Reconstructing Sentinel-2 Optical Data from Sentinel-1 SAR Data Using a Machine Learning Approach [1]

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Introduction

Remote sensing is a critical technique for many applications including forest detection, agriculture, and disaster monitoring [2]. These applications rely on both visible and non-visible light detection. Unfortunately, many of the wavelengths in the visible spectrum cannot pass through clouds. Given that approximately 67% of land mass is covered by clouds, on average [3], accurate and consistent visible light measurements are difficult. Methods are needed to consistently recover visible light data.

Fortunately, Synthetic Aperture Radar (SAR), can pass through clouds. As such, we aim to reconstruct optical data (Red, Green, Blue, and NIR) from geographically and temporally matched SAR data.

We design an image specific machine-learning strategy to reconstruct Sentinel-2 optical data from Sentinel-1 SAR data by independently predicting Red, Green, Blue, and NIR pixel intensities given local SAR data (VV and VH polarization). We then test this strategy using three types of regressors: Linear, Decision Tree, and Light Gradient Boosting regressors.

Data

Ten geographically paired Sentinel-1 (SAR) and Sentinel-2 (optical) images were processed and provided by Space Intelligence. Due to computational limits, we selected one (aoi_1) for analysis. Representative images are shown in Figure 1.

Image Processing Steps:

1. Align Sentinel-1 and Sentinel-2 Images
2. Impute missing Sentinel-1 pixels
3. Generate circular clouds (10% of image)
   - 10 clouds created to assess variance

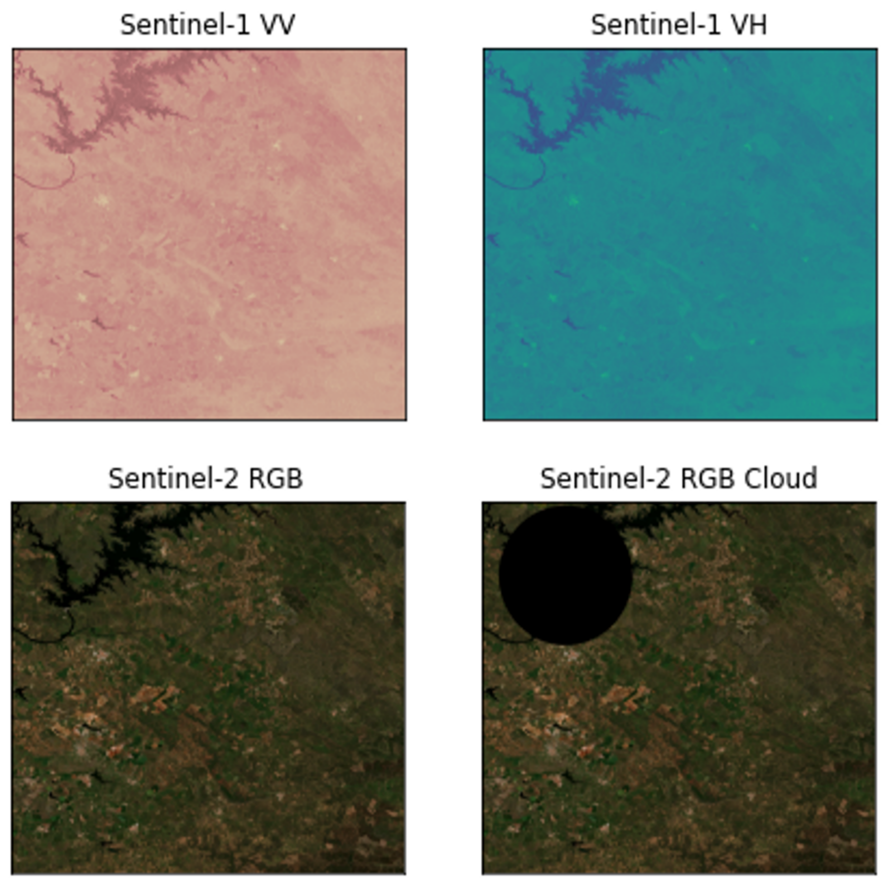

Fig 1. Fully Processed Sentinel-1 and Sentinel-2 Images. Top Left: Sentinel-1 VV Band. Top Right: Sentinel-1 VH band. Bottom Left: Sentinel-2 RGB Image (NIR not shown for visualization). Bottom Right: Representative cloud image. All images are normalized to 0-1 and brightened (with Microsoft photos) for visualization.

