Response to referee comments: Anonymous Referee #2

We appreciate the reviewer for dedicating time and offering valuable suggestions to improve the quality of our manuscript. Below, we provide detailed responses to each specific comment and the corresponding revisions made in the manuscript (written in blue) to address the concerns.

Comment: I believe the use of LST differences for irrigation mapping needs better justification. It raises the question of why not directly use satellite-based retrievals and evapotranspiration (ET) derived from the hydrological model to detect irrigation, instead of reverting to simulate LST from energy balance. In other words, existing methods for estimating actual irrigation could be used to identify irrigated areas simply by masking where irrigation is detected. For example, Olivera-Guerra et al. (2020, https://doi.org/10.1016/j.rse.2019.111627) used the coupling between an energy and water balance model to estimate irrigation, which was evaluated in both non-irrigated and irrigated fields. Although it is argued that errors in ET retrievals may hinder irrigation mapping, the errors involved in both satellite-based and modeled LST are equally significant. Additionally, the use of LST-derived products (e.g., ET, root-zone soil moisture, water stress) in estimating or detecting irrigation should be introduced and discussed in the introduction section, as shown by some studies (Droogers et al. 2010, https://doi.org/10.1016/j.agwat.2010.03.017; Olivera-Guerra et al. 2018, 2020, https://doi.org/10.1016/j.agwat.2018.06.014; Chen et al. 2018, https://doi.org/10.1016/j.rse.2017.10.030). Without this context, the use of LST is presented as the key point and the novelty in estimating irrigation. Therefore, I believe the novelty in using LST to detect irrigated areas should be well justified.

Response:

We appreciate the comments and suggestions. We agree that satellite-based retrievals of ET and other LST-derived products offer valuable opportunities for irrigation detection, as demonstrated by Olivera-Guerra et al. (2020). The method for estimating ET in the study relies on extreme LST values on the image representing dry and wet conditions to constrain the partitioning of the available surface energy. In arid and semi-arid regions, identifying these extreme values is less challenging than in humid regions due to the consistent moisture availability, high variability, and overlap of wet and dry periods in humid regions.

Regarding the justification for using LST differences for irrigation mapping, LST provides direct measurements that minimize the uncertainties associated with ET estimates derived from LST products. ET estimates from remote sensing models are highly divergent across products, with inconsistencies attributed to differences in input data, methodology, parameterization, and model structure (Vinukollu et al., 2011; Badgley et al., 2015; Zhu et al., 2022; Lehmann et al., 2022). Zhang et al. (2020) further elaborated on the significant divergence between ET estimates from energy balance approaches and residual water balance methods in humid regions. Although ET models capture monthly variations, they show different sensitivities to rainfall and often fail to capture the spatial patterns of ET from water balance methods, as well as the variability caused by ET peaks following heavy rainfall. It is argued that minimizing ET errors can be achieved by ensuring proper partitioning of the water balance, constraining the magnitude of precipitation, and selecting high-quality datasets (Lehmann et al., 2022).

The estimate of ET from a hydrological model used in our study is constrained by potential evapotranspiration. In humid regions, when precipitation exceeds potential evapotranspiration, excess water tends to contribute to runoff rather than additional ET. To ensure this, we used a model that has been calibrated and validated across several discharge measurement stations with relatively dense gauge observations to perform well for rainfed conditions. This ensures that LST-derived ET estimates are constrained by potential evapotranspiration and that excess precipitation is accurately routed into runoff. The performance of the water balance model used in this study was validated against discharge measurements from various stations in the study basin, resulting in Kling-Gupta Efficiency (KGE) coefficients ranging from 0.60 to 0.90 (Imhoff et al. (2020)). This validation process confirms that excess rainfall is accurately partitioned into runoff rather than ET. We will also ensure to clearly explain why LST was chosen as the primary method for our study.

Comment: Another important point to deepen is the use of LST in wet condition (humid regions or wet years in the study area). It would be interesting to analyze differences in the classification of irrigated areas in dry and wet years to draw more conclusions about the use of LST in such conditions. For example, differences in LST or ET are more important in dry years (i.e., water-limited regimes) than in wet years (energy-limited regimes), particularly in dry years with the presence of fields where the crop water requirement is fully supplied to avoid water stress. Therefore, irrigated areas would be easier to detect in drier conditions, while more errors are likely in wet conditions (energy-limited regimes).

