P5 Presentation

Correcting Global Elevation Models for Canopy and Infrastructure Using a Residual U-Net

Haoyang Dong

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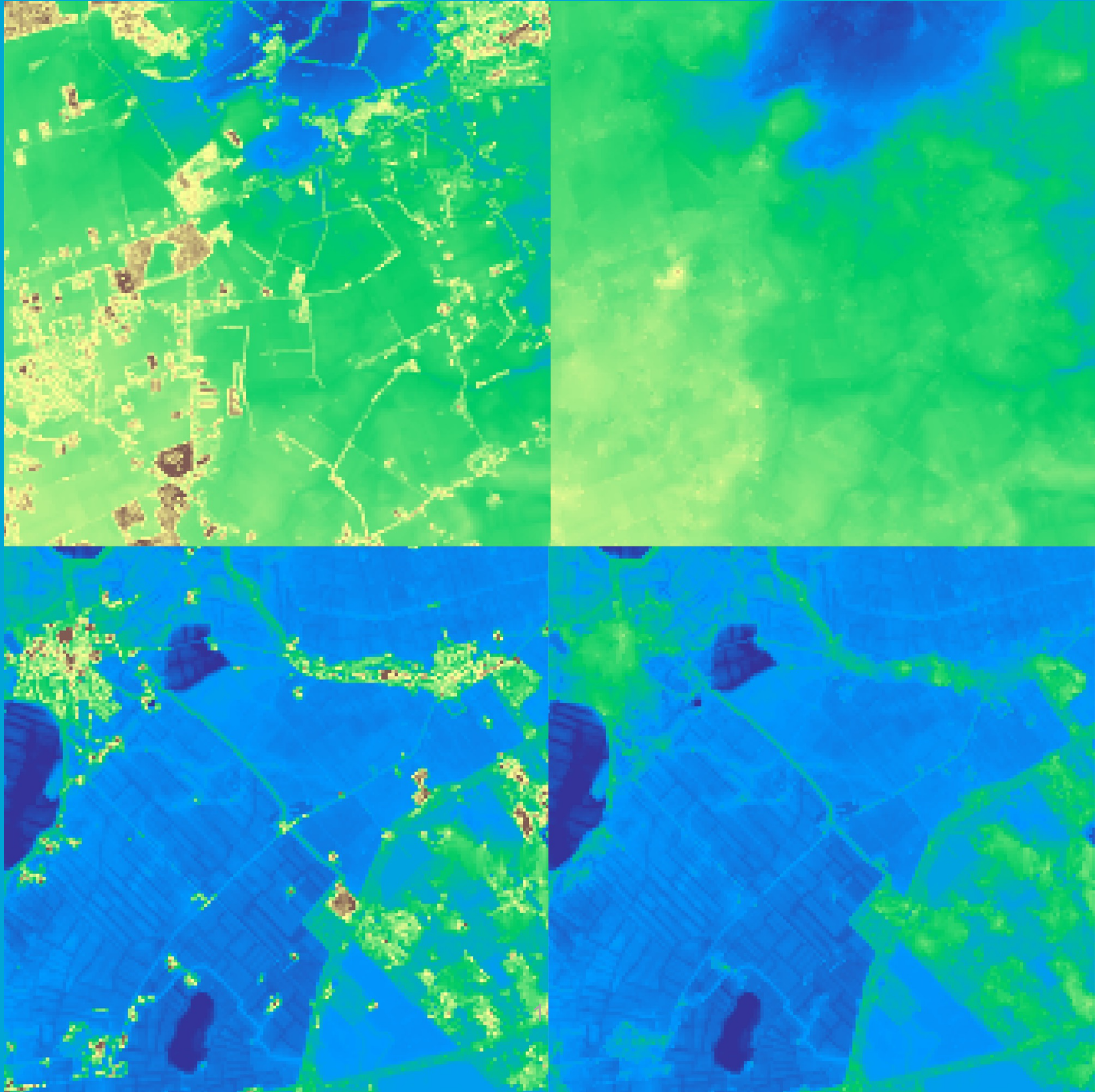

CONTENT

- Introduction
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- Methodology
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- Conclusion & Future Work

Introduction

Background: DEM

- Digital Elevation Model (DEM): "A regular gridded matrix representation of the continuous variation of relief over space.”
- Importance of DEM
    - Hydrology, Geomorphology, Civil Engineering, ...
- Increased availability and accessibility of DEM data

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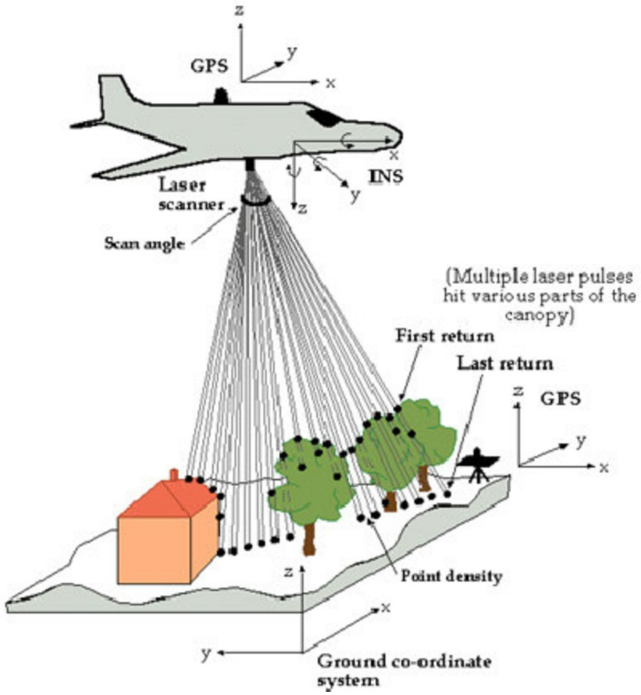
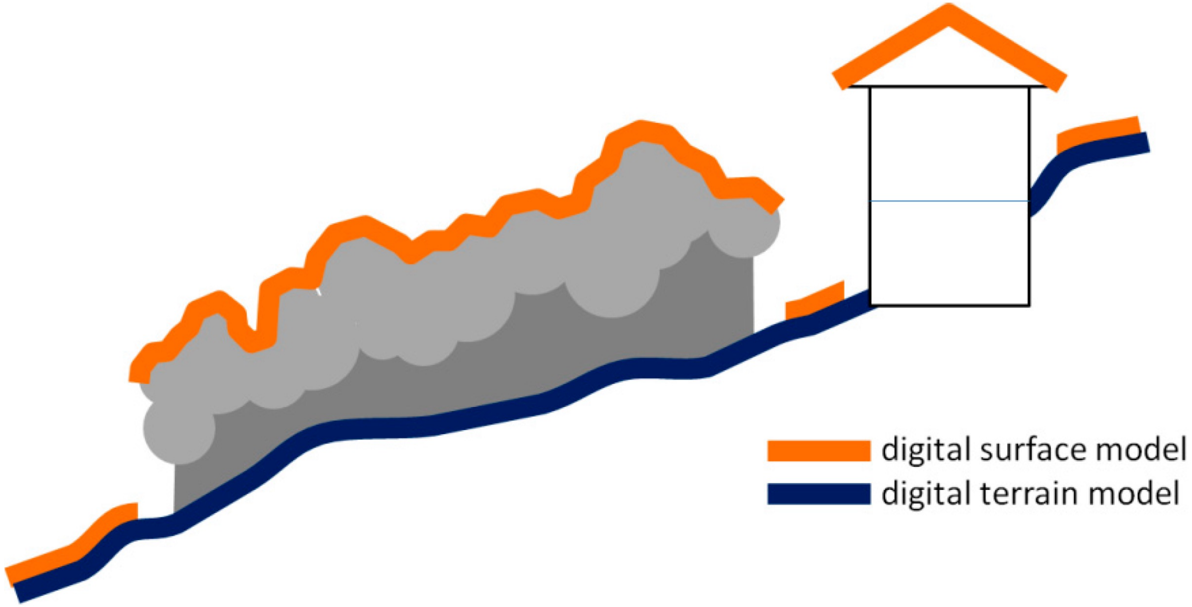
Background: DTM and DSM

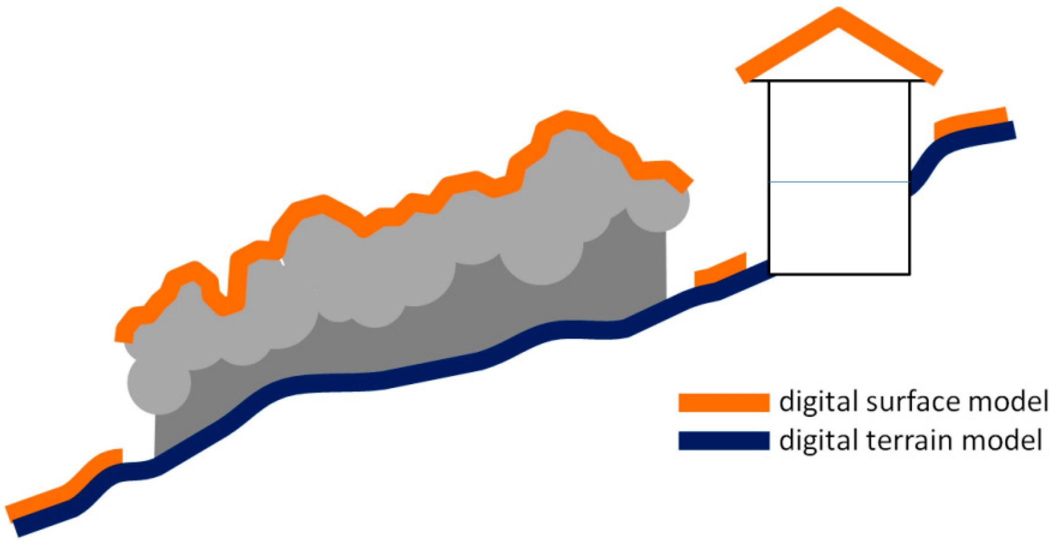
- Evolution of mapping and data acquisition techniques
- Digital Terrain Model (DTM) vs Digital Surface Model (DSM)
- Most current DEMs are DSMs





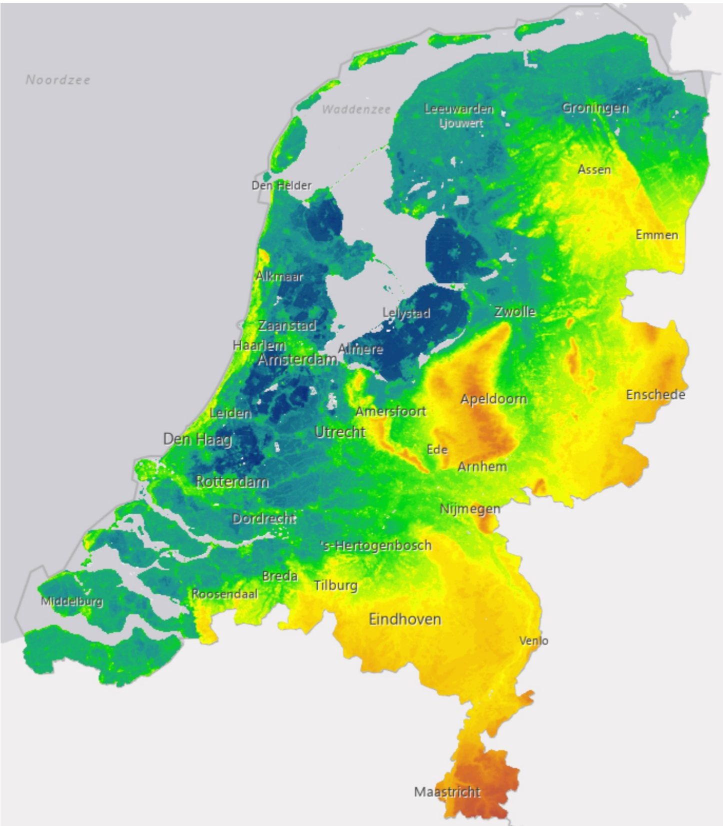
Motivation

- Importance of understanding the true terrain surface
- Problems caused by above-ground features in DSMs
- Need for techniques to convert DSMs to DTMs



