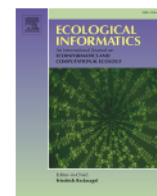


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# Winter tree and terrain shadow correction reveals land cover mapping errors in Sentinel-2 satellite imagery

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## ABSTRACT

This paper presents an approach for detecting and correcting winter shadows cast by trees and terrain. The approach is geographically adaptable and was evaluated across 7 international Sentinel-2 10 m images located over Denmark, Japan, New Zealand, Sweden, and the UK. The detection method employs a physical-based approach using a Digital Elevation Model (DEM), solar angles, tree height layer, and adaptive thresholds to reduce errors. We evaluated the approach with two tree canopy height models (CHMs), the Meta CHM and UMD CHM, Meta was most accurate, yielding an overall accuracy of 83.6% ( $\pm 1.4\%$ ) over 5 non-snow images, and 82.8% ( $\pm 1.6\%$ ) over 2 snow images. We found shadows occupy a substantial land surface area ranging between 8% and 30% within each image, indicating detection and correction importance for environmental monitoring studies. Subsequently, we tested deep learning and ensemble regression models for shadow correction via a gap-filling approach with multitemporal SAR, texture, and a novel shadow-independent focal layer, all combined with hyperlocal training to enable locally-relevant predictions. LightGBM and XGBoost delivered the highest accuracy and speed, ensuring scalability for larger datasets. The Mean Absolute Error (MAE) for the LightGBM model were: MAE = 440 Near-IR, MAE = 302 Red, MAE = 259 Green, and MAE = 0.037 NDVI. Evaluation of the Dynamic World land cover model indicated approximately 10–18% of water pixels in two selected images were erroneous and caused by tree or terrain shadows. This manuscript highlights the importance of accounting for shadows when using earth-observing imagery for environmental monitoring in moderate-to-high latitudes.

## 1. Introduction

Shadows are a prominent aspect of earth-observing research applications, and they can be cast by natural topographic features such as terrain relief or trees, as well as features from the built environment like buildings, bridges and infrastructure. While each type of shadow has fundamentally different radiometric properties, they all result in reduced pixel values which lead to incomplete and inaccurate representations of features on the earth's surface, and are not directly representative of the typical values for a given land surface feature (Mostafa, 2017). While shadows on the earth's surface can provide useful photogrammetric information to derive metrics such as tree or building geometries and heights (Dong et al., 2024; Greenberg et al., 2005; Liasis and Stavrou, 2016; Shao et al., 2011; Xu et al., 2024b), shadows also obscure spectral signatures and can lead to issues in spectral index values, image interpretation or map classification errors due to similar reflectance values of land surface features such as shadows and water

(Giles, 2001; Li and Strahler, 1985). Shadows have greatly impacted the quality and accuracy of remotely sensed data, and the derived estimation of variables related to vegetation, impervious surfaces, water, snow, albedo, soil moisture, evapotranspiration, land surface temperature, and more (Alavipanah et al., 2022; He et al., 2024; Lu et al., 2022; Zhu et al., 2024).

Thus, because of the need to overcome shadow errors, methods to detect and correct for various types of shadows have been developed. Topographic correction methods have focused on correcting shadowed pixels caused by mountains or terrain relief, including a variety of empirical and semi-empirical approaches. For example, the C-factor method is a Lambertian correction with an adjustment factor from regression that considers linear reflectance variation with illumination (Teillet et al., 1982). The Gamma correction approach is more empirical and uses a simple power model, offering rapid normalization (Gu and Gillespie, 1998). The SCS + C method includes canopy geometry as an additional factor and does not assume a Lambertian surface (Soenen

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et al., 2005), but still has issues in cast shadow terrain. These approaches have challenges with correction in winter imagery due to high solar zenith angles (Ma et al., 2025). More recently, improved terrain correction methods have been developed. For example, Zhang et al., 2015 introduced synergistic use of atmospheric correction and BRDF-aware topographic correction, for improved performance compared to the prior methods as it included input from the MODIS albedo product. Another approach corrected reflectance based on the difference between sunlit and shadowed areas with promising results and an efficient approach; but was limited to NDVI (Yang et al., 2022). Recently, one effort integrated topographic correction with atmospheric correction and achieved promising results for shadow reduction in a single test site (Carmon et al., 2022), but may still have challenges with high solar zenith angles. Similarly, another study integrated MODIS atmospheric products with Landsat for high accuracy shadow correction, however, deep shadows still persisted (Zhang et al., 2018). High solar zenith angles, such as those greater than 55 degrees, which are commonly present in high latitude winter imagery, have led to low accuracy derivative products (Wang and Zender, 2010), supporting the need for new methods which can have more success under these difficult illumination conditions.

