Cartography M.Sc.

Investigate Geographical Generalizability of GeoAI Methods for OpenStreetMap Missing Building Detection

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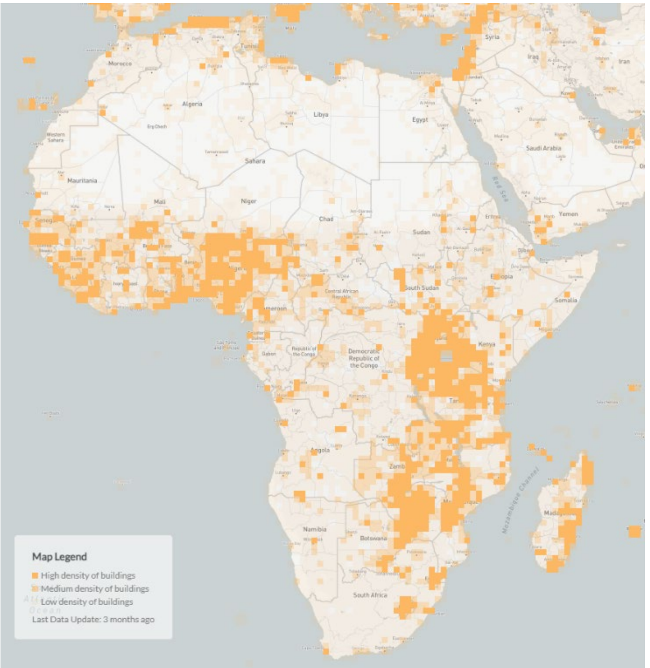
Outline

- Introduction
- Methodology
- Experiments and Results
- Discussion
- Conclusion

Introduction - *Motivation*

- Humanitarian Mapping in OpenStreetMap
  - Open source
  - Crowdsourced geospatial data

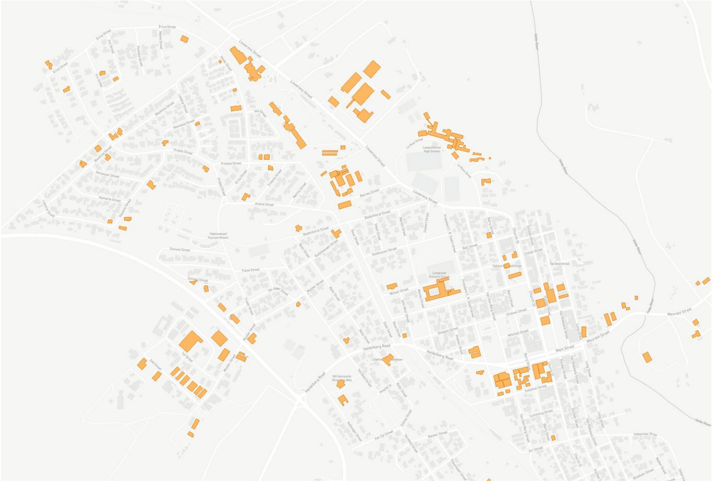


Density Map of OSM Buildings (https://osm-analytics.org/#/)

Zoom In

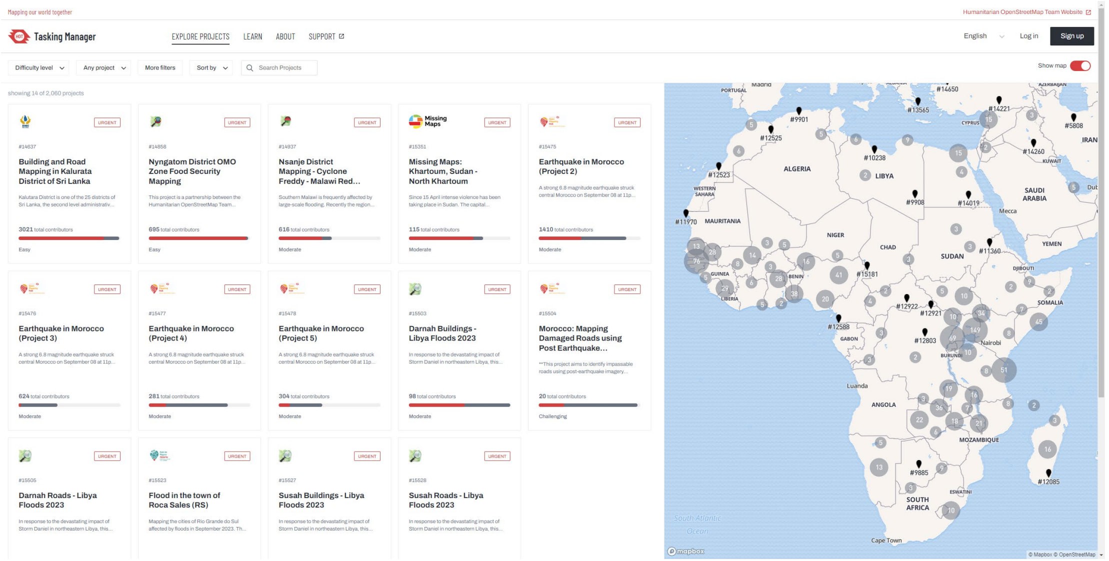
Where are missing buildings?

Bing Aerial Imagery



Introduction - *Motivation*

- Mapping Tools in OpenStreetMap
  - Volunteers mapping: time- and human-resource- consuming
  - AI-assisted mapping: lack of reliability and generalization capability

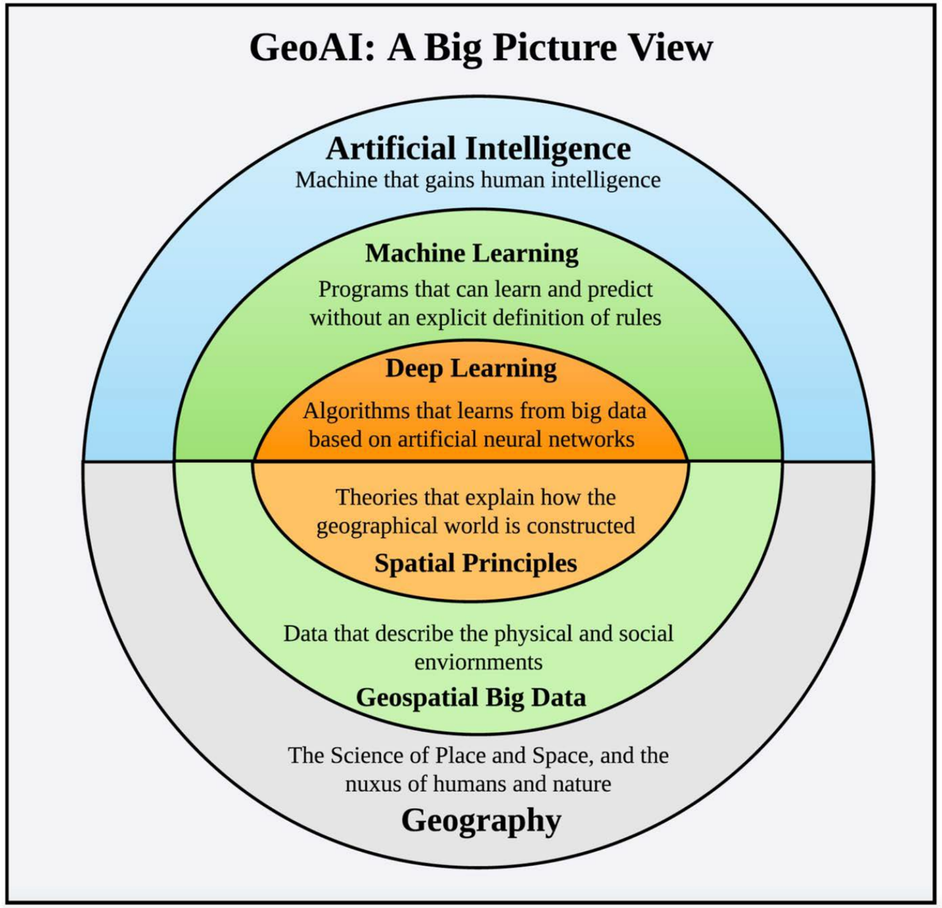


HOT Tasking Manager (https://tasks.hotosm.org/explore)

