Flood Map Prediction Challenge, phase two

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1 Performance Evaluation

1.1 Model performance: AUC ROC

Explain how you optimize the performance of your model. What methods did you use to process your data, select your features, choose your model and hyperparameters?

We first found that two major difficulties of the challenge were (i) the size of images in the data (up to 5953x3936 pixels per image), and (ii) the strong imbalance between classes (most labels are zeros, and only a few are ones). To address both of these issues, we divided the images into patches, or sizes $p \times p$, where $p << 3936$ is a hyperparameter to optimize. These patches are much smaller than the original image and were easier to pass as input to our neural networks, while allowing for a larger batch size and therefore more stable training. Another advantage of the patch approach is the fact that we can choose to keep only certain patches for training: in practice, we kept only those patches that had flooding at some time step within the training period, or were close to one of such patches. In addition, to have the same resolution for all inputs in our training data, we upsampled the low-resolution spatiotemporal features to match the resolution of the geospatial features. We used an interpolation technique based on implicit neural representations [Naour et al., 2023].

We chose to use convolutional neural networks (CNNs) because they are a standard approach for deep learning-based image classification. We also tried vision transformers (ViTs), but they didn't achieve the same performance as CNNs, probably due to the type of information they encode: ViTs are better at capturing global information, while CNNs are very good at pattern recognition [Raghu et al., 2021]. We tried different convolutional architectures, including a UNet [Ronneberger et al., 2015], but in the end we decided to keep a simpler and flatter CNN architecture, as it was able to achieve similar performance when carefully tuned, but was more frugal.

Regarding hyperparameter tuning, we adjusted hyperparameters manually, following an incremental strategy as suggested by Godbole et al. [2023]. We first tuned our model architecture (kernel size and number of convolutional layers). Since both kernel size and network depth can interact with the learning rate, we tuned each parameter over multiple learning rates to compare them fairly, i.e., we treat the learning rate as a nuisance parameter [Godbole et al., 2023].

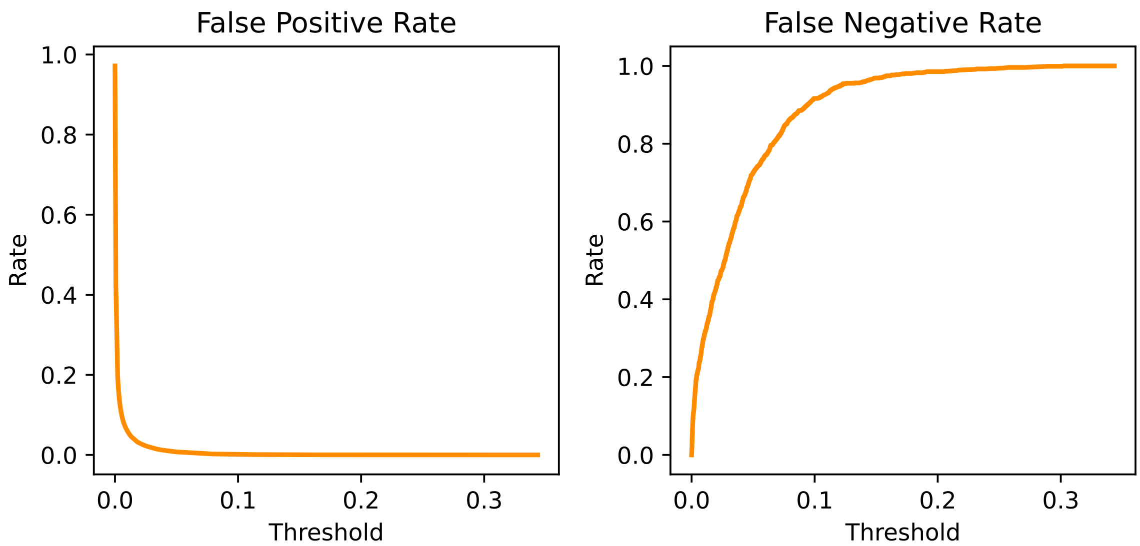


Figure 1: Error rates as a function of classification threshold.

1.2 Use case performance: False positive rate

False positive: $y_{pred} \geq 0.9$ when $y = 0$.

