# GeoAI for Stabilization Preparedness - Haiti

Proof-of-Concept (PoC): Leveraging GeoAI and Remote Sensing for stabilization preparedness in Haiti.

**UNDP**
**June 13, 2025**

# Introduction

As part of UNDP's stabilization preparedness in Haiti, a high-resolution 3D drone scan of the broader Port-au-Prince area is being conducted to capture the full extent of damage across urban infrastructure. This effort includes the capital and selects parts of the Croix-des-Bouquets Arrondissement, areas currently impacted by gang activity and security challenges. Unlike traditional aerial imagery, 3D drone scans offer an unprecedented level of spatial detail—capturing the geometry, elevation, and texture of buildings, roads, and public infrastructure. These datasets enable analysts and decision-makers to evaluate structural damage, detect rubble piles, and identify urban obstructions such as barricades with high accuracy. The resulting 3D scan products—point clouds, 3D meshes, digital elevation models (DEMs), and orthomosaics—are critical for planning secure access routes, prioritizing reconstruction efforts, and supporting community-led recovery and stabilization.

To unlock the full potential of this spatial data, UNDP is leveraging Geographic Artificial Intelligence (GeoAI) to automate and enhance the damage assessment process. By training AI models on annotated 3D drone imagery, GeoAI can detect damaged buildings, pinpoint rubble accumulations and barricade locations. This capability significantly accelerates analysis, ensures consistency across large and complex urban areas, and delivers actionable insights to humanitarian and development teams and national authorities.

In a context, such Haiti, where on-the-ground verification is often limited due to security risks, GeoAI offers a scalable and timely solution to guide recovery operations, facilitate the return of public services, and engage communities in shaping a safer, more resilient Port-au-Prince.

In this PoC, UNDP has selected two priority areas—**Morne-à-Tuf** and **Bas Peu de Chose**, in the elevated residential zones north and northwest of downtown Port-au-Prince—for piloting GeoAI-based damage assessment.

This interactive report presents the key findings of the PoC, with the aim of refining the current workflow and scaling the approach to cover the broader Port-au-Prince region.

## What we are proving

UNDP aims to prove the effectiveness of combining GeoAI and 3D Drone scans in achieving the following objectives:

### 1. Precise Detection of Structural Damage

Using GeoAI and Drone Orthoimages to identify the damaged buildings and rubble/debris piles with an overall accuracy not less than 80%.

### 2. Precise Mapping of Road Obstructions

Identify and geolocate debris piles and barricades along roads and access routes, within 3 meters of the road centerlines.

### 3. Engineering-Ready Deliverables

Provide engineering teams with detailed maps and tables (Excel), including locations of damaged buildings and their sizes (the area and height). The aim is to complete datasets delivered in interoperable formats (GIS shapefiles or CAD + Excel) within two - three weeks of data capture.

## Pilot Areas

This proof of concept focused on two pilot areas: **Morne-à-Tuf** and **Bas Peu de Chose**, both located in Port-au-Prince, Haiti. These neighborhoods have recently experienced significant instability and gang-related violence, leading to widespread damage and disruption. The selection of these areas was based on their high vulnerability and need for stabilization support. Drone imagery revealed extensive damaged zones and visible debris, underscoring the urgency of recovery planning and the relevance of applying GeoAI tools in such crisis-affected settings.

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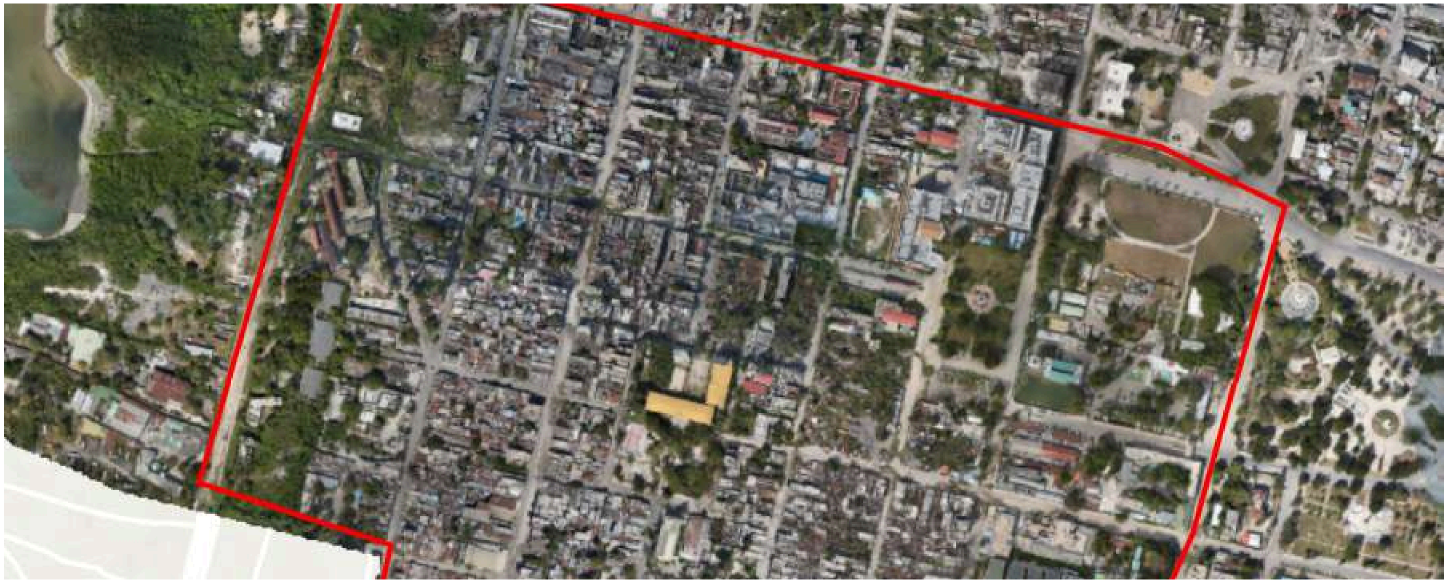
## Pilot Areas

