Comments to RC1

The reviewer's comments are in **black** and our answers in **blue.**

General Information

The study investigates spatial and temporal dynamics of river intermittency in the Umbuzeiro River (Brazilian semiarid region) using a combination of UAV surveys, remote sensing, and Random Forest (RF) modeling. The authors assess water presence classes: "Wet", "Transition", "Dry", and "Not Determined", across different times and river segments. They evaluate three RF model variants based on different dynamic predictors: Sentinel MNDWI, Planetscope NDVI, and 30-day accumulated precipitation.

This is a well-structured and technically rigorous study that addresses a critical gap in intermittent river monitoring in semi-arid environments. It provides an important proof of concept for combining UAV-based mapping and machine learning for ecohydrological research. The results are promising and provide a methodological blueprint for future upscaling efforts, though there is room for refinement in automation, validation, and generalization.

Despite the interest in the topic, I believe some changes in the paper are needed before it can be considered ready for publication, listed in the specific comments.

We thank the reviewer for their thoughtful and constructive feedback. We are pleased that the reviewer recognized the relevance of our study and the potential contribution of our methodology to ecohydrological research in semi-arid intermittent rivers. We appreciate the positive assessment of our approach, particularly the integration of UAV-based mapping and machine learning, as well as the acknowledgment of its promise for future upscaling efforts.

We have carefully considered the reviewer's comments and have made the suggested revisions to improve the manuscript, particularly in relation to automation, validation, and generalization, as detailed in our responses to the specific comments below.

Specific Comments

1. LL121-123:"***The "Not Determined" class included those reaches where it was not possible to discern"***. It may be useful to evaluate the integration of soil moisture indices or evapotranspiration estimates as additional dynamic predictors.

   We appreciate the reviewer's suggestion to explore additional predictors such as soil moisture and evapotranspiration, which are indeed relevant variables for understanding flow intermittency and ecohydrological dynamics in dryland river systems. We agree that these parameters have the potential to enhance predictive models and contribute to a more comprehensive understanding of the hydrological processes at play.

   However, in the context of our study, such data are not available at the spatial and temporal resolution required for integration into our current framework. In semi-arid and data-scarce regions like our study area, in situ measurements of soil moisture and evapotranspiration are typically unavailable, and reliance on remotely sensed or modeled estimates—while valuable at broader scales—can introduce additional uncertainty, particularly when applied at fine spatial scales.

We emphasize the value of fine-scale hydrological monitoring in data-scarce semi-arid environments, such as the AEB (Aiuaba Experimental Basin), where long-term field-based studies have provided critical insights into local runoff generation processes (Figueiredo et al., 2016) and soil moisture dynamics (Costa et al., 2013). These efforts demonstrate that small-scale, in situ monitoring can reveal ecohydrological processes and spatial patterns that are not captured by coarse-resolution remote sensing products.

Given these limitations, our methodological choice was to prioritize field-based and directly observable predictors, such as vegetation cover and geomorphological attributes, which could be reliably mapped and validated at high resolution. We believe that this approach reduces uncertainty and strengthens the applicability of the model in small-scale, heterogeneous environments. We agree that future studies could benefit from incorporating additional hydrological variables as data availability improves, we added a brief discussion of this point in section 4.6 Work limitations of the revised manuscript.

2. L143: ***"These indices are are summarized in Table 1"***. The two verbs reported need to be corrected.

   Thank you for pointing this out. The duplicated verb has been corrected in the revised manuscript. The sentence now reads: "These indices are summarized in Table 1."

3. L189-192: ***"Damming structures are mapped all along the Umbuzeiro River by using Planetscope images so as to visually locate each dam."*** The river path and dam structures are mapped manually using high-resolution imagery and field data. In particular, the geolocation of the dams was also performed manually, which limits scalability and reproducibility for larger or other basins. Could automated surveying using satellite data be considered?

   We appreciate the reviewer's observation regarding the scalability and reproducibility of manually mapped features. In our study, the mapping of small dams was performed manually based on high-resolution UAV imagery and the authors' prior field knowledge. While a full validation campaign was beyond the scope of this work, a subset of the mapped structures—approximately 10%—was verified through field visits and drone imagery, providing some level of confirmation of their existence and location.

   We acknowledge, however, that manual mapping can be a limiting factor for broader applications. To address this concern, we note that our method is flexible and can be applied using publicly available global datasets. In particular, the Global Surface Water Explorer (Pekel et al., 2016) offers valuable information on water occurrence and seasonality and can serve as a proxy for identifying surface water bodies and small reservoirs in other regions. Variables derived from this dataset were already incorporated into our model as predictors, which supports the potential for scaling the approach beyond our study area.