Rapid Editor (https://rapideditor.org/)

Introduction - *Motivation*

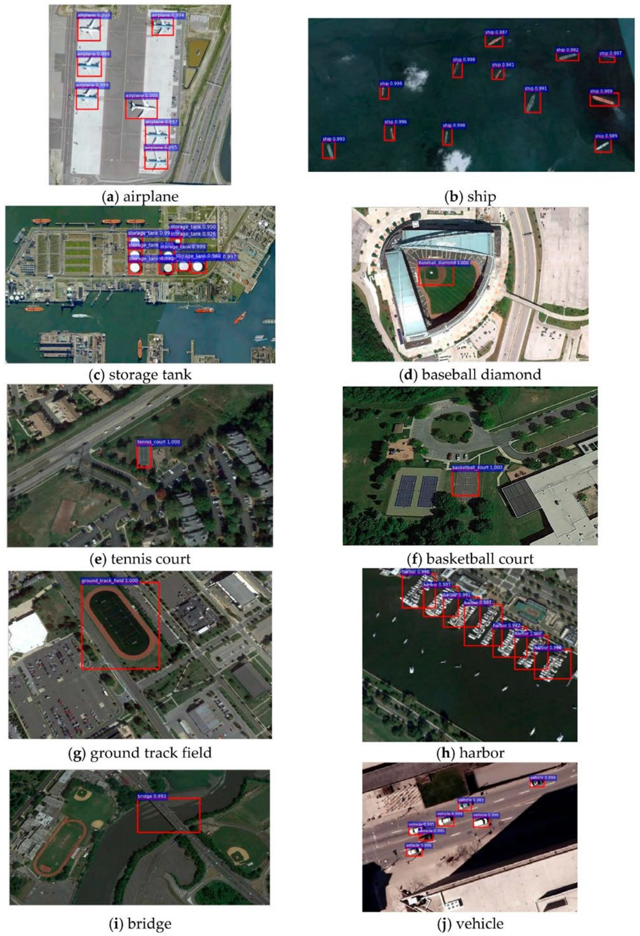
- Geospatial Artificial Intelligence
  - "Geospatial artificial intelligence (GeoAI) is the **application** of artificial intelligence (**AI**) fused with **geospatial data, science, and technology** to accelerate real-world understanding of business opportunities, environmental impacts, and operational risks." (ESRI)
  - "we define GeoAI as a new transdisciplinary research area that exploits and develops **AI** for location-based analytics using **geospatial (big) data**." (W. Li & Hsu, 2022)



GeoAI (W. Li & Hsu, 2022)

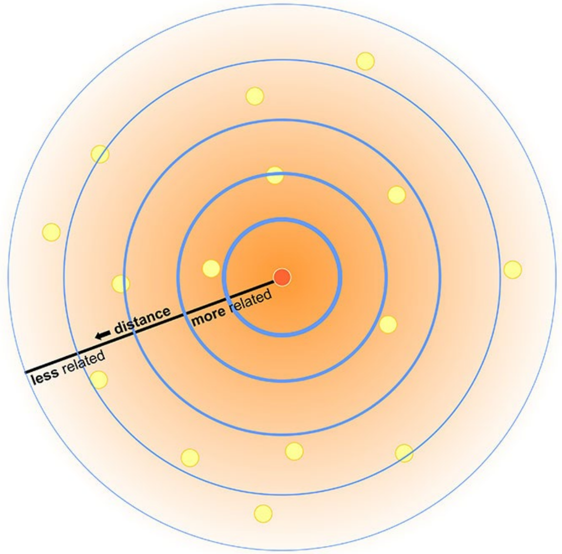
Introduction - *Motivation*

- Geospatial Object Detection



Geospatial detection examples (X.Han et al., 2017).

- Challenge: Spatial Heterogeneity and Geographic Generalizability

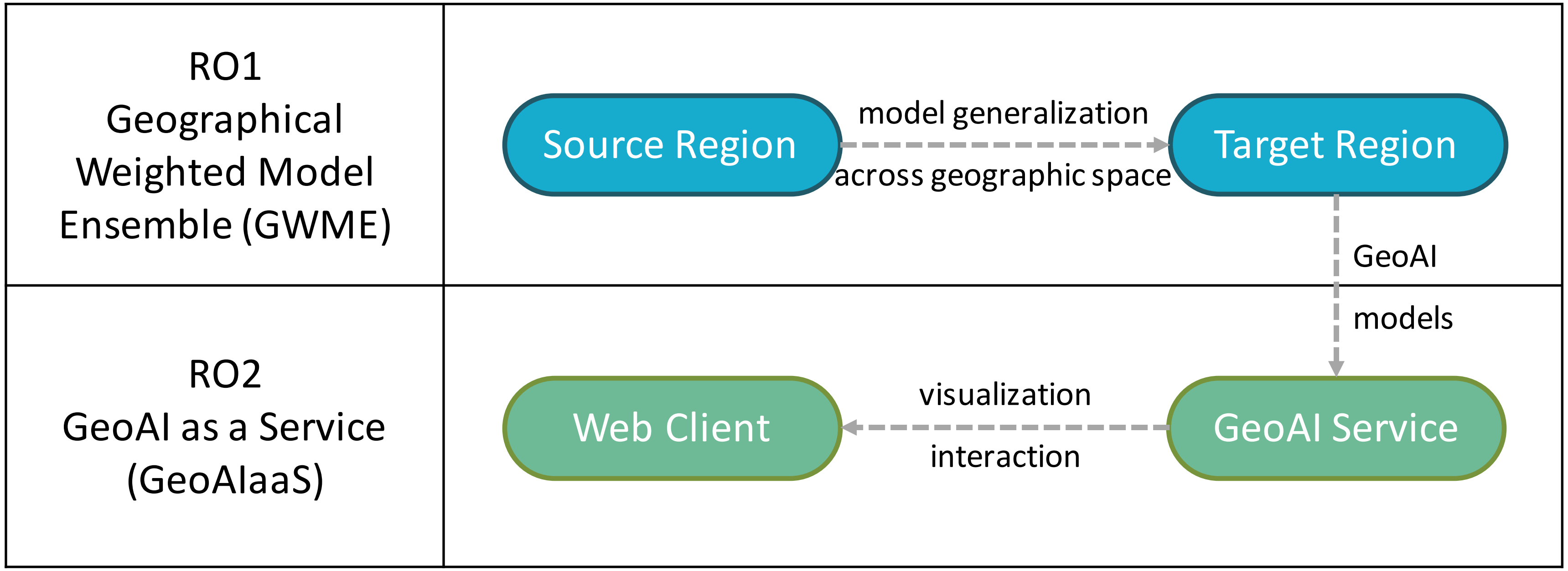


A graphic illustration of Tobler's first law of geography (Anthony C. Robinson, n.d.).

Herein, the generalization capability of a GeoAI model to **be reused or replicated across spatial space** is called **geographic generalizability** (Mai, Huang, et al., 2023), or **replicability across space** (M. F. Goodchild & Li, 2021).

