Advancing Interpretability of Deep Active Learning in Flood Mapping with Multispectral Imagery

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I. Background

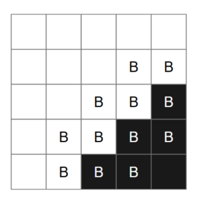
- Flood mapping is a critical task in disaster management, with multispectral satellite imagery as one of the primary data sources.
- While advances in deep learning have led to its increasing adoption in flood mapping, supervised learning still faces the challenge of time-consuming and labor-intensive data labeling in this field.
- Deep active learning is a feasible strategy to overcome these limitations, though research on its interpretability remains limited in flood mapping from the perspectives of remote sensing.

II. Data and Method

- **Dataset: Sen1Floods11**
  - Flood mapping benchmark dataset (Bonafilia et al., 2020)
  - 11 global flood events from 2016 to 2019
    - Unlabeled pool (8 events), target (3 events)
  - 446 data samples with manually labeled data, Through preprocessing, the data was split into 1,784 non-overlapping data samples.
- **Proposed Class Ambiguity Indices**
  - Boundary Pixel Ratio (BPR): Class ambiguity index for limited spatial resolution

    (BPS: Boundary Pixels, TPS: Total Pixels)

$$\mathrm{BPR} = \frac{\mathrm{BPS}}{\mathrm{TPS}}$$



  - Mahalanobis Distance for Flood-segmentation (MDF): Class ambiguity index reflecting spectral similarity between classes

    ($\mathbf{p}_{\text{flood}}$: Pixel-level vector along the band axis in the flood class, $\mathbf{p}_{\text{non-flood}}$: Pixel-level vector along the band axis in the non-flood class)

$$\mathrm{MDF} = \sqrt{(\mathbf{p}_{\text{flood}} - \mathbf{p}_{\text{non-flood}})^T \Sigma^{-1} (\mathbf{p}_{\text{flood}} - \mathbf{p}_{\text{non-flood}})}$$

- **Proposed Framework**
  - Interpretable Deep Active for Flood Inundation Mapping (IDAL-FIM)

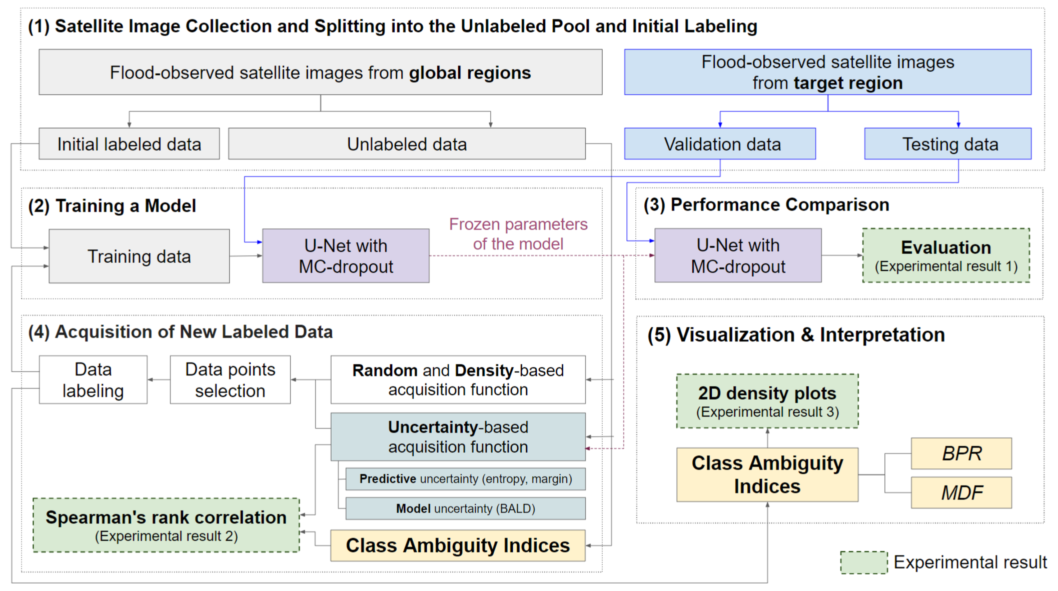


Fig 1. The process of the IDAL-FIM framework.

