Reply on Comment (Anonymous Referee #2)

We thank the anonymous referee for the valuable suggestions on our manuscript.

As detailed below, the referee's comments are *in italicized font*, and our responses in red normal font. Any new or added text in the manuscript is underlined in red, deleted text is with ~~a strikethrough~~ in red, and these changes will be incorporated into the next revision.

All the line numbers in this reply refer to the original version of EGUsphere Manuscript ID: **egusphere-2025-2004**

Referee #2's General Comments:

Reply: We appreciate the referee's time and efforts devoted to reviewing our work. Since the general comment raises multiple major issues, we will **separate it into individual points** and provide the point-to-point responses below.

General Comments, Point #1:

The authors propose an approach for detecting irrigation signals through discrepancies between SMAP L3 (potentially able to track irrigation) and L4 data (unable to track irrigation). The strength of the methodology consists in solely relying on data without the need of any modeling. Analyses are performed rigorously and results are clearly presented.

Reply: Thank you for your revision and valuable comments, and we are grateful for the positive remarks regarding the clarity of our methodology and results.

General Comments, Point #2:

Nevertheless, the study appears as a bit out-of-date with respect to the current status of *the art in terms of irrigation monitoring through satellite data. In fact, in light of several well-established methodologies for detecting in space and time irrigation events and for estimating irrigation water use, with some of them even close to facing operational implementation, the current study appears limited in its scope.*

Reply: We appreciate the referee's valuable opinions, although we perceive that some of the comments may stem from different expectations regarding the study's scope and methodology. We agree that satellite-based irrigation monitoring is an active research area, with several methods that are even practically applicable. However, synergistically leveraging SMAP L3 and L4 for irrigation detecting purpose and in a purely data-driven manner, as in our study, provides a unique approach to resolve the common problems of inconsistent soil moisture climatology among different datasets, and efficiently reduce the complexity of model tuning, as detailed below:

- **Consistent soil moisture climatology:** Unlike methods that rely on comparing satellite data to independent models or reanalysis (e.g., using MERRA-2 as a non-irrigated baseline in Zaussinger et al's research[1]), our approach uses two products showing highly consistent soil moisture climatology. SMAP Level 3 is a direct satellite retrieval (which includes the real-worlf irrigation-induced soil moisture increases), while SMAP Level 4 is a model-assimilated product that assimilates only brightness temperature anomalies, containing no irrigation effects. Both products employ nearly identical radiative transfer algorithms, ensuring their soil moisture climatology is highly consistent. This consistency minimizes potential biases and false signals; a key novelty compared to prior studies that often struggled with climatological mismatches between different datasets.
- **Purely data-driven (no complex tuning or manual screening):** Our method does not require any additional model calibration or tuning beyond the standard SMAP processing. By taking the difference between SMAP Level 3 and Level 4, we detect irrigation signals directly from observations. This stands in contrast to approaches that integrate satellite data into hydrological models or require sophisticated adjustments.

Our SMAP Level 3 vs Level 4 differencing approach offers **a novel, simple way to identify irrigation signals**. By using two standard SMAP products, we ensure data consistency and avoid the biases that can arise in other techniques. We believe this is the first study to use SMAP L4's inherent "non-irrigation" baseline in tandem with L3_E for irrigation detection, and we will underscore this innovative aspect more clearly in the revised paper as follows:

Line 451: In this study, we proposed a method to detect irrigation signals directly from SMAP L3_E and L4 soil moisture products. This method requires minimum additional data or model tuning, yet preserves a consistent soil-moisture climatology between the satellite observations (SMAP L3_E) and the non-irrigated baseline (SMAP L4). To our knowledge, this is the first study to employ SMAP L3 and L4 synergistically for irrigation detection.

[1] *Zaussinger, F., Dorigo, W., Gruber, A., et al, 2019. Estimating irrigation water use over the contiguous United States by combining satellite and reanalysis soil moisture data. Hydrol. Earth Syst. Sci. 23, 897–923.*

General Comments, Point #3:

In addition, the capability of SMAP retrievals in detecting irrigation in California has been already proved in previous studies (see, e.g., https://doi.org/10.1002/2017GL075733, https://doi.org/10.1016/j.hydroa.2023.100169).

