Mapping Floodwater Using High-Resolution Satellite Imagery and Machine Learning: Insights from the STAC Overflow Challenge (Short Essay for Writing Demonstration)

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August 20, 2023

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Abstract

Floods, being the most frequently occurring and economically detrimental natural disasters on a global scale, require precise monitoring in order to facilitate efficient response and risk evaluation. This research paper presents a comprehensive analysis of the STAC Overflow: Map Floodwater from Radar Imagery competition, which is a worldwide endeavor that seeks to enhance flood mapping by utilizing machine learning techniques on high-resolution synthetic-aperture radar (SAR) imagery. The utilization of the Sentinel-1 mission's C-band Synthetic Aperture Radar (SAR) data was employed in this challenge, taking advantage of its ability to provide imaging capabilities unaffected by weather conditions and operational during both day and night. The dataset used in the competition was curated by Cloud to Street and Microsoft AI for Earth. It comprised satellite photos from the years 2016 to 2020, enabling the creation and assessment of flood mapping algorithms. The competition received contributions from over 660 individuals globally, resulting in a total of more than 1,400 entries.

Introduction

According to the World Health Organization, floods have had extensive consequences, impacting a population exceeding two billion inhabitants from 1998 to 2017. The intensification of severe weather phenomena as a result of global warming underscores the imperative need for precise flood monitoring. Conventional approaches, which heavily rely on ground-based observations obtained from rain and stream gauges, provide flood information that is limited in spatial coverage and entails significant expenses. The utilization of synthetic-aperture radar (SAR) images, namely the C-band SAR data obtained from the Sentinel-1 mission, has become increasingly significant in the realm of flood detection. The ability of this technology to effectively traverse diverse air barriers confers a significant benefit in the process of mapping floods under difficult circumstances.

The primary focus of the STAC Overflow challenge revolves around the utilization of machine learning techniques for the purpose of detecting floodwater in synthetic aperture radar (SAR) imagery. The dataset consists of Sentinel-1 radar images and their corresponding metadata, providing a valuable chance to develop novel models for classifying floodwater at a pixel level. Radar imagery provides a distinctive vantage point that facilitates the identification of features even in challenging circumstances, including situations including vegetation, cloud cover, and limited illumination.

Challenge Objective

The primary objective of the STAC Overflow competition was to leverage the capabilities of machine learning in order to accurately map floodwater using high-resolution satellite imagery. The competition dataset comprises Sentinel-1 Synthetic Aperture Radar (SAR) pictures obtained from 2016 to 2020. These photos were revised and annotated by Cloud to Street and are now available for access through Microsoft's Planetary Computer. The integration of extensive environmental datasets within the Planetary Computer facilitates the utilization of artificial intelligence by scientists, developers, and policymakers to effectively tackle environmental concerns. The main aim of this study was to create models that could effectively utilize Synthetic Aperture Radar (SAR) imagery in order to improve the accuracy of flood mapping. This improvement would subsequently boost disaster preparedness, risk assessment, and response methods.

Dataset Features

The collection consists of Sentinel-1 radar pictures that are recorded in the form of GeoTIFF files. The presented photos include measurements of dual polarization, specifically VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) [3]. Microwave frequency measurements are of significant importance in enhancing various physical characteristics of a given scene. Each image in the dataset has dimensions of 512×512 [4] pixels and represents the quantification of reflected energy in decibels (dB). These images span a range of both negative and positive values. Pixels that possess a value of 0.0 are indicative of data that is absent or missing. The training dataset comprises 542 chips obtained from 13 flood episodes. Each chip is accompanied by labels in GeoTIFF format, indicating the presence of water, absence of water, or missing data.

Performance Metric

The assessment of model performance relies on the utilization of the Jaccard index, which is alternatively referred to as the Generalized Intersection over Union (IoU). This metric quantifies the resemblance between two sets of labels by evaluating the proportion of overlapping pixels in relation to the combined number of non-missing pixels. The calculation of the Jaccard index is limited to valid input pixels, with missing data being excluded. A greater numerical value signifies enhanced precision. The Jaccard index can be expressed mathematically as follows:

The formula J(A,B) represents the Jaccard similarity coefficient, which is calculated by dividing the cardinality of the intersection of sets A and B by the sum of the cardinalities of sets A and B, minus the cardinality of their intersection.

$J(A, B) = |AB|/|A| + |B| - |AB|$

In this context, the symbol A denotes the collection of pixels that are accurately classified as true, while the symbol B represents the collection of pixels that are anticipated to be true. The computation of the Jaccard index in Python can be readily performed by utilizing the $sklearn.metrics.jaccard_score(y_true, y_pred, average =' binary')$ function provided by the scikit-learn library.

Results and Contributions

The competition witnessed significant participation, with individuals from various regions globally submitting over 1,400 ideas. The evaluation of performance utilized the Intersection over Union (IoU) metric [6], which involved the comparison of predicted picture pixels with the corresponding ground truth pixels. The benchmark solution, which utilized a ResNet-34 [2] encoder and U-Net decoder, attained an Intersection over Union (IoU) value of 0.44. Nevertheless, in a span of seven days, numerous teams managed to exceed this standard, thereby demonstrating the efficacy of synthetic aperture radar (SAR) imaging and machine learning techniques in the field of flood mapping.

The highest-performing models demonstrated Intersection over Union (IoU) scores of 0.80, indicating significant advancements compared to the benchmark. The utilization of the Planetary Computer STAC API in these models facilitated the successful integration of additional elevation data and global surface water data, resulting in an improved comprehension of geographical phenomena. The successful methodologies showcased a fusion of U-Net and U-Net++ [8] convolutional neural networks (CNNs) alongside gradient-boosted decision trees [9, 5, 7]. Furthermore, the researchers also investigated novel methodologies, including adversarial training and picture augmentations, in order to effectively tackle the issue of label imbalances and improve the quality of the training data.

Approaches of Top Participants

The top participants elucidated their methodologies, providing valuable perspectives on their techniques. The employed methodologies included the implementation of U-Net models, classification at the pixel level, mathematical equations for flood detection, and the utilization of ensemble techniques. Significantly, a hybrid approach that integrates pixel-by-pixel categorization and mathematical formulas has exhibited efficacy in accurately detecting and quantifying instances of severe floods. The use of NASADEM [1] elevation data resulted in a notable enhancement of the models' performance.

Conclusion

The STAC Overflow challenge brought attention to the possibilities of machine learning and high-resolution synthetic aperture radar (SAR) imagery in enhancing the precision of flood mapping. The models that demonstrated superior performance exhibited inventive techniques and original strategies, hence providing improved insights into the intricate process of floodwater detection. The use of these technologies carries significant consequences for the field of disaster management and response. They enable the timely and precise mapping of floods, hence enhancing the evaluation of risks and preparedness measures. The models that were created as a result of this competition have been made accessible to the general public, thereby aiding in the continuous endeavors to tackle worldwide flood-related issues.

This short essay covered the results of an online AI competition[1]. Top competitors have experimented with many methods in search of the best result. Readers can get the best result and necessary documents in the DrivenData GitHub[2] repository.

Acknowledgements

The authors would like to express their gratitude to Microsoft AI for Earth and Cloud to Street for their significant contribution in coordinating and enabling the challenge. The successful outcome of this initiative was greatly influenced by the availability of data and infrastructure.

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