III. Results

Finding 1: Deep active learning is effective in selecting informative samples for flood mapping training.

- Predictive uncertainty-based acquisition functions, such as Margin and Entropy, demonstrated superior performance compared to other acquisition functions within the IDAL-FIM framework.
- Models trained on subsets of the dataset (n = 500) selected using the predictive uncertainty-based acquisition functions achieved performance comparable to models trained on the entire dataset (n = 1,532).

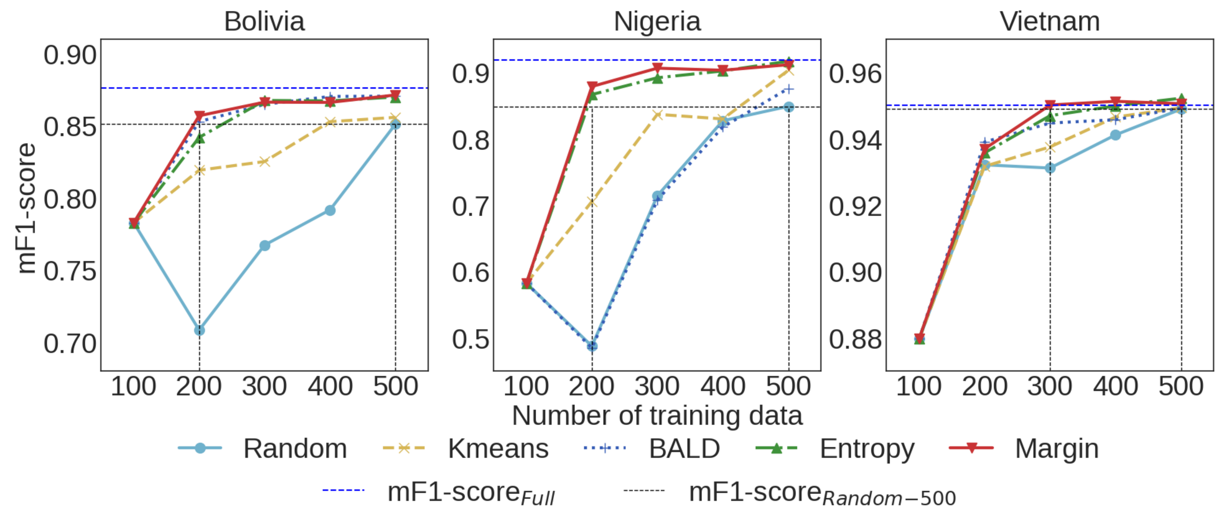


Fig 2. The comparison of the mean F1-score in different five acquisition functions (Random, Kmeans, BALD, Entropy, Margin)

Finding 2: The proposed class ambiguity indices show a statistically significant correlation with the scores of the predictive uncertainty-based acquisition functions.

- BPR and the scores of the predictive uncertainty-based acquisition functions (UBAFs), such as margin and entropy, exhibit a positive rank correlation.
- MDF and the scores of the predictive uncertainty-based acquisition functions demonstrate a negative rank correlation.
- When combining our findings with the uncertainty propagation theory, the observed statistically significant correlations strongly support a causal relationship between the class ambiguity of the input satellite image and the score of the predictive uncertainty-based acquisition functions.