- The two pilot areas, **Morne-à-Tuf** and **Bas Peu de Chose** are hillside quarters within the Port-au-Prince metropolitan area (Ouest Department). Both neighborhoods lie just north and northwest of the city center.



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**Morne-à-Tuf (0.965 km²)**

- Morne-à-Tuf was directly affected by armed confrontations on 28–29 January, 2025 which triggered displacement and heightened insecurity in this hillside quarter amid escalating gang battles.

- The damaged buildingsand rubble piles can be easily observed from the drone ortho image.

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### Bas Peu de Chose (0.695 km²)

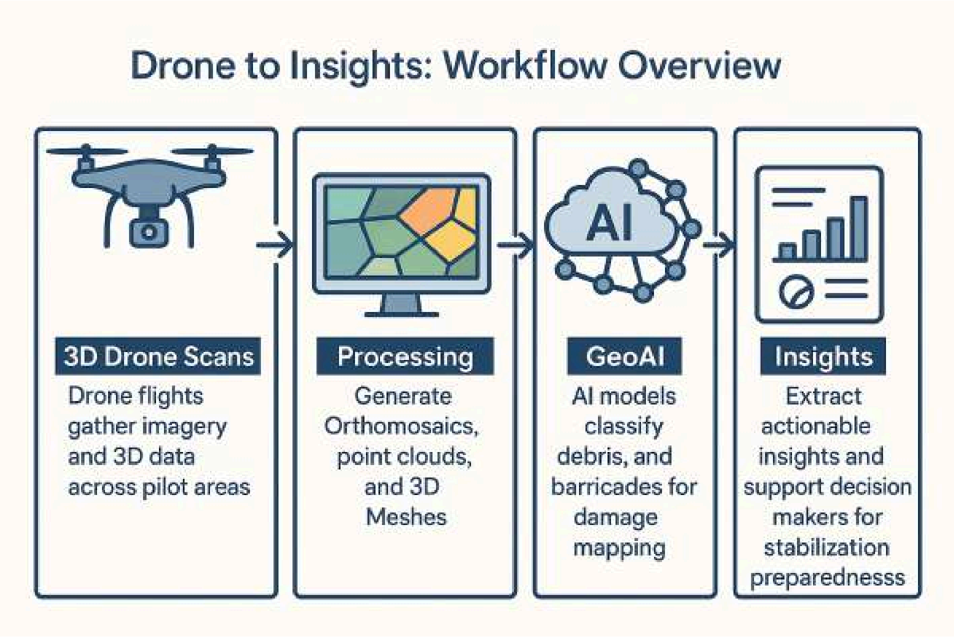
- This area is also reportedly as active zone of urban violence and humanitarian disruption. Intense shootings between 28–29 January, 2025 Bas Peu de Chose and Morne-à-Tuf contributed to a broader wave of urban violence and internal displacement.

- This drone orthoimage, acquired in February 2025, clearly shows an absence of human activity and vehicles, indicating significant internal displacement due to gang violence.

- Source: OCHA Situation Report #13

# Drone to Actionable Insights: Workflow Overview

The general workflow is illustrated below. It begins with drone flights capturing high-resolution imagery and 3D data across the pilot areas. This data is then processed to generate Orthomosaics, Digital Elevation Models (DEMs), 3D meshes and point clouds. Subsequently, GeoAI models are applied to detect damaged buildings, debris piles, and barricades. The final step involves extracting engineering-ready deliverables to support informed decision-making and planning.




Workflow overview (generated by AI)

# 3D Drone Scans and Processing



### A high-resolution 3D scan conducted

It encompasses the entire Port-au-Prince Arrondissement in Haiti. Additionally, the scan covered relevant portions of the Croix-des-Bouquets Arrondissement.

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**The 3D mapping provides crucial insights into:**

- **1. The extent of damage** to infrastructure, such as roads, bridges, and buildings, which can hinder stabilization after security is returned to different areas.
- Rubble concentration, damaged structures, and barricades are other obstacles that may be prioritized.

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Rubble concentration and damaged structures can be identified in many areas of the city.

2. 3D remote sensing also provides insights into **the location and condition of key public facilities**, including schools, hospitals, and administrative buildings that are essential for restoring normalcy and fostering trust, helping the costing and prioritization of future stabilization investments.