According to this definition, we do not get any false positives, as none of our predicted probabilities surpass 0.9. This is not surprising as there are not many flooded areas in the training data (both spatially and temporally) and the model cannot usually be certain that a flood event will happen. Yet, we can adjust the classification threshold and observe its effect on the false positives and false negatives. In Figure 1, we show the false positive and false negative rates as a function of the threshold. We can see that both rates have most of their variation at low threshold values. Moreover, the false negative rate increases more slowly that the false positive rate decreases, indicating that the model gets very averse to false positives before it starts being overly conservative and predict mostly false negatives.

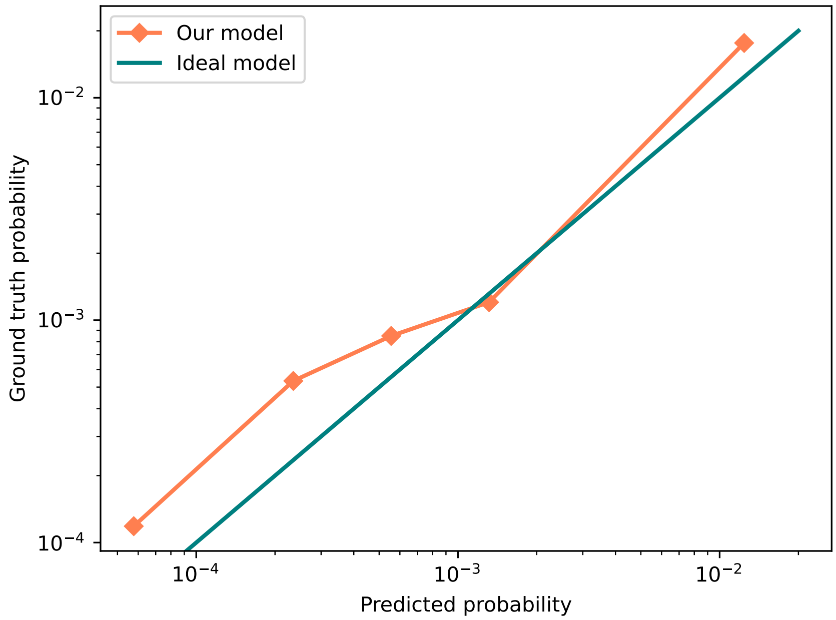


Figure 2: Calibration plot of our model.

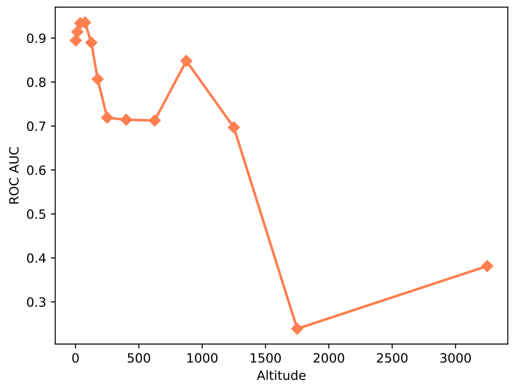
2 Robustness

2.1 Calibration

Explain how you calibrated your model.

We found that it is difficult to get stable training and end up with calibrated probabilities from the whole training images because the label distributions are highly unbalanced. To get better calibrated probabilities, we split the training data into patches that had at least one flood event in the training period (as well as patches close to them) and those that did not, and therefore were very unlikely to see a flood event in the future, most likely because they were far from a major river or body of water. We fed the former as input to our convolutional network trained with the binary cross-entropy loss function, which is known to provide well-calibrated probabilities, at least when the classes are not too unbalanced, since it directly performs maximum likelihood estimation. For the rest of the patches, we assigned a prediction of 0, since it was very likely that almost all of them would not be subject to flooding in the future.

We report in Figure 2 a calibration plot of our model obtained by creating bins of similar prediction probabilities in the data. We can see that the model is well calibrated, as the predicted probabilities in each bin closely match the ground truth probabilities.



(a) AUC by altitude

(b) AUC by watershed

Figure 3: Performance of our model across different geographical features.

2.2 Validity Domain

Analyse the validity of your model on the provided data and give recommendations on how the model should be used (strength and limitations) for the prediction of floods

Overall, the model has a good performance profile across classification thresholds, and its ability to avoid false positives (see Section 1.2) means that a practitioner has the flexibility to set the desired level of false negative rate without creating too many false alarms. However, the 0 probabilities obtained on the patches we discarded from the training data do not indicate that a flood is completely impossible. Ideally, the training period should be extended and/or the choice of patches should be refined thanks to domain knowledge, especially about the occurrence of extremely rare flood events.

