Deforestation Quantification in Satellite Images using Deep Learning & AI

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Introduction

Forests play a vital role in climate regulation, biodiversity, and human well-being, but deforestation driven by logging, agriculture, and pollution threatens ecosystems, with satellite technology and AI now enhancing monitoring and detection of deforestation trends [1, 2, 3, 4].

Satellite image analysis using spectral indices like NDVI and SAVI helps assess vegetation health, traditionally requiring subject-matter expertise (SME) to interpret the indices and environmental factors [5].

Here we investigate how AI can simplify the process by analyzing data patterns and leveraging machine learning to track forest cover changes and quantify deforestation with minimal SME [6, 7].

Methods

We performed object detection through image classification using Deep Learning and Transfer Learning.

Transfer Learning improves image classification efficiency by fine-tuning pretrained models, typically trained on large datasets like ImageNet, but a key drawback is that the input size is standardized to a relatively low resolution (e.g., 224 x 224 pixels in our case), which may limit the model's ability to capture finer details [11][12].

In applications like deforestation analysis, high-resolution satellite images (e.g., 8192 x 4320 pixels) are used to capture detailed information about large geographic areas. However, traditional image classification models require resizing and cropping, leading to a significant loss of resolution, which can compromise accuracy, especially for tasks requiring fine detail such as estimating forest cover [13].

High-resolution challenge

To address this challenge, we adopted a novel approach that improves quantification accuracy by leveraging image patch classification.

Instead of resizing the entire image, we divided the large satellite images into smaller, non-overlapping patches and applied our classification model to each patch.

The approach benefits from the small patch size required by our model thus functions similarly to an image segmentation model, facilitating detailed forest detection.

By comparing before-and-after satellite images of the same geographic area [14], we can identify deforestation patterns [15] with greater precision, offering actionable insights for environmental conservation efforts.

Implementation

The model was developed using TensorFlow and Keras [16], fine-tuning the pre-trained MobileNet [17].

A dense, fully connected layer (FCN) was added as the trainable component to leverage the embeddings generated by the frozen MobileNet model for forest classification.

The model was trained on an NVIDIA GeForce GTX 1050 Ti GPU for 15 epochs with a batch size of 32 images.

Methods

Model parameters

Layer (type)	Output Shape	Param #
keras_layer (KerasLayer)	(None, 1280)	2257984
dense (Dense)	(None, 13)	16653

Total params: 2274637 (8.68 MB)

Trainable params: 16653 (65.05 KB)

Non-trainable params: 2257984 (8.61 MB)

Data: Satellite images dataset used for training

For training our forest classification model , we utilized the NWPU-RESISC45 dataset, developed by Northwestern Polytechnical University (NWPU), China [15].

While the original dataset contains 45 classes, we focused on **13** large, non-man-made objects relevant for large-scale forest detection:

['beach' 'circular_farmland' 'cloud' 'desert' 'forest' 'freeway' 'lake' 'meadow' 'mountain' 'rectangular_farmland' 'river' 'snowberg' 'wetland']

Our 13 classes subset consisted of 9,100 images. Each class contains 700 images, consistent with the original dataset, since we subsampled the classes rather than the examples within each class.

- training 5,460 images (60%)
- Validation: 3,640 images (40%)

Data: Satellite images used for deforestation quantification

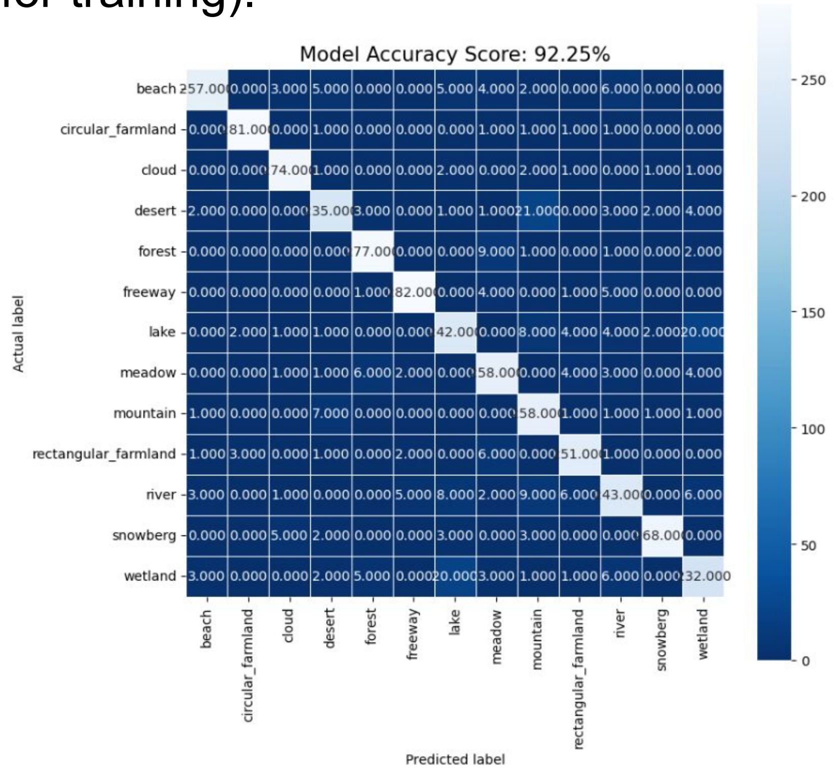
- High-resolution satellite images of deforestation in California's national forests, focusing on the Modoc and Tahoe regions.
- Cover the same geographic areas over time
- Image source: Google Earth [14]