Feature Engineering

Response Variables

We develop a unique model for each Sentinel-2 color band, so we have four response variables: $\mathbf{y}_{\mathbf{red}}$, $\mathbf{y}_{\mathbf{green}}$, $\mathbf{y}_{\mathbf{blue}}$, $\mathbf{y}_{\mathbf{nir}}$

Feature Matrix

The feature matrix ($\mathbf{X}$) contains a combination of SAR VV and VH band data. For each y_i we use the corresponding SAR pixel and surrounding pixels from VV and VH.

Modelling

The relationship between SAR and optical data is not linear and potentially bimodal (Not shown here for brevity). As such, we use two different decision tree models since they handle non-linear, mixed distributions well. We also use a baseline linear model (for comparison):

1. Linear Regressor (Baseline)
2. Decision Tree Regressor (Default and Tuned; **Non-linear Method**)
   - Non-parametric technique used to partition data into decision nodes that define prediction values
3. Light Gradient Boosting (LGB) Regressor (Default and Tuned; **Non-linear Method**)
   - Boosted decision tree regressor that minimizes the error from previous trees to improve the results of the subsequent trees
   - Improves efficiency by dropping low importance data points and combining sparse features

Results

Distribution Analysis

Distribution analysis lets us identify how well the model captures the true pixel diversity. The default decision tree regressor captures the true data's bimodal structure and diversity the best.

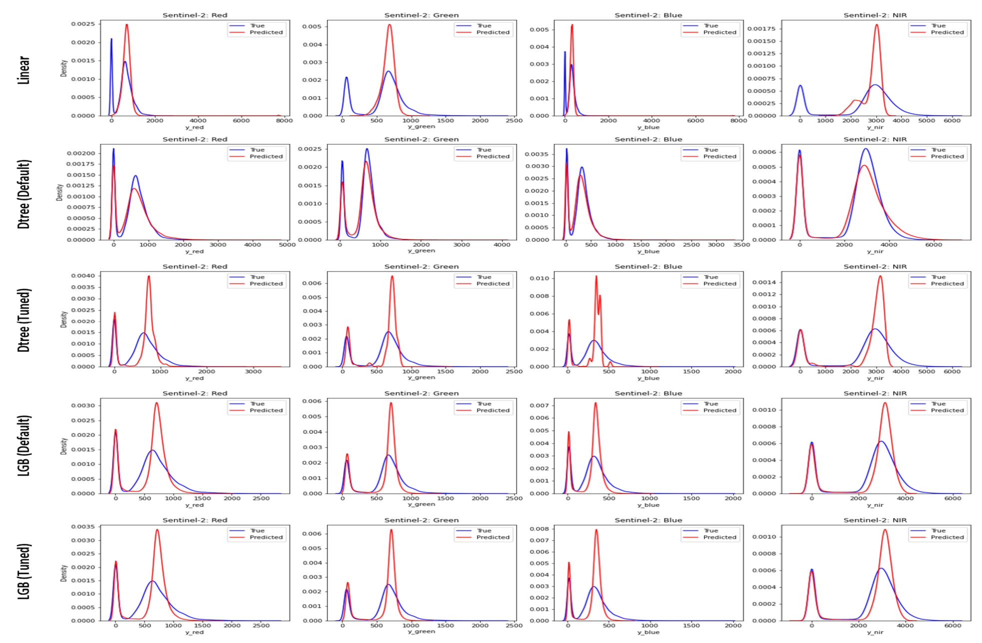

Fig 2. Distribution of true and predicted Sentinel-2 cloud pixel intensities for cloud 1. True is shown in blue and predicted is shown in red. The distributions were plotted using a normal kernel density estimator on 100,000 samples.