Reply: Thank you for pointing this out and recommended papers.

We also agree that the studies you mentioned have demonstrated the potential of SMAP series to detect irrigation signals in California's Central Valley (e.g., Lawston et al., 2017[1]; Soylu and Bras, 2024[2]). These works greatly inspired our research. **However, we would like to clarify that our approach is fundamentally different from these studies in two key ways: (1) we combine SMAP Level 3 and Level 4 datasets in our analysis, a combination not explored in prior studies, and (2) we extend the analysis from a single-pixel demonstration to a spatially continuous regional map of irrigation signals.**

Lawston et al. (2017) relied on the SMAP Level 3 product only, comparing one known irrigated pixel with an adjacent non-irrigated pixel and attributing the difference in their time series to irrigation effects[1]. This elegant experiment proved that the SMAP Level 3 dataset does contain irrigation effects. However, the method requires prior knowledge of which areas are irrigated and involves labor-intensive, pixel-by-pixel comparisons, making it difficult to scale up. Moreover, while it qualitatively shows the presence of an irrigation effect, using it for quantitative estimates would raise questions about whether the chosen “non-irrigated” baseline is comparable across different grid cells. Soylu and Bras (2024) analyzed a single grid cell in California using SMAP Level 2 observations in conjunction with a calibrated bucket-type hydrological model as a non-irrigation baseline[2]. By comparing the observed soil moisture against this modeled baseline, they estimated the irrigation amount. As the authors acknowledged, their approach likely overestimates irrigation amounts and necessitates substantial effort to calibrate the model in order to maintain a consistent soil moisture climatology with SMAP Level 2 product. In other words, their method, while innovative, relies on model tuning and site-specific calibration beyond the satellite dataset itself.

Inspired by these studies, we sought to advance the concept of SMAP-based irrigation detection in a simpler yet more expansive way. In our approach, we **synergistically leverage SMAP Level 3 and Level 4 products**. By differencing these two products, we obtain an “irrigation signal” map that represents the irrigation intensity, while **maintaining climatological consistency between the soil moisture with irrigation effects and without irrigation baseline**. This method avoids the need for any external model or additional calibration, without extra forcing data or hydrological models. Furthermore, compared to the above studies, our study **moves beyond single-pixel analysis to generate a spatially continuous *IS* map** for the California Central Valley. It does not require pre-selecting control pixels or tuning models for each location, which makes it more practical for large-scale estimation.

To address your concerns, we will add a new table (Table R1 as follows) that compares our method with the above two studies, along with a new text based on our discussion above. We believe these clarifications emphasize the novelty and broader applicability of our work, and we thank you for giving us the opportunity to explain this issue.

Table R1: Comparison between the proposed method and previous studies

	(Potentially) irrigated reference	Non-irrigated reference	Requirements	Outputs
Lawston et al. (2017)	SMAP L3 product	SMAP L3 product at a **nearby** grid cell **known** to be non-irrigated	The non-irrigated reference is in fact not irrigated	**Qualitative evidence** of irrigation effects in SMAP L3 product
Soylu and Bras (2024)	SMAP L2 product	**Non-irrigated model simulation** of the potentially irrigated grid cell	The bias between model and SMAP L2 is known	Estimate of **irrigation amount** at the potentially irrigated grid cell
This work	SMAP L3 product	SMAP L4 product	A nearby grid cells known to not be irrigated to test the soil moisture climatology	**Irrigation intensity map**

[1] *Lawston, P.M., Santanello, J.A., Kumar, S.V., 2017. Irrigation Signals Detected From SMAP Soil Moisture Retrievals. Geophys. Res. Lett. 44.*

[2] *Soylu, M.E., Bras, R.L., 2024. Quantifying and valuing irrigation in energy and water limited agroecosystems. J. Hydrol. X 22, 100169.*

General Comments, Point #4:

On top of this, in addition to limitations discussed by the authors, those linked to the mismatch between the spatial resolution of SMAP retrievals and the extent of irrigated areas elsewhere are not mentioned but represent a critical point in the irrigation detection domain (https://doi.org/10.1016/j.jag.2022.102979).