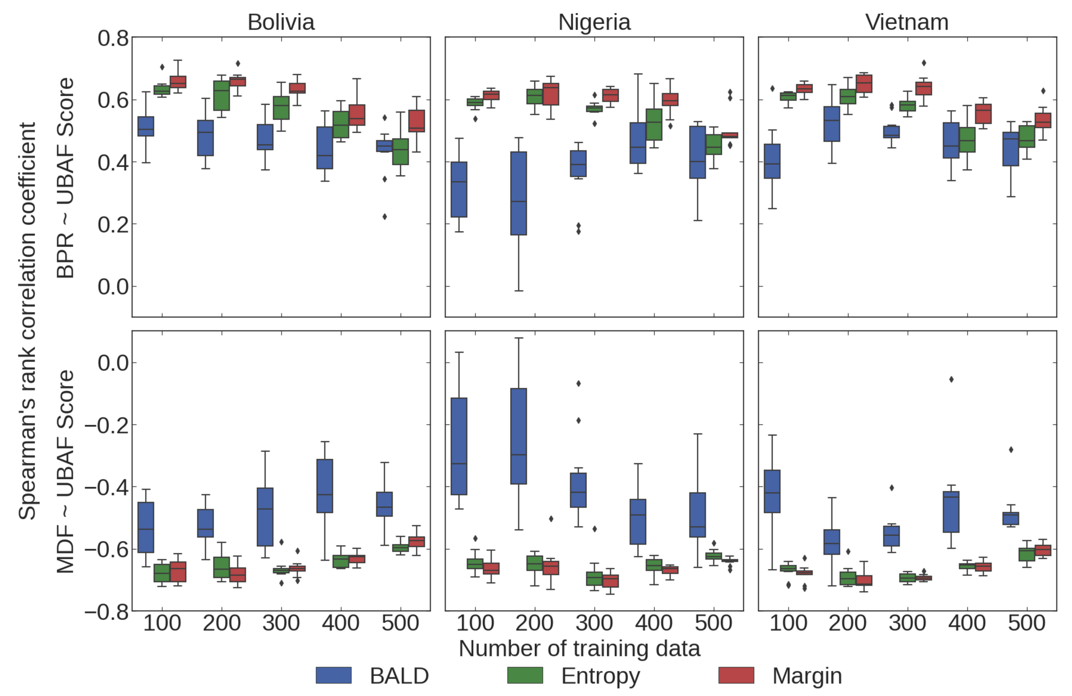


Fig 3. The comparison on the Spearman's rank correlation coefficient between class ambiguity indices and the score of the uncertainty-based acquisition functions

Finding 3: The proposed class ambiguity indices are effective variables for interpreting the behavior of active learning in flood mapping.

- Fig. 4 visualizes the distribution of data points in the unlabeled data pool in terms of MDF and BPR.
- Fig. 5 illustrates the distribution of the selected 100 data points at each selection step in the IDAL-FIM framework, in terms of MDF and BPR.
- Particularly in iteration 1, the predictive uncertainty-based acquisition functions showed a tendency to actively select data points with high class ambiguity in terms of MDF and BPR.

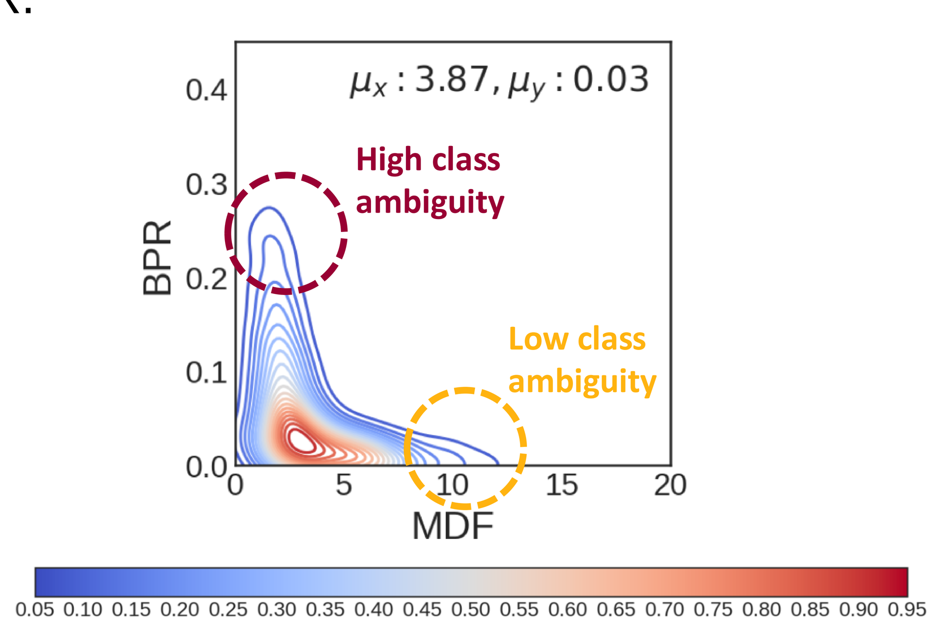


Fig 4. The MDF-BPR density plots of the unlabeled data pool.