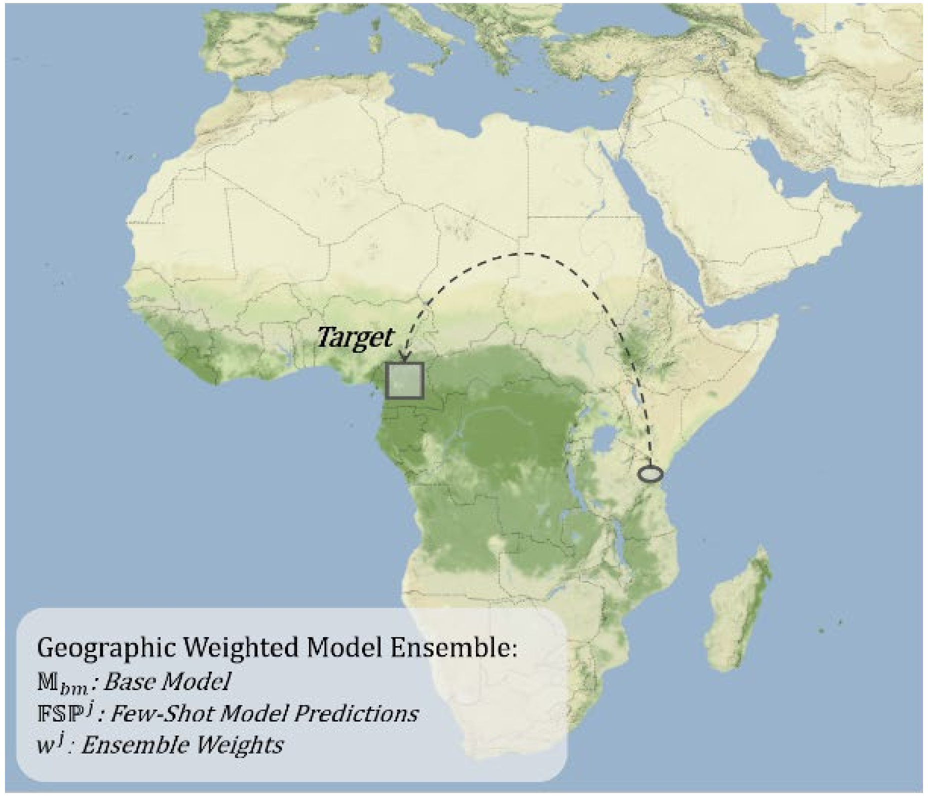
Introduction - *Research Objectives*

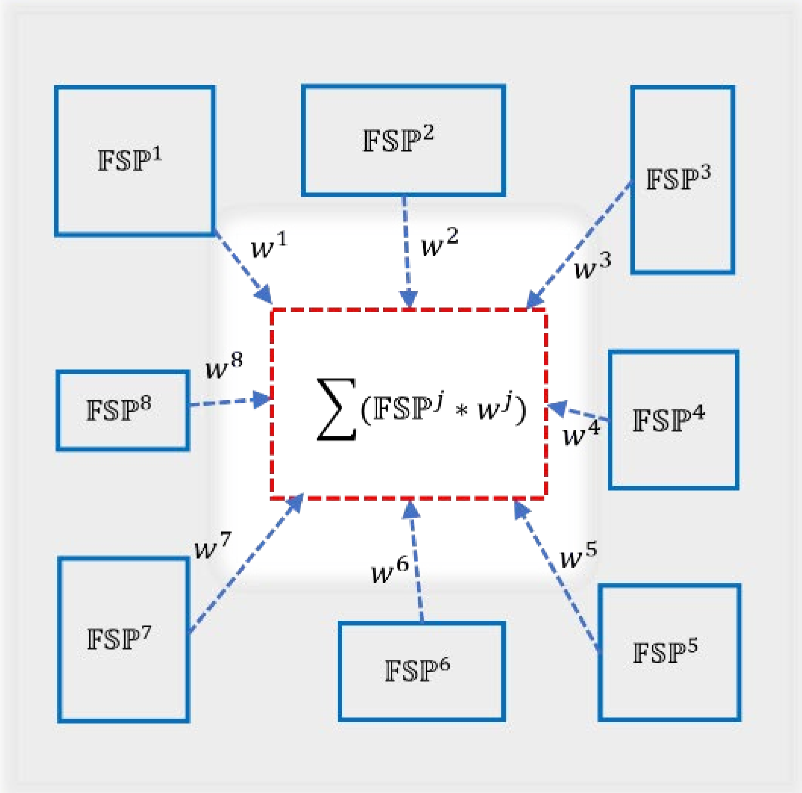
- Research Objectives
  - RO1: To implement Geospatial Artificial Intelligence (GeoAI) methods, which can be well-generalized for OpenStreetMap missing buildings detection across geographical space.
  - RO2: Design a GeoAI application to efficiently manage, evaluate, and visualize machine-generated geographic contents.



Methodology - *GWME*

- Geographical Weighted Model Ensemble (GWME)





GWME

Methodology - *GWME*

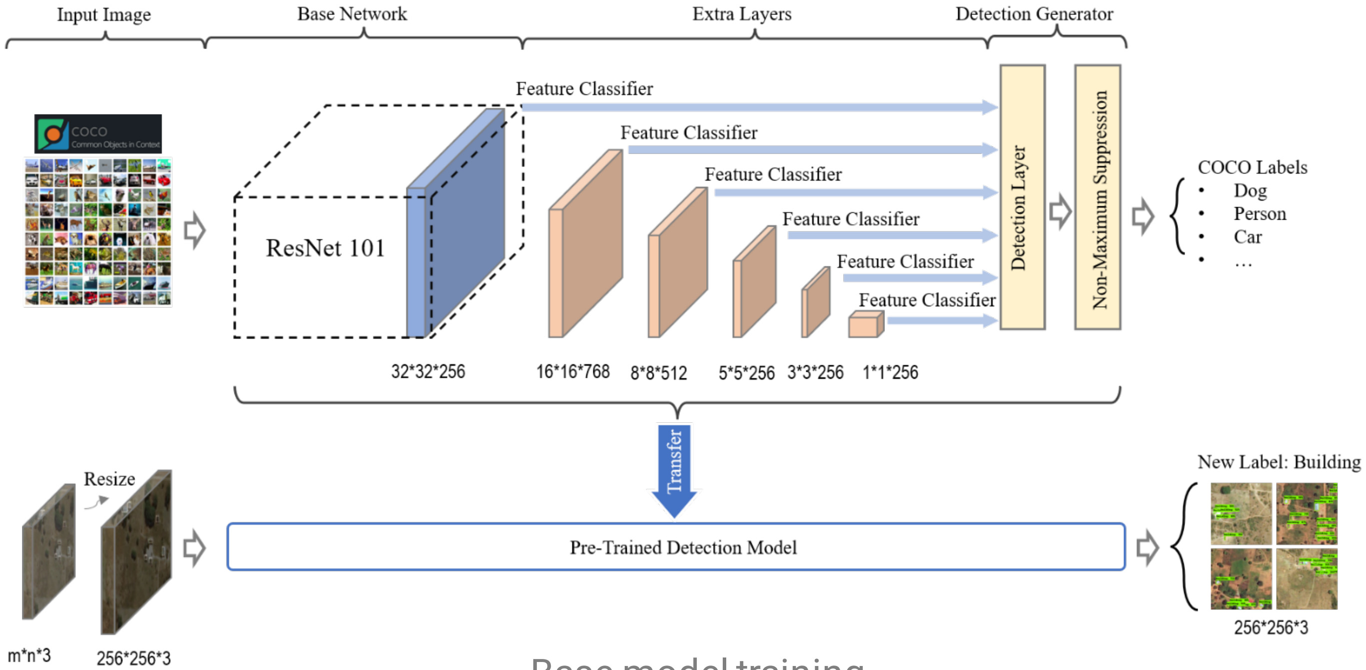
- Data Preparation: ohsome2label tool
  - For base model training: 1744 samples
  - For Few-shot transfer learning: 5 – 10 samples
- Base Model Training: TensorFlow Object Detection API 2
  - Single Shot Detector (SSD): pre-trained with Microsoft COCO dataset