Reply: Thanks for your helpful suggestions.

We agree with your comment about the spatial resolution mismatch as an important consideration. The SMAP ~9 km grid, although relatively fine for passive microwave observations, is still coarse for detailed irrigation monitoring, for which a resolution on the order of 100 m is often desirable. As reported by Zappa et al. (2022), coarse pixels attenuate irrigation signals and can lead to underestimation of irrigation water use; reliable detection generally requires that at least one-third of a pixel be irrigated [1]. Consequently, our SMAP-based method may overlook small or fragmented irrigation.

We will state this limitation explicitly in the next version of the manuscript:

Line 179: It is important to note, as previous studies reported (Zappa et al., 2022; Zaussinger et al., 2019), that the coarse spatial resolution of satellite soil-moisture pixels often weakens irrigation signals. Consequently, satellite-based detection is most dependable in large, contiguous, and intensively irrigated regions, whereas results for small or scattered irrigation patches should be interpreted with caution.

[1] *Zappa, L., Schlaffer, S., Brocca, L., et al., 2022. How accurately can we retrieve irrigation timing and water amounts from (satellite) soil moisture? Int. J. Appl. Earth Obs. Geoinformation 113, 102979.*

General Comments, Point #5:

In my opinion, the limited scope of this paper with respect to the current status of knowledge does not incentivize its publication. The paper does not propose an irrigation quantification method (because of the limits in retrieving irrigation fluxes clearly explained by the authors) neither an irrigation mapping approach (as the a priori knowledge of irrigated and non-irrigated pixels is required). It could be seen as a method for detecting irrigation events but definitely an effort is required for highlighting advantages with respect to previous studies (e.g., https://doi.org/10.3390/rs15051449 or https://doi.org/10.3390/rs12091456, to cite a few).

Reply: Thanks for your valuable comments. However, we respectfully disagree with your opinions and would like to clarify our position as below:

Firstly, the novelty and unique aspects of our study have been addressed in our response to the **General Comments, Point #2 & #3** above. While our method cannot explicitly quantify irrigation volume (due to the limitations in retrieving absolute irrigation fluxes, as we acknowledge in the manuscript), **it can be considered as a form of irrigation intensity mapping**. After confirming the consistent climatology of SMAP Level 3 and Level 4 products, **this intensity map can be interpreted as a map of relative irrigation intensity or area**. In the Results section of original manuscript, we showed that this map correlates reasonably with validation datasets: it aligns with the Global

Map of Irrigated Areas (GMIA) in terms of spatial extent and with the ZL21 irrigation water use map. Moreover, our method can capture interannual variability in irrigation signals (year-to-year changes), which static irrigation maps cannot provide.

Second, **we emphasize that different satellite missions offer different strengths**. We appreciate the two recommended references. Those studies have indeed achieved satisfying results at finer spatial scales. However, the **Sentinel satellites have unique advantages of very high spatial resolution, whereas SMAP provides more frequent revisits, and a consistent modeling framework**. We believe **the success of Sentinel-based approaches does not diminish the value of exploring irrigation monitoring with other satellite products like SMAP**. The diverse applications of different soil moisture satellite observations can enrich the technological landscape of satellite-based approaches for irrigation detection, which will ultimately enhance the capability and accuracy of space-based irrigation studies.

In conclusion, while we respect the referee's valuable comments and expertise in this field, we insist that our study offers a novel perspective by exploiting the potential of SMAP satellite in irrigation detection, and that our research provides a complementary reference which can add to the community's knowledge of irrigation monitoring from space.

Specific Comments #1:

L 21: To what temporal resolution do the correlation coefficients refer?

Reply: Thanks for your valuable comments.

The irrigation signal (*IS*) map in this study is natively computed **annually**: for each year we take the difference between the mean SMAP L3_E – L4 soil-moisture difference during the cropping season and that during the non-cropping season. Thus, the native temporal resolution of each *IS* map (and of any correlation derived from it) is one year.