Response: Thank you for your suggestions. We divided the catchment area into subcatchments with different climatic conditions. The evaluation of classification results was conducted for the years 2013 and 2016, which had higher mean annual precipitation compared to the rest of the simulation period. This approach allowed us to assess the model's performance under dry and wet regions. The dry regions were classified as NUTS level 2 areas located in the Middle Rhine subcatchment. Meanwhile, the wet regions are located in Moselle, Neckar, Main, and Lower Rhine subcatchment. The results indicate that the classification performs better in these drier regions (see Figure 1). The evaluation of the classification is also influenced by the effects of large agricultural holdings in the dry regions. We will revise the current discussion and discuss the limitations of the methodology in wet regions.

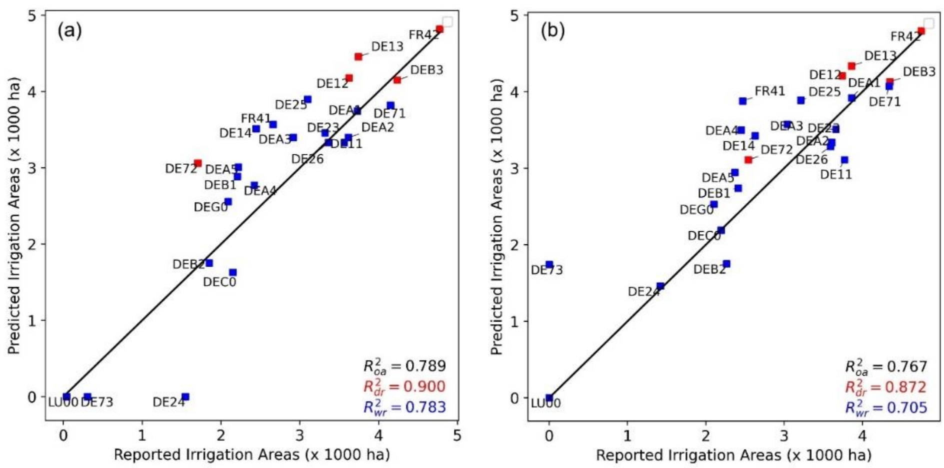

Figure 1: The mapped irrigated area of the Rhine basin as identified through classification ($A_{i,sim}$) is compared with the total irrigated areas reported in Eurostat data at NUTS level 2 ($A_{i,obs}$) for the years (a) 2013 and (b) 2016.

R_2 values were calculated for the overall region (oa), dry regions (dr), and wet regions (wr). The values of the total irrigated areas [× 1000 ha] were transformed using log(A + 1) transformation.

Comment: According to Lines 301-304, the fact that the model trained with data from a specific year cannot be used to identify irrigated areas for the entire study period could justify the use of existing models for estimating irrigation and consequently detecting irrigated areas, rather than relying on LST differences. Comparing irrigation mapping using LST differences and ET differences should be performed for further analysis. Such analysis would allow for a more robust justification of the use of LST for irrigation mapping.

Response: We appreciate the comment regarding the limitations of using a model trained on data from a specific year across an entire study period. While this suggests the need for a more generalized classifier for multiyear irrigation detection, our study demonstrates that LST differences provide a valuable method in regions where rainfed and irrigated signals often overlap. At the plot scale, LST and ET may exhibit different magnitudes between irrigated and non-irrigated areas. However, mapping irrigated plots at the catchment level in our study region presents challenges due to insufficient distinct features between irrigated and non-irrigated areas during dry years, and even more so in years with adequate precipitation, when non-irrigated croplands exhibit the same LST temporal features as irrigated croplands (Figure 2). By using LST differences, evapotranspiration from precipitation estimated through water balance can be excluded, isolating only the evapotranspiration driven by irrigation. The temporal features of LST differences provides more distinct features for classification.

The main reason a model trained on data from a specific year cannot be applied across the entire study period is the dynamic nature of irrigation decisions, fallow practices, and the interannual variability in meteorological conditions, which also affect LST and ET products. A model trained on data from a single year may fail to account for these variabilities, as it uses LST and ET features or thresholds from irrigated or non-irrigated pixels to years with differing conditions. Although comparing irrigation mapping using both LST and ET differences could offer additional insights, the significant variability in ET products in humid catchments discussed in the first question would likely introduce uncertainties into the classification.