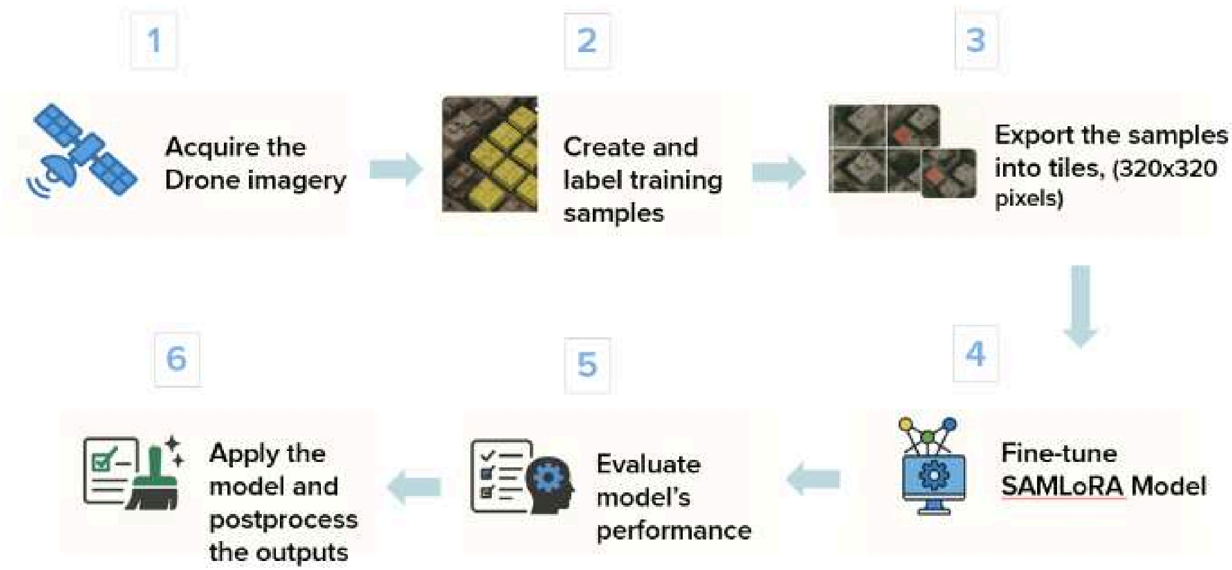
The green markers show the locations of health sites, for which remote sensing can provide early assessment.

3D scanning enables precise estimation of rehabilitation and reconstruction costs.

## GeoAI for Damage and Debris Mapping

The UNDP ITM GIS Team applied the methodology outlined below to develop a GeoAI model for damage assessment in the neighborhoods of Morne-à-Tuf and Bas Peu de Chose. The model segments drone orthoimages into three key classes: **damaged buildings**, **debris**, and **undamaged buildings**.

Using the deep learning framework within ArcGIS Pro—developed by Esri—the team fine-tuned a pretrained model on locally labeled data, enabling precise detection of post-crisis impacts in the dense urban environment in Port-au-Prince.




## General GeoAI methodology

The methodology followed is composed of six steps:

1. Acquire the Drone imagery for the pilot areas
2. Create and label training samples
3. Export the labelled samples into small tiles of size **320x320** pixels
4. Fine-tune the GeoAI model (SAMLoRA model)
5. Evaluate the model performance
6. Apply the model and postprocess the outputs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## 1. Create and label the training samples

- To create well-representative training samples, 22 **training samples** across Port-au-Prince were randomly selected. Within each block, training samples were digitized and labeled.

- In total, 1,342 **polygon samples** were digitized and labelled. Each sample is labelled as one of the following classes:
    - ***Damaged building (1)***: Any building with minor, major, or total damage yet with visible outline (walls can still be observed).
    - ***Debris:*** Any pile (dense or sparse) of rubble, solid waste, damaged vehicles on the roads, in open areas or on the roofs of buildings
    - ***Undamaged Building (3)***: Any building with no visible damage is observed. This class includes old buildings, buildings with rusted roofs, or with debris on roofs.
    - ***Background (0)***: This class is generated automatically by the model, representing any undigitized or unlabeled features, including tress, green areas, roads, intact vehicles, etc.
- **Map legend:**

## Haiti – Training Samples and Sampling Blocks – FL – E08F0621 –2025

### SAM01 training samples

Classvalue

- Damaged Building
- Debris
- Undamaged Building

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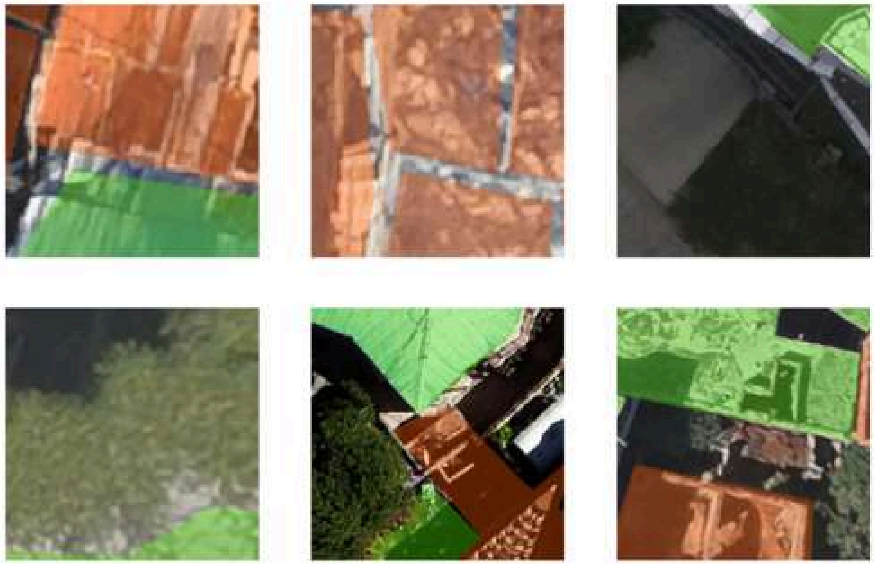
### SAM01 training sampling blocks

