Responses to Referee #2

Interactive comment on "A Multi-sensor Data-driven methodology for all-sky Passive Microwave Inundation Retrieval" by Zeinab Takbiri, Ardeshir M. Ebtehaj, and Efi Foufoula-Georgiou

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The manuscript has successfully demonstrated a new algorithm for estimating subpixel inundated fractions under all weather conditions. By pairing SSMIS multifrequency observations with MODIS-based flood area values during the training period, a weight matrix is identified such that the inundated fraction of a given pixel can be estimated solely from the multi-frequency SSMIS observations over the K-nearest neighbors. This research is built upon traditional wetland/flood mapping approaches that use either passive microwave or VIS/IR alone. The improved spatial and temporal resolutions will contribute to flood monitoring skills during monsoonal seasons. The manuscript is overall well written, but a few areas need further clarification and/or improvement.

We thank the referee for the valuable insights and comments. We will incorporate the comments into a thorough revision of the manuscript. Detailed replies are provided below.

Detailed comments:

1) I strongly recommend improving the description of the retrieval algorithm (Section 3).

New descriptions will be added to the manuscript based on the below comments.

a) The most important component missing in this section is information about estimating inundated fraction solely from passive microwave observations (e.g., for the year 2015, or during the monsoon season). As shown in the flowchart (Figure 3), the last step is to calculate the inundated fraction using Eq (2), where the coefficient matrix c is optimized from microwave observations (Eq. (4)) and the corresponding inundation fraction (in Fs) is from MODIS (i.e., MWP). How does this work in cases where the Fs value from MODIS is unavailable? I assume the 'dictionaries' (from 2010-2014) are used, but I couldn't find the relevant text?

F_s is known and represents the inundation dictionary for which each column is attached to the corresponding SSMI/S vector of brightness temperatures B_s. These two dictionaries are collected using 5 years (2010-2014) of near coincident SSMI/S brightness temperatures and MODIS-MWP inundation fraction. Please see lines 13-15 on page 6 that explains this concern. For each vector, b_i in the dictionary of brightness temperatures there is an inundation fraction f_i from MODIS-MWP. The collection of these pairs from historical observations forms the two dictionaries. We will provide more explanations in the manuscript for further clarification is this issue.

b) The number of vectors in matrix B needs to be consistent throughout the manuscript. The dimension is n-by-M according to Line 12 on Page 6, where n is the number of frequency channels (i.e. 7) and M is the number of vectors. However, according to Figure 2 N is the number of vectors (and N=n×m), which is confusing. Similarly, it is unclear if the M vectors (Page 6, Line 11) refer to microwave observations in both time and space âA˘T˘or just in space? Assume the domain contains 10 rows and 20 columns, and there are microwave observations for over 300 hundred time steps. Does this mean that M=10×20 (as indicated in Figure 2), or that M=10×20×300 (which is more likely)?

We believe that the notation is correct. Capital letters represent the number of vectors. M is the number of total vectors of brightness temperatures collected for all involved orbits in five years of data. However, N<<M represents the maximum number of pixel level vectors of brightness temperatures in each orbital observation that might be associated with inundated areas. We will revise the caption of Figure 2 to further clarify this issue and address the concern.

c) Because the K-nearest neighbor search is essential for this study, a bit more information on this process will be helpful. This also relates to the above comment (1b)âA˘T˘will the K- neighbors be selected from one time step, or from multiple observations that occur during different time steps? Since the K- neighbors have a better chance of being geographically close to the pixel of interest (and are from the same time step), will the random selection of 2×106 pairs of brightness temperature and inundation fraction make the Knn less representative?

The k-nearest search in this paper did not directly constrain its searches on any specific time steps. For every pixel-level vector of brightness temperatures, the knn search is run over the entire dictionary regardless of any specific time steps or spatial locations. Obviously, stratification of the dictionary based on different land surface types and period of times (e.g. seasons) can be the subject of future research.

d) Parameters λ1 and λ2 in Eq. (4) are not defined until at the end of Section 3. The selection of λ and α are made through "cross validation studies", which are not explained.