Attribute	Value
Image Size (pixels)	8192 x 4320
Field of View (meters)	6282 x 3189, 5025 x 2550
Pixel Size (meters)	0.75 x 0.75, 0.6 x 0.6

Properties of the manually selected images used for deforestation quantification.

Classification model performance

The performance of our the deep learning model trained on the subset of RESISC images was first evaluated on the validation data (not used for training).



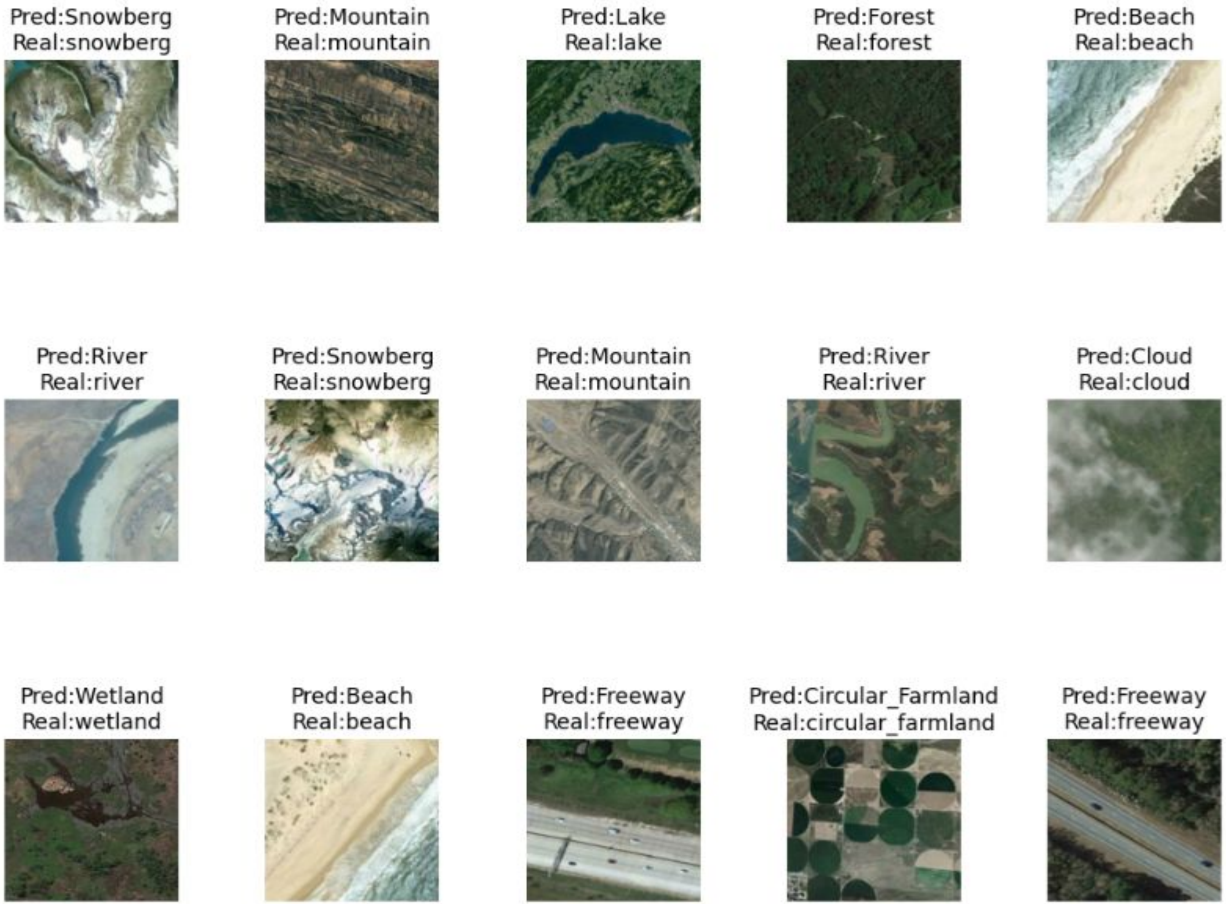
Accuracy and confusion matrix analysis on validation dataset