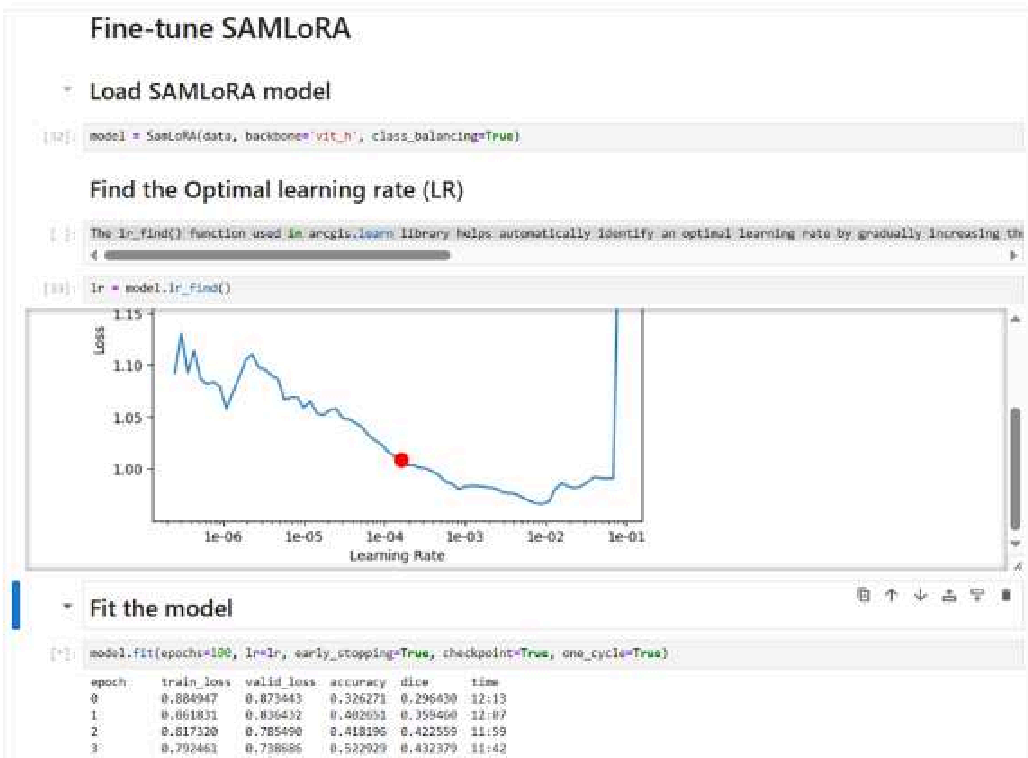


### 2. Export training samples

- The large drone orthoimage was tiled into 320×320-pixels tiles to ensure compatibility with deep learning model input requirements and to fit within GPU memory constraints during training.
- The drone orthoimage and the labeled polygons (representing damaged buildings, debris, and undamaged

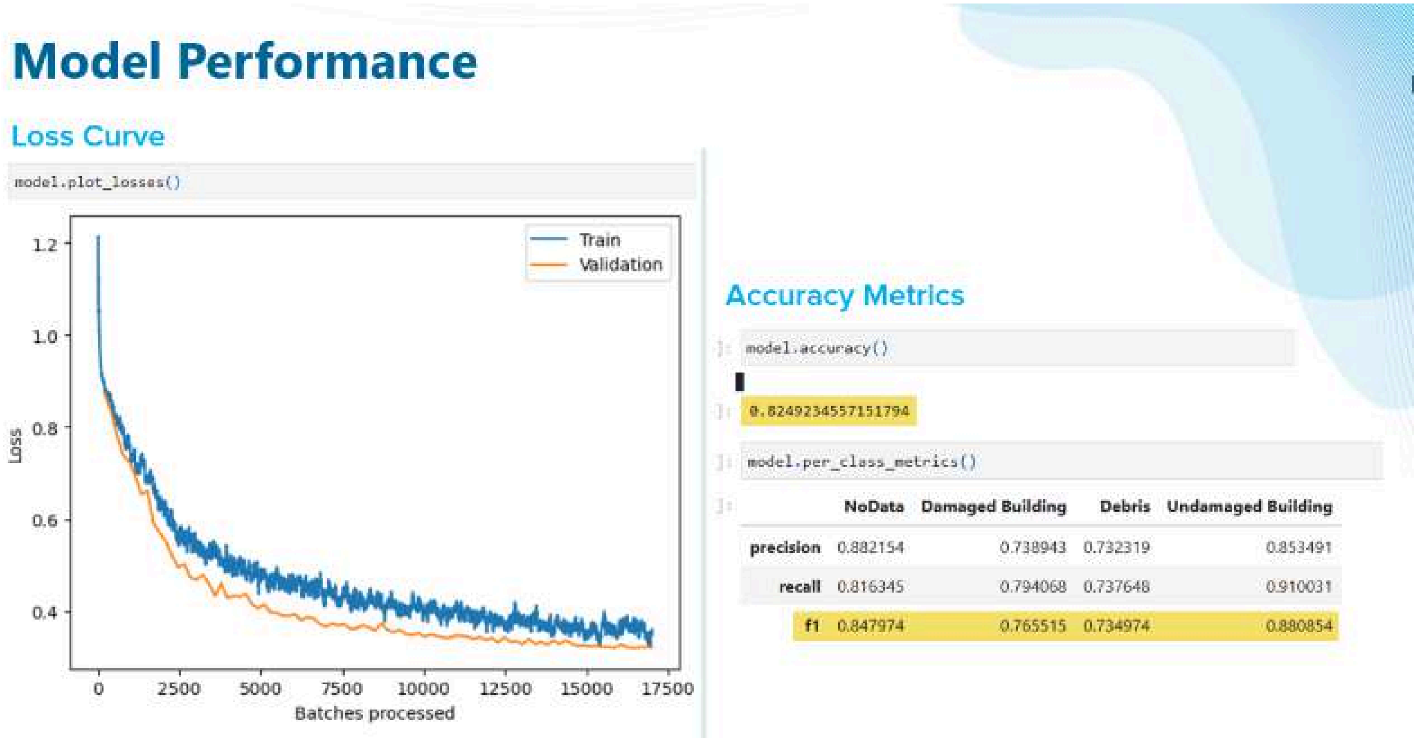
buildings) were converted into corresponding image and mask tiles using these fixed dimensions.