Study Area & AHN4 Dataset

- The Netherlands: Vulnerable to flooding, extensive infrastructure, diverse landscape
- Actueel Hoogtebestand Nederland 4 (AHN4): High-resolution DEM of the Netherlands
  - Accurate
  - Classified
  - Multiple distributions



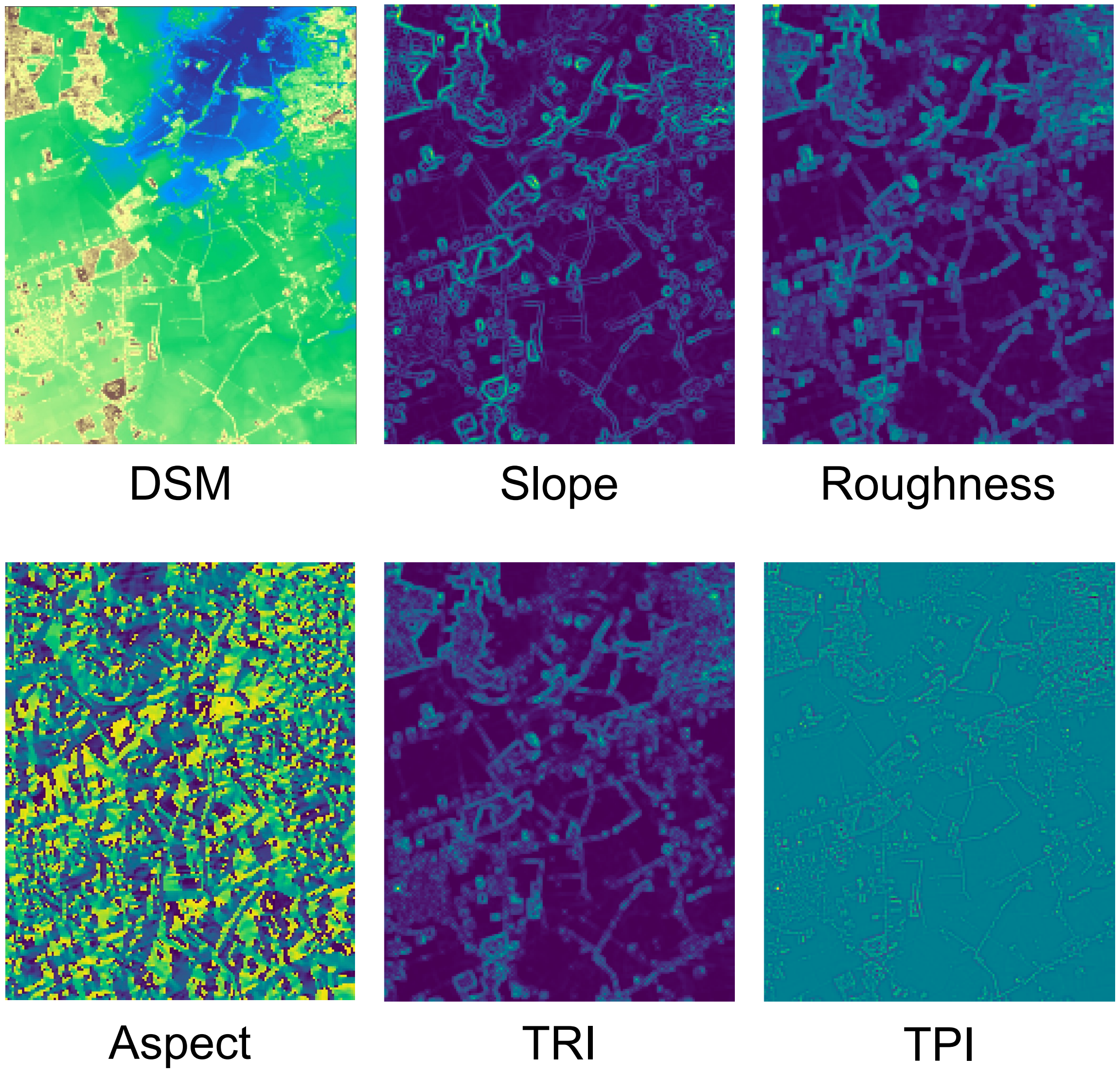
Research Objective

- Main Goal: Develop and assess a Residual U-Net model for reliable DTM extraction from DSMs
- Sub-questions:
  - Comparing the performance of the Residual U-Net with other methods
  - Comparing the model's results to global DEMs
  - Influence of resolution on the model's performance
  - Advantages and limitations of the Residual U-Net approach

Related Work

DEM Analysis

- Slope
- Roughness
- Aspect
- Topographic Roughness Index (TRI)
- Topographic Position Index (TPI)



DTM Extraction & Machine Learning

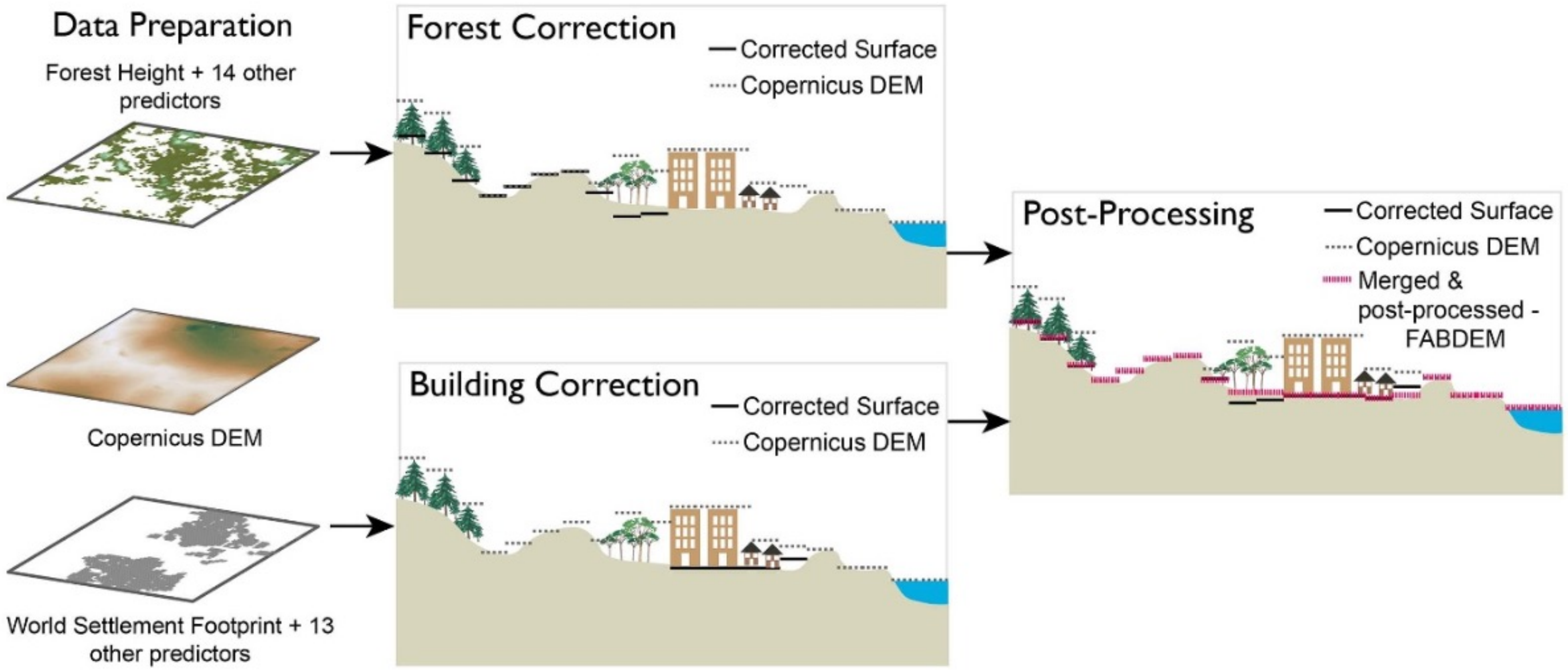
- Traditional Regression Analysis
- The problem with traditional approaches
  - The "Curse of Dimensionality”
- Machine Learning as a solution

Emerging Approaches for Elevation Error Correction

- Forest and Building Digital Elevation Model (FABDEM)
- Progressive morphological filter
- Convolutional Neural Networks (CNNs)
- Residual U-Net framework
- Current Research Gap

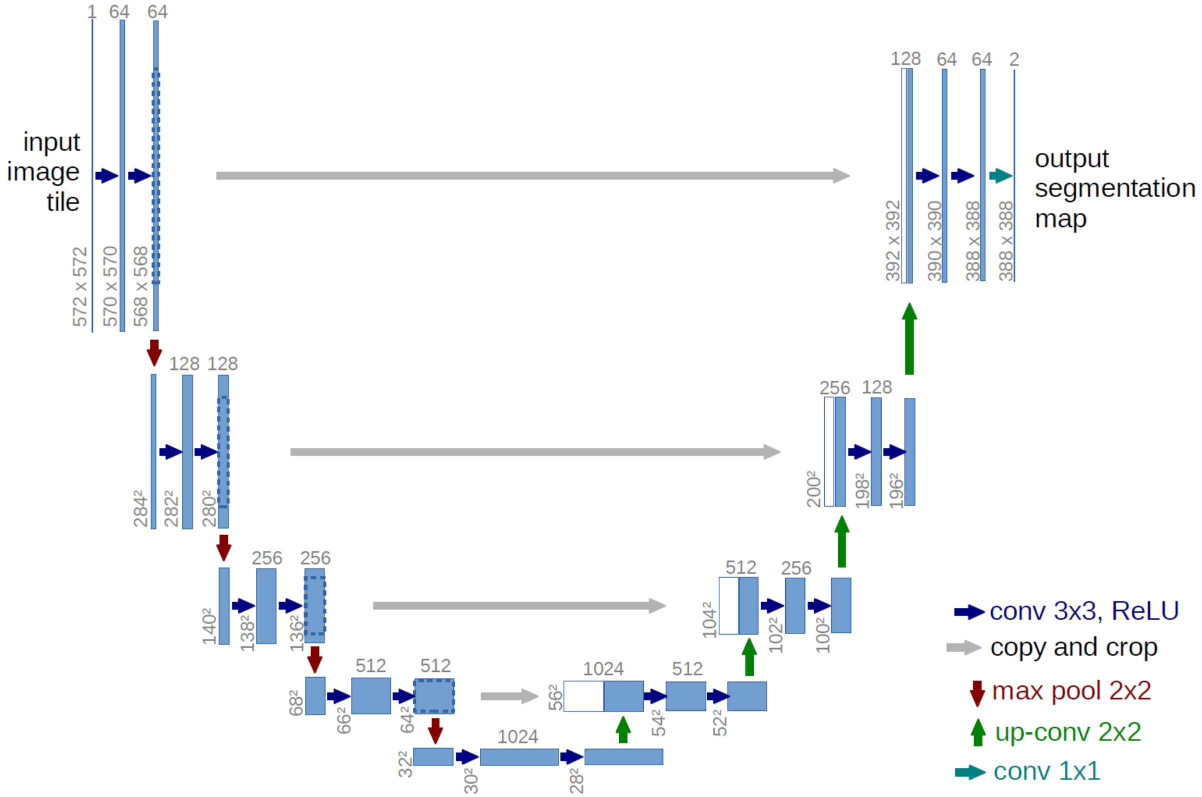
FABDEM

- Multi-source data utilization
- Pre-classification of zones
- Random Forest Regression Models
- Improved accuracy and lower RMSE (root-mean-square errors)