For cast shadows, much of the research has focused on clouds and cloud shadows, as they are the most prominent data gaps present in remotely sensed imagery. Prior efforts to detect cloud and cloud shadow eventually resulted in unified algorithms with accuracies in excess of 98% for cloud and 90% for cloud-shadow (Li et al., 2022b). Generally, cloud and cloud shadow classification methods focused on varying combinations of classifiers using: physical-rule based (Qiu et al., 2020; Zhai et al., 2018), temporal-change algorithms (Hagolle et al., 2010), variational-model (Chen et al., 2019; Duan et al., 2020), or machine-learning based algorithms (Shendryk et al., 2019; Xie et al., 2017; Lasko, 2022; Miao et al., 2022; Li et al., 2022b; Li and Wang, 2024; Wright et al., 2024), with many of the machine-learning based algorithms only reliant upon mono-temporal imagery. Recently, sensor-agnostic, deep neural network algorithms have taken hold with very high accuracy (Wright et al., 2025). The resulting accurate classification methods for cloud and cloud shadow enabled the advent of cloud-free image compositing (Francini et al., 2023; Hermosilla et al., 2023; Man et al., 2018; Potapov et al., 2011; White et al., 2014).

Other types of shadows pose a significant challenge in remotely sensed imagery including building shadows, and tree shadows. The latter has the least amount of research available and is the focus of the manuscript. Building shadows have been accurately identified with spectral indexes (OA between 0.90 and 0.99) (Huang and Zhang, 2011; Zhou et al., 2021), deep learning models for high-resolution aerial or satellite imagery with F1-scores between 0.71 and 0.92 (Luo et al., 2020; Luo et al., 2021), and the use of digital building models (DBMs), solar zenith, and solar azimuth in a photogrammetry-based approach (Zhou et al., 2023). Additional research with highly efficient unsupervised classification based on multichannel features yielded F1 scores around 83% for buildings, with noted issues and challenges in detected trees (He et al., 2022). Additional building shadow correction research results are available in recent reviews and manuscripts (Li et al., 2022a; Xie et al., 2022; Chen et al., 2023a; Dong et al., 2024; Yang et al., 2024; Zhang et al., 2025). For generic shadows, one study produced several methods, including histogram matching with image classification to produce accurate compensation of shadows for land cover classification (Wu et al., 2014). Another approach has accurately detected terrain and cloud shadows at 93% overall accuracy using a multistage, self-training neural network (Nambiar et al., 2022).

Limited research on the detection and correction specifically of tree and terrain shadows has been conducted. One recent study using high resolution Maxar imagery in mountainous environments detected and corrected terrain shadows with an overall accuracy of about 95% in China, which yielded significantly improved classification of coniferous trees (Zhu et al., 2024), but the identification and correction of tree

shadows was outside of the study's scope. Another recent study detected a combination of building and tree shadows in a single class with high accuracy in high resolution imagery across urban environments with F1-scores ranging from about 83% to 93% for different datasets (Zhu et al., 2022). One study produced an approach to detect shadows cast by crops at the high-resolution scale using imagery acquired from a drone on several dates, with accuracies ranging from 84% to 93%; the study also noted the shadow areas resulted in artificially decreased NDVI which negatively impacted modeled evapotranspiration levels (Aboutaleb et al., 2019). Another study quantified tropical forest under-canopy tree shadows with a straightforward voxel-based trees approach (Fujiwara and Takeuchi, 2022). Studies have yet to generate terrain and tree shadow detection and correction at the Sentinel-2 scale with quantification of shadow extent and impacts.

