Geographic and Socioeconomic Bias in Satellite-Based Flood Detection Datasets: Implications for Equitable Disaster Response

Matthew Landon

IDAI-720: AI Research Methods

Rochester Institute of Technology

ml3275@g.rit.edu

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Abstract

Satellite-based flood detection using machine learning has become critical for rapid disaster response and resource allocation during flooding events. However, current flood detection datasets exhibit significant geographic and socioeconomic bias, with training data predominantly sourced from well-monitored, high-income regions such as the United States, Europe, and East Asia. This concentration of data in affluent regions creates systematic performance disparities when models are deployed in underrepresented areas, many of which face the highest flood vulnerability due to climate change and limited infrastructure. This research proposes an experimental investigation into the extent and impact of geographic bias in flood detection datasets, hypothesizing that models trained on geographically imbalanced data will demonstrate degraded performance in underrepresented regions during actual flood events. Through systematic analysis of existing datasets, evaluation of state-of-the-art models across diverse

geographic contexts, and design of targeted data collection strategies, this work aims to quantify these disparities and propose methodologies for more equitable flood monitoring systems. The outcomes of this research have direct implications for climate justice, as they will inform strategies to ensure AI-powered disaster response systems serve all vulnerable populations effectively, regardless of geographic location or economic status.

1 Introduction

Flooding represents one of the most destructive and frequently occurring natural disasters globally, affecting millions of people annually and causing billions of dollars in economic damage [1]. Climate change is intensifying the frequency, severity, and unpredictability of flood events worldwide, with projections indicating that flood risk will increase substantially in the coming decades, particularly in vulnerable regions across South Asia, Sub-Saharan Africa, and small island developing states [2]. In this context, the development of rapid, accurate flood detection and mapping systems has become critical for effective disaster response, emergency resource allocation, and post-disaster recovery planning.

Satellite remote sensing has emerged as a powerful tool for flood monitoring, offering the ability to rapidly assess large geographic areas that may be inaccessible to ground-based observers during active flooding events [3]. Recent advances in machine learning and computer vision have enabled automated flood detection from satellite imagery, with deep learning models achieving impressive performance in delineating flood extent from synthetic aperture radar (SAR) and optical satellite data [4]. These AI-powered systems promise to accelerate disaster response by providing near-real-time flood maps to emergency managers, humanitarian organizations, and affected communities.

However, the effectiveness of machine learning models is fundamentally dependent on the quality, diversity, and representativeness of their training data [5]. An emerging body of research in fairness and bias in AI systems has demonstrated that geographic and demographic imbalances in training datasets can lead to systematic performance disparities, with models exhibiting reduced accuracy when applied to populations or contexts underrepresented in their training data [6,7]. In the domain of satellite-based Earth observation, these concerns are particularly acute, as data collection, annotation, and validation efforts have historically concentrated in well-resourced regions with established research infrastructure and government monitoring programs.

1.1 Problem Statement

This research investigates the following central question: **Do current satellite-based flood detection datasets exhibit geographic and socioeconomic bias, and does this bias lead to degraded model performance in underrepresented regions during actual flood events?**

Preliminary examination of widely-used flood detection datasets reveals concerning patterns of geographic concentration. The Sen1Floods11 dataset, one of the most comprehensive publicly available datasets for training flood detection models, contains 4,831 image chips covering flood events, yet the geographic distribution of these events is heavily skewed toward North America, Europe, and East Asia [8]. Similarly, the FloodNet dataset, designed for high-resolution flood damage assessment, primarily includes imagery from the United States [9]. The MODIS-based flood products and Copernicus Emergency Management Service flood maps, while more globally distributed, show disproportionate validation and ground-truth collection in high-income countries [10].

This geographic imbalance is particularly troubling because the regions most underrepresented in training data are often those facing the highest flood vulnerability. According to the United Nations Office for Disaster Risk Reduction, approximately 90% of disaster-related deaths occur in low- and middle-income countries, with flooding being a leading cause [11]. Countries in South Asia, Sub-Saharan Africa, and Southeast Asia experience frequent devastating floods but lack the satellite monitoring infrastructure, ground validation networks, and labeled datasets that characterize better-resourced regions.

The hypothesis underlying this research is that machine learning models trained on geographically biased datasets will exhibit performance degradation when applied to flood detection in underrepresented regions. This degradation may manifest as reduced detection accuracy, increased false positive rates, or decreased sensitivity to flood extent in these critical areas. Such disparities would have profound implications for disaster response equity, potentially resulting in delayed emergency response, misallocation of humanitarian resources, and ultimately, preventable loss of life in the communities most vulnerable to climate change impacts.