These parameters are regularization parameters (it was mentioned in line 30 page 8). Their definition has been added in section 3 of the revised manuscript. There is no closed form solution to find these regularization parameters and they are often determined empirically through cross-validation (Zou & Hastie, 2005; Zhang & Saligrama, 2015). Cross-validation means that a series of tests has been conducted by a set of independent data and we found that the selected values perform reasonably well. We did not include the result of those trial and error experiments as we found them not very important at this step of the research when we attempt to validate the algorithm as a proof of concept. It is clear that for any kind of operational applications proper estimation of these parameters shall be thoroughly studied.

e) In Figure 3, there are a few constants that are never explained and never provided with values in the manuscripts (such as K, Kp, and p).

K is the number of the nearest neighbors and has been repeatedly mentioned in the manuscript, see page 6 line 16 and page 7 line 5. The parameter *p* is the detection probability. An observation vector was considered inundated if the number of its nearest neighbors with non-zero inundation was greater than *pK*. More explanation will be added to the revised acronym table on page 17 and throughout the text in the revised manuscript.

2) In Section 4, the validation conducted using the probability of "hit" and "false alarm" should be compared between the dry season and wet season. This will help to better understand the results. For

instance, there are much fewer missing data points from the MWP during the dry season than during the wet season. Does this mean that there will be a smaller probability of false alarms accordingly âĂŤor can the cloud cover/flag from the MODIS product be used to compare results over the 12.5 km pixels with and without cloud contamination?

We appreciate this comment. The scope of this paper is largely confined to demonstrate the effectiveness of the algorithm as a proof of concept. We can certainly break down the windows of validation to seasonal and monthly scales to provide further insights into the conditional performance of the algorithm. In future work, we aim to address thoroughly the seasonal performance of the method to increase our understanding of the role of missing data and seasonal dependency on the results. We will address this issue in the discussion session of the revised manuscript. Moreover, we would like to emphasize that our current analysis indicates that the probability of hit is around 0.92 for both dry and wet seasons. However, the probability of false alarm is around 0.12 for the dry season and reaches the value of 0.34 for the wet season, which might be due to MODIS missing data during the winter.

3) Figures 7a and 7c indicate an overestimation (as compared to 7b and 7d) in regions close to the rivers, and an underestimation in regions not connected to major rivers. Please consider adding some discussion on this.

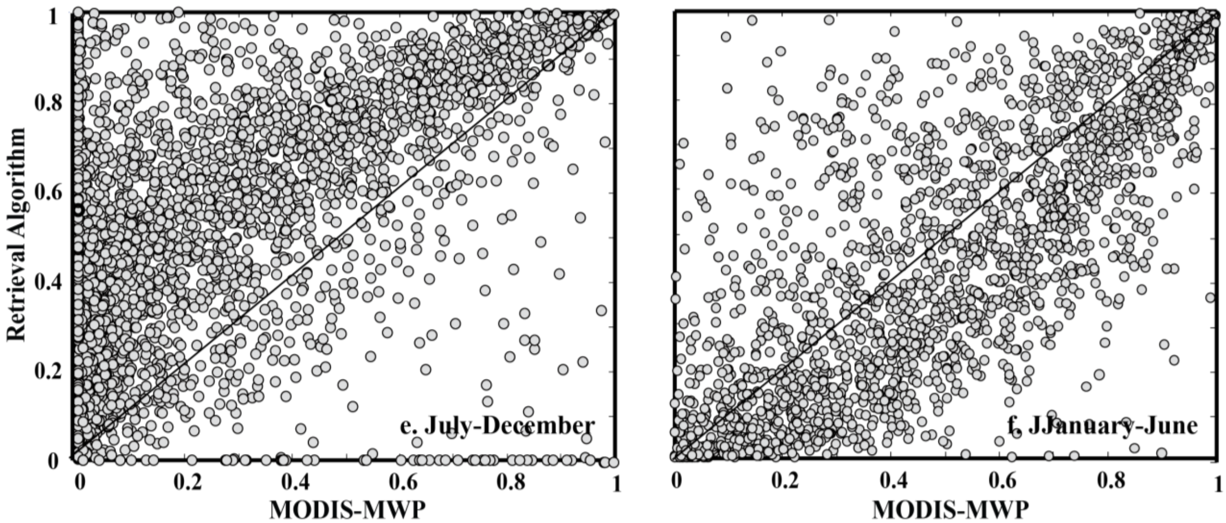
The overestimation of inundation near the riverbanks of major rivers might be due to high soil moisture content (≥ 0.8) during the wet season that increases the dielectric constant of the soil up to 30-50 (Alharthi & Lange 1998) which is very close to the dielectric constant of the water surfaces (75-80). Another reason, as we discussed in page 10 (line 2-5), is the cloud coverage. Since the riverbanks are inundated less frequently than the coastlines, it is possible that those few inundation events were missed by MODIS because of the clouds. There is also some underestimation in the inundation fractions from the proposed algorithm over the hillslopes far away from the riverbanks compared to the MODIS-MWP product. We feel that those sporadically inundated areas, which appear on MODIS-MWP map (Fig 6. b