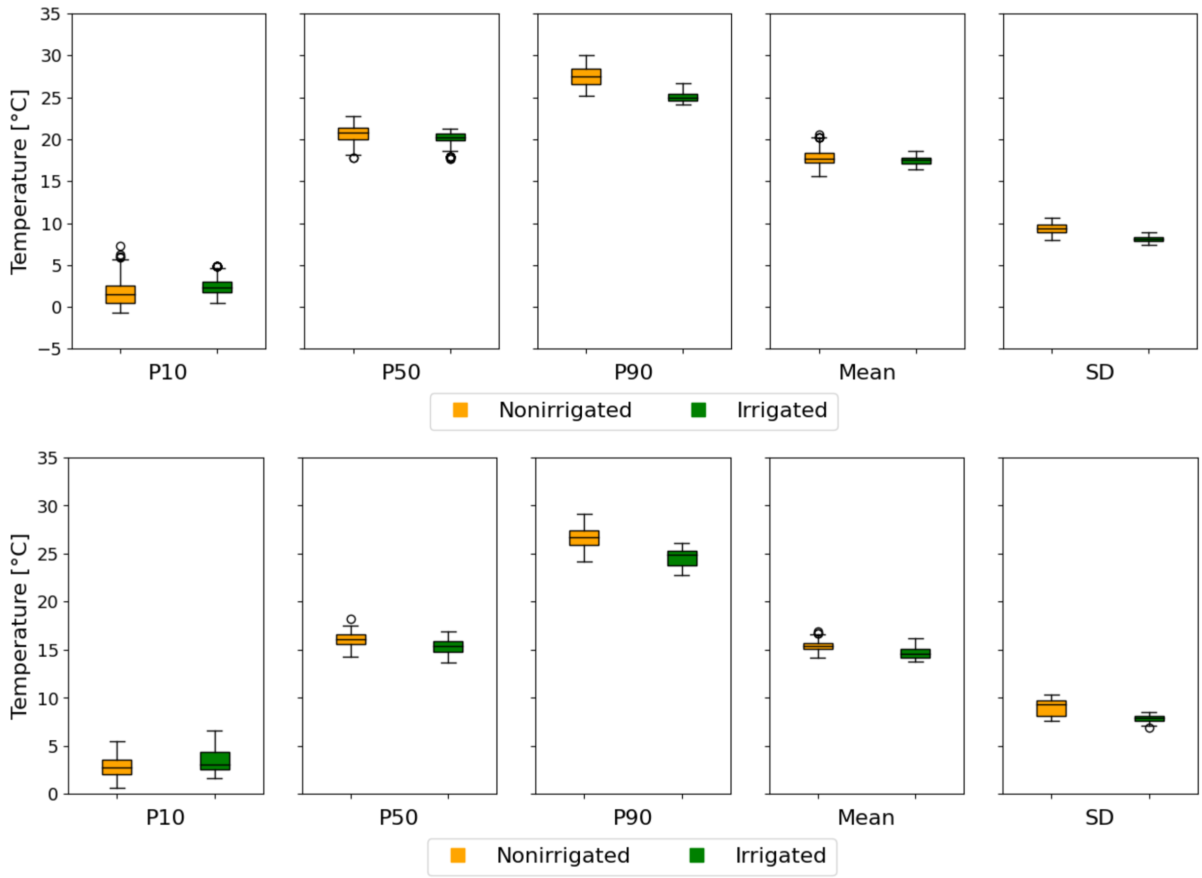

Figure 2: The box-plot shows statistical summary of LST data for non-irrigated and irrigated pixels for (a) 2018 and (b) 2019.

Comment: Lines 421-429. The limitations of LST in humid regions should be discussed. Even though decreased precipitation may lead to reductions in the extent of irrigated areas during the driest years, particularly in semi-arid regions (e.g., Afghanistan and the Ebro basin), this may not necessarily be the case in more humid regions where precipitation amounts are still substantial, such as the Rhine basin. In wet conditions, detection of irrigation using LST becomes more challenging and errors are more likely, leading to potential compensations that hamper the establishment of a clear relationship between precipitation and irrigated areas. Therefore, further evaluations should be carried out. For instance, Appendix B confirms that less precipitation leads to more irrigated areas, as detection is more easily captured by LST and more areas require irrigation.

