

# Improving the understanding of Machine Learning predictions through maps



by ISAAC NEWTON KISSIEDU

The use of Machine Learning (ML) models is increasing due to their capacity to discover complex patterns in data [1]. However, they are labelled as black-boxes as a result of interpretability and transparency concerns [2], leading to the emergence of Explainable ML (EML). This effort, with the objective to explain a ML model is still at the infant stage and produces outputs that target experts [3]. Thus, overwhelming the average user. This thesis therefore aims to develop a workflow that integrates EML with maps in order to enhance the interpretability and understanding of ML outputs for everyone. It uses Random Forest (RF) and Digital Soil Mapping of soil nitrogen in Burkina Faso as a case study.

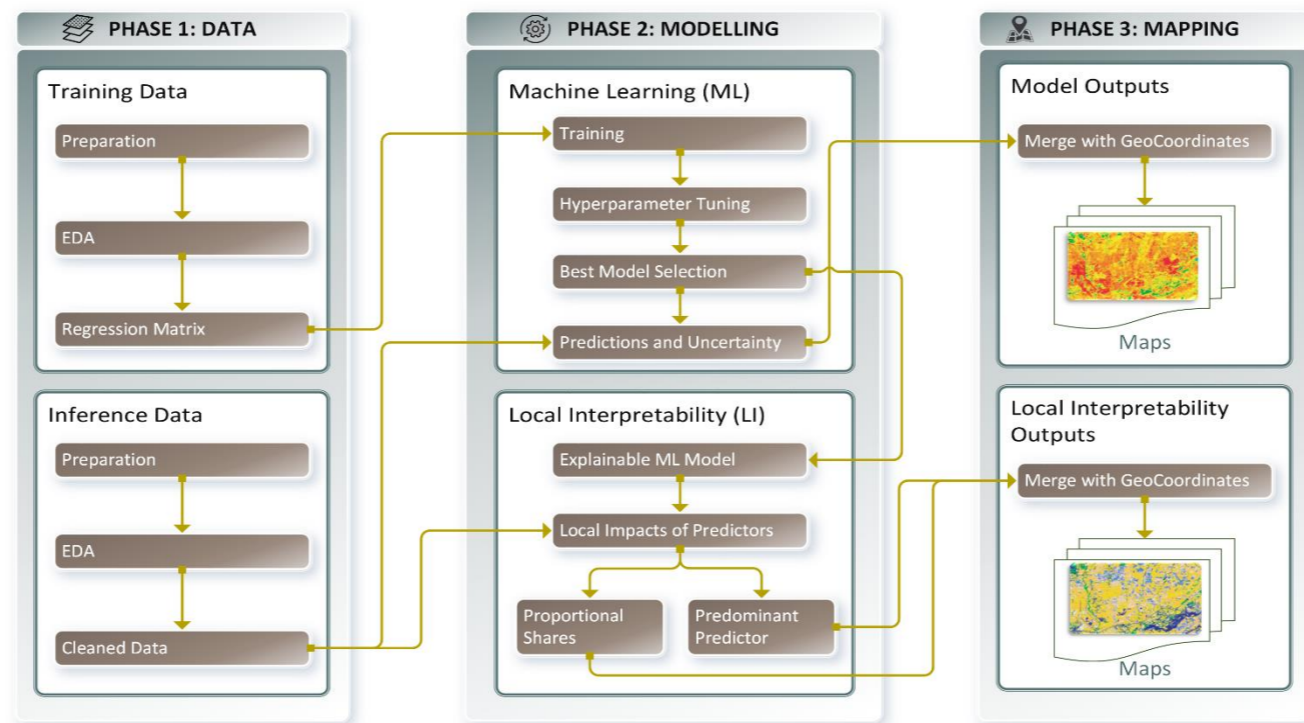


Figure 1 – Design of Local Interpretability Workflow

## DATA

Soil nitrogen training data was acquired from the December 2023 World Soil Information Service (WoSIS) dataset published by ISRIC-World Soil Information. In addition, 450 explanatory inference data were obtained from earth observation sources through the Google Earth Engine platform. The data categories include climate, surface reflectance, vegetation indices, and relief.