ohsome2label

Bing Maps

OSM

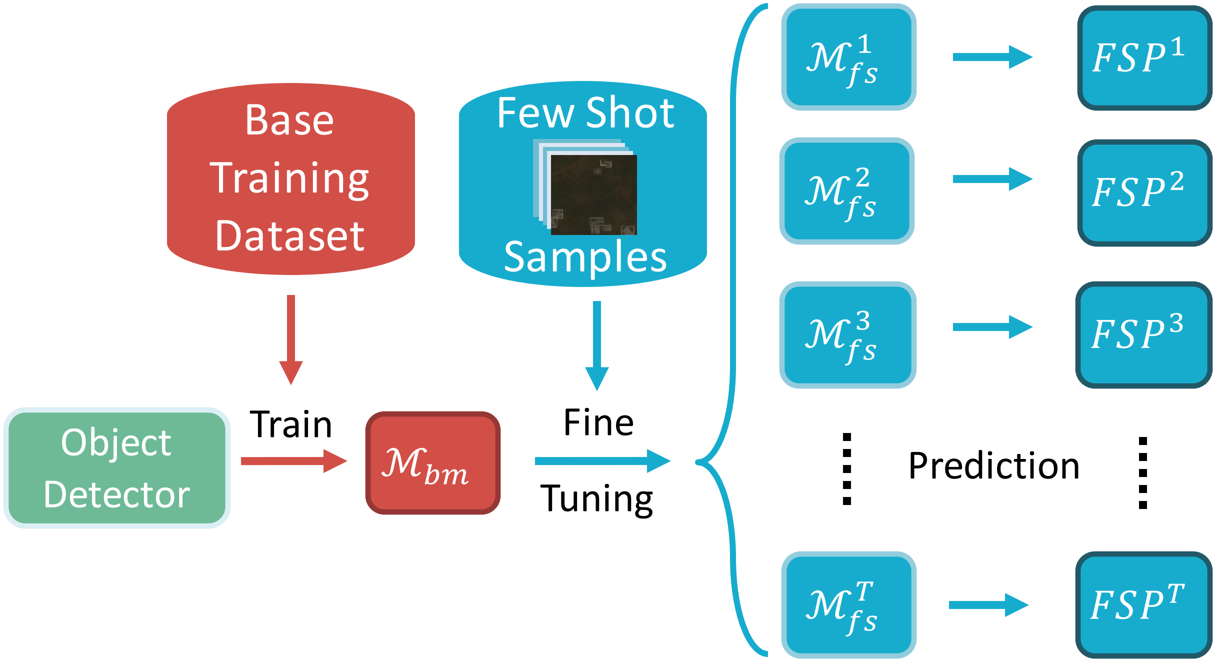
Training samples made by ohsome2label



Base model training

Methodology - *GWME*

- Multiple Few-Shot Transfer Learning (FSTL)
  - Use limited training samples to improve performance of GeoAI models.



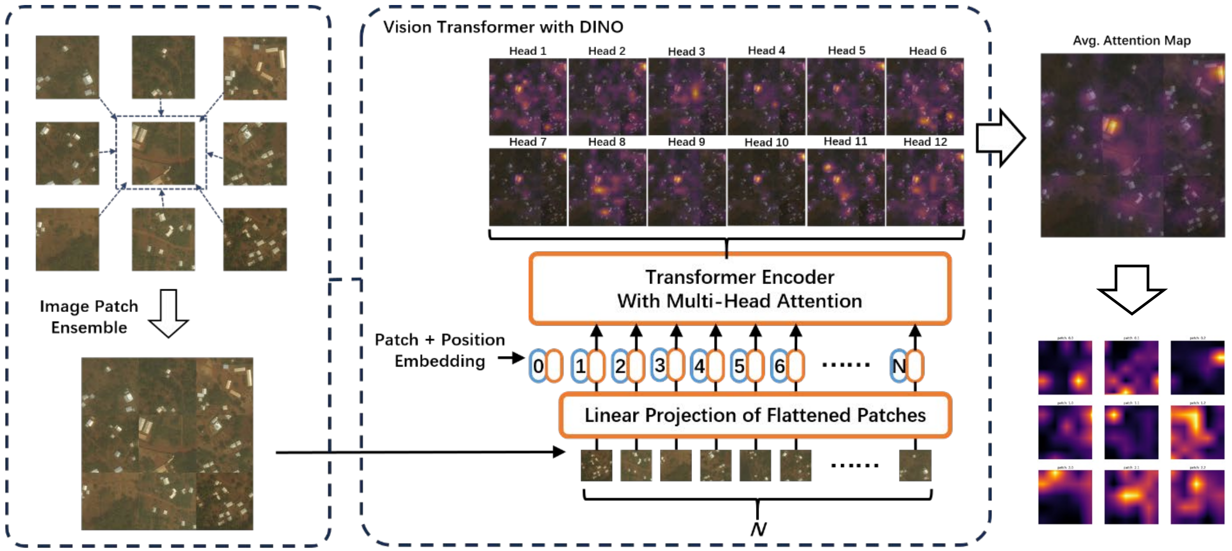
Multiple FSTL Training Workflow

Algorithm 1 Multiple Few-Shot Transfer Learning and Predictions

```
Input:
M_bm: the base model;
T: number of reference areas neighbouring the test area;
S^j_fs = {(x^j_i, y^j_i, g^j_i)} (i = 1,...,n, j = 1,...,T): FSTL samples from reference areas;
M^j_fs ← {}: few-shot models fine-tuned on reference areas;
S_target = {(x_i, g_i)} (i = 1,...,M): dataset from the test area;
FSP^j, j = 1,...,T ← []: predictions from single FSTL models;
for dataset S^j_fs of each reference area A_j in {S^j_fs}^T_{j=1} do
    few-shot model M^j_fs ← F(S^j_fs, θ);
    for each (x_i, g_i) in S_target = {(x_i, g_i)}^M_{i=1} do
        update FSP^j_i ← P(M^j_fs, (x_i, g_i));
    end for
end for
Output:
{FSP^j}^T_{j=1}: list of objects and scores predicted from reference few-shot models;
```

Methodology - *GWME*

- GWME Self-Attention Weighting
  - Image correlation
  - Relative location correlation



Attention Weighting

Algorithm 2 Geographical Weighted Model Ensemble (GWME)

Input:
$\mathbf{M}_{ViT}$: the pre-trained ViT model;
$\mathbb{S}^j_{fs} = \{(\mathbf{x}^j_i, \mathbf{y}^j_i, \mathbf{g}^j_i)\}$ with $i = 1, \ldots, n$ and $j = 1, \ldots, T$: FSTL training samples from reference areas;
$\mathbb{S}_{target} = \{(\mathbf{x}_i, \mathbf{g}_i)\}$ with $i = 1, \ldots, M$: test dataset from the target area;
$\mathbb{FSP}^j, j = 1, \ldots, T$: list of objects and scores predicted from different detection models;
TH: threshold of prediction score
$\mathbb{P}$: ensembled objects and scores;
Mode: weighting mode;
$\mathbf{w}^j$: corresponding weights for $\mathbb{M}^j_{fs}$.
Weights $\mathcal{W} \leftarrow []$;
for each $(\mathbf{x}_i, \mathbf{g}_i)$ in $\mathbb{S}_{target} = \{(\mathbf{x}_i, \mathbf{g}_i)\}^M_{i=1}$ **do**
  for dataset $\mathbb{S}^j_{fs}$ of each reference area A_j in $\{\mathbb{S}^j_{fs}\}^T_{j=1}$ **do**
    if Mode == "average" **then**
      average weights $\mathbf{w}^j_i = 1$;
    else if Mode == "similarity" **then**
      $\mathbf{w}^j_i = \frac{1}{n}\sum_{(\mathbf{x}^j_i, \mathbf{y}^j_i, \mathbf{g}^j_i) \in \mathbb{S}^j_{fs}} COS(HIS(\mathbf{x}^j_i), HIS(\mathbf{x}^j))$;
    else if Mode == "distance" **then**
      $\mathbf{w}^j_i = DIS(\mathbf{g}_i, CEN(\mathbb{S}^j_{fs}))$;
    else if Mode == "attention" **then**
      image patches **patch_list**[] $\leftarrow \{\mathbf{x}_i, \mathbf{g}_i\} \in \mathbb{S}_{target}$;
      patch_list.*append_patch*$(\{\mathbf{x}^j_i, \mathbf{g}^j_i\}), \{\mathbf{x}^j_i, \mathbf{g}^j_i\} \in \mathbb{S}^j_{fs}$;
      multi_heads_attentions = $\mathbf{M}_{ViT}$(**patch_list**);
      attention_map = *attention*(multi_heads_attentions);
      $\mathbf{w}^j_i = subset$(attention_map);
    end if
    $\mathbf{w}_i \leftarrow \mathbf{w}^j_i$
    prediction candidates $\mathbb{FSP}_i \leftarrow \mathbb{FSP}^j_i$;
  end for
  $\mathcal{W} \leftarrow normalize(\mathbf{w}_i)$;
  update $\mathbb{P}_i = \mathcal{Q}(\mathbb{FSP}_i, \mathbf{w}_i,)$;
end for
Output:
$\mathbb{P}$: ensembled results and scores;