   A brief discussion was added to section 4.6 Work limitations of the revised manuscript highlighting this methodological flexibility and the use of global datasets.

4. L257: ***"4.1 Observed water intermittency: UAV imagery".*** From the text, it appears that the UAV-based classification is visual and not verified with in-situ hydrological measurements or ground truth sampling. The lack of objective thresholds could introduce bias in the classification of "Transition" and "Wet" classes. Probably longer UAV survey campaigns, covering more years, could better capture interannual variability.

   We thank the reviewer for this insightful comment. The UAV-based classification was indeed based on visual interpretation, supported by field observations and local knowledge of the study area. Although no streamflow measurements or water level sensors were available, presence/absence of ponded water in specific river reaches was verified during field visits conducted during the UAV survey.

   We acknowledge that the lack of objective thresholds—such as fixed depth criteria—introduces some degree of subjectivity, especially in distinguishing between "Wet" and "Transition" conditions. Additionally, we agree that longer-term UAV monitoring campaigns, capturing multiple hydrological years, would enhance the ability to detect interannual variability and improve the robustness of the classification.

   These aspects will be acknowledged as limitations in section 4.6 Work limitations of the revised manuscript, along with a brief reflection on the trade-offs involved in using visual interpretation in data-scarce environments.

5. LL326-328: ***"Temporal variations along the year can also be observed in comparison to monthly precipitation."*** What is the period used to calibrate the model to identify the seasonality of events? The model using 30-day precipitation (Model c) underperforms in capturing seasonal transitions. This approach limits the model's ability to generalize across varying wet/dry years.

   We thank the reviewer for this important observation. Model c was trained using data from five UAV campaigns conducted over a single hydrological year, encompassing a range of seasonal conditions—from wetter months with ponded water to dry season and the rewetting period in November. The model used precipitation accumulated over the 30 days prior to each UAV campaign as a proxy for short-term hydrological conditions.

   While this variable helped capture intra-annual variability and presented good accuracy for testing datasets, we agree that the use of a single-year time series and an accumulation window limit the model's ability to fully represent seasonal transitions and interannual variability. This is particularly relevant in semi-arid environments, where the timing and intensity of rainfall events vary significantly from year to year. The limited performance of Model c in capturing transitional classes may reflect these constraints.

   We acknowledge this as a limitation of our current dataset, and a brief note was added to section 4.6 Work limitations of the revised manuscript suggesting that future work incorporating multi-year datasets and other precipitation accumulation periods may improve the model's generalization to other hydrological years.

6. LL351-353***: "Model (a) is even more specific in this respect and indicates mainly areas in the lowest part of the basin. The identification of areas prone to wetter conditions is very important even in the smallest of scales because they can be key areas for river ecology, for instance".*** Although model (a) achieved the best results, the use of Sentinel MNDWI data may not be generalizable to narrower or canopy-covered watercourses, especially in forested catchments.

   We thank the reviewer for raising this important point. We agree that the use of MNDWI derived from Sentinel-2 imagery has known limitations when applied to narrow channels or watercourses under dense canopy cover, where spectral signals from water may be obstructed or diluted by surrounding vegetation.

   Additionally, we note that areas with dense canopy cover, where the riverbed is obscured and water detection is not possible, were classified as "Not Determined" in our approach. This category itself may indicate zones of persistent canopy cover, which can be related to local hydrological conditions, such as groundwater influence or permanent pools beneath vegetation. Thus, even in forested stretches, the vegetation structure can provide indirect information about wetness patterns.

   Nonetheless, we recognize that in more heavily forested or topographically complex catchments, alternative data sources or higher-resolution sensors may be needed to accurately identify surface water. We included a brief note in section 4.6 Work limitations of the revised manuscript acknowledging this limitation and suggesting caution when applying this approach to other regions with different land cover characteristics.

7. L378: ***"for spectral indexes based on UAV data".*** It's better to use indeces. "Indexes" is commonly used to refer to alphabetical lists in books, for example. In contrast, "indeces" is used in more technical, scientific, and mathematical contexts.

   Thank you for this observation. We agree with the reviewer's suggestion and have replaced "indexes" with "indices" in the revised manuscript to better align with scientific terminology.