Response: Based on the additional evaluation, we will include a more detailed discussion on the limitations of LST in humid regions and the possible causes of misclassification.

Other comments

Comment: Lines 40-42. I would recommend delving deeper into the irrigation detection in diverse climates, discussing the advantages of using LST in semi-arid to arid regions and the challenges in temperate to humid climates under an energy-limited regime.

Response: Thank you for your suggestions. We will discuss the advantages and disadvantages of using LST in semi-arid to arid regions as well as in temperate humid climates as follows:

> "The use of LST as an indicator of crop health status resulting from irrigation has been widely applied in arid and semi-arid regions. Zhu et al. (2022) highlighted the effectiveness of using LST observations in crop model to quantify the evaporative cooling effects caused by changes in water and surface energy due to irrigation on maize croplands across Nebraska in the United States. Their findings demonstrate that LST provides valuable information on the impacts of irrigation on heat and water stress in crops. On basin level, Haddeland et al. (2006) investigated the impact of irrigation on the water and energy balances in the Colorado and Mekong River basins using the Variable Infiltration Capacity (VIC) hydrology model. The results show that irrigation increases latent heat flux, resulting in a reduction in surface temperature. On an annual scale, the cooling effect averaged 0.04°C across both basins, with a more significant decrease of up to 2.1°C in regions with high concentrations of irrigated croplands during peak irrigation months. Olivera-Guerra et al. (2020) used LST as complementary data in crop models to estimate irrigation water use. When crops experience water stress, land surface temperature increases due to increased sensible heat flux. By comparing the elevated LST values with the canopy temperature of well-watered fields, they were able to quantify coefficient of crop water stress (Ks).
>
> While LST provides clear difference in irrigated and rainfed croplands in arid and semiarid regions, its effectiveness diminishes in more energy-limited conditions such as in temperate and humid climates. In regions with low surface energy availability, the use of LST is more challenging due to high moisture levels and reduced temperature variability, which complicate the separation of irrigation effects from natural variations in soil moisture and temperature (Roth et al., 2017). Zhang et al. (2022) used LST to estimate evapotranspiration from irrigation in the North China Plain, achieving higher accuracy during the winter season when precipitation is lower than in the summer months. Meanwhile, in the summer months, the effects of irrigation on land surface temperature are more difficult to detect. This is because precipitation often meets crop water requirements, making irrigation only supplemental and reducing its impact on land surface temperature changes. In such climates, complementary methods are required for accurate irrigation detection and monitoring. The more stable moisture levels and less pronounced temperature fluctuations in these regions make it difficult to differentiate between irrigated and non-irrigated areas based solely on LST. In this research, we propose integrating a water balance approach to account for evapotranspiration driven by precipitation, limiting the attribution of surface energy to water routed to runoff. This method will help to refine irrigation detection by excluding the effects of precipitation-induced evapotranspiration."

Comment: Lines 42-44 are not in context with irrigation retrievals in diverse climates.

Response: The paragraph containing lines 42-44 discusses current efforts to identify irrigation in both arid and humid regions, noting that fewer studies have been conducted in humid areas compared to arid and semi-arid regions. We understand that it may appear to be addressing existing approaches in irrigation retrievals in various climates. We will revise the paragraph to deliver a clearer message to the reader.

Comment: Line 63. Add references of existing approaches.

Response: References of existing approaches will be added.

Comment: Line 80. The wflow_sbm should be previously introduced.

Response: wflow_sbm will be previously introduced in the introduction section.

Comment: Line 139. PTFs?

Response: "PTFs" will be changed to "pedotransfer functions (PTFs)".

Comment: Section 2.3. Since the LST module is simply the inversion of the energy balance equations, I would recommend moving most of the equations related to the energy balance (for example, those from lines 160-179 and 186-197) to the appendix. This would give more prominence to the irrigation mapping methodology.

Response: Section 2.3 would be reworked so it would give more prominence to the irrigation mapping methodology.

Comment: Section 2.4.2. Classification based on visual detection is prone to errors and should be evaluated accordingly. Are there irrigated plots available to assess the classification?