## METHODOLOGY

Firstly, a Literature Review was conducted to explore available EML models. The SHapley Additive exPlanations (SHAP) EML model was ultimately selected for the calculation of local impacts of predictors in RF, due to its strong mathematical underpinnings in the Game Theory and wide adoption.

Secondly, a detailed workflow was designed to integrate the selected EML model with maps as a visualization component (see Figure 1).

Thirdly, the designed workflow was implemented in a custom python program to produce maps including Predicted Soil Nitrogen, Uncertainties, Local Impacts of Predictors (see Figure 2), and the Local Predominant Predictor at the pixel level (see Figure 3).

Finally, a user survey was conducted to assess the readability, interpretability and understanding of the maps.

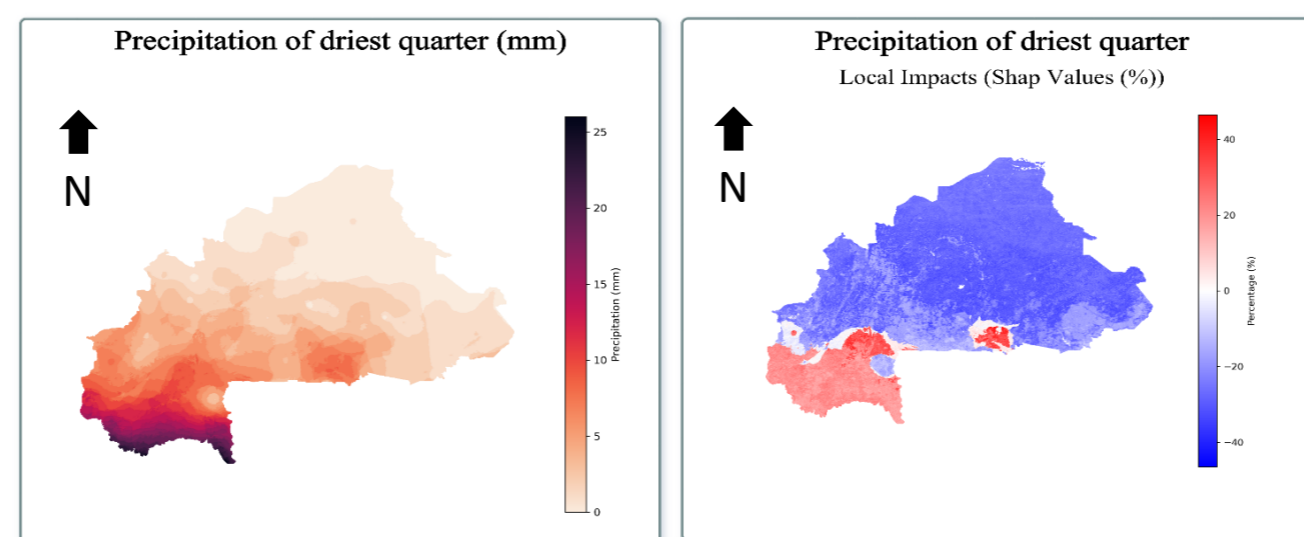


Figure 2 – The most significant predictor (left) and its local impacts to predictions (right)