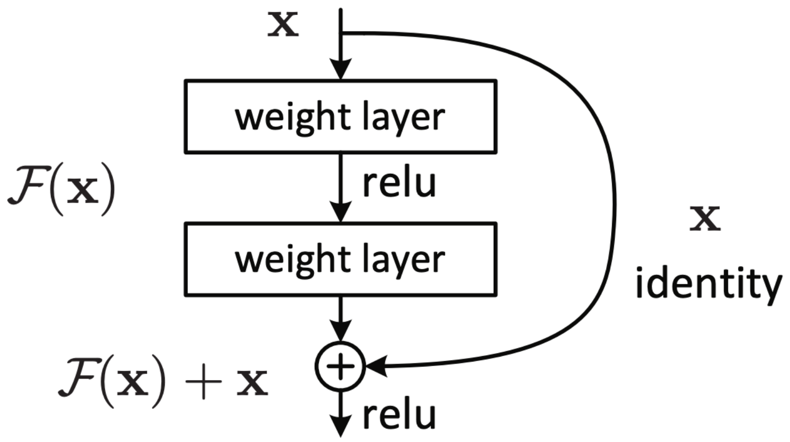
The U-Net Architecture

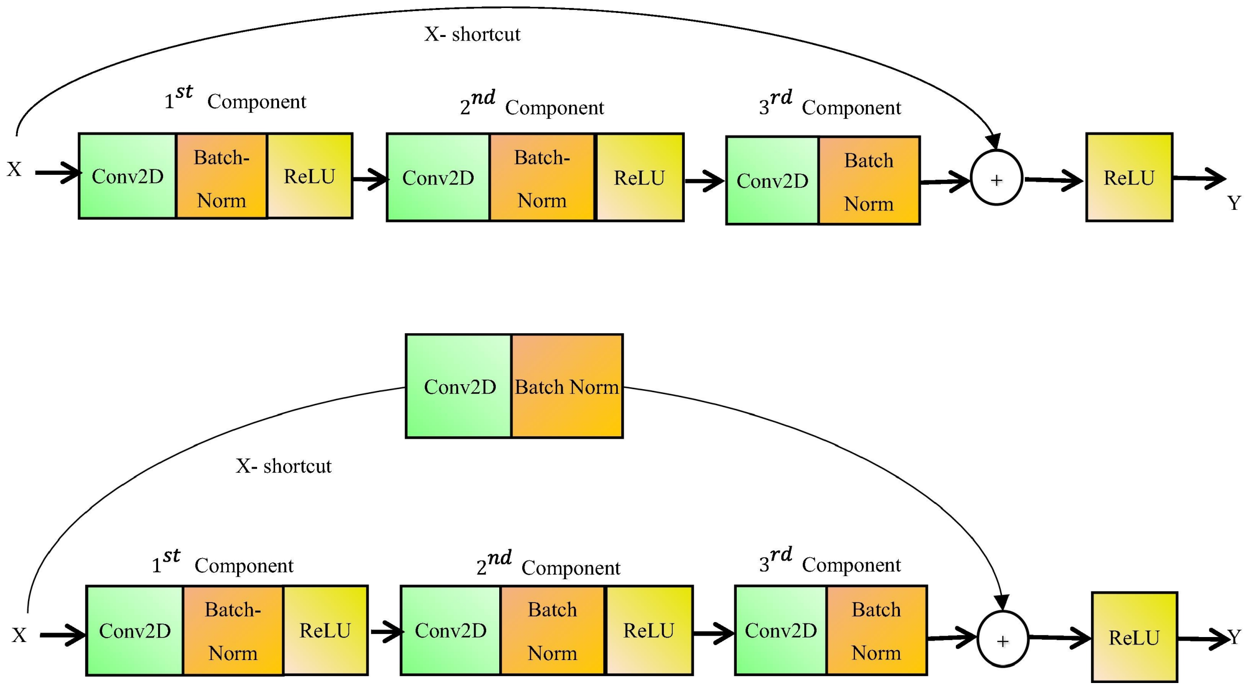
- Effective in various applications
- Two primary components: Contracting and Expansion Path
- Pixel-level **segmentation**



Residual Networks (ResNets)

- Mitigation of the vanishing gradient problem
- Residual layers
- Identity and Convolutional Blocks





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Residual U-Net

- U-shaped structure of original U-Net
- Incorporates residual blocks
- Enhanced depth of the network

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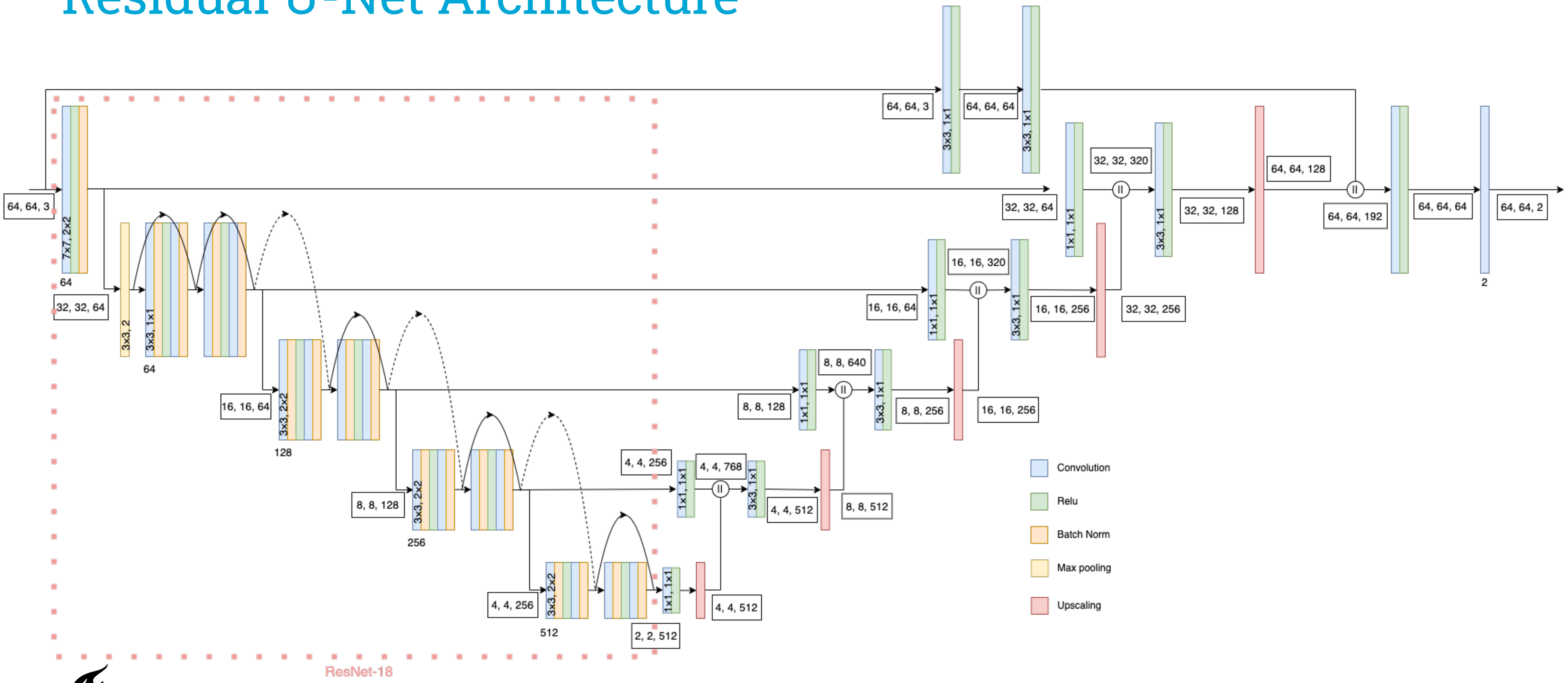
Methodology

Residual U-Net Architecture

- Integration of U-Net and ResNet-18
    - Downscaling path (Contraction): Based on ResNet-18
    - Upscaling path (Expansion): Follows U-Net architecture
- Pre-trained