Shadows cast by terrain and vegetation have led to challenges and data inaccuracies in derived remote sensing datasets. Studies have been conducted with varying success on image classification of various features which are afflicted by terrain shadow. For example, Li et al. 2018 used log-transformed data with a Normalized Difference Water Index (NDWI) to achieve reasonable success in mapping glacial lakes under shadow. Other efforts have achieved reasonable accuracy in image classification workflows by altering training data to synthetically correct for reduced spectral value from shadowed pixels in each phenomena (Peker et al., 2024). Another effort found substantially reduced classification accuracy in tree canopy shadows when attempting to map invasive plant species (Lopatin et al., 2019). Terrain shadow effects have negative influence on various other aspects such as spectral characteristics of glacial meltwater (Wójcik-Długoborska and Bialik, 2020). Further, over permafrost thaw ponds, vegetation shadows have been found to reduce spectral values by 51–70% depending on spectral band (Freitas et al., 2022). Tree and landscape shadows play a major role in northern latitudes and during winter times when solar zenith angles are very low and yield substantially more shadows than in summer months when the sun is often directly overhead at time of image acquisition. However, research has minimally explored tree and terrain shadows; and has not yet quantified how much land surface area the shadows occupy in moderate-to-high latitude regions during winter. As studies have shown improved, but imperfect land cover products when integrating topographic correction; there is a need for highly accurate correction in winter images (Chen et al., 2023a, 2023b; Yin et al., 2022). Accordingly, this study: (1) proposes a photogrammetry-based approach for efficient detection of tree and landscape shadows which is efficient for computation at broad spatial scales, (2) implements a multi-sensor, hyperlocally-trained, data gap-filling model for correction of tree and terrain shadow-afflicted pixels with inter-comparison of several deep learning and ensemble regression models with hyperparameter tuning, (3) evaluates accuracy of detection and correction across 7 globally-distributed images with Sentinel-2 imagery, including snow-on and snow-off dates in high-latitude regions (evaluated due to variation in spectral brightness), (4) demonstrates the role landscape and tree shadows have on errors in a major globally-available land cover product through a select case study evaluation, and (5) evaluates spatial extent of tree and landscape shadows across select geographical regions with comparison of two tree Canopy Height Models (CHMs) produced at different spatial resolutions. The core innovations of this research include (1) the use of ultra-local training with multi-sensor fusion for shadow correction, (2) evaluation of two tree CHMs for shadow detection, (3) evaluation of a novel shadow-independent focal layer for shadow correction, and (4) highlight of the spatial extent occupied by tree and terrain shadows during peak winter months.

## 2. Study area and datasets

### 2.1. Study area

The study evaluates 7 different images across 5 different globally-



**Table 1**  
Characteristics of the Sentinel-2 imagery evaluated in this study.

| Location                                 | Date       | Sentinel-2 Granule | Latitude | Snow?   | Tree proportion? | Geographic Features                                    |
|------------------------------------------|------------|--------------------|----------|---------|------------------|--------------------------------------------------------|
| Esbjerg, Denmark (DEN)                   | 2022-12-16 | T32UMG             | 55.5 N   | Yes     | Moderate         | Mixed urban, forestry, grassland, agriculture, coastal |
| Esbjerg, Denmark (DEN)                   | 2022-12-23 | T32UMG             | 55.5 N   | Minimal | Moderate         | Mixed urban, forestry, grassland, agriculture, coastal |
| Takaoka, Japan (JPN)                     | 2023-12-06 | T53SPA             | 36.8 N   | Minimal | Low              | River, mountains, agriculture, trees                   |
| Wellington, New Zealand (NZ)             | 2020-06-09 | T60GUV             | 41.2S    | Minimal | Low-Moderate     | Rugged mountains, cropland, lake, grassland, Urban     |
| Linköping, Sweden (SWE)                  | 2023-11-24 | T33VWE             | 58.3 N   | Minimal | High             | Lakes, forestry, agriculture, urban                    |
| Linköping, Sweden (SWE)                  | 2024-01-18 | T33VWE             | 58.3 N   | Yes     | High             | Lakes, forestry, agriculture, urban                    |
| Birmingham, England, United Kingdom (UK) | 2022-11-25 | T30UWD             | 52.5 N   | Minimal | Moderate         | Mixed land use, rolling hills                          |

distributed test sites at moderate-to-high latitudes ranging from 36 degrees North to 58.3 degrees North and one site in the Southern Hemisphere at 41.2 degrees South. Dates of imagery were selected to correspond with the winter and autumn seasons to maximize tree and terrain shadows; the acquisition dates ranged from November through January in the Northern Hemisphere, and June for the Southern Hemisphere site. To consider potential spectral variation and accuracy due to snow cover, the study compares a snow cover date vs non-snow cover date at 2 sites: Denmark and Sweden. Table 1 shows a list of locations evaluated in this study, and which are used to demonstrate the shadow detection and correction approaches. The locations include: (1) Esbjerg, Denmark (snow and not snow images), (2) Takaoka, Japan, (3) Wellington, New Zealand, (4) Linköping, Sweden (snow and not snow images), and (5) Birmingham, England, United Kingdom.

## 2.2. Sentinel-2 multispectral imagery

Sentinel-2 Multispectral Instrument (MSI) imagery is provided by the European Space Agency (Gascon et al., 2014). We acquired the Bottom of Atmosphere (BoA) reflectance, Level 2 A (L2A), from the Microsoft Planetary Computer's SpatioTemporal Asset Catalog (STAC) API via python programming. The L2A product contains geometrically and radiometrically corrected imagery, along with a quality assurance layer called the Scene Classification Layer (SCL) that contains a layer of clouds and cloud shadows, which was used to mask out afflicted pixels, and it includes snow pixel identification which is used as described in the methods. Sentinel-2 imagery includes a metadata file within the SAFE architecture entitled 'MTD\_TL.xml', which contains solar zenith angle (SZA) and solar azimuth angle (SAA) for each image; these were subsequently used as described in the methods. Sentinel-2 MSI imagery includes 13 spectral bands at three spatial resolutions (10 m, 20 m, and 60 m). This study used the 10 m dataset with 4 provided bands (RGB and Near-IR). The Sentinel-2 granules were subset to exclude clouds, no data pixels, and ocean.