For ease of presentation, however, Figure 7 shows the **multi-year average *IS* map for 2016–2020**. The correlation coefficients reported in the manuscript therefore refer to this five-year mean field; in other words, they represent the spatial correlation of the 2016-2020 average *IS* map with the validation.

We will revise the title of Figure 8 of the manuscript to make this part clearer as follows:

Line 356: Figure 8 displays the scatterplot and *R* values between the estimated average *IS* map <u>for 2016–2020</u> and the irrigated area fraction from the GMIA (Fig. 8a) as well as the average irrigation water use estimations from the ZL21 map (Fig. 8b).

Line 365: Figure 8: Scatterplot of grid cell values in the *IS* map <u>(averaging value for 2016–2020)</u> compared with those from the GMIA and the ZL21 map in SJV.

Specific Comments #2:

L 62-75: SM-based methodologies for retrieving irrigation information can be divided into two main categories, namely baseline approaches (as for instance <u>https://doi.org/10.5194/hess-23-897-2019</u>, <u>https://doi.org/10.3390/rs13091727</u>) or methodologies based on the soil water balance (e.g., <u>https://doi.org/10.5194/essd-15-1555-2023</u>). Note that such methodologies led to the development of satellite-based irrigation water use datasets (<u>https://doi.org/10.5281/zenodo.8086046</u>), also available for the US (<u>https://doi.org/10.5281/zenodo.14988198</u>).

Reply: Thanks for your suggestions. We agree that soil moisture-based irrigation retrieval methods fall into two main categories (baseline vs. soil water balance approaches) and that our manuscript needs to acknowledge this. We respectfully note that while soil water mass balance approaches are highly valuable, a deep evaluation of those methods is beyond our current scope. **Our goal in this work is to demonstrate the potential of a baseline method**.

We propose to retain the original structure of the paragraph while making the additions outlined below. The revised paragraph first introduces the classification (baseline vs. mass balance), then discusses baseline methods (our focus). We are confident that this addresses your concern without deviating from our paper's focus on the baseline approach (i.e., using differences between SMAP Level 3 and Level 4 products to detect irrigation). We will revise the manuscript as follows:

Line 59: Satellite soil moisture methods for retrieving irrigation information are generally divided into two categories: baseline approaches and soil-water mass-balance approaches. The latter estimate irrigation by closing the mass balance with satellite soil-moisture observations and other hydrological fluxes, and they typically require assimilating these soil moisture data into complex land-surface models (Dari et al., 2023). The present study concentrates on the baseline approach. The basic principle for this soil ~~moisture-based~~ baseline method is taking the difference between two soil moisture time series with irrigation effects (usually from satellite products) and without irrigation effects (usually from model simulations without considering irrigation events) (Brocca et al., 2018).

Line 62: The key to the soil moisture-based irrigation ~~monitoring~~ baseline approach is to ensure that the time series with and without irrigation effects are climatologically consistent.

Thank you again for pointing this out, and it has helped us improve the manuscript's scholarly completeness.

Specific Comments #3:

L 90-92: So why California only is mentioned in the title?

Reply: The California Central Valley is **the primary focus of our study**, and the most thorough testing and validation are carried out there (see Sections 4.1–4.3). Results from other irrigated regions in the CONUS are included only to illustrate how the method performs outside the Central Valley and to highlight potential limitations; they do not alter the main conclusions drawn for the Central Valley.

As noted in Line 90-92 of the original manuscript: We also examined several heavily irrigated regions elsewhere in the contiguous United States (CONUS) to further evaluate the performance and applicability of the proposed method.

Central Valley remains the core study area, and the paper's key findings and figures are based on that region; consequently, we referenced California alone in the title. If the reviewers or the editor feel a broader title would better reflect the supplementary analyses, we are willing to revise the title accordingly.

Specific Comments #4:

L 170: performances of ZL21 should be reported to understand its reliability as a comparative dataset.

Reply: We will add a description of the reliability of the ZL21 product in the next version of the manuscript as follows:

Line 170: Derived from model simulations that integrate remote sensing-based evapotranspiration with simulated root zone soil moisture, the ZL21 map offers high-resolution (1 km) monthly irrigation water use estimates for the CONUS over the period 2000–2020. Compared against state-level Farm and Ranch Irrigation Survey dataset, this product achieved R^2 values ranging from 0.74 to 0.84, demonstrating high accuracy at the state level.