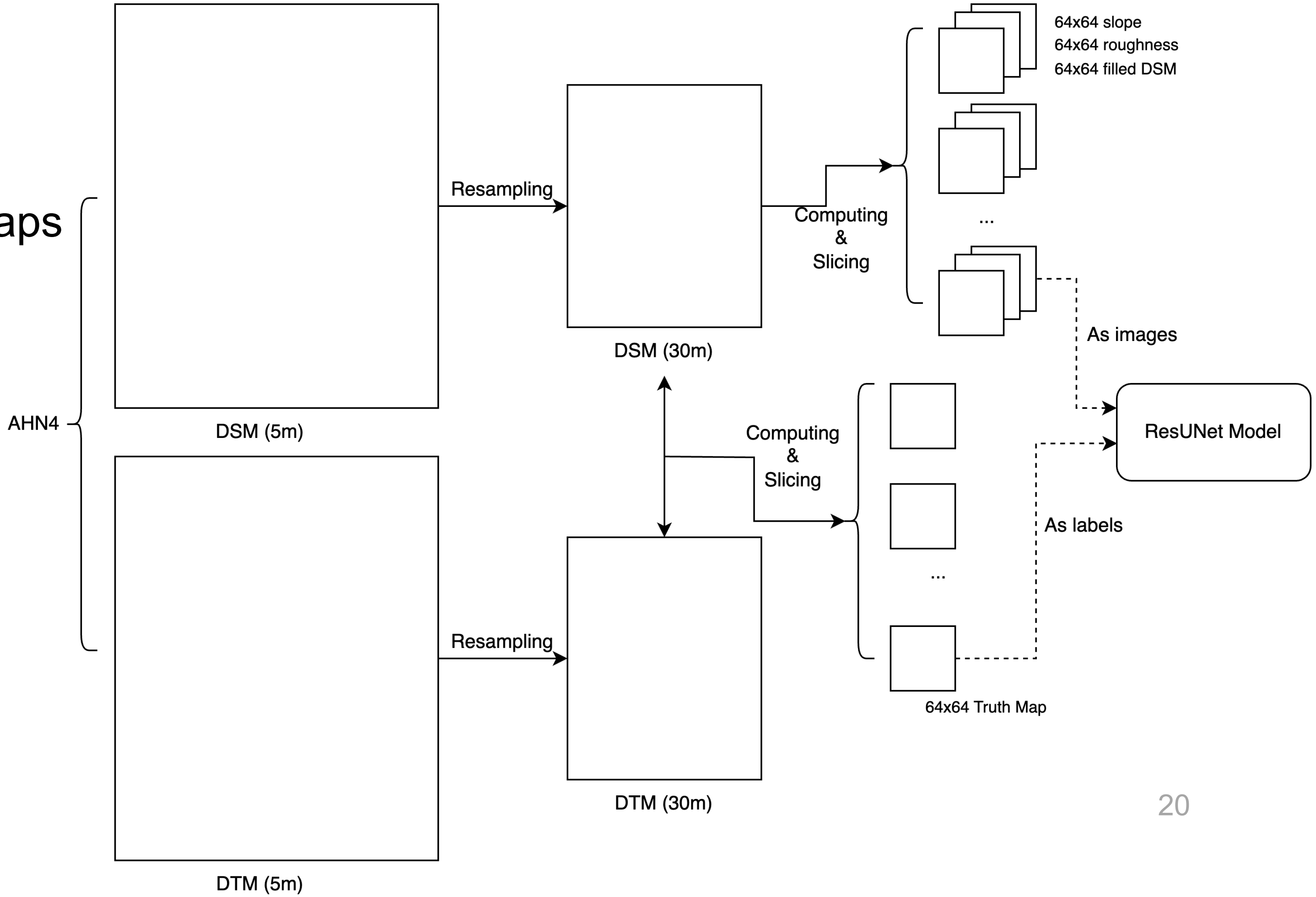
Residual U-Net Architecture



DEM Preprocessing Overview

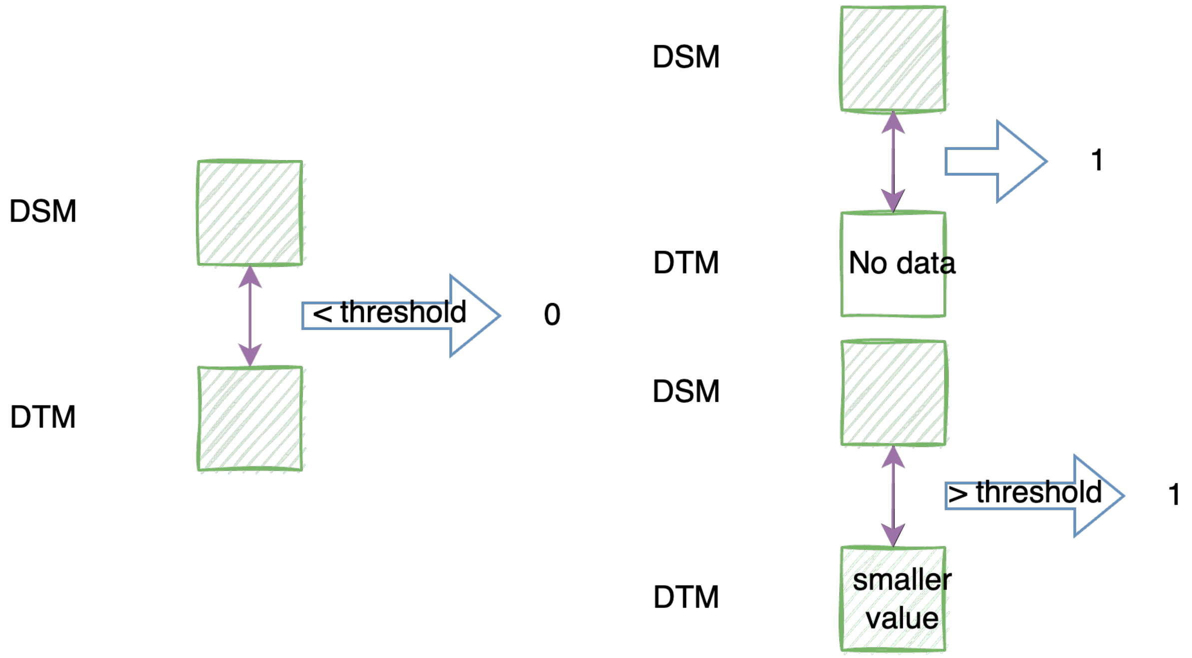
Input data	Number	Shape (height, width)
Orignal AHN4 DSM	455	(1250, 1000)
DSM @ 30 m resolution	455	(208, 167)
Image-like array after slicing	5460	(64, 64)
Image-like array after augmentation	43680	(64, 64)

- Utilization of AHN4 DTMs and DSMs
- Resampling to a 30m resolution
- Generation of ground truth data
- Handling of no-data values in the DSMs
- Computation of slope and roughness maps
- Division of data into 64x64 slices
- Data normalization



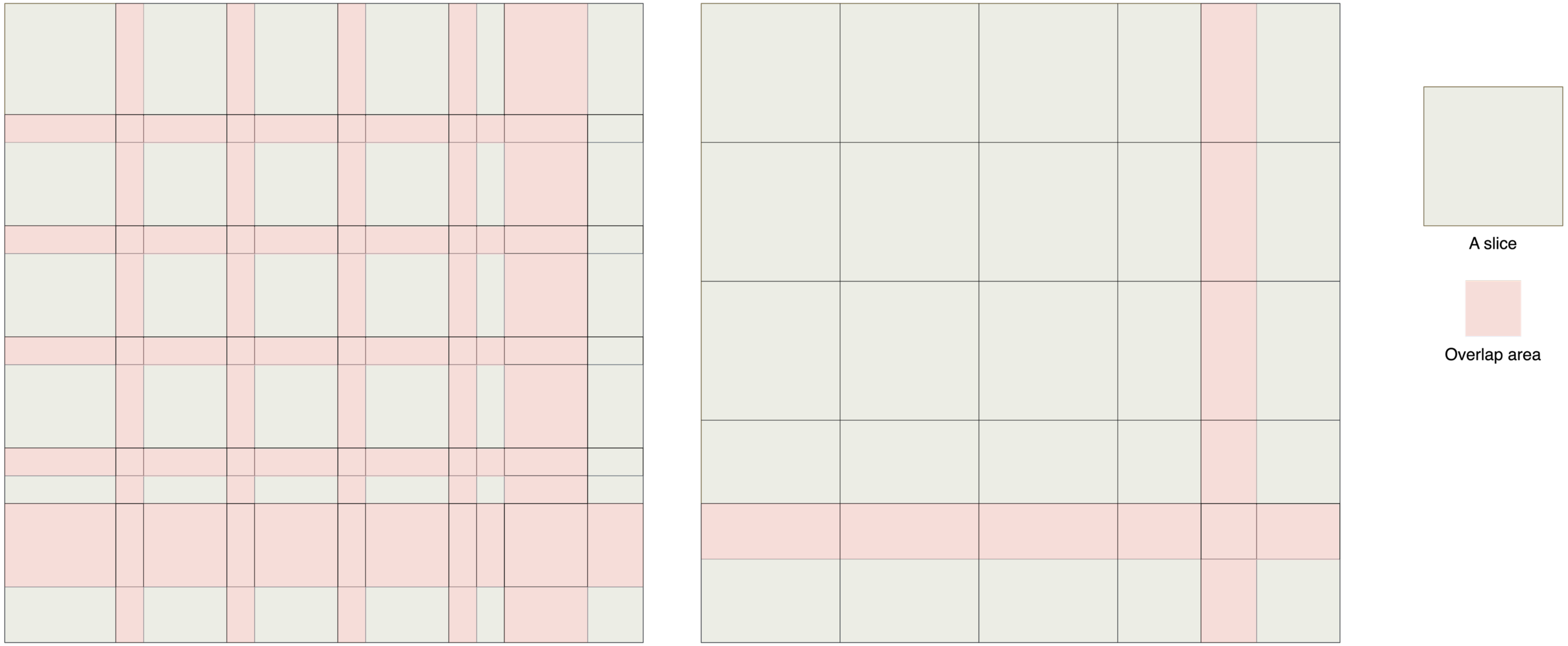
Ground Truth Labelling

- The main goal is to remove pixels representing the canopy and infrastructure
- Criteria based on the comparison between DSM and DTM pixels
  - Terrain pixels (labelled as 0)
  - Pixels representing canopies and infrastructures (labelled as 1)



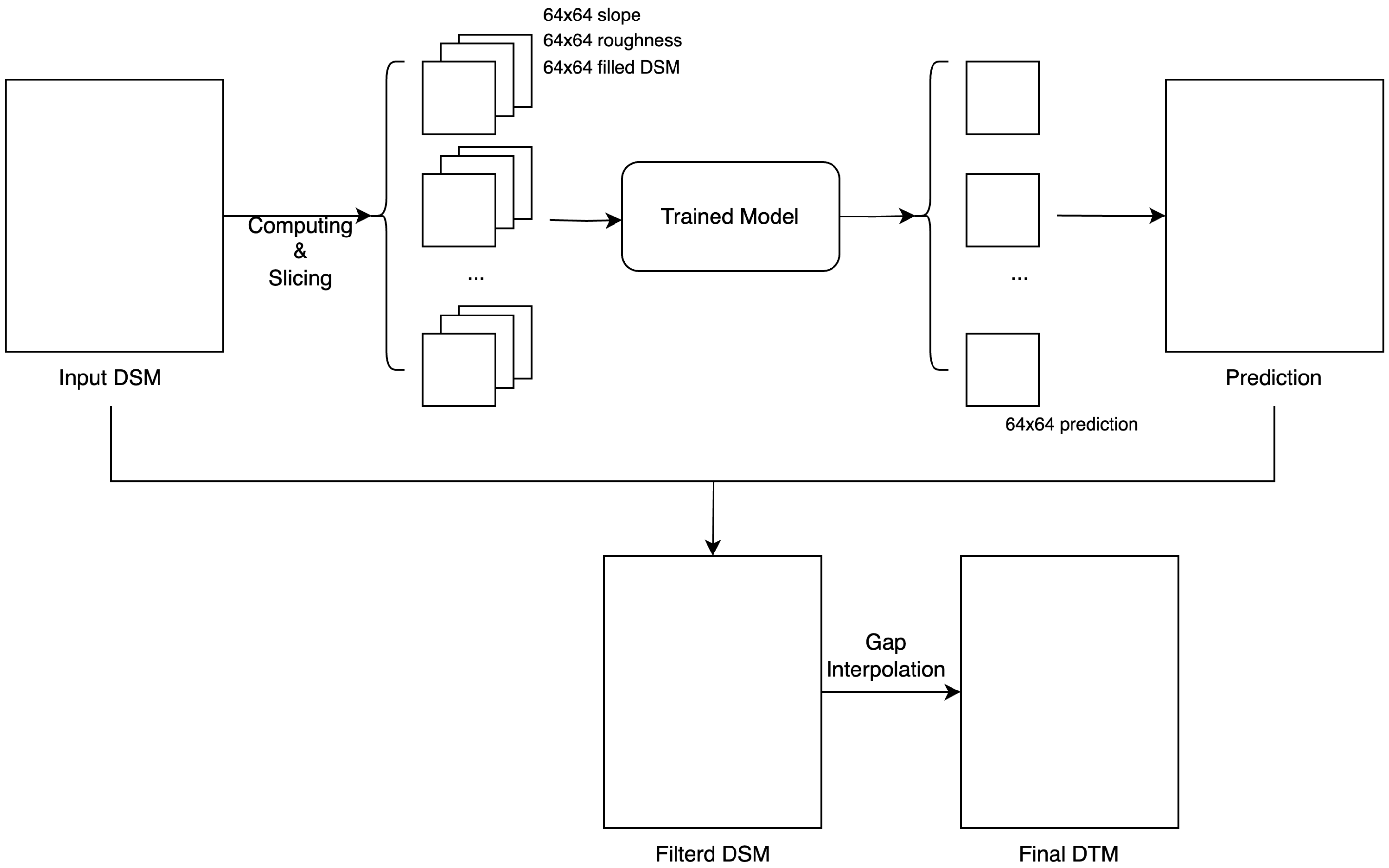
Slicing with Overlap

- The term "slicing" refers to the procedure of partitioning an image-like array into smaller segments
- Preservation of all relevant information for subsequent reassembly
- Incorporation of overlaps between adjacent segments