Methodology - *GWME*

- Other Weighting
  - Average Weighting
  - Image Similarity Weighting

$$weight = Avg(Cosine(Histogram(target, reference)))$$

  - Inverse Geographic Distance Weighting

$$weight = InverseDistance(Centroid(target), Centroid(reference))$$

- Weighted Boxes Fusion

Ensemble Function

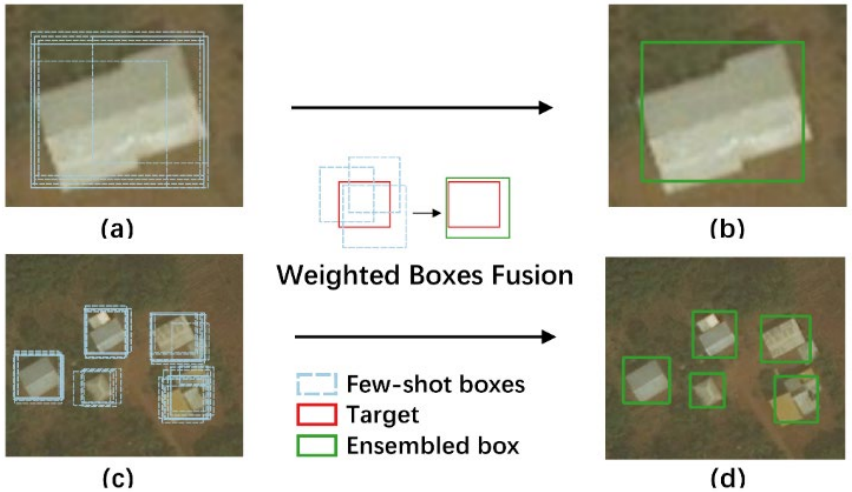
Weights

$$\mathbb{P} = \sum_{j=0}^{T} \mathcal{Q}(\mathbb{FSP}^{j}, \mathbf{w}^{j}, \mathbf{TH})$$

Final prediction

FSTL prediction

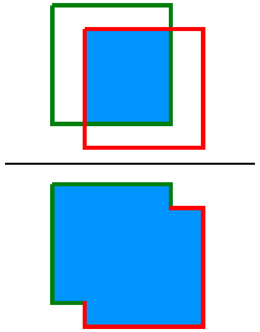
Threshold



Methodology - *GWME*

- Evaluation
  - Intersection Over Union (IOU)
  - True Positive (TP) - A correct prediction with IOU ≥ threshold (0.5).
  - False Positive (FP) - A wrong prediction with IOU ≤ threshold (0.5).
  - False Negative (FN) - A ground truth object is not predicted.
  - True Negative (TN) - A correct false prediction. However, in object detection tasks, there are countless possible bounding boxes that should not be predicted within an image. Thus, TN is not used as a metric here.
  - Precision
  - Recall
  - Accuracy
  - F1 Score

$$IOU = \frac{\text{area of overlap}}{\text{area of union}} =$$



$$Precison = \frac{TP}{TP + FP} = \frac{True\ Positive}{Total\ Positive\ Predctions}$$

$$Recall = \frac{TP}{TP + FN} = \frac{True\ Positive}{Total\ Ground\ Truths}$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} = \frac{Correct\ Predictions}{Total\ Instances}$$

$$F1 = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

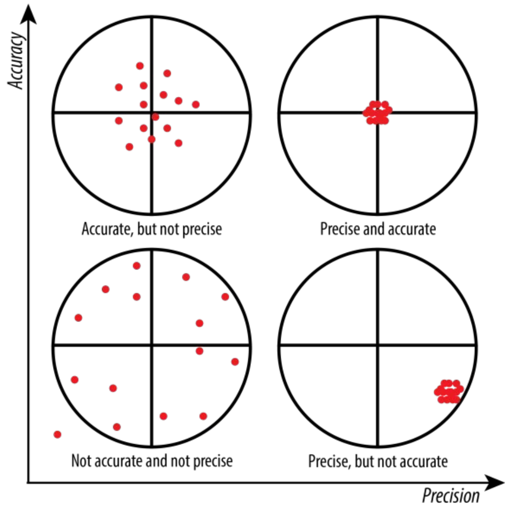
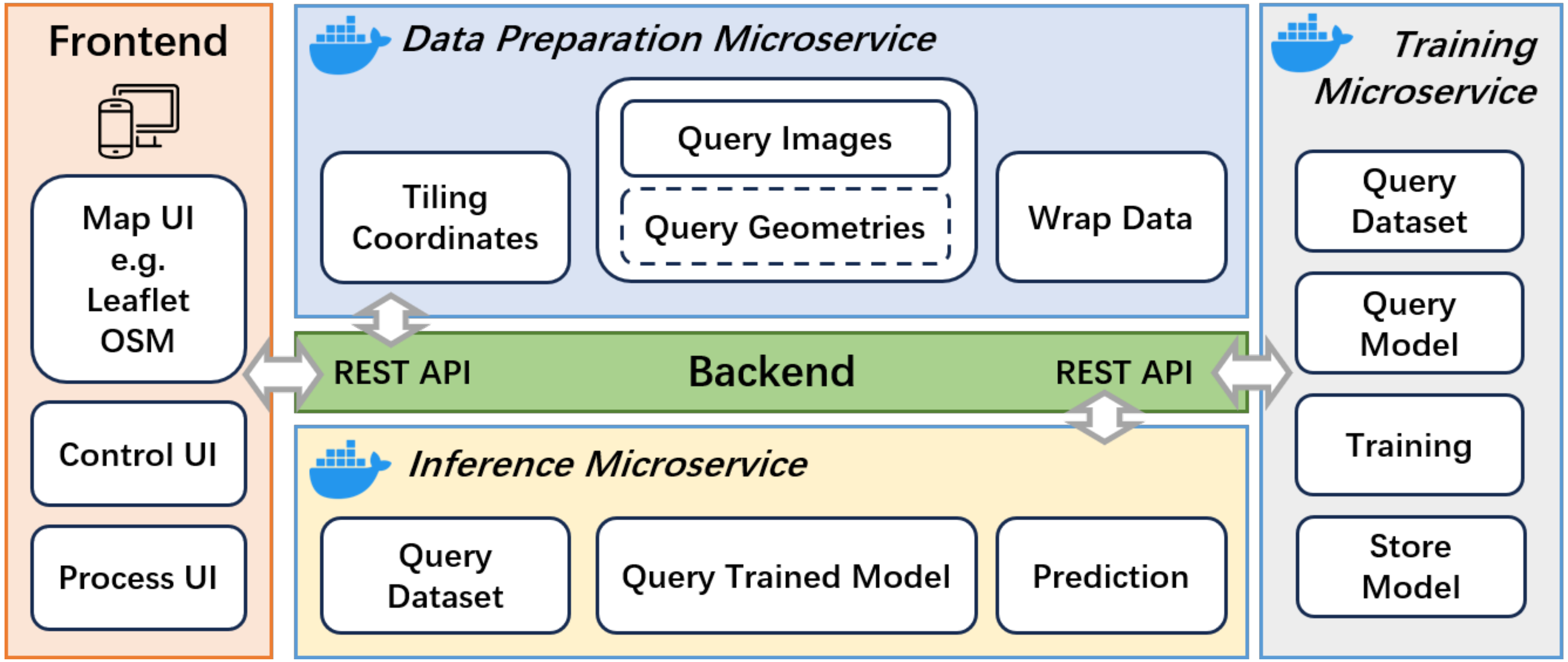


Image from https://wp.stolaf.edu/it/gis-precision-accuracy/

Methodology - *GeoAIaaS*

- Modern Web Mapping
  - Cloud services, XaaS
  - Intelligent mapping

How to deploy GeoAI solutions with web mapping applications?