- A total of **1,427** **image and mask tile pairs** were generated using the ***Export Training Data for Deep Learning tool*** in ArcGIS Pro.
- See the stage on the right for an example—mask tiles are overlaid on their corresponding image tiles to visualize how damage features align spatially with the imagery.



## 3. Fine tune the GeoAI model

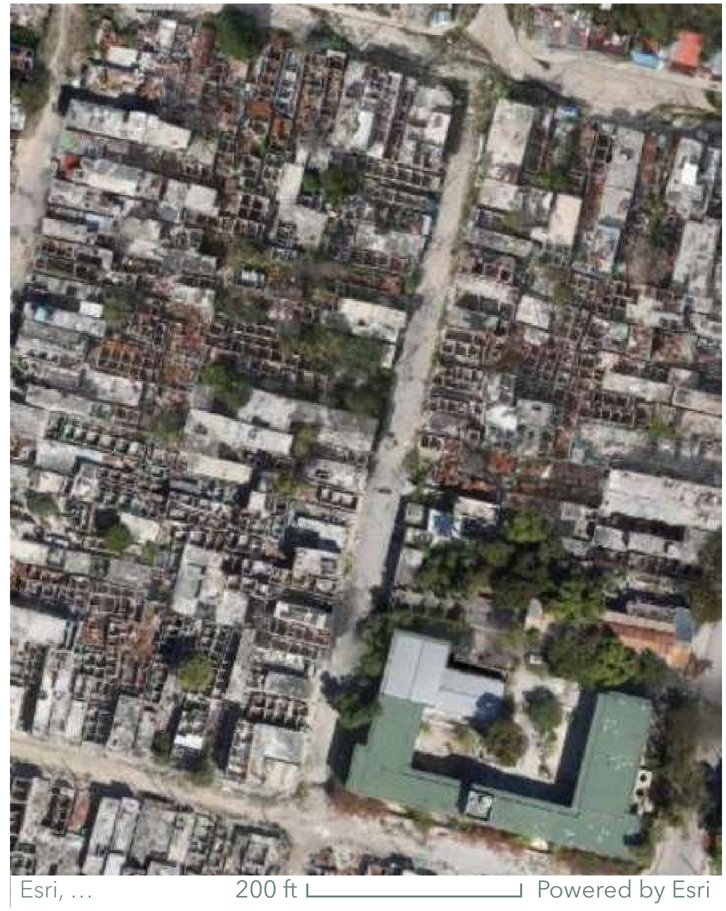
- The exported image and mask tiles were preprocessed and formatted as input datasets for training the deep learning model.
- The ***SAMLoRA*** model was selected for fine-tuning due to its high accuracy and efficiency. It is based on ***Meta's Segment Anything Model (SAM)*** and enhanced with ***LoRA (Low-Rank Adaptation)*** to enable faster and resource-efficient fine-tuning.
- The learning rate was optimized using the ***lr_find*** function, and the model was trained for up to **100 epochs** with early stopping enabled. Training concluded at epoch **89**.
- **Jupyter Notebook** was used to fine-tune the SAMLoRA model, enabling an interactive and traceable training process. The screenshot on the right captures the notebook interface during model training.




## 4. Evaluate the model's performance

- The ***loss curves***
- generated during training confirmed that the model was learning effectively and that fine-tuning was proceeding as expected.
- To evaluate the performance of the model, ***20% of the training samples*** were held out as validation samples.