Generating DTMs

- Input DSM undergoes processing methodology
- Subsequent feeding into the trained model to generate prediction maps
- Assembling individual prediction maps into a comprehensive one
- Identifying and removing certain pixels in DSM
- Interpolation of the partially emptied DSM to result in final DTM



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Stitching

- Stitching as the complementary procedure to slicing
- Objective: to integrate individual slices into a complete array
- Slicing and stitching applied to distinct types of arrays
- For binary prediction maps, method ensures more representative estimation for each pixel
- No-data pixels in the slice do not overwrite valid pixels in the merged image

Evaluation: Root-mean-square Error (RMSE)

- RMSE as a measure of the differences between predicted and observed values
- Serves to aggregate prediction errors into a single measure of predictive power
- Used when comparing prediction errors of different models or configurations
- RMSE equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

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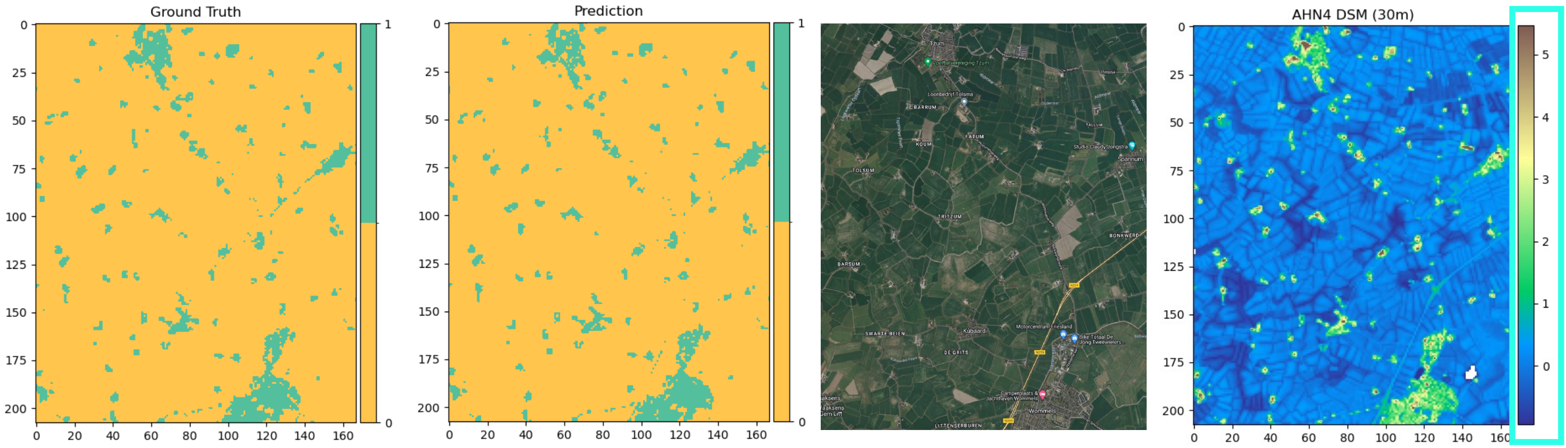
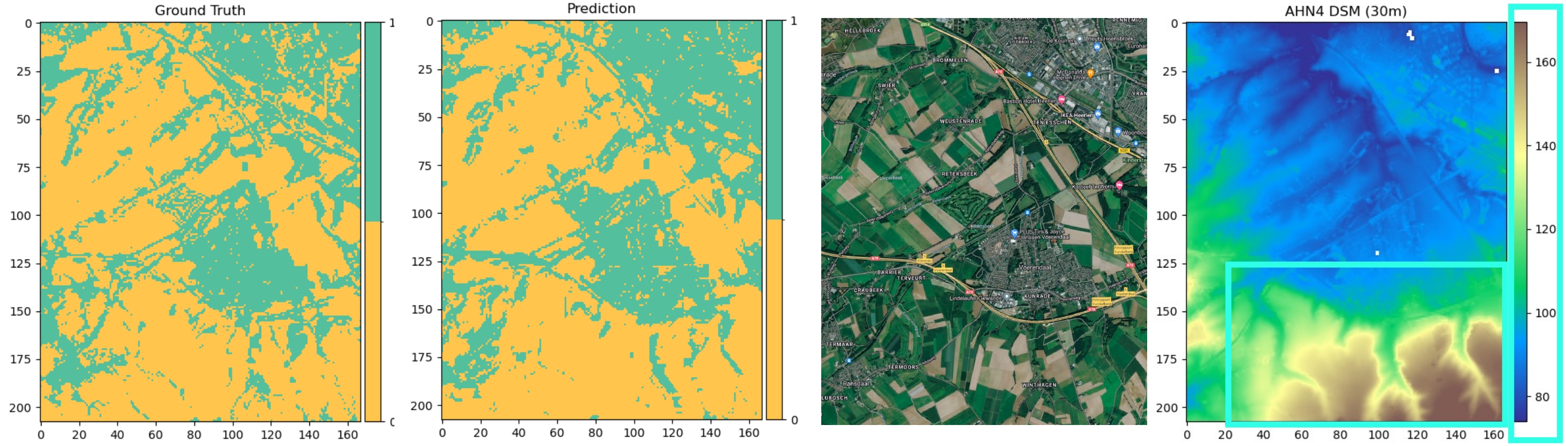
Results & Discussion

Segmentation Accuracy

- The accuracy of the Residual U-Net model was assessed by comparing predicted and ground truth label maps
  - Mean accuracy: 94.21%
  - Accuracy range: 86.03% to 98.93%
- The minor variation in patch accuracies shows the model's effectiveness
- encounters challenges when processing areas characterized by significant changes in elevation and in regions with mountainous terrain



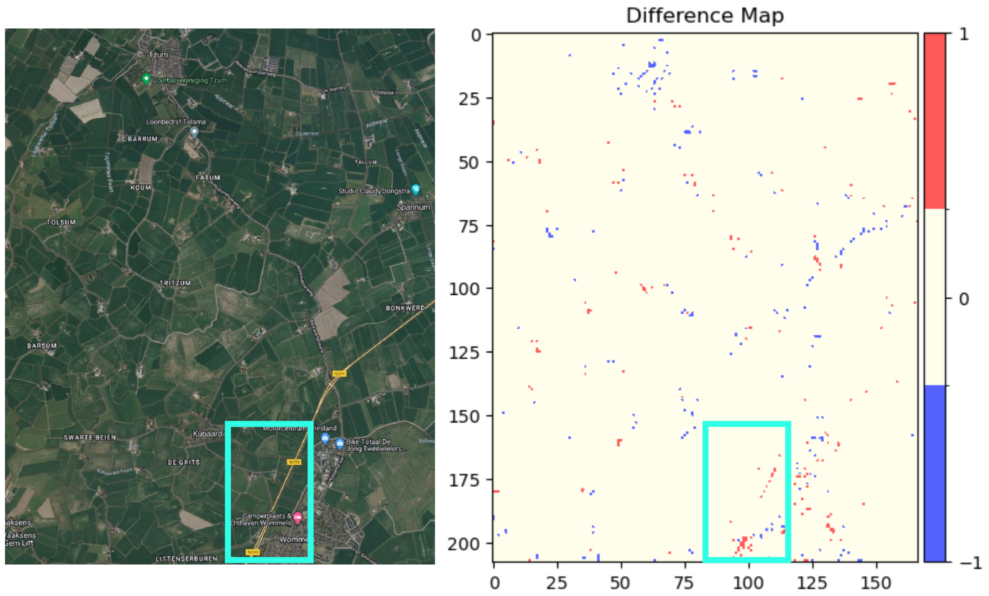
the best performance area

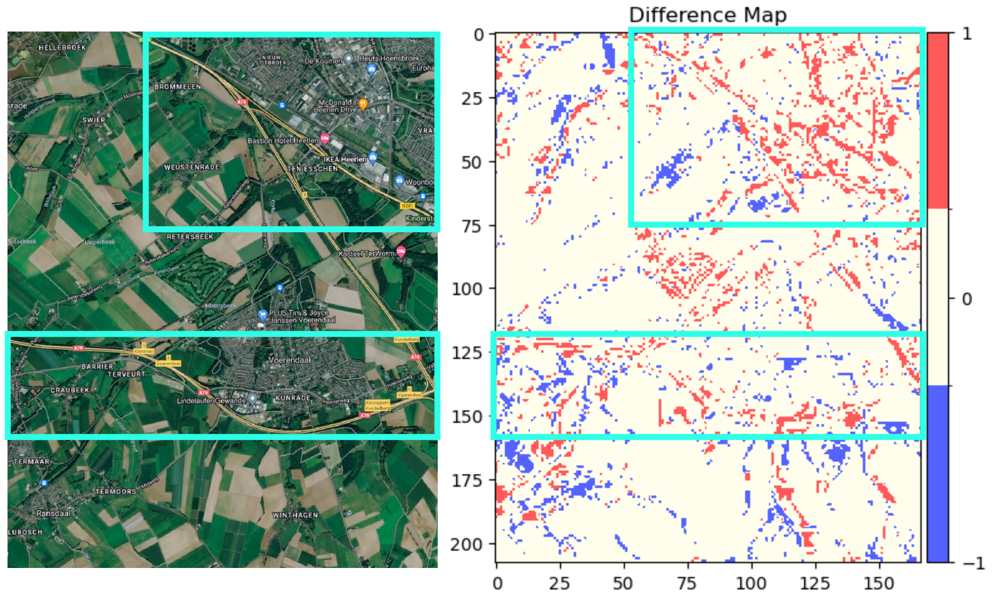


the worst performance area

Visual Comparison and Positive-negative maps

- Positive-negative maps
  - 1: the prediction erroneously classified the pixel as 1 while the ground truth labelled it as 0
  - -1: the prediction map incorrectly identified the pixel as 0 while the ground truth classified it as 1
  - 0: correct predictions
- the positive and negative pixels are distributed randomly
  - No bias observed in the model towards either removing or retaining more pixels
- tendency to remove roads





Comparison with FABDEM

- FABDEM: a suitable example for comparison
- Root Mean Square Error (RMSE) Computation
  - reference: AHN4 DTMs
  - 3 sets:
    - DTMs from the model with AHN4 DSMs as inputs
    - DTMs of FABDEM
    - DTMs from the model with COP30 DSMs as inputs

	The method	FABDEM
Inputs	Resampled AHN4 DSMs	COPDEM30, **AHN3**, forest heights, ICESAT2 canopy heights, Travel Times, Night Lights, WorldPop Constrained, GHS Urban Centre Database, World Settlement Footprint
Outputs	DTMs	DTMs
ML Method	Residual U-Net Segmentation	Random Forest Regression
Postprocessing	IDW	Pit-filling and bilateral filter

DTM set	RMSE
DTMs generated from AHN4 DSMs	0.60
FABDEM	0.93
DTMs generated from COP30 DSMs	1.18