GeoAI as a containerized service

Experiments and Results - *GWME*

- Case Study
  - Tanzania --> Cameroon
  - Across 2700+ km
  - 8 reference regions surrounding the target region

Table 4.1.: Summary statistic of the datasets.

Counts	A_{bm}	A_{target}	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
Buildings	6,272	1,811	66	45	116	46	71	61	40	79
Areas (km^2)	232.50	8.57	0.35	0.16	0.35	0.22	0.34	0.44	0.25	0.20
Tiles n	1,744	343	5	5	9	7	9	9	7	7

Overview of study areas

Experiments and Results - *GWME*

- Multiple FSTL Predictions
  - FSTL performs much better than the base model.

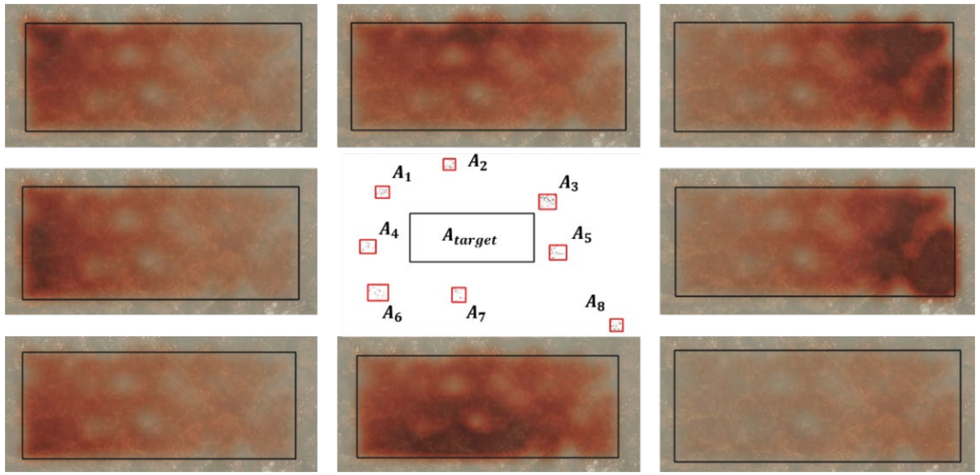
Table 5.1.: Evaluation metrics of predictions from the base model and single FSTL models on the test dataset. BMP and $\mathbb{FSP}^j$ indicate the model predictions of the base model $\mathbb{M}_{bm}$ as well as different FSTL models $\{\mathbb{M}_{fs}^j\}_{j=1}^T$.

Predictions	Precision (%)	Accuracy (%)	Recall (%)	F1
BMP	97.66	13.71	13.75	0.2411
$\mathbb{FSP}^1$	99.00	60.90	61.27	0.7570
$\mathbb{FSP}^2$	96.94	**68.93**	**70.46**	**0.8160**
$\mathbb{FSP}^3$	98.18	53.06	53.58	0.6933
$\mathbb{FSP}^4$	98.22	49.06	49.50	0.6582
$\mathbb{FSP}^5$	98.44	61.27	61.87	0.7598
$\mathbb{FSP}^6$	84.65	40.90	44.18	0.5806
$\mathbb{FSP}^7$	**99.12**	52.66	52.91	0.6899
$\mathbb{FSP}^8$	98.73	52.60	52.96	0.6894
$Mean(\{\mathbb{FSP}^j\}_{j=1}^8)$	96.66	54.92	55.84	0.7055

Multiple FSTL predictions in different colors

Experiments and Results - *GWME*

- Weighting Visualization



Geographic Distance Weighting Distribution

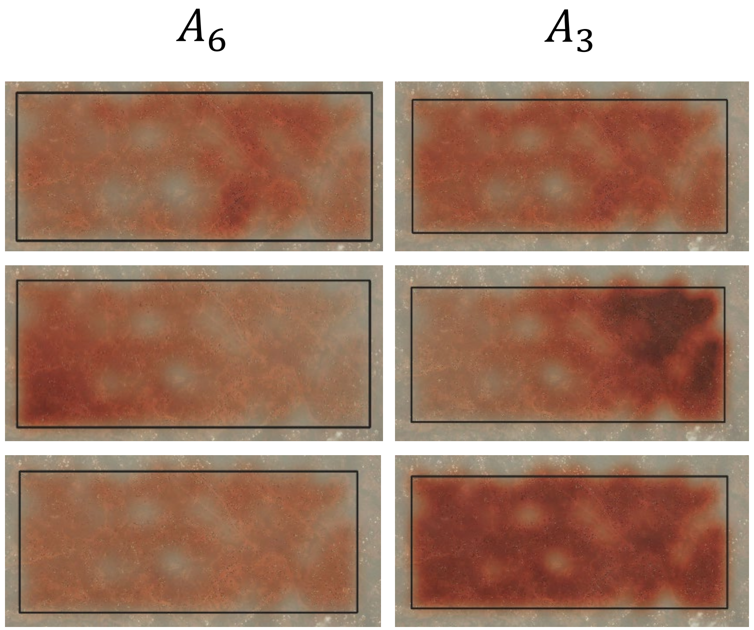
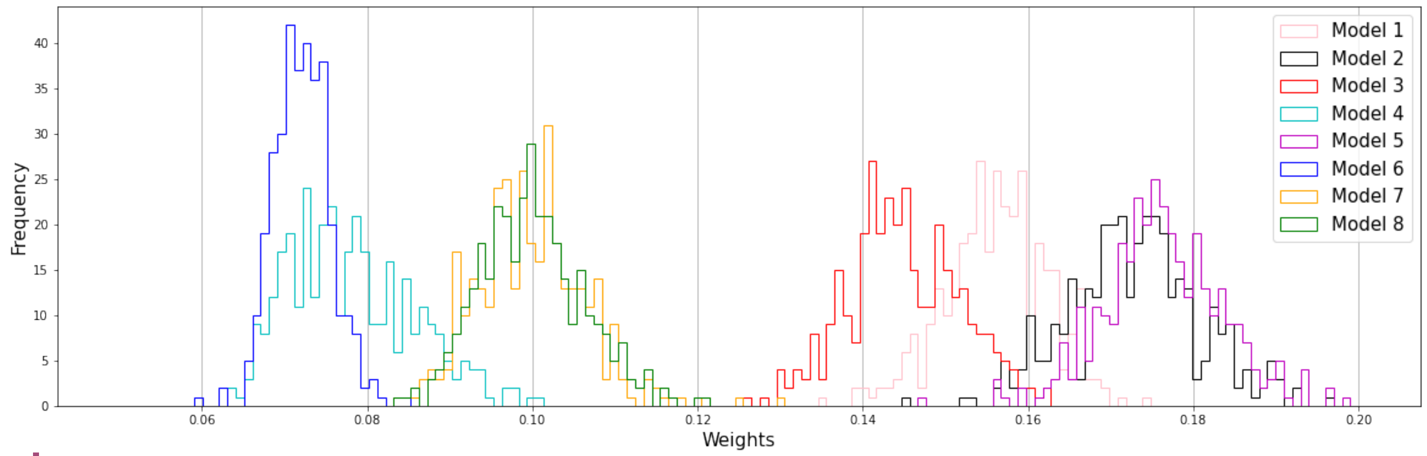