## 2.3. SRTM Digital Elevation Model (DEM)

The Shuttle Radar Topography Mission (SRTM) DEM was acquired for the geographic region of each of the seven images using the Microsoft Planetary Computer STAC API via python. The SRTM DEM is provided at 1 Arc-second (30 m) with void-filled data at the near-global scale with the latest re-processed version entitled NASADEM (Crippen et al., 2016). The SRTM DEM was acquired in February of 2000 and is considered as one of the best available near-global DEMs at 30 m spatial resolution. However, as with most DEMs, the SRTM DEM suffers from some artifacts due to terrain; varied penetration within vegetation canopy; and challenges with other dense obstructions (Jarihani et al., 2015). While a variety of DEMs are available such as Copernicus GLO-30, FABDEM, and

earlier versions of SRTM, we selected the NASADEM (the latest SRTM DEM version) as its C-band frequency at latitudes below 60 N and above 37S offers better tree canopy penetration performance than the other X-band derived datasets (Meadows et al., 2024; Simard et al., 2024). To maintain the original resolution of the Sentinel-2 imagery, the DEM was resampled to 10 m resolution with the nearest neighbor option.

## 2.4. Tree Canopy Height Models (CHMs)

Two tree canopy height models (CHMs) were collected and evaluated. The high-resolution 1 m global CHM was acquired over each study site. It contains tree canopy heights with imagery primarily derived from the 2018–2020 timeframe. It was produced through a collaboration between Meta and World Resources Institute and leveraged deep learning models such as DiNOv2 with lidar (such as from GEDI) to train the model, resulting in a Mean Absolute Error (MAE) of 2.8 m for tree heights at the tested sites (Tolan et al., 2024, Meta and World Resources Institute (WRI), 2023; High Resolution Canopy Height Maps (CHM), n. d). This product is referred to as the 'Meta CHM'. Accordingly, this dataset was acquired from the Registry of Open Data from Amazon AWS. The 1 m pixels were resampled with a mean aggregation scheme to match the size and alignment of the 10 m Sentinel-2 imagery.

The second dataset collected was from the University of Maryland, Global Land Analysis and Discovery (GLAD) Lab. They produced a 30 m spatial resolution global forest CHM based on GEDI lidar and Landsat analysis-ready time series imagery for the year 2019 based on data availability. The global forest height map is considered a prototype product as it contains issues from the GEDI data as well as the inherent inability of multispectral imagery to directly measure heights. We refer to this product as the 'UMD CHM' in the text. A future Sentinel-2 based product is forthcoming and will resolve issues with underestimation of tree height. This product was acquired from the UMD GLAD Lab (glad.geog.umd.edu). The study reported a mean absolute error of 4.45 m evaluated with GEDI and 6.3 m evaluated with airborne lidar (Potapov et al., 2021). For this manuscript, the 30 m product was resampled to match Sentinel-2 10 m resolution using nearest neighbor resampling.

## 2.5. WorldCover land cover version 2

The Worldcover land cover type product was produced for the year 2021 with the latest version 2 at 10 m spatial resolution using Sentinel-2 and Sentinel-1 imagery time series (Van De Kerchove et al., 2021; Zanaga et al., 2022). It contains 11 land cover classes aligned with the UN-FAO land cover classification system. Some studies have found Worldcover to be the most accurate globally-available 10 m dataset at 83.8% overall accuracy (Xu et al., 2024a), while other studies have found it to have the lowest accuracy as compared with Dynamic World and Esri / Impact Observatory (Venter et al., 2022). These differences