Traditional Statistics Analysis

RMSE and MAPE provide quantitative estimates for model error. As point estimates, they do not capture the full complexity of an image, but we use them to assess model consistency.

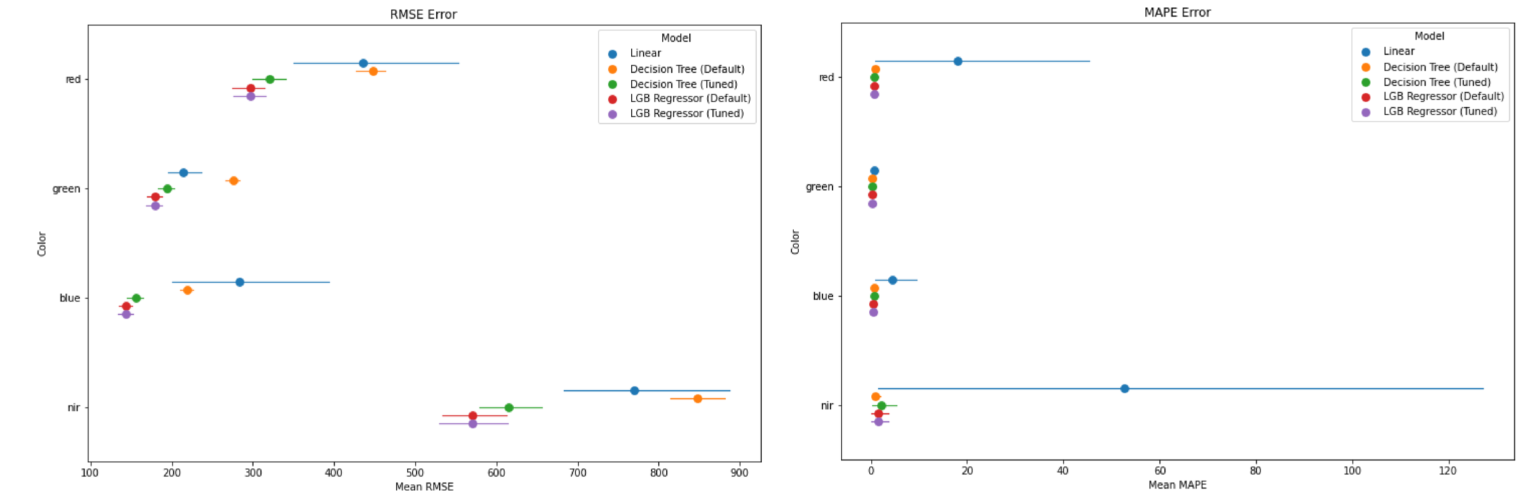

Fig 3. Mean RMSE and MAPE statistics with 95% confidence intervals for each model. Averages were calculated across the 10 cloud samples. Confidence intervals were calculated via a 1000 sample bootstrap.

Figure 3 demonstrates that all models are consistent except the linear model (narrow confidence intervals), but the LGB and tuned decision tree regressors yield the lowest average error.

Results

Image Reconstruction

Viewing predicted images helps assess how "real" a reconstructed image appears. If a person cannot distinguish between the reconstructed and ground truth image, the reconstruction method works well.