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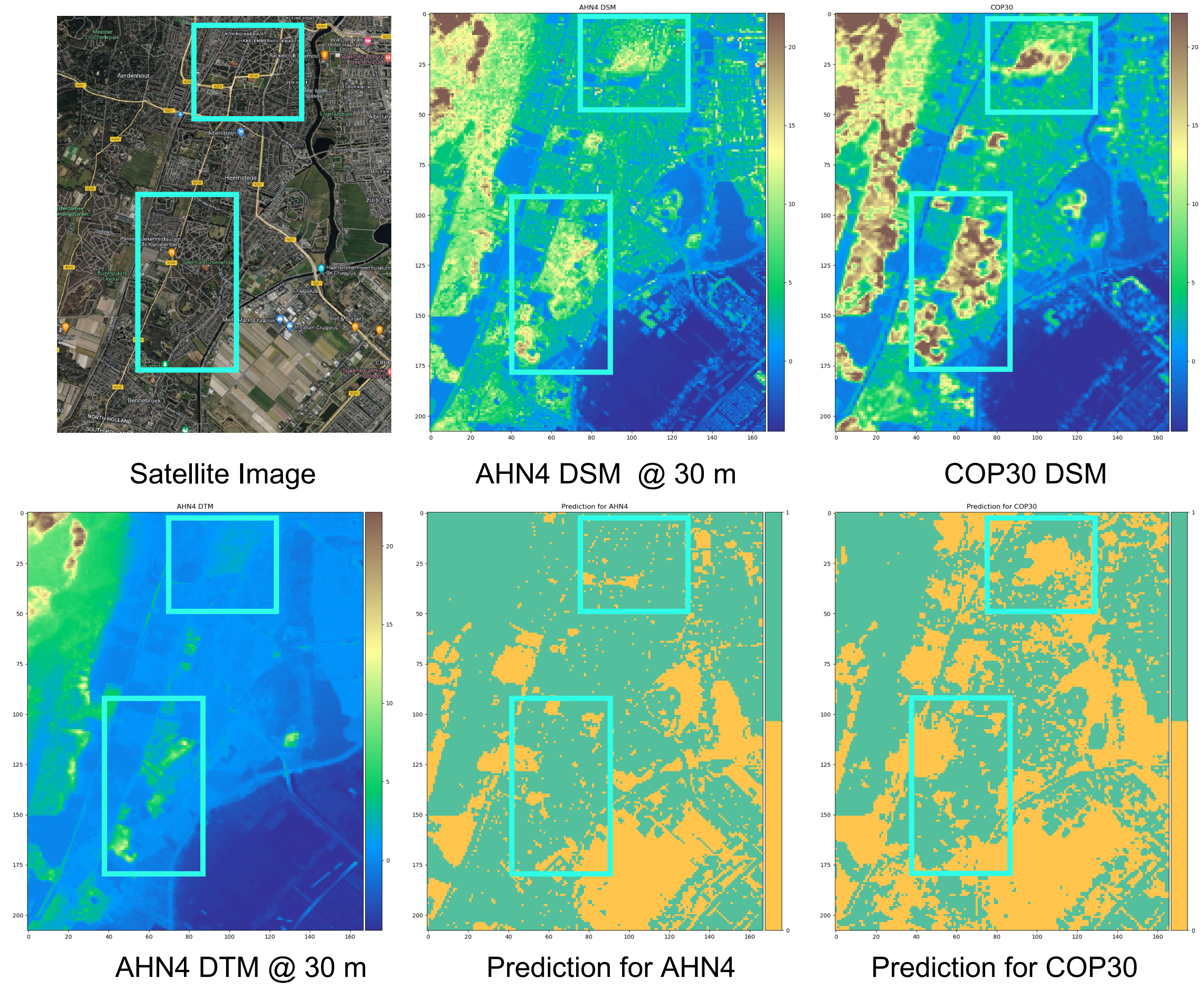
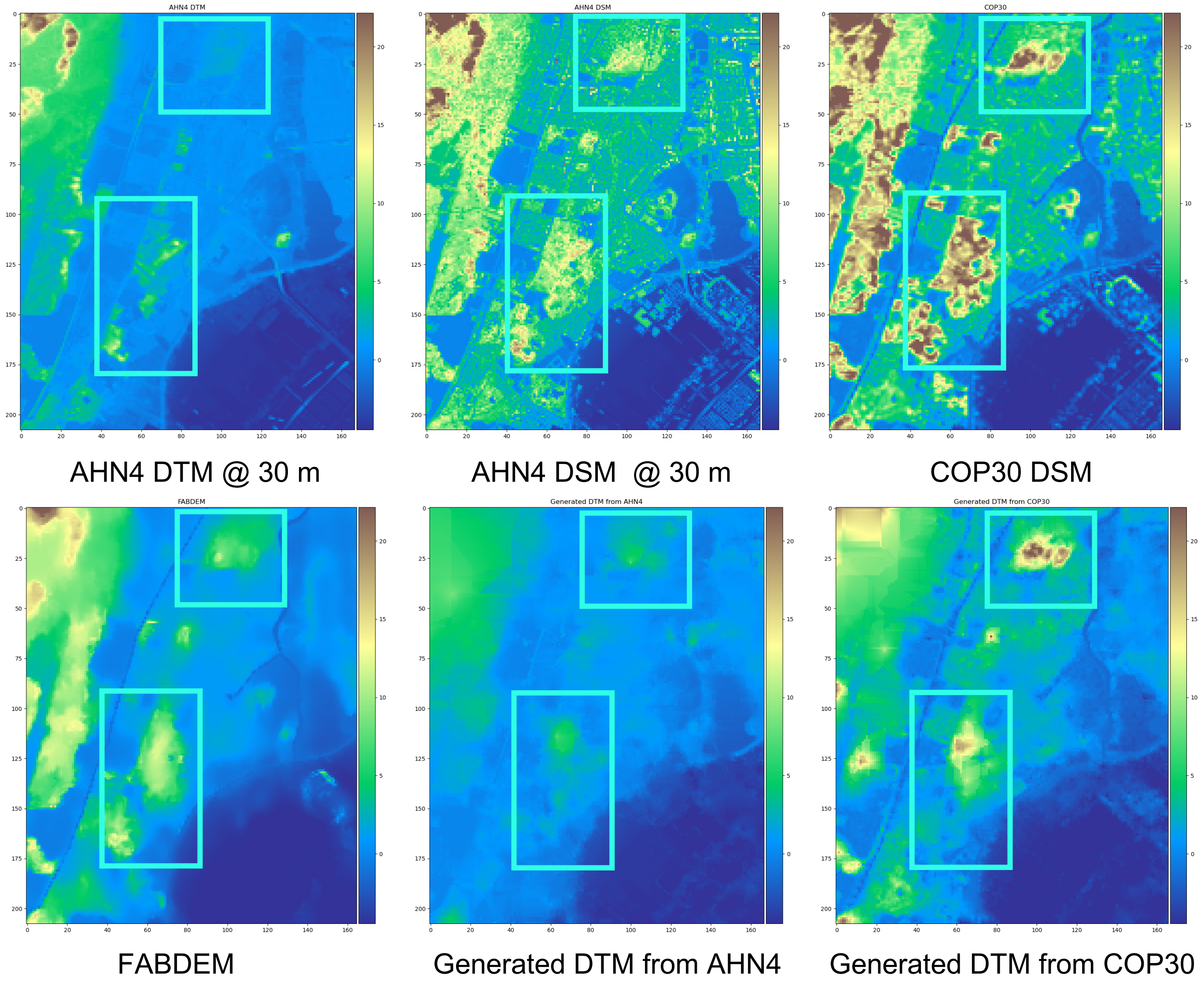
COP30 DSMs as Inputs

- the difference in model predictions with COP30 and AHN4
- the increased errors in areas with canopy coverage
  - the model struggles with canopy areas when fed COP30
- the consequent effect on the RMSE



Comparison with FABDEM

- the DTM generated from AHN4 DSM mirrors the reference DTM more accurately.
  - also reflects in the lower RMSE
- The model, not trained on COP30 data, shows predictably less precision with these DSMs.
- My method creates artifacts that can resemble fake hills after interpolation
- FABDEM appears more blurred due to its post-processing step



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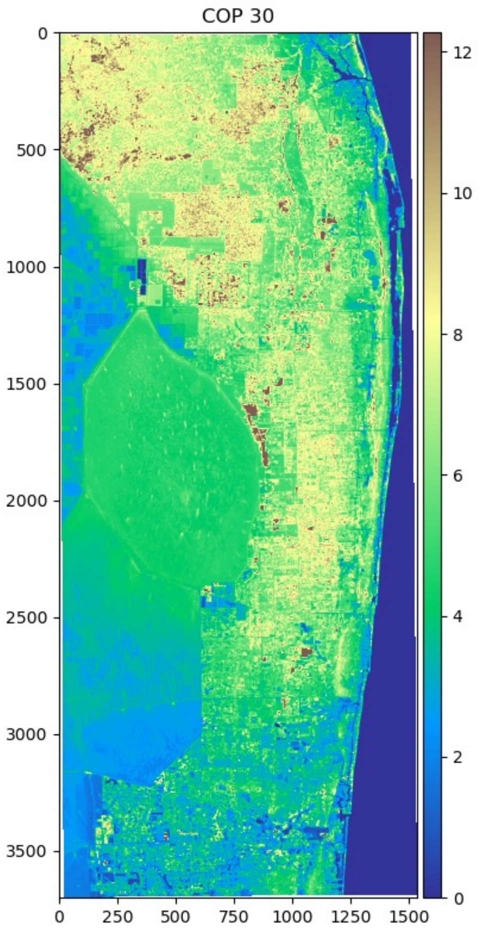
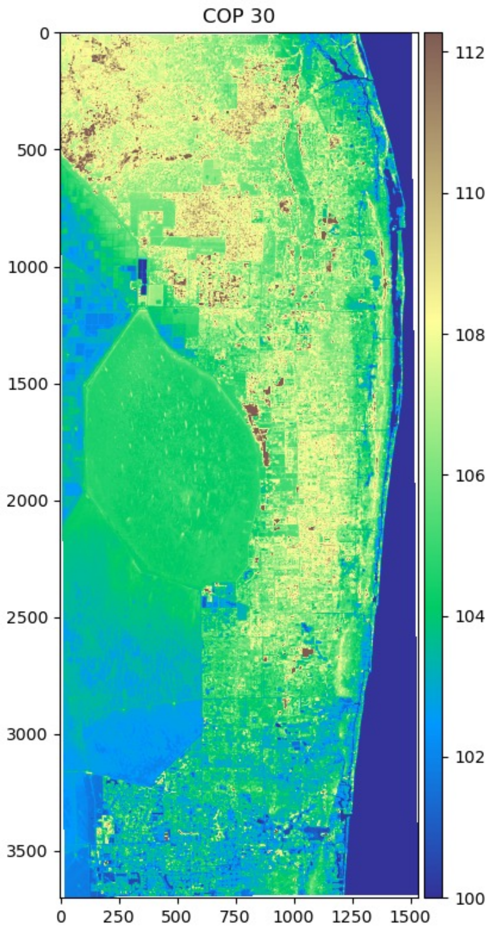
Evaluating Model Performance in Miami and Elevated Miami

- Testing model performance outside of the Netherlands
- Choosing Miami for its similar elevation characteristics
- Utilizing Copernicus DEM (COP30) for Miami as input data and NOAA Sea Level Rise Viewer DEM dataset as reference DTM
- Creation of an elevated version of Miami to assess model's performance
- Remarkable reduction in RMSE demonstrates model's efficacy

	RMSE
Generated DTM of Miami	0.74
Generated DTM of elevated Miami	0.87
FABDEM	0.67
COP30	1.43