To further understand how the model behaves depending on where it is applied, we plot in Figure 3 the AUC values at different altitudes (Figure 3a) and for different watersheds (Figure 3b). The performance decreases significantly at higher altitudes, indicating that the model is probably not adapted to forecasting floods in mountainous areas. It is also likely that floods are simply more difficult to predict in the mountains, as they are often more sudden than in the valleys. Interestingly, the performance also varies from basin to basin. The model performs best in the Seine basin and struggles the most in the Somme basin. This result is quite surprising, especially since this area is largely flat and the poor performance cannot be explained by the higher altitudes in this region.

3 Frugality

Explain how you minimized the computational footprint of your solution

Our filtering of training patches drastically reduces the amount of computations needed to train the model. Moreover, we prioritized when possible smaller networks that can yield strong results when tuned correctly but don't require as much computations for both training and inference.

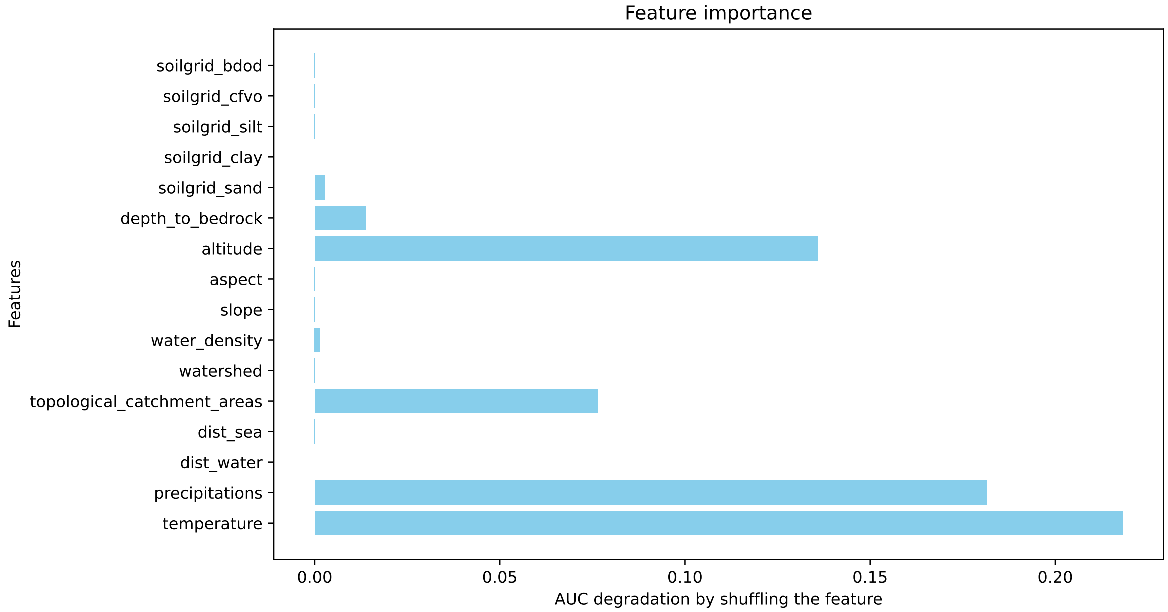


Figure 4: Permutation feature importance of our model.

4 Explainability

What features are important for your model and how do they influence predictions? Using explainability: evaluate the coherence of your model with your understanding of flooding mechanisms. Can you provide insights on flooding patterns and causes that could be useful for the user?

We performed a permutation importance analysis of our features, i.e., for each feature, we randomly shuffle the patches corresponding to the feature of interest and recompute the ROC AUC. The degradation in performance represents the importance of the feature. In Figure 4, we can see that spatio-temporal features (precipitation and temperature) are the most important among all features. This is an interesting result because it shows that our model is able to distinguish between flood and non-flood conditions in the same area depending on the weather. Among the geospatial features, the altitude and the topological catchment area have the greatest impact on the AUC.

Note that a feature with no reported importance may be an indicator of flooding, but either our model was not able to extract the relevant information from this feature, or the information it was able to extract is redundant with the information extracted from another feature. For example, it is likely that our model does not use the watershed data to make its prediction because the topological watershed feature contains the information it uses for the prediction. It is not surprising to us that the most distinctive features are spatio-temporal features, as they are known to have a large effect on flood events and cannot be accurately predicted from geospatial features alone. We were initially more surprised by the importance of altitude compared to other geospatial features, but this is not entirely unexpected since mountainous areas are known to have very specific topographic and climatic patterns and can be subject to large floods in a short period of time.

References

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