Image Similarity

Geographic Distance

Attention

Weights heatmap

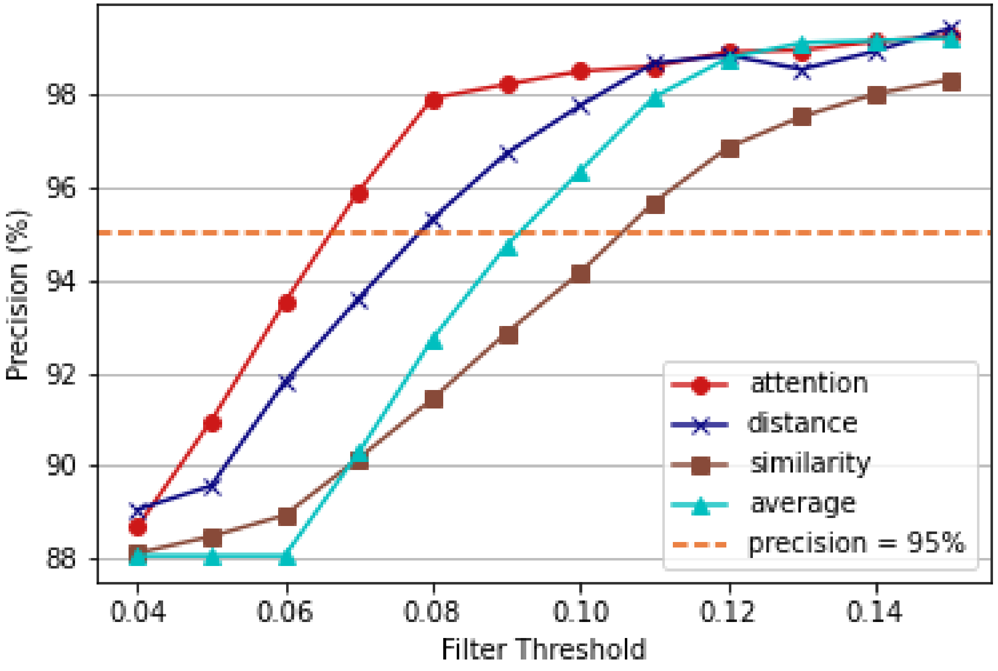


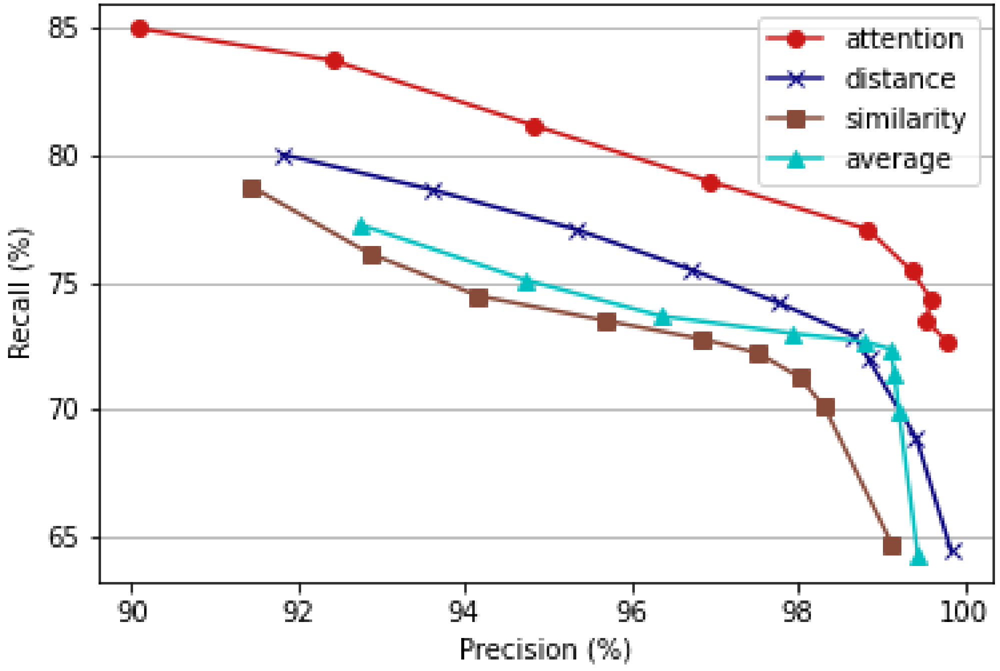
Attention Weights Histogram Distribution

- Clustering
- Differential

Experiments and Results - *GWME*

- Hyperparameters search
  - Threshold for prediction score
  - Precision-Recall curve



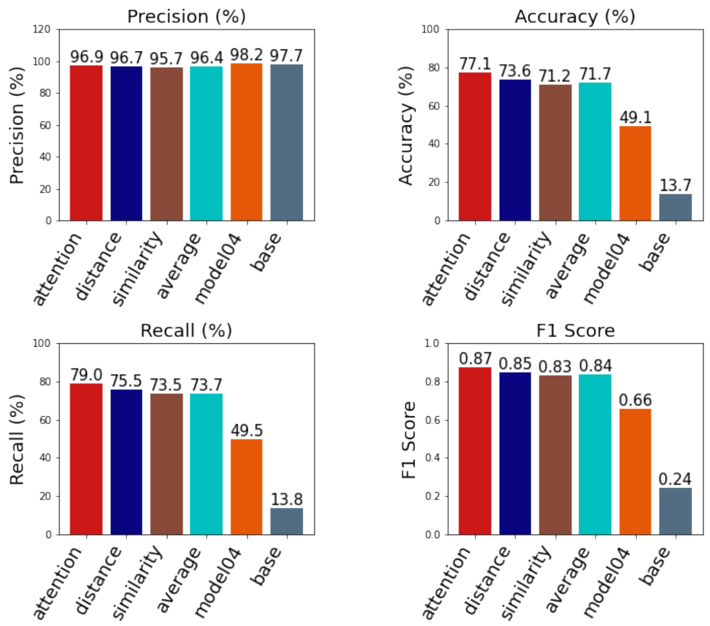


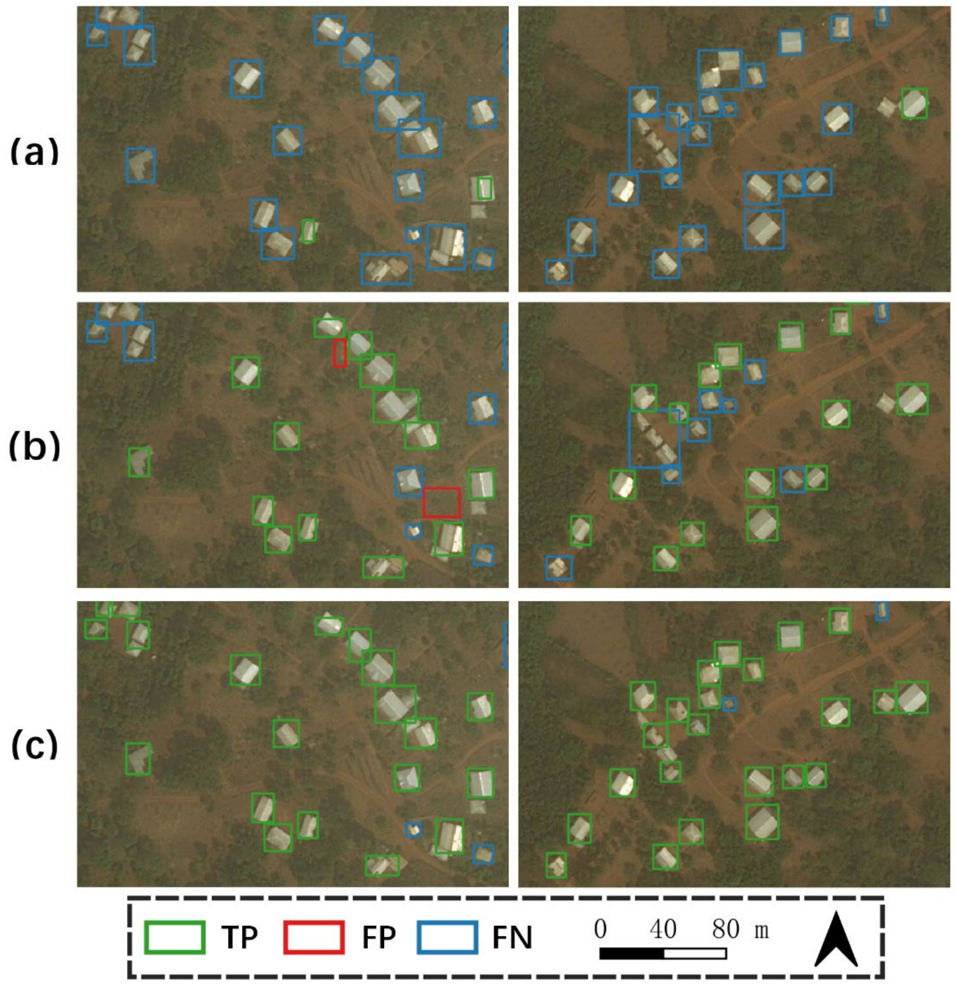
Experiments and Results - *GWME*

- Ensemble results

Table 5.2.: Evaluation metrics of predictions from ensembled results by different weighting modes.

