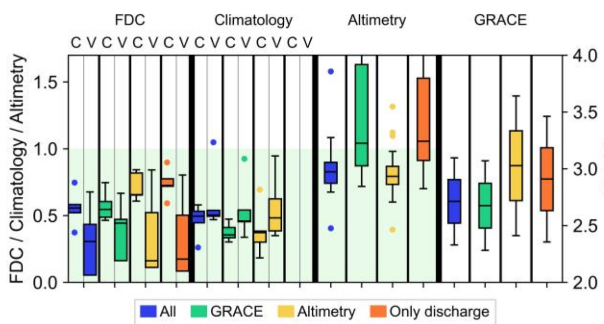

Figure 2 Model performance with and without GRACE and altimetry for the four criteria: Flow duration curve, daily discharge climatology, water level RMSD and total water storage anomaly RMSD (C=calibration, V=Validation).

The effect on model performance from including Sentinel-3 WSE and/or GRACE TWS is shown in Figure 2. In all cases, the weighted objective falls between 0 and 1, which is the accepted interval for a behavioral model. Thus, the performance of the individual objectives may be worse, but the overall performance is improved, suggesting the model structure is more robust overall. There is a clear improvement on respectively WSE and TWS simulations when including additional information from remote sensing, particularly for the former.

Figure 3 shows the discharge daily climatology and flow duration curve at downstream gauging station Lambaréné against observations from 1929-1983. The long-term statistics are slightly shifted in the second wet season (Figure 3). This is consistent with trends in the region, which suggest a shift in precipitation patterns in Western Africa in recent decades [22].

Accuracy and robustness are paramount to disaster monitoring and prevention. Our results emphasize the value of the multi-objective calibration and the urgent need for in-situ monitoring campaigns to support modelling and forecasting efforts and to validate remote sensing datasets and quantify local uncertainties.

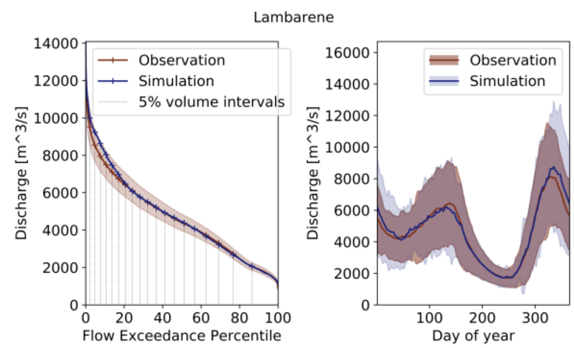

Figure 3 Flow duration curve and daily climatology at Lambaréné station, downstream Ogooué. The confidence interval represents the inter-annual variability of the observations and simulations.

5. CONCLUSION

Hazard predictions are entirely dependent on reliable simulations and monitoring. Climate change is very likely to perturb flooding mechanisms. Quantifying the impact of climate change on the land surface water balance is important to understanding the consequences of future hydrological hazards, i.e., floods and droughts. Multi-mission remote sensing is necessary to bridge the data gap in poorly instrumented catchments, such as the Ogooué. Combining multiple data sources and observations strengthens our understanding of the mechanisms driving hazards, bringing us one step closer to operational warning systems. As data continuity is ensured through the launch of new missions carrying state-of-the-art instruments, models can be updated and improved. This increases the value of model simulations to support decision making.

Challenges remain in adequately quantifying uncertainties. Possibilities are limited due to lack of reference (most often in-situ) observations. An interesting perspective may be exploring multi-model ensembles and the propagation of input and parameter uncertainties into the model outputs.

Future work will include looking into the relationships between upstream WSE and associated discharge simulations relative to the downstream flooding patterns recorded in the surface water extent maps.

6. REFERENCES

[1] K. Smith, *Environmental Hazards*, 6th ed. Routledge, 2013.

[2] H. Madsen, D. Lawrence, M. Lang, M. Martinkova, and T. R. Kjeldsen, "Review of trend analysis and climate change projections of extreme precipitation and floods in Europe," *J. Hydrol.*, vol. 519, no. PD, pp. 3634–3650, 2014, doi: 10.1016/j.jhydrol.2014.11.003.

[3] M. E. Mann, S. Rahmstorf, K. Kornhuber, B. A. Steinman, S. K. Miller, and D. Coumou, "Influence of Anthropogenic Climate Change on Planetary Wave Resonance and Extreme Weather Events," *Sci. Rep.*, vol. 7, no. January, 2017, doi: 10.1038/srep45242.

[4] P. Blair and W. Buytaert, "Socio-hydrological modelling: A review asking 'why, what and how?,'" *Hydrol. Earth Syst. Sci.*, vol. 20, no. 1, pp. 443–478, 2016, doi: 10.5194/hess-20-443-2016.

[5] D. M. Hannah *et al.*, "Large-scale river flow archives: Importance, current status and future needs," *Hydrol. Process.*, vol. 25, no. 7, pp. 1191–1200, 2011, doi: 10.1002/hyp.7794.