Miami

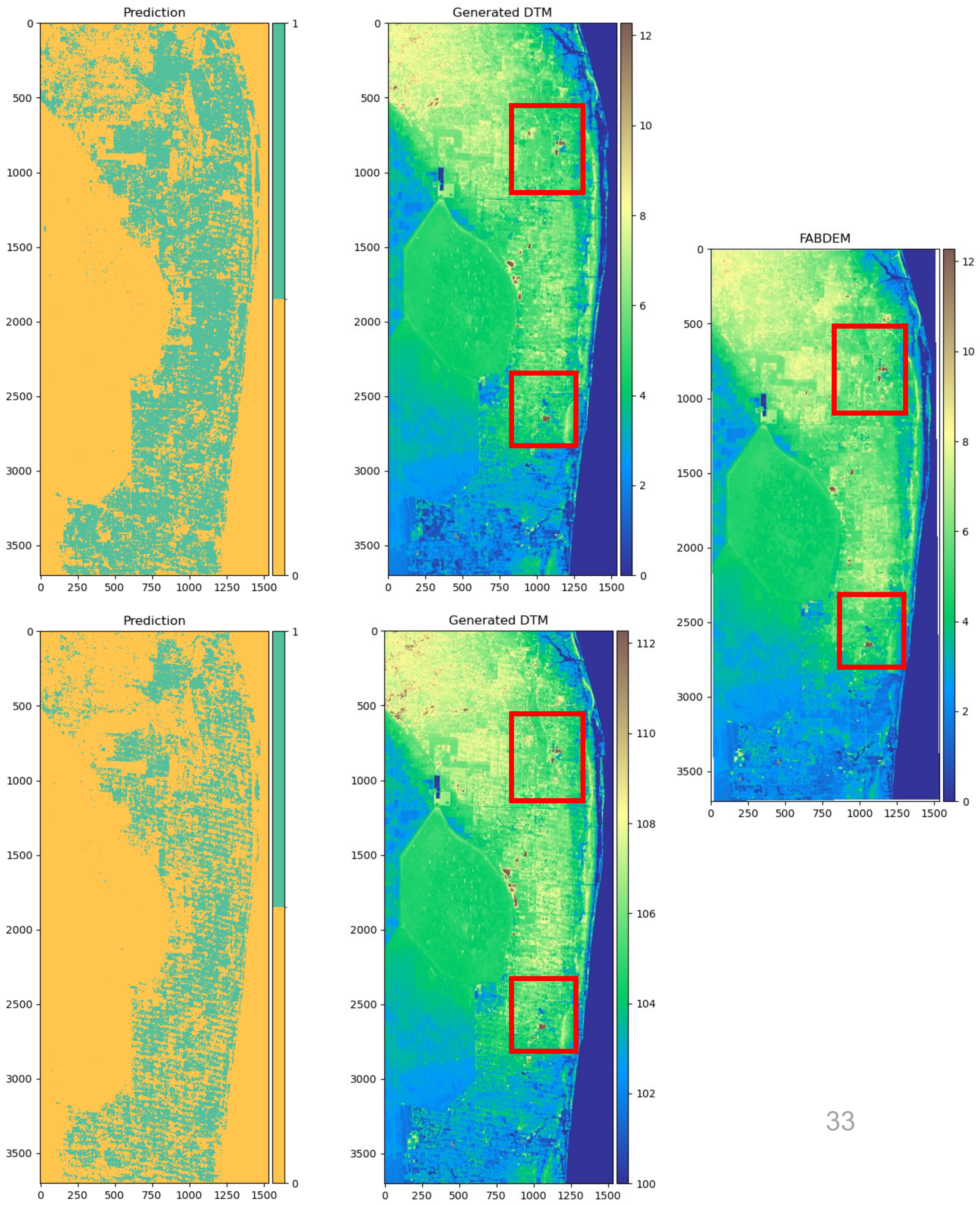


Elevated Miami

Performance in Elevated Miami

- Model's performance remains robust with elevated Miami
- Effective elimination of certain pixels while retaining key terrain features
- challenges with higher elevations

	RMSE
Generated DTM of Miami	0.74
Generated DTM of elevated Miami	0.87
FABDEM	0.67
COP30	1.43



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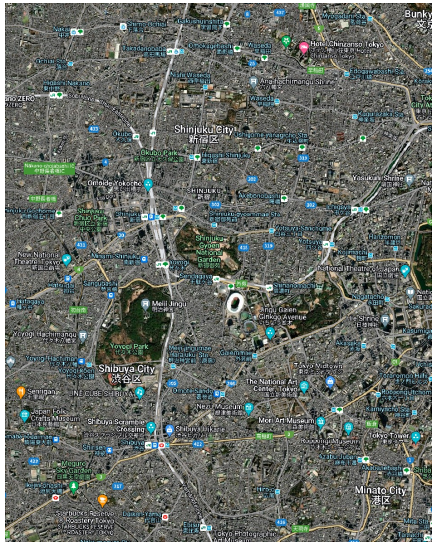
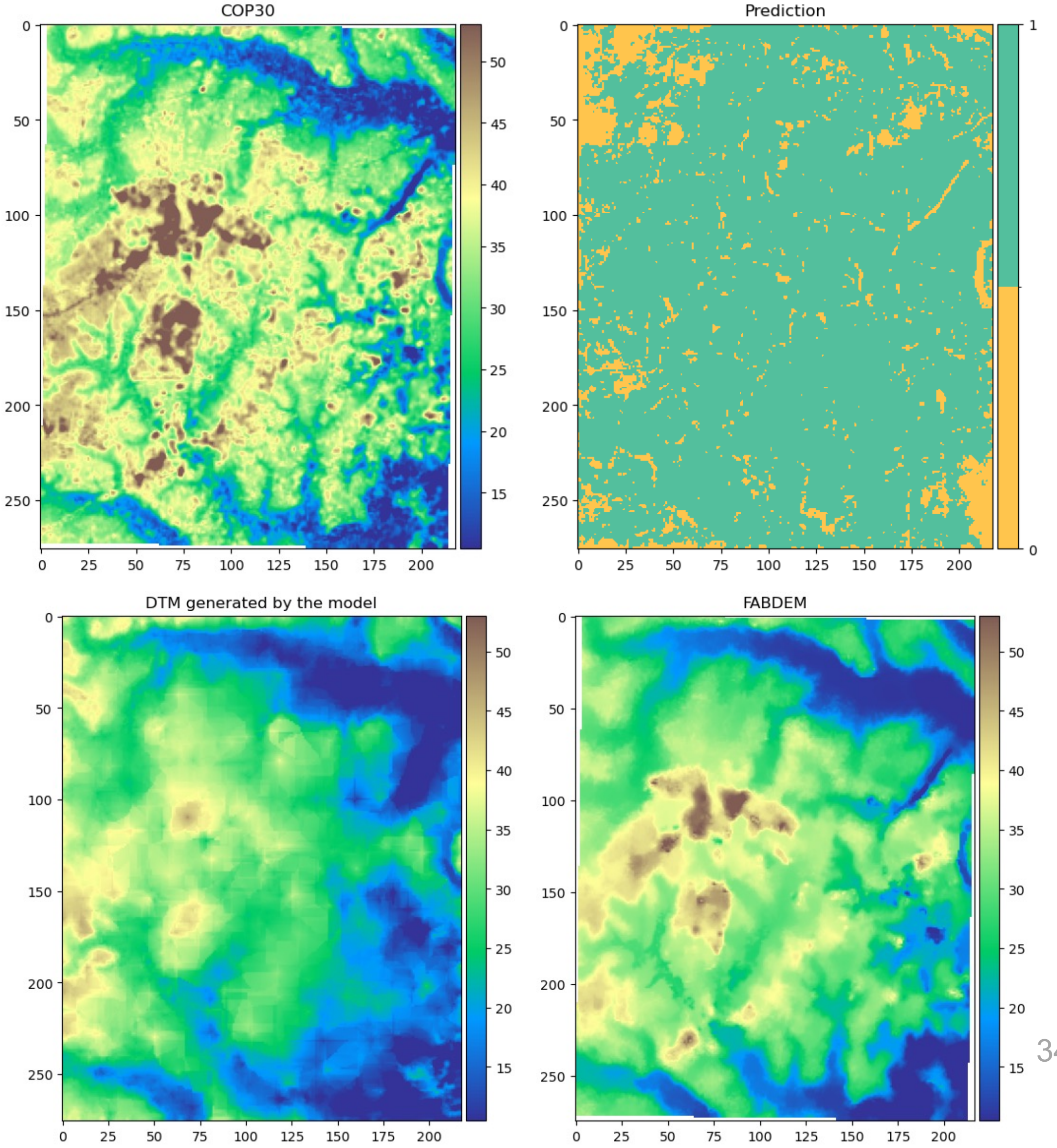
Visual Comparison: Dense Urban Area (Shibuya and Shinjuku in Tokyo)

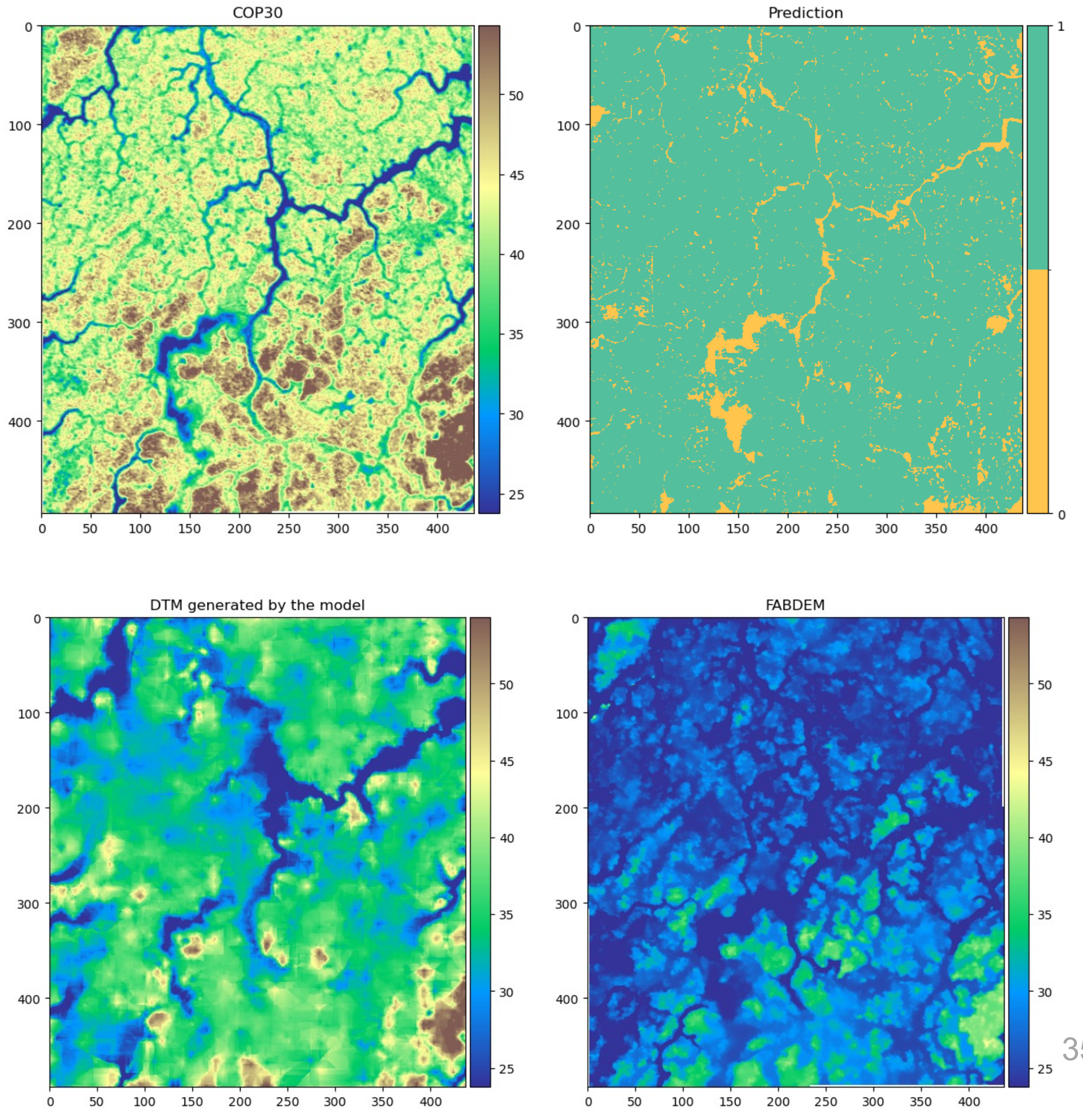
- dense urban landscapes, combination of natural and built environments, and generally flat terrain.
- The model successfully identified most building pixels and removed trees in park areas
- DTM generated by the model has noticeable artifacts