GWME Weightings	Precision (%)	Accuracy (%)	Recall (%)	F1
average	96.35	71.70	73.70	0.8352
similarity	95.68	71.16	73.52	0.8315
distance	**97.76**	72.98	74.22	0.8438
attention	96.95	**77.07**	**78.99**	**0.8705**





Base Model

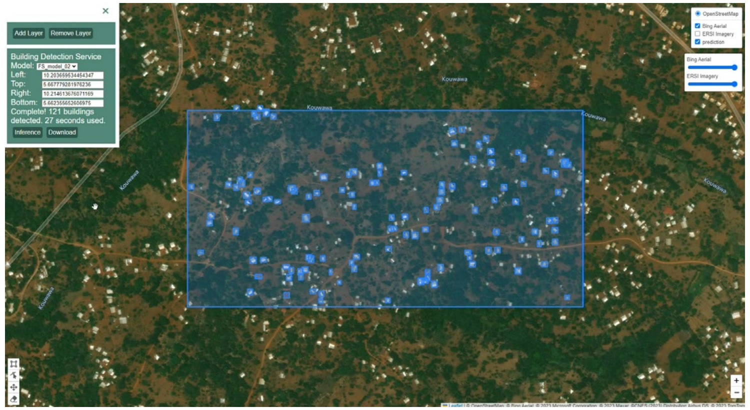
Single FS Model

Ensembled

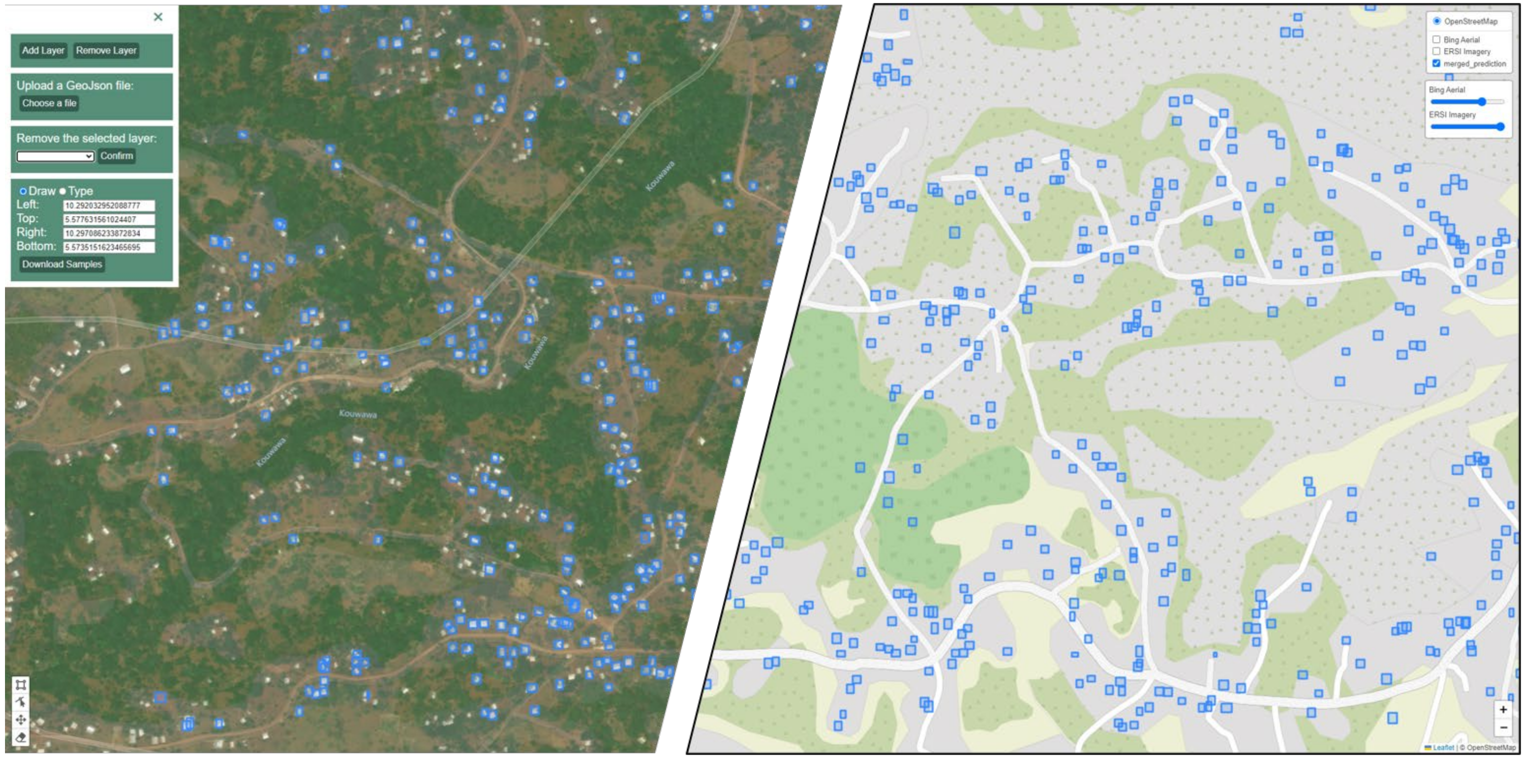
Comparison of different methods

Experiments and Results - *GeoAIaaS*

- Main features
  - Base map (OSM) + Overlay maps (Aerial Imagery, Machine-generated GeoJSON)
  - Layer control, opacity control
  - Local GeoJSON visualization
  - Drawing area of interest (AOI)
  - Inference service
  - Download predictions



Inference service



A demo of GeoAI web mapping application

Discussion

- Findings
  - The GeoAI model's performance was influenced by spatial heterogeneity.
  - FSTL is an efficient way to improve geographic generalizability with limited training samples.
  - Models ensemble significantly improves the performance of single FSTL models.
  - Attention-based GWME method performs better than other weighting strategies.
  - Microservice-based structure can integrate GeoAI solutions into web mapping applications.
- Limitations and Future Work
  - Models ensemble occurs at a prediction level, which may be improved by parameter-level ensemble.
  - Self-attention weighting considers relative location correlation, which may be improved by spatially explicit location embedding into the training process.
  - The reference regions in the case study are close to the target region, and future work could consider a larger-scale study area for more challenging geographic generalizability.
  - The single-class object detection task could be extended to multi-class object detection tasks.

Conclusion

- Reviewed current OSM mapping challenges, SOTA GeoAI research, and modern web mapping applications.
- Proposed a Geographical Weighted Model Ensemble (GWME) method to improve the geographical generalizability of building detection models across diverse regions.
- Compared performances of the model ensemble by different weighting methods and decided to use self-attention-based weights.
- Conducted experiments transferring the OSM building detection model from Tanzania to Cameroon, achieving a promising result (0.87 F1 score) on the target area.
- Used a microservice-based GeoAIaaS infrastructure to develop and deploy a GeoAI web mapping application providing visualization, inferencing, and comparing functions.

THANKS!

Thesis Assessment Board (TAB)

- The TAB chair: Prof. Dr. Liqiu Meng
- The supervisor: Dr. Hao Li
- The reviewer: Assoc. Prof. Dr. Rolf de By (UT)

ITC UNIVERSITY OF TWENTE.

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Technical University of Munich TUM

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- TensorFlow Object Detection API GitHub repository. https://github.com/tensorflow/models/tree/master/research/object_detection