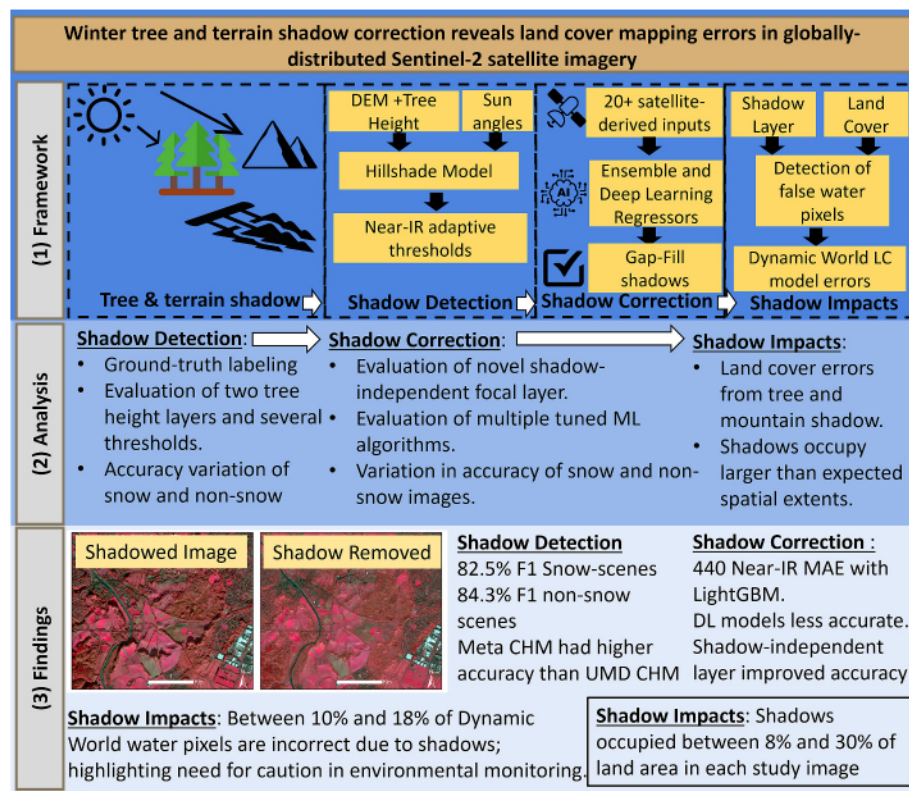


Fig. 1. Flowchart of study methods, analysis and findings.

are likely due to differing sampling and accuracy assessment procedures. Nevertheless, all of the globally produced 10 m land cover products are robust and appropriate for land cover and land use change studies.

## 2.6. Dynamic world land cover product

Dynamic World is a near-real time land cover product based on Sentinel-2 10 m imagery which produces maps primarily based on a single image date, as opposed to an annual time series like many other global land cover products (Brown et al., 2022). This approach has distinct advantages, such as the ability to capture intra-annual change, while yielding disadvantages such as the potential for more errors and data gaps due to clouds or smoke. The authors reported an accuracy ranging from around 71% to 88% depending on the assessment scheme. In this manuscript, the Dynamic World product is used to highlight how tree and terrain shadows can yield errors in a land cover type product generated from Winter imagery.

## 2.7. Global surface water dynamics layer

The global surface water dynamics layer is produced at 30 m spatial resolution from the Landsat series of sensors with output available between 1999 and 2023 (Pickens et al., 2020). It includes layers of annual water percentage, mean monthly water percent, and individual monthly water percent. The data were acquired from the authors' cloud repository (<https://storage.googleapis.com/earthenginepartners-hansen/waterC2/download.html>). The product has reported user's and producer's accuracies of 93.7% and 96.0% for the monthly water map. This study used the annual percent surface water product which corresponded to the year of our Sentinel-2 imagery. This product was used as part of the workflow for evaluating shadow errors in a global land cover product.

## 2.8. Sentinel-1 Synthetic Aperture Radar (SAR)

Sentinel-1 is a C-band (5.4 GHz) SAR produced by the European Space Agency. It operates in a near-polar, sun-synchronous orbit with a constellation of several satellites (Geudtner et al., 2014). The constellation was planned for four satellites and it offers a variable local repeat pass based on the number actually in orbit and latitude, which most recently has been 2 satellites. Sentinel-1 collects imagery in several modes including interferometric wide swath (IW), which was used for this study. The IW imagery has a nominal spatial resolution of  $5 \times 20$  m, but was reprocessed into a nominal 10 m resolution with square pixels aligned with the Sentinel-2 imagery. We processed the IW imagery using the Sentinel SNAP software. Because Sentinel-1 operates in the C-band, it is capable of penetrating clouds and aerosols and is therefore not significantly affected by atmospheric effects. As an active sensor, it produces its own light source and is not afflicted by solar shadows, unlike multispectral imagery. However, very oblique look angles can still lead to similar shadow affects, but due to a different cause. The Sentinel-1 backscatter images were acquired from the Microsoft Planetary Computer. The data were processed into gamma naught calibration, which subsequently undergoes radiometric terrain normalization with the SRTM DEM to correct for local topographic effects. The final product is scaled to decibels and included both the VV and VH polarizations. The Sentinel-1 imagery was acquired corresponding as best as possible with the dates of the Sentinel-2 imagery, and it is used during the shadow correction process.