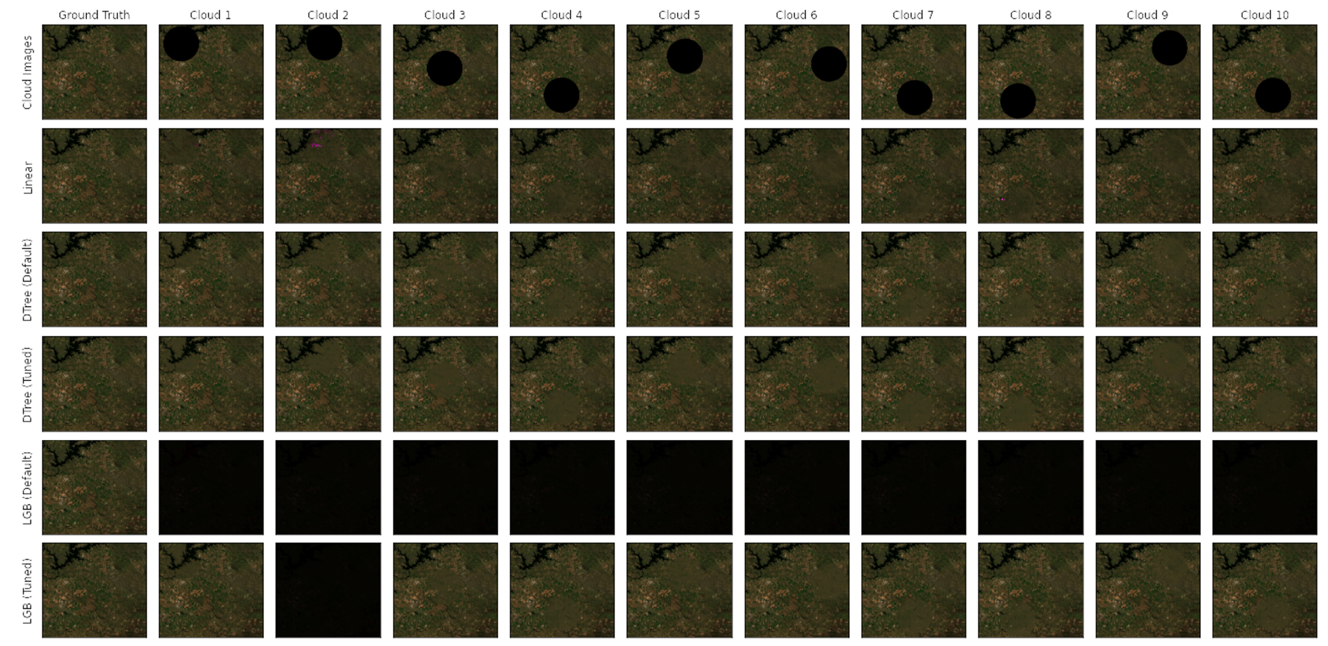

Fig 4. Cloudy Sentinel-2 RGB images reconstructed from Sentinel-1 SAR Data. All images are normalized to 0-1 and brightened (with Microsoft photos) for visualization. 10 Clouds were generated and analyzed.

Figure 4 suggests that the default decision tree regressor is the best at consistently constructing images that are difficult to distinguish from ground truth (relative to other models).

Conclusions & Discussion

The results suggest the default decision tree regressor recovers structural complexity of the image best. Additionally, both traditional statistics and reconstructed images suggest the default decision tree is invariant to cloud location.

Default Decision Tree Summary:

- Captures true pixel diversity
- Produces images that are (relatively) difficult to distinguish from ground truth
- Yields (relatively) high RMSE and MAPE values, but has narrow confidence intervals
  - invariant to cloud location

Limitations

Computational Limits

1. Analyzed only one image
2. Training and hypertuning sets were subsets (N = 1,000,000 and 10,000)
3. Hypertuning done with random search

Modelling Limits

1. Only reconstructed whole images
2. Should consider reconstructing indices (vegetation index)

Future Directions:

- Distribution analysis results closely match image reconstruction results. Thus, it may be useful to minimize distribution loss (using Kullback-Leibler)
- Train a deep learning (cGAN) network for image reconstruction

References

[1] Hoover J. "Reconstructing Sentinel-2 Optical Data from Sentinel-1 SAR Data Using a Machine Learning Approach". In: (2022).

[2] Ranganath R. Navalgund, V. Jayaraman, and P. S. Roy. "Remote sensing applications: An overview". In: *Current Science* 93.12 (2007), pp. 1747–1766. ISSN: 00113891.

[3] Michael D. King et al. "Spatial and Temporal Distribution of Clouds Observed by MODIS Onboard the Terra and Aqua Satellites". In: *IEEE Transactions on Geoscience and Remote Sensing* 51 (7 July 2013), pp. 3826–3852. ISSN: 0196-2892. DOI: 10.1109/TGRS.2012.2227333.