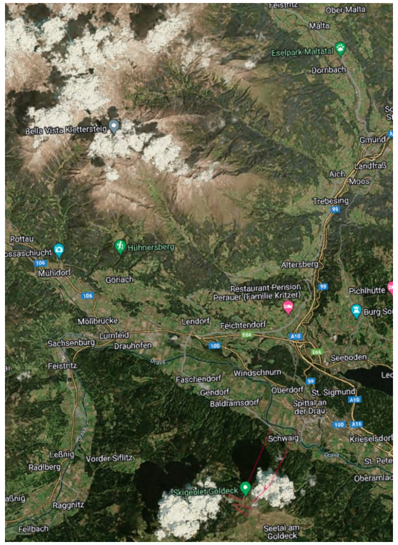
Visual Comparison: Vast Forested Region (Amazon Basin)

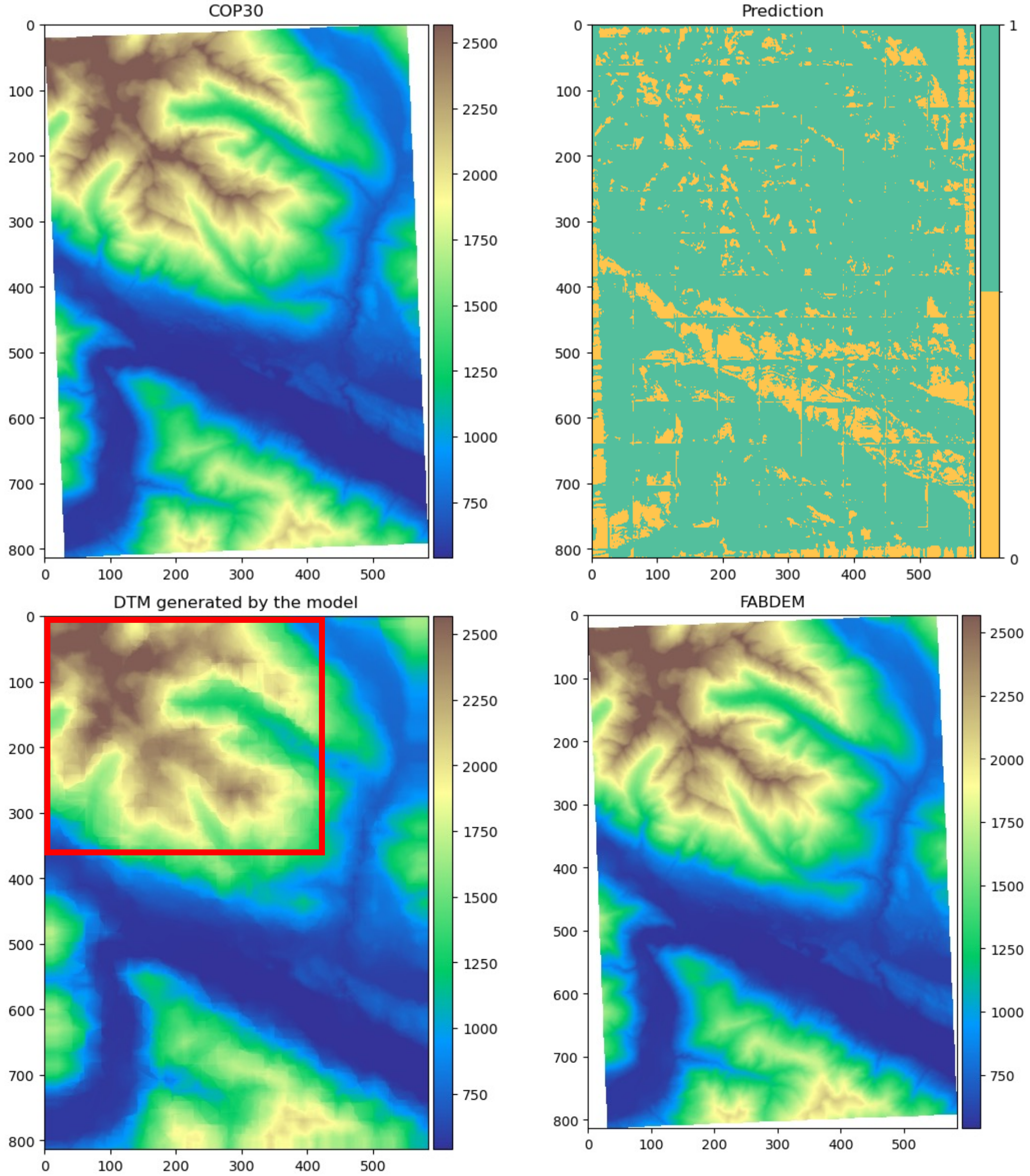
- dense tropical rainforests, diverse flora and fauna, complex hydrological system, and predominantly flat terrain
- The model correctly identified a significant number of trees within the basin
- Some remaining pixels led to higher elevation areas in the DTM, showing differences compared to FABDEM



Visual Comparison: Mountainous Area (Alps in the western region of Austria)

- rugged landscapes, steep slopes, high elevation changes, and a mix of vegetation types
- Challenges faced by the model due to the extensive geographical extent and the wide range of elevations
- The ridge section in the upper left corner of the generated DTM appears blurred, suggesting difficulties in accurately capturing steep slopes.

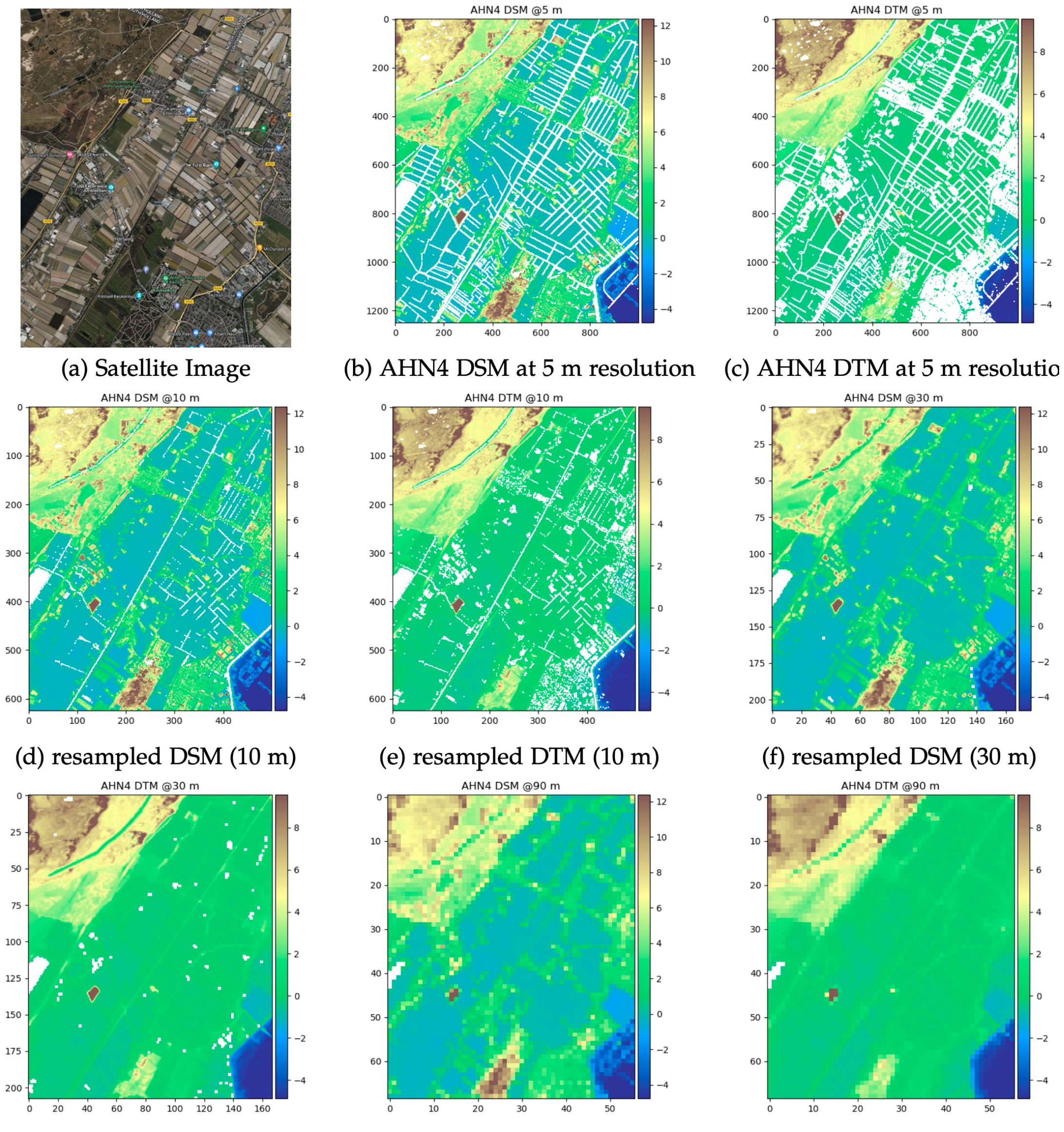




Model Performance Across Different Resolutions

- Evaluation of model performance when applied to 10-meter and 90-meter resolutions
- The model performs best on 30m resolution data

Input resolution	Accuracy	RMSE
30 m	94.1%	0.59
10 m	77.5%	2.16
90 m	68.8%	1.85



(a) Satellite Image
(b) AHN4 DSM at 5 m resolution
(c) AHN4 DTM at 5 m resolutio
(d) resampled DSM (10 m)
(e) resampled DTM (10 m)
(f) resampled DSM (30 m)
(d) resampled DTM (30 m)
(e) resampled DSM (90 m)
(f) resampled DTM (90 m)

Conclusion & Future Work

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Conclusion

- A novel approach for converting DSMs to DTMs using a Residual U-Net deep learning model
- Model's adaptability to different resolutions and datasets, indicating potential in various geoscience applications
- Despite limitations, the model shows promising results for DTM extraction

Future Work

- Addressing model's limitations with additional data sources, such as optical and radar imagery
- Exploring different deep learning architectures and techniques to optimize model's performance

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Thank you for your attention

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