This study proposes a method for the detection and subsequent correction of shadows cast by trees and or terrain (i.e. hills or mountains), as observed in multispectral satellite imagery, such as Sentinel-2. These shadows are often seasonal in nature, and most prominent during winter, when sun elevation angles are low in the sky, resulting in longer shadows (Revuelto et al., 2021), and reduced capability of traditional radiometric terrain correction algorithms (Ma et al., 2025). These shadows result in reduced pixel values and can lead to errors in

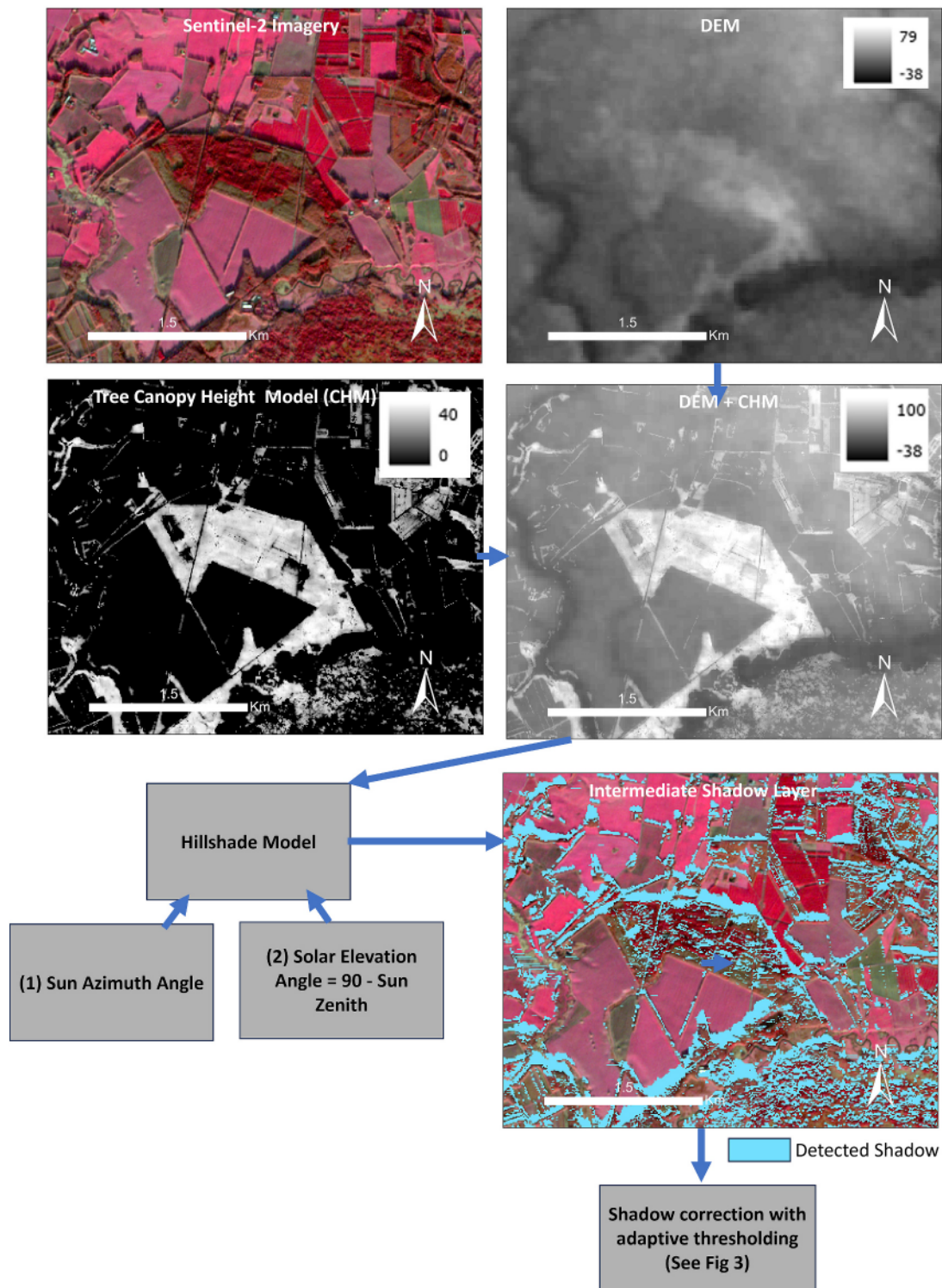


Fig. 2. Workflow of the tree and terrain shadow layer.

derivative products such as evapotranspiration (Tams et al., 2023), vegetation health (Wang et al., 2022), or land cover type maps (Wu et al., 2014; Lasko et al., 2021; Lasko et al., 2024), which play an important role in environmental monitoring or forestry efforts. Moderate-to-high latitude areas are most afflicted by terrain and tree shadows due to the lower sun elevation angles during months closest to the winter solstice, which is why this study has focused on these areas and time periods. However the proposed methodology is broadly applicable to other areas, but the shadow effects would be expected to be

less prolific at lower latitudes. Further, the approach should not be considered for deriving surface reflectance parameters such as albedo.