Specific Comments #5:

L 195: is flood irrigation an issue for detecting the irrigation signal?

Reply: Thanks for your valuable comments.

We noted that the Sacramento Valley is dominated by flood irrigation systems, whereas the southern San Joaquin Valley primarily employs sprinkler irrigation to demonstrate that our method performs well under different irrigation practices, which has been confirmed by our results.

In principle, different irrigation practices can influence monitoring. Flood irrigation may create artificial standing water, and, as discussed in our Response to Referee #1, Specific Comment #7, large areas of standing water can lead to an overestimation in SMAP Level 3 product and thus a more pronounced irrigation signal.

In summary, we believe **flood irrigation did not compromise our ability to reasonably detect irrigation signals using the SMAP Level 3 and Level 4 products in this study**.

Specific Comments #6:

Figure 2: grid cell e) seems to show slightly different dynamics.

Reply: Thanks for your careful revision and comments.

Compared with the other grid cells shown in Figure 2, grid cell e exhibits slightly different dynamics between SMAP L3_E and L4. We would like to first clarify that all non-irrigated grid cells were selected by a random-sampling procedure as described in Section 3.1 of the original manuscript. The feature of grid cell e is the higher SMAP L3_E soil-moisture values during the non-cropping season. As explained in our Response to **Referee #1, Specific Comment #7**, this behavior is likely caused by standing water after consecutive rainfall events, which can spuriously elevate SMAP L3_E.

Nevertheless, **this slightly different dynamics in grid cell e do not affect our overall assessment of climatological consistency** between SMAP L3_E and L4 over non-irrigated grid cells: their temporal variability and the *MD* between cropping and non-cropping seasons remain consistent, staying below 0.04 $m^3 m^{-3}$.

We thank you again for highlighting this detail.

Specific Comments #7:

L 309: what is the entity of MD discrepancies?

Reply: Thanks for your valuable comments.

As defined in Eq. (1) of the original manuscript: $MD = \frac{1}{n}\sum_{i=1}^{n}(\theta_{L3,i} - \theta_{L4,i})$, *MD* represents the mean difference between SMAP L3_E and L4 soil moisture values over a given period.

In Line 309 we state: "At the irrigated grid cells (Figs. 4a–d), we generally observed higher *MD* values during the cropping season compared to those during non-cropping season (p-value < 0.05)", this means that, in irrigated grid cells, L3_E and L4 diverge more strongly during the cropping season than in the non-cropping season; in other words, SMAP L3_E shows higher soil-moisture levels than SMAP L4 during the cropping period but not because of the systematic errors. This systematic behavior constitutes the empirical basis for our subsequent irrigation-signal detection.

Specific Comments #8:

Figure 7: panel c), how il this map converted to m^3/m^3? Is porosity taken into account?

Reply: Thanks for your careful revision and comments.

Figure 7, Panel (c) is taken from the validation dataset: ZL21 map.

In this dataset, the authors use the ERA5-Land volumetric soil-moisture product, which is provided in units of $m^3\ m^{-3}$. **Porosity is explicitly accounted for within the ERA5-Land land-surface model when it simulates soil-moisture dynamics**, so no additional conversion or porosity adjustment was required for their analysis.

Specific Comments #9:

L 420-421: what about GLEAM, Sen-ET, ...

Reply: Thanks for your valuable suggestions.

In the manuscript we noted the potential to refine our analysis by incorporating large-scale evapotranspiration products, while also mentioning the limited availability of independent observations. We appreciate your recommendation to consider GLEAM and Sen-ET. Both data sets indeed provide valuable ET estimates derived from satellite observations and/or reanalysis forcing, and we acknowledge their relevance to irrigation studies. Although they remain, like most global ET products, indirectly constrained by remote-sensing or model inputs, they could nonetheless enhance the evaluation of water-balance components in future work.

We will explore integrating GLEAM and Sen-ET in follow-up studies and will reference these products in the revised manuscript.

Thank you again for your professional comments and suggestions.