& c), can be due to the terrain shadows that are misclassified as water. While we cannot directly prove the above assertions in the scope of this manuscript, the elevation map (Fig. 1) indicates that those hillslopes are very unlikely to get flooded. A brief discussion will be added to the revised manuscript.

4) The highlight of this algorithm is the capability to produce inundated subpixel fraction results under all-weather at a daily temporal resolution. Therefore, results and validations which contribute to evaluating these skills are preferred. Specifically, it would be interesting to see 1-2 examples showing the daily results (similar to Fig. 7), and comparisons of the sub-pixel fraction values (e.g. using scatter plots) between the MWP and microwave based estimations.

We totally understand your concern and definitely believe that the validation shall be extended to shorter time scales. However, a thorough validation requires a lot of effort and access to more detailed ground-based observations that go beyond the scope of the current research. This study is a proof of concept and a thorough validation is needed to fully understand the capability of this approach for daily scale retrievals.

Comparison of inundation fractions from MODIS-MWP and the proposed algorithm at daily scale is also challenging. This is because daily MODIS data are often severely corrupted by cloud coverage. On the other hand, under a clear sky, the MODIS-MWP inundation fractions are more precise than the results of the retrieval algorithm (as discussed in line 13-20, page 10). To show this more clearly, we have plotted scatterplots of daily inundation fractions from our retrieval algorithm against those from MODIS-MWP in wet and dry seasons, separately. The scatterplots further demonstrate larger inundation fractions from the retrieval algorithm in July-to-December. However, in January-to-June, when there are fewer clouds, the inundation fractions from the proposed algorithm are more correlated with the MODIS-MWP data and are slightly underestimated.



Figurer. Scatterplots of daily inundation fractions from the retrieval algorithm against those from MODIS-MWP in wet (e) and dry seasons (f).

5) There are a number of reasons contributing to the mismatch between the MWP and microwave based estimations. Something important missed in the discussion is the error associated with the MWP. Some discussion about the uncertainties associated with the results is recommended.

We have addressed this major source of uncertainty in the original manuscript (page 10 line 14-20). The second source of error is with respect to using the 3-day composite MODIS-MWP data in the daily retrieval. We agree that this affects the inundation retrieval at the daily basis, but 3-day composite data from MODIS-MWP are the best available datasets in the context of the manuscript. MODIS-MWP daily inundation fraction data are very uncertain because of the terrain shadows and clouds (Nigro et al. 2014). Typically, there are numerous missing pixels in the daily products, which reduce the sample size dramatically. These errors are significantly reduced in 3-day composite products, as it is less likely for clouds (and their shadows) to stay at the same spot in 3 days (Nigro et al. 2014). Because the presented method uses a weighted average representation of the dictionary atoms, we believe that less uncertain averaged atoms (obtained based on 3-day MWP data) will provide improved estimates of inundation—compared to more uncertain daily samples. However, a more detailed investigation is certainly needed in future studies. A brief discussion on these sources of uncertainty will be added to the revised manuscript.

6) Although I agree that the water level and the inundated area are correlated, I don't think it is the best practice to simply average the water levels from 11 gauges to represent the basin. During a flood event, the water level at an upstream gauge located in a steep valley may increase a lot more (and/or faster) than a downstream gauge. However, the downstream gauge is more representative of the basin's condition.