[6] Q. Tang, H. Gao, H. Lu, P. Dennis, and D. P. Lettenmaier, "Remote sensing: hydrology," *Prog. Phys. Geogr.*, vol. 33, no. 4, pp. 490–509, 2009, doi: 10.1177/0309133309346650.

[7] X. Xu, J. Li, and B. A. Tolson, "Progress in integrating remote sensing data and hydrologic modeling," *Prog. Phys. Geogr.*, vol. 38, no. 4, pp. 464–498, 2014, doi: 10.1177/0309133314536583.

[8] C. M. M. Kittel, K. Nielsen, C. Tøttrup, and P. Bauer-Gottwein, "Informing a hydrological model of the Ogooué with multi-mission remote sensing data," *Hydrol. Earth Syst. Sci.*, vol. 22, pp. 1453–1472, 2018, doi: 10.5194/hess-22-1453-2018.

[9] S. Bogning *et al.*, "Monitoring water levels and discharges using radar altimetry in an ungauged river basin: The case of the Ogooué," *Remote Sens.*, vol. 10, no. 2, 2018, doi: 10.3390/rs10020350.

[10] S. Bogning *et al.*, "Hydro-climatology study of the Ogooué River basin using hydrological modeling and satellite altimetry," *Adv. Sp. Res.*, 2020, doi: 10.1016/j.asr.2020.03.045.

[11] S. Dinardo *et al.*, "Coastal SAR and PLRM altimetry in German Bight and West Baltic Sea," *Adv. Sp. Res.*, vol. 62, no. 6, pp. 1371–1404, 2018, doi: 10.1016/j.asr.2017.12.018.

[12] C. M. M. Kittel, L. Jiang, C. Tøttrup, and P. Bauer-Gottwein, "Sentinel-3 radar altimetry for river monitoring - A catchment-scale evaluation of satellite water surface elevation from Sentinel-3A and Sentinel-3B," *Hydrol. Earth Syst. Sci.*, vol. 25, no. 1, pp. 333–357, 2021, doi: 10.5194/hess-25-333-2021.

[13] M. M. Watkins, D. N. Wiese, D. Yuan, C. Boening, and F. W. Landerer, "Improved methods for observing Earth's time variable mass distribution with GRACE using spherical cap mascons," *J. Geophys. Res. Solid Earth*, vol. 120, pp. 2648–2671, 2015, doi: 10.1002/2014JB011547.

[14] D. N. Wiese, F. W. Landerer, and M. M. Watkins, "Quantifying and reducing leakage errors in the JPL RL05M GRACE mascon solution," *Water Resouces Res.*, vol. 52, pp. 7490–7502, 2016, doi: 10.1002/2016WR019344.Received.

[15] D. N. Wiese, D. Yuan, C. Boening, F. W. Landerer, and M. M. Watkins, "JPL GRACE Mascon Ocean, Ice, and Hydrology Equivalent Water Height Release 06 Coastal Resolution Improvement (CRI) Filtered Version 1.0," 2018. https://podaac.jpl.nasa.gov/dataset/TELLUS_GRACE_MASCON_CRI_GRID_RL06_V1 (accessed Jan. 04, 2020).

[16] F. W. Landerer *et al.*, "Extending the Global Mass Change Data Record: GRACE Follow-On Instrument and Science Data Performance," *Geophys. Res. Lett.*, vol. 47, no. 12, pp. 1–10, 2020, doi: 10.1029/2020GL088306.

[17] T. Hahmann, S. Martinis, A. Twele, A. Roth, and M. Buchroithner, "Extraction of water and flood areas from SAR data," *Proc. Eur. Conf. Synth. Aperture Radar, EUSAR*, vol. 1–4, 2008.

[18] L. Zhang, N. Potter, K. Hickel, Y. Zhang, and Q. Shao, "Water balance modeling over variable time scales based on the Budyko framework - Model development and testing," *J. Hydrol.*, vol. 360, pp. 117–131, 2008, doi: 10.1016/j.jhydrol.2008.07.021.

[19] P. Berrisford *et al.*, "The ERA-Interim archive Version 2.0," no. 1, p. 23, 2011, [Online]. Available: https://www.ecmwf.int/node/8174.

[20] G. J. Huffman *et al.*, "NASA Global Precipitation Measurement (GPM) Integrated Multi-satellitE Retrievals for GPM," 2015. [Online]. Available: https://pmm.nasa.gov/sites/default/files/document_files/IMERG_ATBD_V4.5.pdf.

[21] T. Houska, P. Kraft, A. Chamorro-Chavez, and L. Breuer, "SPOTting model parameters using a ready-made python package," *PLoS One*, vol. 10, no. 12, pp. 1–22, 2015, doi: 10.1371/journal.pone.0145180.

[22] G. Mahé *et al.*, "The rivers of Africa: Witness of climate change and human impact on the environment," *Hydrol. Process.*, vol. 27, no. 15, pp. 2105–2114, 2013, doi: 10.1002/hyp.9813.