1.2 Motivation

The motivation for this research stems from both scientific and ethical imperatives. From a scientific perspective, understanding the geographic biases in flood detection datasets is essential for improving model robustness and generalization. Current evaluation practices often rely on test sets drawn from the same geographic distributions as training data, potentially masking significant performance gaps that emerge when models are deployed in novel contexts [7]. By systematically quantifying these biases and their impacts, this research will contribute to the broader understanding of dataset representativeness in Earth observation applications and inform best practices for more robust model development.

From an ethical standpoint, the stakes are considerably higher. Flood detection systems are not academic exercises—they are deployed in life-or-death situations where accurate, timely information directly influences emergency response decisions. When AI systems exhibit geographic performance disparities, they effectively encode and amplify existing global inequalities. Communities in low-income countries, which have contributed least to climate change yet face its most severe impacts, are doubly disadvantaged: first by increased flood risk, and second by AI systems that may be less reliable in their regions due to training data imbalances.

This research is aligned with growing calls for climate justice and equitable AI systems. The benefits of solving this problem are multifaceted:

- **Improved Disaster Response:** More accurate flood detection across all regions will enable faster, more targeted emergency response, potentially saving lives and reducing economic losses in currently underserved areas.

- **Resource Allocation Equity:** Humanitarian organizations and government agencies rely on flood maps to allocate resources. Reducing geographic bias will ensure that all affected populations receive appropriate assistance based on actual need rather than artifacts of model training.

- **Climate Adaptation Planning:** Accurate historical flood mapping across diverse regions is essential for long-term climate adaptation planning, infrastructure investment, and community resilience building.

- **Scientific Advancement:** Addressing geographic bias will improve our fundamental understanding of how to develop robust, generalizable machine learning models for Earth observation, with implications extending beyond flood detection to other environmental monitoring applications.

- **Methodological Innovation:** This research will develop and validate experimental methodologies for detecting and mitigating geographic bias in satellite-based datasets, providing a template for similar investigations across other domains.

Moreover, this research is timely. The rapid advancement of satellite technology, including new constellations offering higher temporal and spatial resolution, creates unprecedented opportunities for global flood monitoring. However, without deliberate attention to geographic representativeness in dataset creation and model development, these technological advances risk perpetuating or even exacerbating existing disparities. By identifying specific gaps and proposing targeted data collection strategies, this research can help guide the Earth observation community toward more equitable system development.

1.3 Research Approach

This research will proceed through several integrated phases of experimental investigation. First, a comprehensive analysis of existing flood detection datasets will quantify geographic distribution, examining the spatial coverage, temporal distribution, and socioeconomic characteristics of regions represented in training data. This analysis will employ geospatial visualization and statistical methods to identify specific underrepresented regions and flood event types.

Second, state-of-the-art flood detection models will be evaluated on carefully constructed test sets that include both well-represented and underrepresented regions. Performance metrics including precision, recall, F1-score, and intersection-over-union will be computed separately for different geographic strata, enabling quantification of performance disparities. This evaluation will utilize publicly available flood event records and satellite imagery to ensure reproducibility.

Third, targeted data collection from underrepresented regions will be proposed and, where feasible, executed. This phase will explore partnerships with regional organizations, government agencies, and citizen science initiatives to gather ground-truth flood extent data that can validate and supplement satellite observations. The experimental design will include protocols for quality assurance, metadata documentation, and ethical data collection practices.

Finally, the research will assess whether incorporating data from underrepresented regions into training sets leads to improved model performance across all geographic contexts. This will test whether more balanced training data can produce models that generalize better globally, or whether region-specific model adaptation strategies are necessary.

Throughout these investigations, particular attention will be paid to the practical constraints of real-world deployment. The research will consider factors such as satellite revisit times, cloud cover patterns, data latency, and ground validation infrastructure that vary systematically across regions and may contribute to performance disparities beyond simple training data imbalances.

1.4 Expected Contributions

This research will contribute to both the scientific understanding of geographic bias in machine learning systems and the practical development of more equitable flood monitoring technologies. Specific expected contributions include:

1. Quantitative characterization of geographic and socioeconomic bias in existing flood detection datasets, providing baseline metrics for the community.

2. Empirical evidence of performance disparities across geographic regions, demonstrating the real-world impact of training data imbalances.

3. Methodological frameworks for detecting and measuring geographic bias in Earth observation datasets, applicable to other environmental monitoring domains.

4. Targeted data collection strategies and partnerships to address identified gaps in underrepresented regions.
5. Recommendations for dataset development, model evaluation, and deployment practices that promote geographic equity in AI-powered disaster response systems.

By addressing these objectives, this research aims to advance both the technical capabilities and ethical foundations of satellite-based flood detection, ensuring that AI technologies serve all vulnerable populations equitably in an era of increasing climate impacts.

References

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