Class	Precision	Recall	F1-Score
Beach	0.96	0.90	0.93
Circular Farmland	0.98	0.99	0.98
Cloud	0.96	0.97	0.97
Desert	0.92	0.86	0.89
Forest	0.94	0.93	0.94
Freeway	0.97	0.94	0.96
Lake	0.86	0.85	0.85
Meadow	0.88	0.93	0.91
Mountain	0.83	0.96	0.89
Rectangular Farmland	0.93	0.95	0.94
River	0.88	0.86	0.87
Snowberg	0.97	0.96	0.97
Wetland	0.85	0.84	0.85

Model performance at class level

Model predictions on Validation DS

Sample predictions



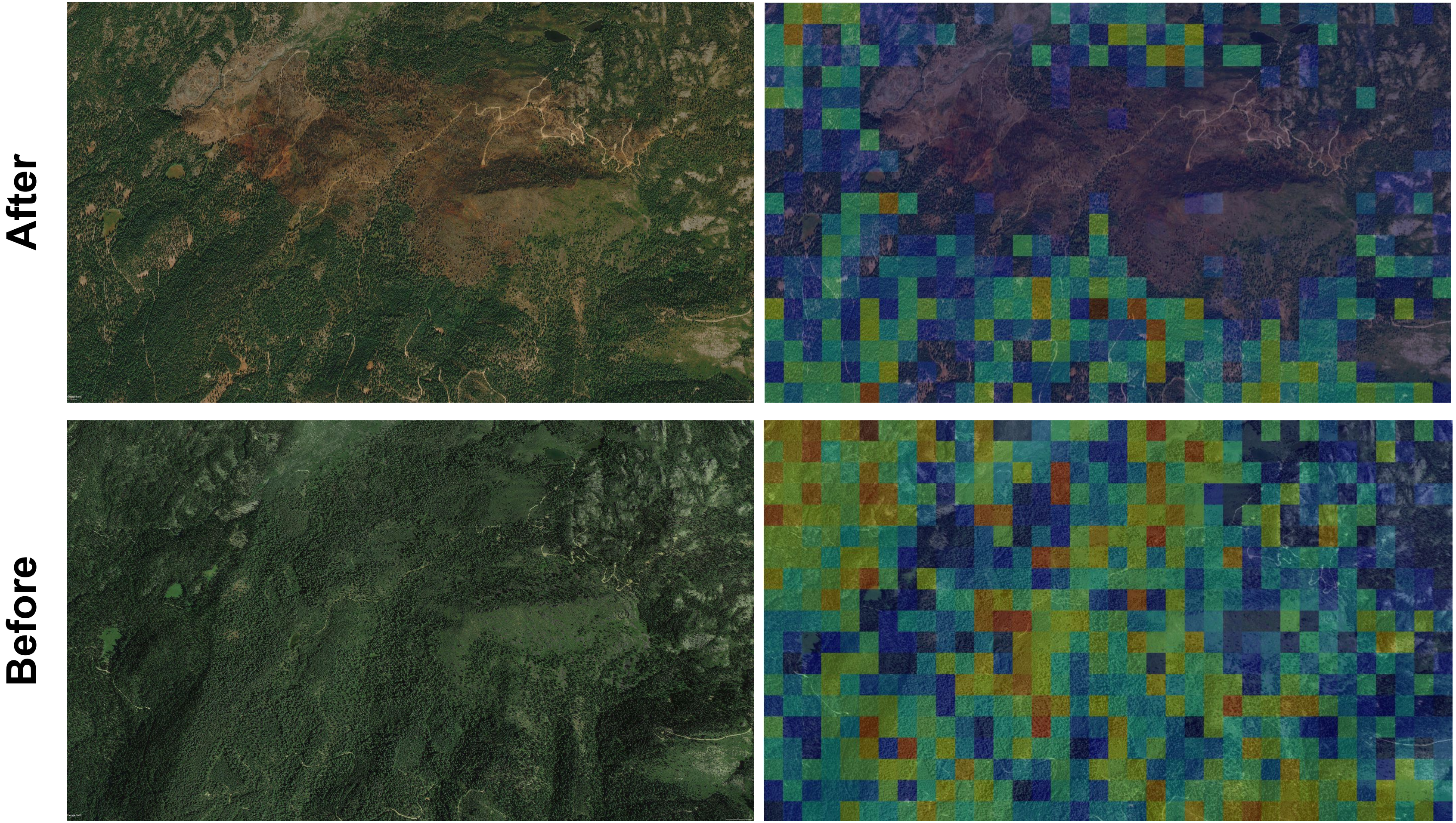
Deforestation quantification

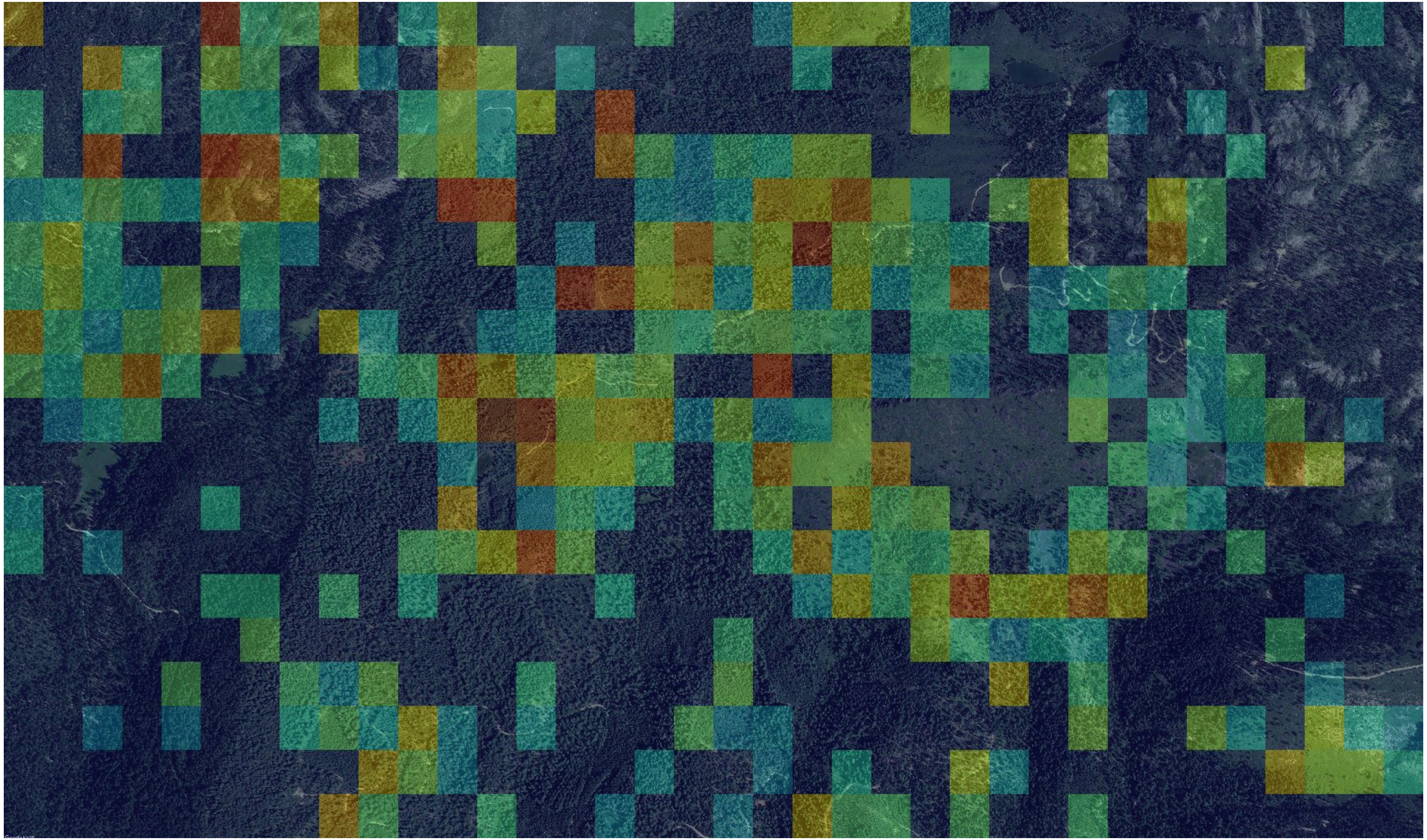
Real-World Scenario

- **Paired Satellite Images**: Two large satellite images were captured, one before a wildfire and one after. These images were divided into smaller patches for analysis.
- **Model Classification**: Each patch was classified individually by the model, predicting the probability of the **Forest** class for each patch.
- **Detailed Detection**: The probabilities were combined to create precise object detection for forest land cover.
- **Heatmap Visualization**: Detection results are displayed as a heatmap, showcasing the spatial distribution of forest cover and deforestation across the satellite images.