### 3. Methods

This study presents the following research: (1) The combination of a DEM and tree-only CHM for a unique approach to hillshade modeling, combined with local solar angle information at the time of image acquisition for detection of shadows, and a spectral rule-based,



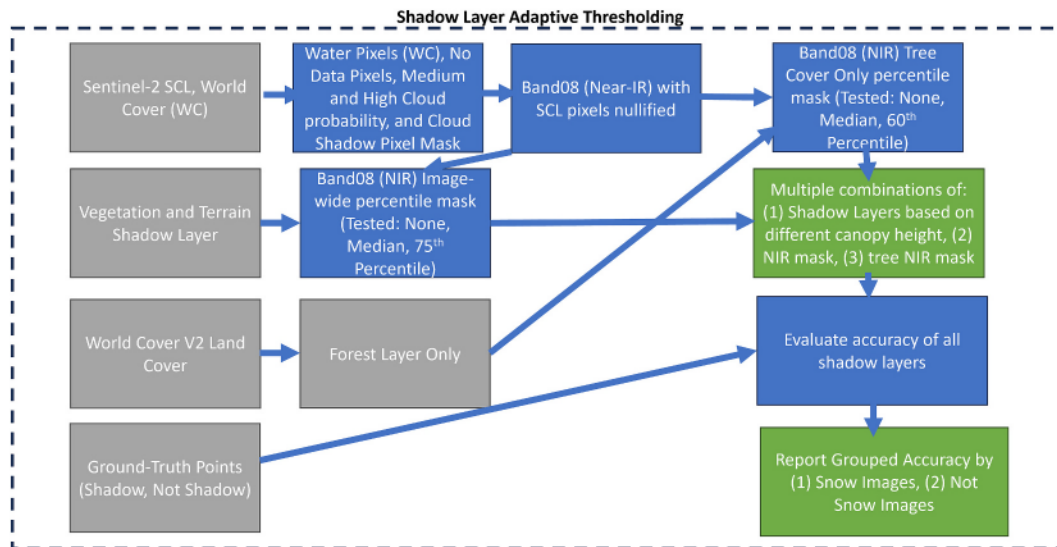


Fig. 3. The adaptive thresholding method applied to the shadow layer to reduce erroneous shadow pixels.

optimized threshold. This method was evaluated with 2 different CHMs and several threshold combinations; (2) The correction of tree and terrain shadow-afflicted pixels using multi-source imagery with a data gap-filling approach including SAR, texture, DEM, prior multispectral imagery, land cover type, and a novel shadow-independent focal layer from the original Sentinel-2 imagery. The correction of shadow-afflicted pixels was compared against several ensemble regressors such as LightGBM (Ke et al., 2017), XGBoost (Chen and Guestrin, 2016), random forest (Breiman, 2001), as well as tabular deep learning regressors such as RealMLP (Holzmüller et al., 2025), PyTorch Neural Network (Paszke et al., 2019), and Fastai neural network (Howard and Gugger, 2020) which underwent appropriate hyperparameter tuning as described in a subsequent section. The detection and correction of shadows is evaluated across the 6 test images using a sample-based accuracy assessment. (3) Quantification of the impacts of tree and terrain shadows on the Dynamic World near-real time land cover model in 2 sites; (4) Quantification of the proportion of shadow in each image and discussion on the broader impacts for environmental monitoring. A flowchart of the generalized study approach is available in Fig. 1.

### 3.1. Tree and terrain shadow detection approach

The approach designed for tree and terrain shadow detection is efficient and scalable to broad geographical areas across a wide range of land surface conditions. Accordingly, the Sentinel-2 multispectral 10 m imagery (Near-IR, Red, Green) bands are acquired for the study area. The Sentinel-2 file contains metadata on sun angles at the time of image acquisition. The approach uses: mean Solar Zenith Angle (SZA) and mean solar azimuth angle parameters, which provide information on the direction of incoming solar radiation and height above the horizon. We compute Solar Elevation Angle (SEA) from the zenith with the following eq. 1:

$$\theta_{SEA} = 90 - \theta_{SZA}$$

A digital elevation model (DEM), such as the SRTM 30 m DEM is acquired and it represents bare earth surface conditions. The DEM is resampled and re-projected to match the 10 m Sentinel-2 imagery. The META CHM and UMD CHMs are subsequently resampled and re-projected to the same scale. The UMD CHM and META CHM are separately added to the SRTM DEM layer which results in a tree and terrain Digital Surface Model (DSM).

