EGU General Assembly 2024

EGU24-19021, updated on 17 Jul 2024
https://doi.org/10.5194/egusphere-egu24-19021
EGU General Assembly 2024

Optimizing crop type mapping for fairness

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Minor crops are crucial for food security, especially due to their resilience against climate change related challenges (Renard & Tilman, 2019) . Consequently, accurate crop mapping is essential for monitoring policies seeking to incentivize minor crop production. However, the class imbalance problem in machine learning introduces a bias against these crops, leading to unfair classifications. This research aims to explore how this bias is mitigated through two main class imbalance correction approaches: sample balancing methods and cost-sensitive learning. Apart from investigating how these methods address the typical class imbalance problem, where there are simply less labelled samples of a specific class, we investigate how these methods can be used to address another level of bias, that created by omitted sensitive attributes. These are attributes such as parcel size, which are not explicitly considered by the classifier, yet significantly impact accuracy and contribute to the unfairness of the classification, as evidenced by notably lower accuracy for smaller parcels. By integrating these attributes into the class imbalance correction methods, we assess the potential for enhancing fairness. This approach is vital, as it corrects performance biases affecting specific sub-groups, which are not necessarily class dependent, thus addressing a critical but overlooked dimension of fairness in classification.

Utilizing the BreizhCrops dataset, we create sub-sampled datasets that represent a variety of class imbalance problems. This enables us to conduct an across-the-board comparison of the selected class imbalance correction techniques, providing insights that may help streamline future research looking to employ these techniques. For the classifier architecture, we select the transformer encoder, chosen for its greater performance among deep learning methods tested on the BreizhCrops dataset (Rußwurm et al., 2020).

This research contributes to the broader understanding of class imbalance correction in classification tasks, particularly for crop mapping, though the methods can also be applied in other GeoAI contexts. By evaluating sample balancing and cost-sensitive learning in varied contexts, we provide insights into optimizing classification tasks for fairness. Our work contributes to the development of responsible AI practices by offering valuable insights on how fairness can be enhanced across GeoAI applications.

Renard, D., & Tilman, D. (2019). National food production stabilized by crop diversity. *Nature*, *571*(7764), 257–260. https://doi.org/10.1038/s41586-019-1316-y

Rußwurm, M., Pelletier, C., Zollner, M., Lefèvre, S., & Körner, M. (2020). *BreizhCrops: A Time Series Dataset for Crop Type Mapping* (arXiv:1905.11893). arXiv. https://doi.org/10.48550/arXiv.1905.11893