- The model achieved an overall accuracy of ***82.5%***, meaning that it correctly learned to interpret most features in the imagery.
- Performance across key classes was as follows:
  - Damaged buildings: ***76.5%***
  - Debris: ***73.5%***
  - Undamaged buildings: ***88%***
  - Background (roads, open areas, vegetation): ***84.8%***
- These percentages reflect a measure known as the **F1-score**, which balances how **precise** the model's predictions are (avoiding false positives) with how **complete** they are (finding all the correct cases).
- In simple terms, the **F1-score** tells us how well the model performs in detecting each class without missing or mislabeling important features:
  - A *76.5%* ***score for damaged*** buildings means the model correctly identified most damaged structures, while minimizing mistakes.
  - An ***88%*** ***score for undamaged*** buildings means the model was highly reliable in recognizing safe, intact buildings.
  - The *73.5%* ***debris score*** indicates solid performance, despite the variability and complexity of scattered rubble.
- These results show that the model is a robust and trustworthy tool for supporting rapid, large-scale damage assessments in complex urban settings in Haiti.


## 5. Apply the model and Postprocess the output layer

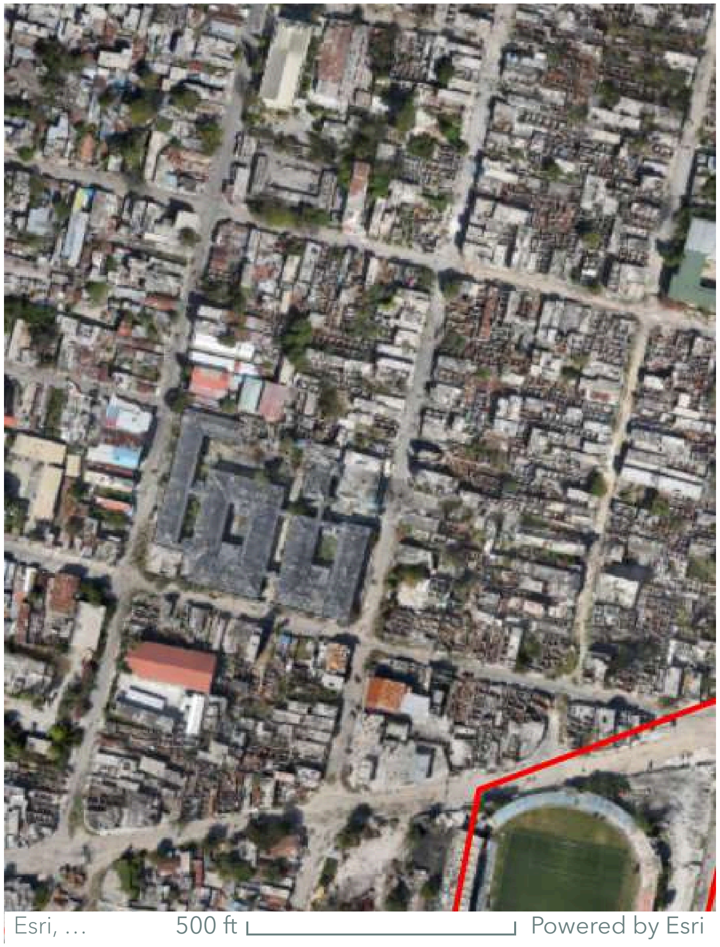
- The SAMLoRA model was applied to two pilot areas in Haiti —**Morne-à-Tuf** and **Bas Peu de Chose**—using high-resolution drone imagery to automatically classify damaged buildings, debris, and undamaged structures. The model generated pixel-level segmentation maps for each class across the urban landscape.

- False positives—cases where the model incorrectly flagged undamaged structures as damaged—were present but limited. These errors are expected in AI-based classification and were concentrated in areas with shadows, occlusions, or partial roof collapses.
- Post-processing steps were applied to refine the output. The classified damage layer was spatially aligned and overlaid with **Google's building footprint dataset** to associate each prediction with a known building structure, improving interpretability and readiness for field validation.

## First Actionable Insights for Stabilization

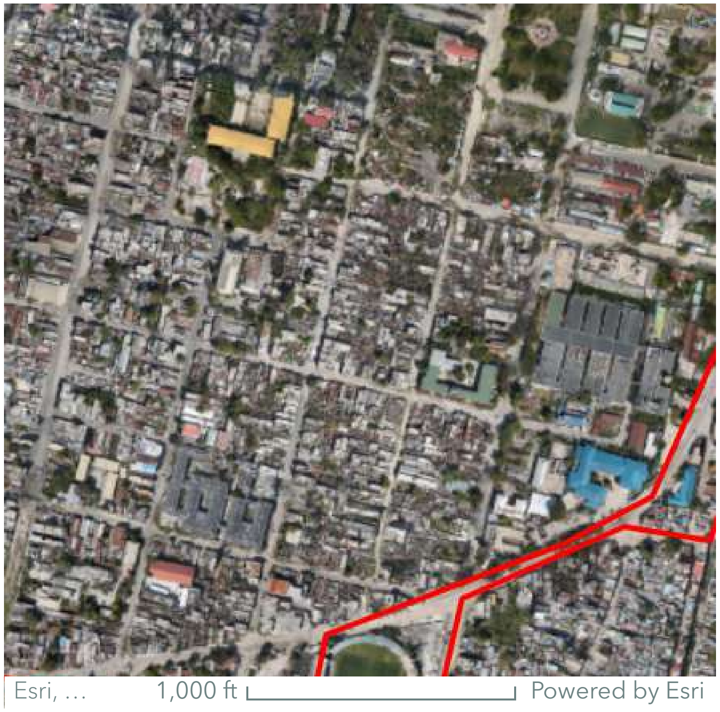
After segmenting the drone imagery into damaged, debris, and undamaged areas, the next step is to transform these outputs into actionable insights to support decision-makers and engineers in planning their early recovery programmes. This PoC enables the generation of four key products:

1. A layer representing damaged and undamaged areas (not individual buildings).
2. A layer delineating damaged and undamaged buildings.
3. A layer identifying the locations of barricades.
4. A layer highlighting vehicles detected using an ESRI pre-trained model.