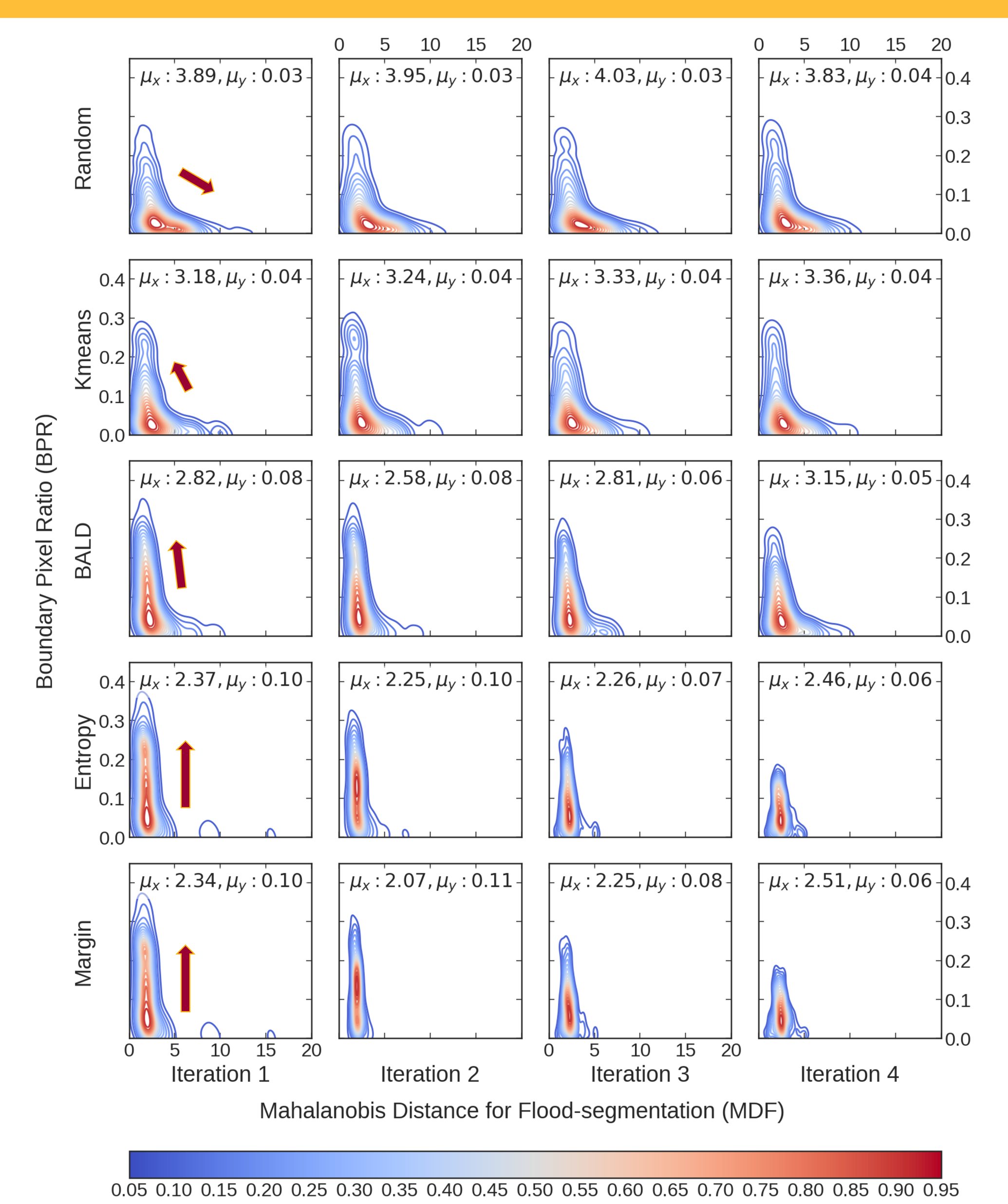


Fig 5. The MDF-BPR density plots in Bolivia. In each plot, μ_x denotes the average of x-axis values, and μ_y means the average of y-axis values.

IV. Conclusion

- We introduced a novel framework of Interpretable Deep Active Learning for Flood inundation Mapping (IDAL-FIM).
- Through experiments, we demonstrated the significance of two proposed class ambiguity indices within the IDAL-FIM framework.
- By visualizing two-dimensional density plots, we illustrated how the behaviors of deep active learning can be interpreted using these two class ambiguity indices within the IDAL-FIM framework.
- From the perspective of class ambiguity indices, our visualization results showed the depletion of informative data points in the unlabeled data pool as iterations progressed. This observation suggests that the proposed class ambiguity indices could function as a quantitative criterion for determining when to update the unlabeled data pool.