> **In response to the reviewer's suggestions, we added the following text to the section 4.6 Work Limitations to the revised version of the manuscript:**
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> *"Although high-resolution UAV imagery enabled detailed visual classification of flow permanence classes, the method relied on expert interpretation without direct hydrological measurements such as streamflow or water level data. This introduces potential subjectivity, particularly in distinguishing between "Wet" and "Transition" conditions. Field observations were conducted during the UAV campaigns and helped inform classification, but were limited to qualitative assessments of ponded water, as no surface flow was observed during the study year."*

"We based our analysis on data from a single hydrological year. While this approach allowed for the capture of short-term hydroclimatic variability, it limits the model's capacity to generalize across years with different rainfall patterns. Future studies including multi-year data and alternative temporal windows could help address this limitation."

"Additionally, we acknowledge the potential value of integrating other dynamic hydrological variables, such as soil moisture and evapotranspiration, into predictive models of flow intermittency. These variables are relevant for ecohydrological modeling, particularly in dryland environments. However, in the context of this study, such data were unavailable at the spatial and temporal resolutions required to support fine-scale modeling."

"As for our choice of predictors, we recognize that spatial resolution and ease of access vary greatly among them. The selected predictors are consistent among models; but great importance is given to dam identification. Both "distance from" and "distance to" dams ranked as highly important in model performance, and they already represent half the number of static predictors. In our study area, we identify many different types of damming structures —ranging from small rural weirs to larger reservoirs— future studies could benefit from classifying them into distinct functional or structural categories." **(This paragraph was already present, but it was rewritten)**

"The manual mapping of small dams enabled a more realistic representation of water retention in the basin. However, dam mapping may also limit applicability of our model to other regions as it requires considerable manual effort and, potentially, familiarity with the study area. That said, the methodology is adaptable: similar analyses can be replicated using global datasets such as the Global Surface Water Explorer (Pekel et al., 2016), which provides historical water occurrence based on Landsat imagery."

Finally, although Sentinel-2 data used in Model a yielded strong results in our study area, the performance of its spectral indices—particularly MNDWI—may decline in more heavily forested or topographically complex catchments. In these cases, alternative data sources or higher-resolution sensors may be needed to accurately identify surface water. However, it may be that dense vegetation can also serve as an indirect indicator of groundwater presence or surface wetness, and these segments were conservatively labeled as "Not Determined" in our classification."

8. L394: ***"Conclusion"***. Probably the conclusion could be more detailed and not a simple summary of the study done; they could report some details shown in the graphs and tables.

We thank the reviewer for this suggestion. We agree that the conclusion section can benefit from a more detailed discussion that goes beyond summarizing the study. In the revised manuscript, we will expand the conclusion to include references to key findings illustrated in figures and tables, as well as highlight the broader implications of the results for ecohydrological monitoring and the scalability of the proposed method. The revised Conclusion section incorporates the following insights:

> *"The "Wet" and "Dry" classes follow the rainy season dynamics, and the longer wet patches are present in the most downstream section. The "Transition" class is very heterogeneous because it represents areas with mixed information: such as wet/dry patches with algae and sparce vegetation. During the rainy season, the vegetation has full and dense canopies, that is why the "Not Determined" class, i.e. the river reaches where we cannot see the riverbed from the UAV-imagery, can be found more frequently during the rainy season and in narrower river stretches. This feature represents a major source of uncertainty, limiting the available data acquired through optical remote sensing."*

> *"The modelling framework developed in this study contributes to a broader understanding of flow intermittency as a spatially complex and highly dynamic process over time. The integration of high-resolution predictors, especially related to dam presence, landscape attributes and satellite indices, offers a scalable and adaptable approach for mapping wetness conditions in other dryland river systems. These insights are particularly relevant in the context of increasing climate variability and water stress, as they point to key landscape features that can be targeted for monitoring or management. Our results demonstrate that even in the absence of extensive hydrometric data, meaningful patterns can be derived from the careful integration of remote sensing and field-based observations."*

References for works used in this response:

Costa, C. A. G., Lopes, J. W. B., Pinheiro, E. A. R., Araújo, J. C. de, & Gomes Filho, R. R. (2013). Spatial behaviour of soil moisture in the root zone of the Caatinga biome. *Revista Ciência Agronômica*, *44*(4), 685–694.

De Figueiredo, J. V., de Araújo, J. C., Medeiros, P. H. A., & Costa, A. C. (2016). Runoff initiation in a preserved semiarid Caatinga small watershed, Northeastern Brazil. *Hydrological Processes*, *30*(13), 2390-2400.

Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, *540*(7633), 418-422.