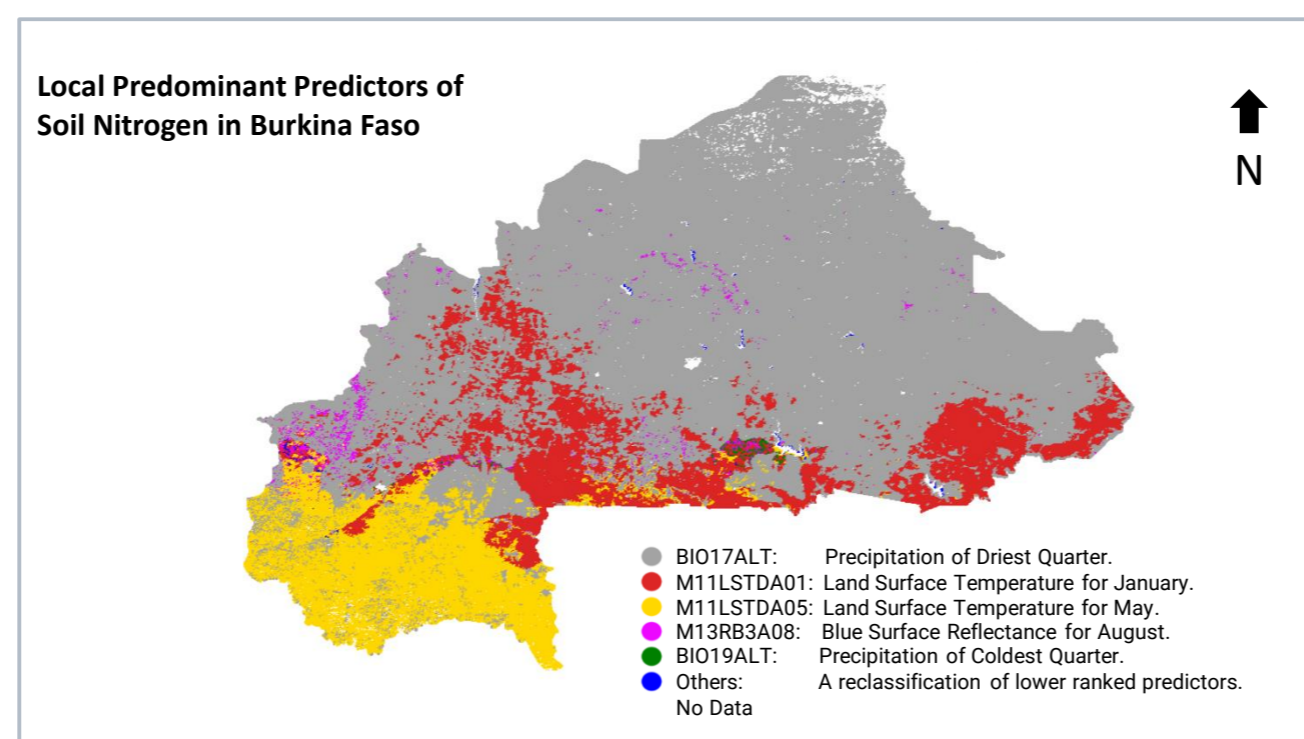


Figure 3 – Local Predominant predictor per pixel, derived from the local interpretability of the top influential predictors.

## RESULTS

The designed workflow proved to be useful in enhancing the transparency of a RF model. Based on 102 user survey respondents, a five-point Likert Scale evaluation achieved median scores of 4, 4, 3 for readability, interpretability and understanding respectively, indicating overall clarity of the maps, and the potential to support understanding.

## CONCLUSION

This thesis has provided a detailed workflow bridging the methodology gap in integrating maps with EML methods. Additionally, it highlights key implementation challenges and recommendations, serving as a strong foundation to inform the methodologies of related future studies.

## THESIS CONDUCTED AT

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Technische Universität Dresden



## THESIS ASSESSMENT BOARD

Chair Professor: Prof. Dipl.-Phys. Dr.-Ing. habil. Dirk Burghardt, TUD

Supervisor: Dr.rer.nat. Nikolas Prechtel, TUD

Reviewer: Prof. Ellen-Wien Augustijn, UT

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Digital Soil Mapping, Machine Learning, Explainable AI, SHAP, Interpretability, Map, Cartography

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