Reference

- Bonafilia, D., Tellman, B., Anderson, T., & Issenberg, E. (2020). Sen1Floods11: A georeferenced dataset to train and test deep learning flood algorithms for sentinel-1. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (pp. 210-211).
- Hertel, V., Chow, C., Wani, O., Wieland, M., & Martinis, S. (2023). Probabilistic SAR-based water segmentation with adapted Bayesian convolutional neural network. Remote Sensing of Environment, 285, 113388.
- Lee, H., & Li, W. (2024). Improving interpretability of deep active learning for flood inundation mapping through class ambiguity indices using multi-spectral satellite imagery. Remote Sensing of Environment, 309, 114213.

Supplementary Materials

- **Model architecture**
  - The U-Net architecture with spatial dropout added to the decoder (Hertel et al., 2023).

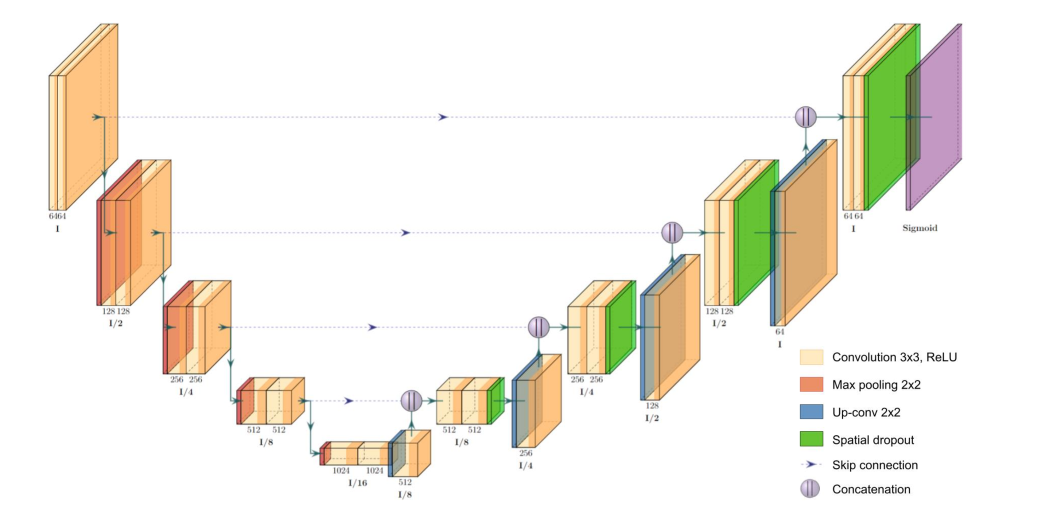


Fig 6. The architecture of U-Net with MC-dropout. The input image assumes uniform width and height (l).