We acknowledge that the validation is not perfect. It was important for us to somehow obtain an idea about ground-based validation of the method and the water level data was the only available option. Obtaining other relevant information such as ground-based inundation maps over the study area was not feasible. By averaging the available water levels over the study area, we obtain a correlated surrogate of inundation in a basin scale, which helps us to check that the algorithm makes sense.

To further address your concern we divided the study area into two sub-regions covering the steeper upper parts (from the top of the study area shown with a box in Fig 1 up to the Phnom Penh gauge) and flatter downstream. The copula analysis for each region has been presented separately and the results will be updated in the revised manuscript. By conducting Copula analysis on each geographic region separately, we have computed the dependence of the water level to the inundation, conditioned on the average basin slope.

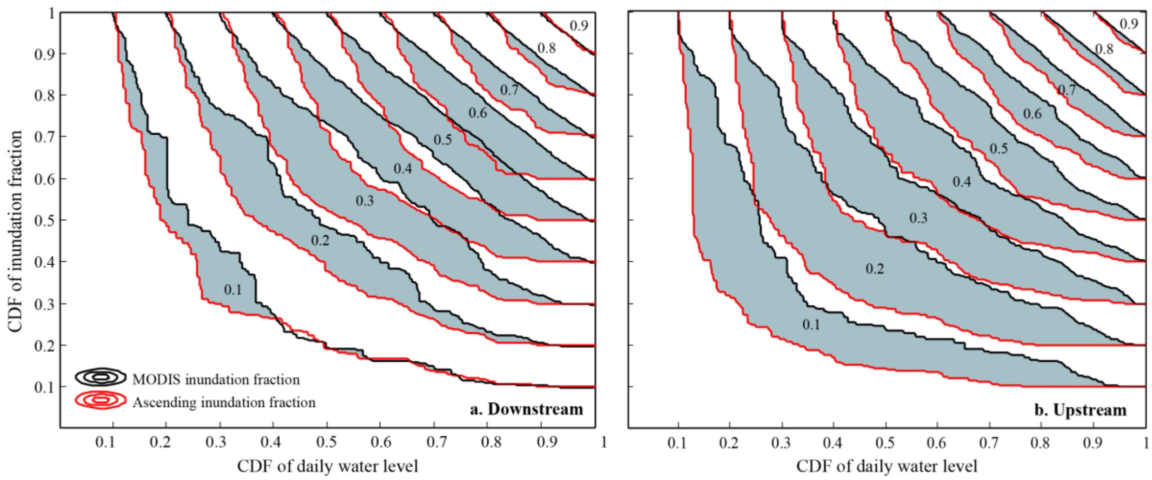


Figure 8. The empirical Copula of the average daily water level versus total daily inundated areas from the proposed retrieval algorithm (red curves) and MODIS-MWP data (black curves). These plots denote that the dependency between the results of our algorithm and water levels is stronger than the MWP product for both downstream (a) and upstream (b) regions of the Mekong Delta. The shaded areas, which quantify the difference between the degrees of dependency of the two retrievals with the water level data, are greater for the upstream region. This observation indicates that the inundation fraction from the microwave retrieval algorithm is more dependent on the daily water level data in the upstream compared to the downstream, perhaps due to the different time-lags in their responses to the increase of water level.

A few minor issues:

We appreciate the reviewer’s attention to minor details and the comments she/he has provided. We have incorporated all of these suggestions in our revised manuscript.

a) Page 9, line 1: Change “problem” to “equation”. -- Revised.

b) Page 9, line 7: It should be Fig. 6, not Fig. 7. -- Fixed.

c) Fig. 3: If the Tb images are intended for all years (see comment 1c), please revise the figure accordingly. -- More clarifications have been added to the caption.

d) Fig. 4b: This figure needs units. -- [°K] has been added.

e) Fig. 5: Should the word “weights” be removed from the top of the right panel? -- Yes, it should and it has been removed now.

f) In some of the figures, the panels are denoted by a, b, c, etc.â but not in all cases. Please be consistent. -- Revised.

References:

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