## 1. Damaged and Undamaged areas

The first layer—damaged and undamaged areas—was extracted directly from the GeoAI output, retaining only the two relevant classes: damaged and undamaged.


## 2. Classified Individual Buildings

The second layer, representing individual buildings classified as damaged or undamaged, was created by overlaying the first layer with Google Building Footprints and assigning each building a corresponding damage status.



## 3. Barricades detected

The third layer, identifying barricades, was derived by selecting debris segments from the main GeoAI output that lie within a 3-meter buffer of road centerlines, assuming proximity to roads as an indicator of potential obstruction.

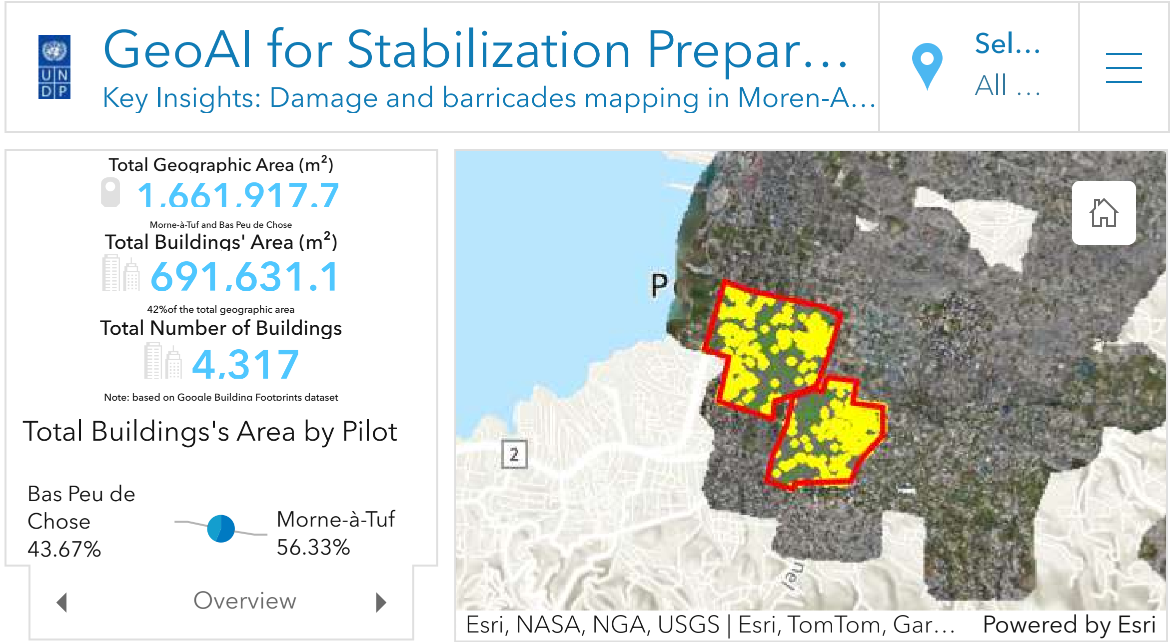


## 4. Vehicles detected

The fourth layer was generated by applying an ESRI pre-trained vehicle detection model, originally trained on datasets from the USA, to the two pilot areas. Although the results have not yet been validated against an independent test dataset, visual inspection indicates that the model effectively detected the majority of vehicles within the pilot areas.