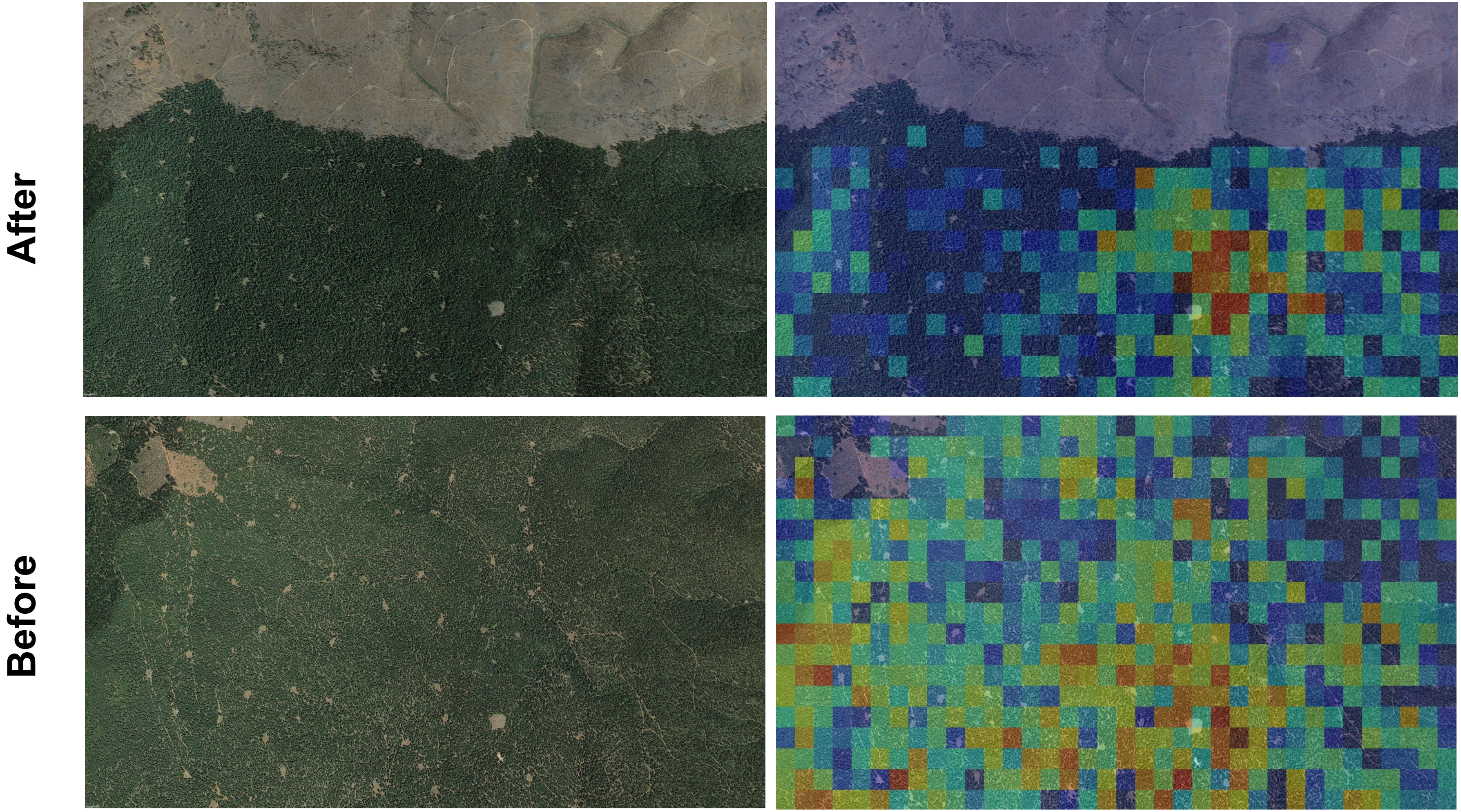
Deforestation Index

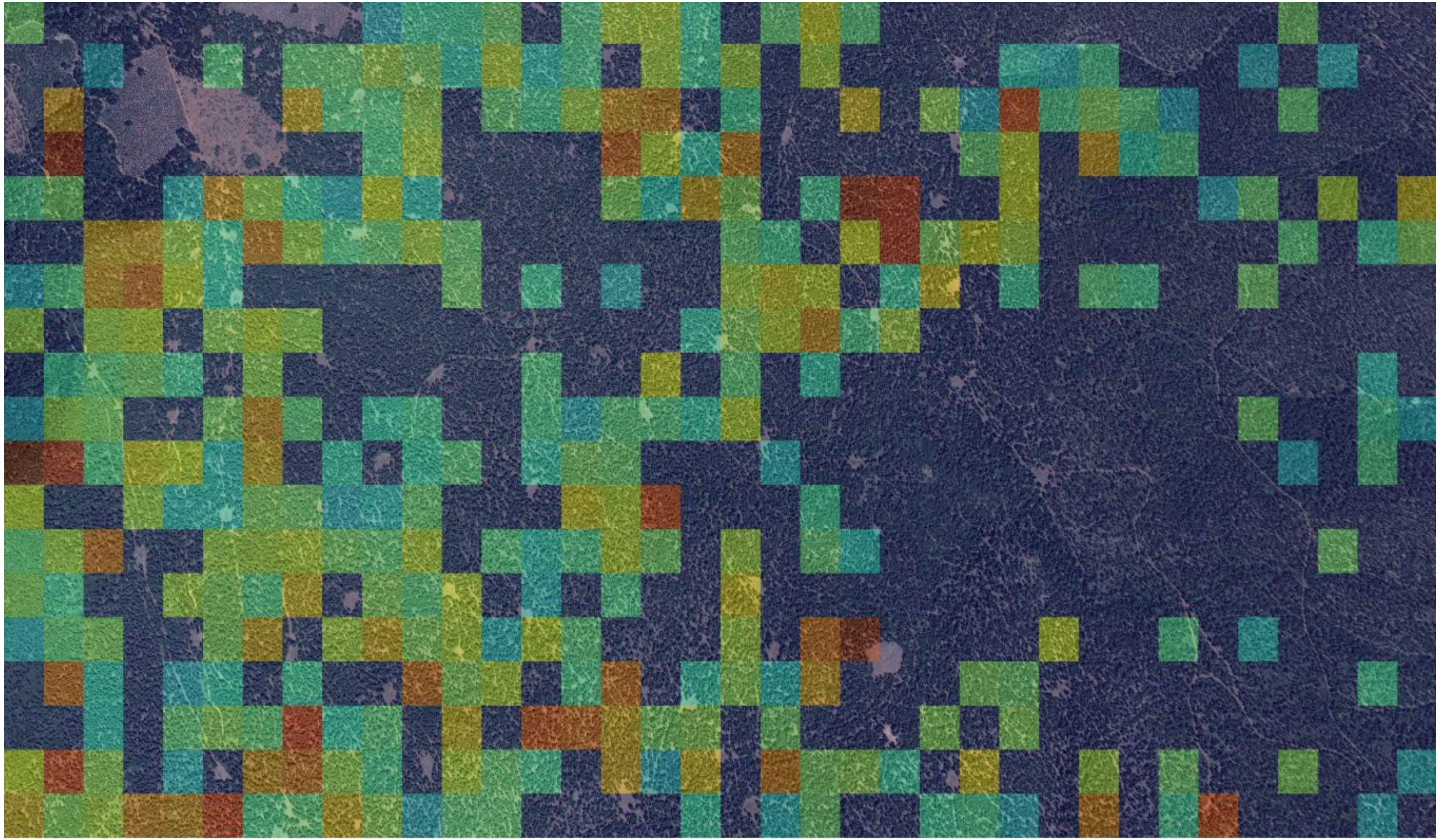
- Based on the **Forest class probabilities** predicted by the model.
- Tracks deforestation by excluding areas not covered in both the "before" and "after" images.