Response: Due to the unavailability of multiyear irrigated plot data for our purpose, we had to rely on visual interpretation. We acknowledge the inherent errors in visual detection primarily due to its subjectivity. To address this, we complemented the visual detection methodology with thermal imagery, which captures differences in land surface temperature signatures at the plot scale with similar meteorological conditions. By combining these methods, the degree of uncertainty regarding the demarcation between irrigated and non-irrigated areas can be minimized, as boundaries are more accurately defined by land surface temperature. Although no ground-based data on irrigated plots is available, we believe this approach reduces inaccuracies associated with using true-color imagery. The limitations of visual interpretation will be discussed in the revised version.

Comment: Lines 245-248. The presence of neighboring land cover types (floodplains and forests as mentioned by authors) may also influence agricultural fields. It would be interesting to evaluate their impact on both the classification of irrigated/non-irrigated areas and the LST itself.

Response: Initially, the classification was conducted for the entire catchment that showed a large part of the natural systems does not produce additional secondary evapotranspiration. However, some systems could tap into deeper subsurface water sources. This additional input for evapotranspiration results in more pixels being identified as irrigated. Therefore, we decided to mask out non-irrigated pixels. We will discuss this in the revised manuscript.

Comment: Figure 6. Reduce the range of the second y-axis to see more details in LST differences. Change this y-axis label to "Temperature difference".

Response: The range and label of the second y-axis will be revised.

Comment: Figure 7. Why negative differences are obtained in irrigated crops between observed and modelled LST? How is that related to possible misclassifications between irrigate/non-irrigated fields. Change the y-axis label to "Temperature difference".

Response: It affects only a small fraction of the data points, which suggests that its impact might be due to random error. Regarding the potential misclassification, these values are represented by p10, the least significant feature in the random forest classification. This means that p10 has minimal influence on the classification results. The y-axis label will be changed to "Temperature difference."

Comment: Figure 8. What are the reasons of the large underestimation of DE24 in 2013 and the overestimation in DE73 in 2016. The year could be added as title to each plot.

Response: The seemingly large underestimation of DE24 in 2013 and overestimation of DE73 in 2016 are influenced by the log scale, which may have exaggerated the reported values. The underestimation is 34 ha and the overestimation is 54 ha, both of which fall below the detection threshold of the spatial resolution. We will also add the year as a title to each plot.

Comment: Line 359. Recall the hectares of the estimated irrigated areas.

Response: The hectares of the estimated irrigated areas will be recalled in the text.

Comment: Figure 10. Correct the caption of the figure (a, b and c).

Response: The caption for Figure 10 will be corrected to “(a) The total irrigated area and (b) the annual sum of climatic variables: precipitation, evapotranspiration, and the difference for the Rhine basin for the period from 2010 to 2019. (c) Linear regression analysis is performed for each climatic variable compared to the annual irrigated area.

Comment: Line 375. east of the border?

Response: We admit there was a mistake in Line 375. It will be corrected to “east of the border”.

Comment: Figure 11. Add the region (Lower, Middle and Rhine valley) as title of each figure and in the caption of the figure.

Response: The name of the region will be added to each figure and in the caption of the figure.

Comment: Figure 12. The period of representation per irrigation map could be add to the tittle of each figure.

Response: It will be added to each figure.

References:

Badgley, G., Fisher, J. B., Jiménez, C., Tu, K. P., & Vinukollu, R. (2015). On uncertainty in global terrestrial evapotranspiration estimates from choice of input forcing datasets. *Journal of Hydrometeorology, 16*(4), 1449-1455.

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Lehmann, F., Vishwakarma, B. D., & Bamber, J. (2022). How well are we able to close the water budget at the global scale?. *Hydrology and Earth System Sciences, 26*(1), 35-54.

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Roth, G., Harris, G., Gillies, M., Montgomery, J., & Wigginton, D. (2013). Water-use efficiency and productivity trends in Australian irrigated cotton: a review. *Crop and Pasture Science, 64*(12), 1033-1048.

Vinukollu, R. K., Wood, E. F., Ferguson, C. R., & Fisher, J. B. (2011). Global estimates of evapotranspiration for climate studies using multi-sensor remote sensing data: Evaluation of three process-based approaches. *Remote Sensing of Environment, 115*(3), 801-823.

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Zhu, P., & Burney, J. (2022). Untangling irrigation effects on maize water and heat stress alleviation using satellite data. Hydrology and Earth System Sciences, 26(3), 827-840.