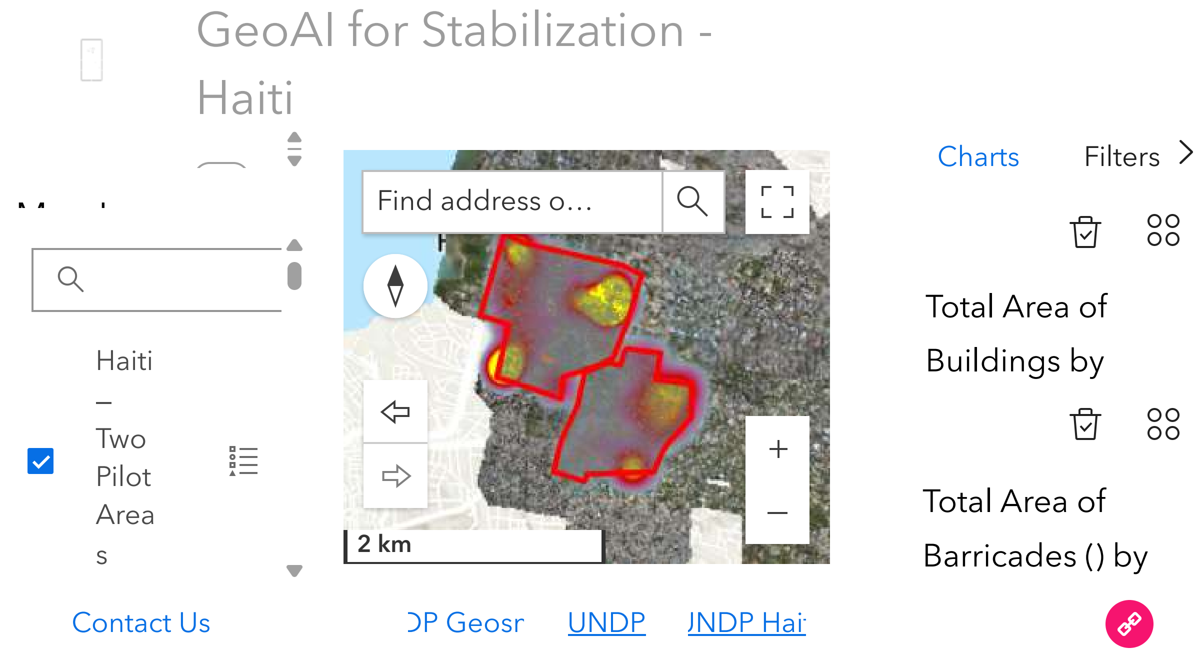
## Key Insights

This dashboard presents the key insights extracted by GeoAI for supporting the decision makers.




To integrate all these products into a unified, user-friendly GIS application, an interactive interface was developed using ESRI Experience Builder. This application presents all layers in an engaging and intuitive format, allowing decision-makers to explore the outputs seamlessly and derive insights efficiently.

You can open the application in a separate window by clicking this link.




## Learning for Scaling Up

Several important lessons were identified during the implementation of this proof of concept that can inform scaling up to larger areas or different contexts:

1. **Use of Multimodal Data**: This proof of concept used only 2D drone orthophotos to map damage and barricades. For more accurate and comprehensive results, future scaling efforts should explore building multimodal GeoAI models that incorporate additional products such as 3D point clouds, 3D meshes, DSMs, and DTMs.
2. **Image Management**: Initially, drone images were provided as separate scenes based on aerial block planning. It was

found that creating a single mosaic image for the entire area greatly reduces processing complexity and improves efficiency. ESRI recommends creating image mosaics for this purpose, and this can be set as a technical requirement for drone image providers.

3. **Training Data Quality**: The accuracy of a GeoAI model is heavily dependent on the quality and representativeness of its training data. When planning future projects, careful attention must be given to collecting diverse, well-distributed, and precisely digitized training samples. A standardized guideline should be prepared in advance to ensure consistency among team members collecting and labeling data.
4. **Model Selection and Fine-Tuning**: It is highly recommended to test and fine-tune multiple models, especially those previously trained on similar contexts. This often leads to more accurate outcomes and reduces the number of required training samples.
5. **Aligning Models with Decision Goals**: It is crucial to remain focused on the end-use of GeoAI outputs. In this case, the goal was to determine the location and status of each building, along with the exact locations and dimensions of barricades. Two general approaches can be followed:
   - Use a semantic segmentation model, then overlay the results with public building footprint datasets to classify each building.

- Use an instance segmentation model that simultaneously segments and classifies individual building objects.

For this project, the first approach was used, leveraging the SAMLoRA model due to its strong performance even with limited training data. However, challenges arose due to misalignment and incompleteness of publicly available building footprints, which led to missed detections. For scaling up, one option is to fine-tune a building footprint extraction model directly on drone orthophotos to address these limitations and shift toward full instance-level segmentation.

6. **Data Validation and Automation**: For large-scale applications, consider developing automated workflows for post-processing, validation, and integration with auxiliary data (e.g., road networks, administrative boundaries, population data) to support broader impact assessments and crisis planning.

By applying these lessons, future implementations can achieve higher accuracy, greater scalability, and better alignment with decision-making needs in humanitarian and stabilization contexts.

## What's Next

The next step is to scale the model to cover the entire city of Port-au-Prince, while simultaneously improving its performance based on the lessons learned from this proof of concept. A key focus will be placed on preparing very high-quality training samples—ensuring they are diverse, representative, and precisely labeled.

In parallel, two models will be fine-tuned: one dedicated to damage mapping and another to extracting building footprints. This dual-model approach will ensure the availability of complete and accurate building footprint data, which is essential for detailed reporting, urban planning, and supporting decision-making at the level of individual buildings and households.

Additionally, integrating height information by extracting building elevations and estimating the number of floors using 3D data sources (e.g., LiDAR, DEMs, DSMs) will enhance the quality of analysis. Estimating the volume and height of debris using DTM-DSM differentials is also a planned improvement.

Future work will also explore the use of advanced foundational models capable of fusing multimodal inputs from 3D drone scans. This continuous process of learning and innovation is a critical component of successful scaling, ensuring that the GeoAI solution remains at the forefront of technological and operational relevance in complex humanitarian settings.

Equally important is to measure the extent to which this proof of concept has supported engineers and decision-makers in their on-the-ground activities. Gathering feedback on how the outputs were used—and identifying any gaps or additional insight needs—will be essential for refining future implementations. These needs should be carefully integrated into the design of the next phases to ensure that scaled-up solutions are fully aligned with real-world requirements and priorities.

**3D Drone Scans & GeoAI** UNDP