After
Before



Deforestation index ignores non forest areas in image before wildfire

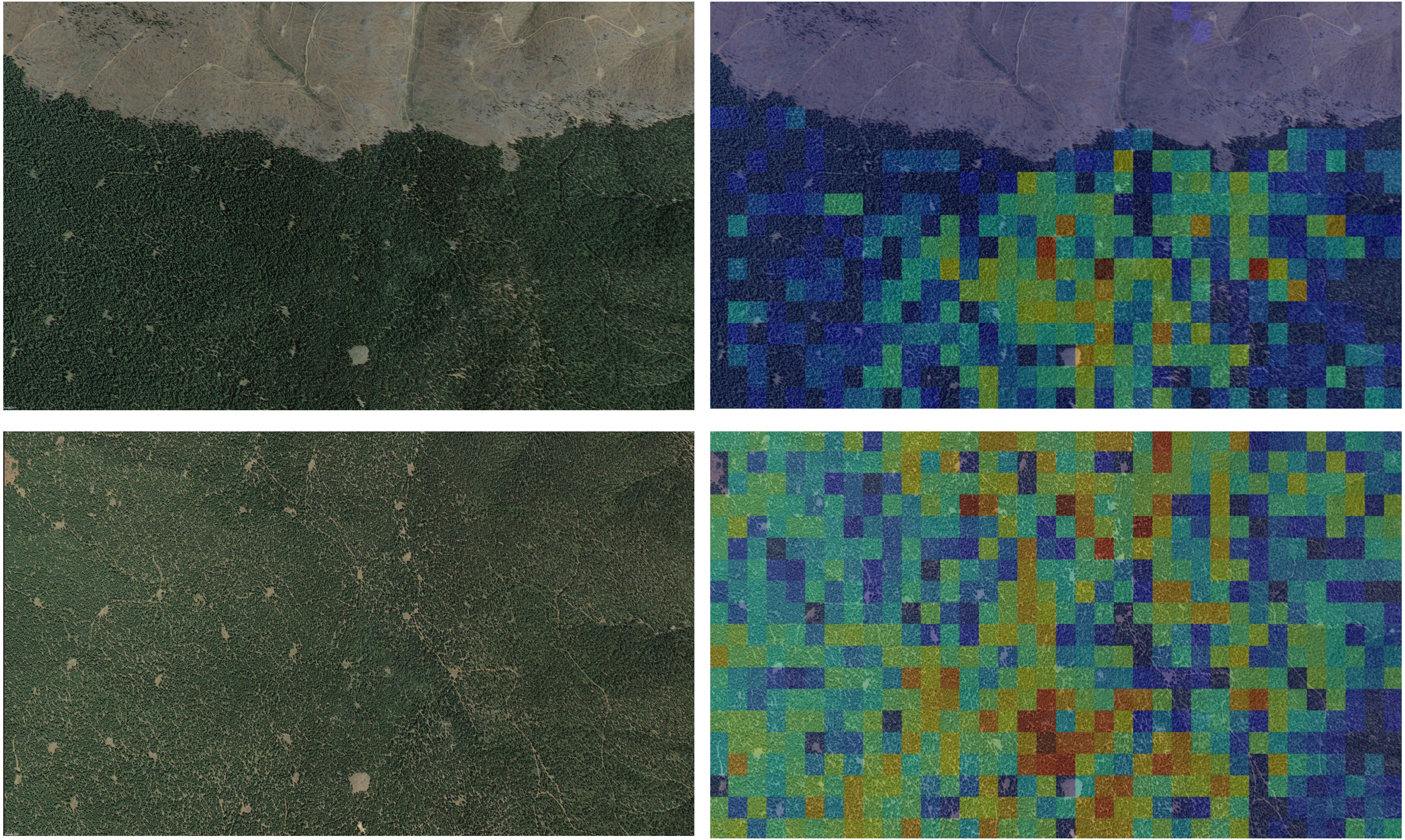

After
Before

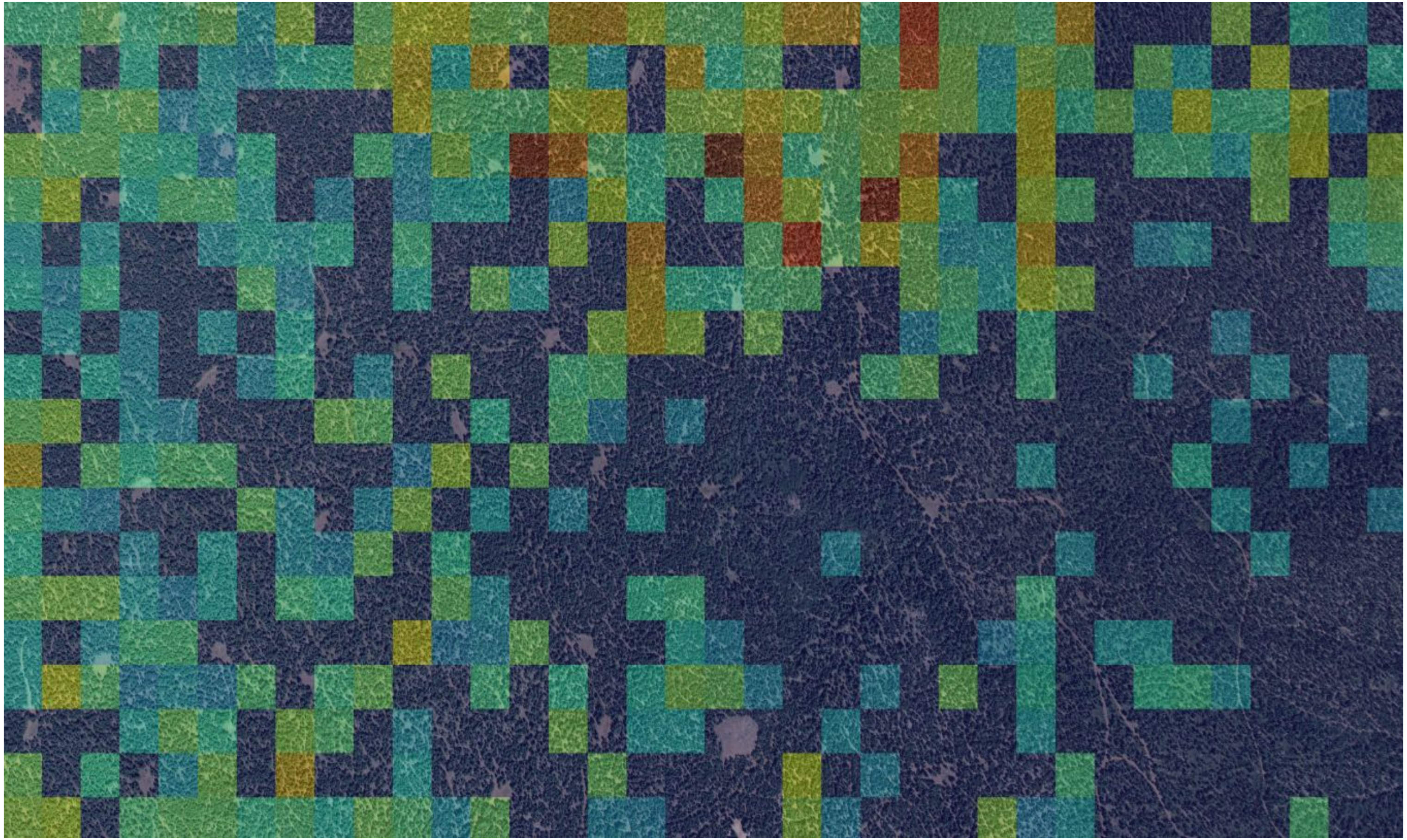


Deforestation index ignores non forest areas in image before wildfire

After

Before





Deforestation index ignores non forest areas in image before wildfire

Discussion

Our classification model achieved 92% accuracy in distinguishing forested from non-forested areas. Its high accuracy on validation dataset makes it a reliable tool for analyzing forest cover changes.

Applied to paired satellite images, the model generated detailed object detection maps of forest land cover, visualized as heatmaps. These provide a detailed detection of forest distribution and deforestation patterns, enabling granular analysis of affected regions.

We developed a Deforestation Index based on Forest class probabilities, focusing on areas with forest cover changes between "before" and "after" images. This approach improves deforestation tracking accuracy and offers a standardized metric for monitoring environmental changes.

Conclusions

Forests play a crucial role in climate regulation, biodiversity, and supporting livelihoods, yet deforestation remains a significant threat. Traditional monitoring techniques are often ineffective due to the vast and remote nature of forests. This project illustrates how deep learning, transfer learning, and AI can be leveraged to accurately quantify deforestation using satellite imagery.

The AI-driven approach allows for scalable, real-time monitoring of environmental changes. By utilizing heatmaps and deforestation indices, stakeholders can effectively visualize and measure forest loss, aiding conservation efforts. This method overcomes challenges such as data scarcity and reduces reliance on subject-matter expertise, highlighting the vital role of AI in detecting illegal logging, tracking habitat changes, and supporting sustainability objectives.

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