The DSM and the solar angles are then used to compute a cast shadows-only hillshade model using the SAGA-GIS Analytical

Hillshading tool (Conrad et al., 2015) with input parameters of: shadows only, solar azimuth and solar elevation, fat shadows (tracing entire cell shadow as opposed to a node), 16 directions, and maximum search radius of 50 pixels. This intermediate output is a cast shadow layer with value of 0 for non-shadow, and value of 1 for shadow. This workflow is visualized in Fig. 2.

### 3.2. Tree and terrain shadow ground-truth points and accuracy assessment

After creation of the intermediate set of tree and terrain shadow layers from the prior section, ground-truth points were generated across each of the 7 images. Pixels from (1) tree/terrain shadow, and (2) not tree/terrain shadow, are selected via stratified random sampling from a total of 3250 points (average of 464 points per image) with a minimum of 125 ground-truth points per class to reduce under-sampling effects from the 'shadow' class which occupies less area than the 'not shadow' class (Congalton and Green, 2019). For selection of the total number of points per image, standard errors were inferred for each class, which typically resulted in class-specific standard errors of 0.03 to 0.15 depending on the image; this information was then used with binomial probability sampling to select the total number of points per scene to attain a 95% confidence interval for the overall accuracy, in accordance with best practice recommendations (Olofsson, 2021; Olofsson et al., 2014). A minimum distance of 300 m between points was specified to reduce spatial bias (Torbick et al., 2010). The ground-truth points were interpreted using a combination of high-resolution imagery basemaps from Google to gain spatial context, as well as the original Sentinel-2 imagery, and spectral indexes. The overall accuracy, user's accuracy, producer's accuracy, and F1 scores are reported for comparative purposes.

Subsequently, the 3250 ground-truth points are then used in the proceeding section to test modifications to the approach to enhance accuracy. For this evaluation, an extra 40 points per image (20 shadow, 20 not shadow) were added. These were non-random points which were chosen in challenging land surface conditions (i.e. water, built-up area, shadow boundaries, small shadows, etc.) which were often incorrect in the intermediate maps. These additional points were not reported in the overall accuracy metric since they are non-random, but were simply used to ensure the most accurate method is selected, as was done in prior studies (Lasko et al., 2021).

### 3.3. Improving tree and terrain shadows with adaptive thresholding

Considering tree CHMs are generated from a fixed date and don't necessarily align with tested imagery, as trees could change height over time, a percentile-based thresholding (i.e. adaptive threshold) was applied to compensate for potential erroneous shadow pixels. This procedure leverages: (1) Sentinel-2 Near-IR band (Band 08), World-Cover land cover (forest and water pixels), Sentinel-2 SCL, and the ground-truth points. The workflow is shown in Fig. 3. First, the SCL is used to mask out (i.e. nullify) pixels labeled as 'no data', 'medium probability cloud', 'high probability cloud', and 'cloud shadow' from the near-IR band. Then using the WorldCover land cover dataset, water pixels and forest pixels are nullified to create a masked near-IR image that excludes clouds, water, and urban pixels. This then produces the SCL-water-urban masked Near-IR image. Then, a percentile table is generated for the masked image using the rasterstats python library to compute the median and 75th percentile values of the masked near-IR image.

A second percentile look-up table is computed for the SCL-masked near-IR image for forest pixels only (class 10 of WorldCover). The median and 60th percentile are computed in the same manner, using a zonal statistics algorithm applied to the near-IR pixels over forest computed for the area of interest. Subsequently, the mentioned percentile thresholds, as well as the exclusion of both or either threshold, are then evaluated against the ground-truth points to determine the most accurate combination across the study area.

For the first SCL-water-urban masked Near-IR image from paragraph 1 of this section, if a near-IR pixel exceeds the percentile threshold, it is considered too bright to be a shadow and is subsequently labeled as not shadow. For the second SCL-tree near-IR image, if a forest pixel is greater than the percentile threshold (i.e. median, 60th percentile), then it is labeled as not shadow.

Finally, all possible combinations of thresholds using the two layers are evaluated using the ground-truth points (e.g. SCL-water-urban mask 75th percentile, and SCL-forest mask 60th percentile, etc.). The accuracy of these layers is evaluated with computation of overall accuracy and F1 score, which is robust to imbalanced datasets. The accuracy metrics are grouped and reported separately for the 4 non-snow images, and 2 snow images to check for variation. It is important to note that a researcher applying this shadow mask workflow can skip the evaluation of percentile thresholds against a ground-truth points, as this study optimizes the value across study sites.

### 3.4. Comparative evaluation using 2 different tree CHMs

The processed tree CHMs from META and UMD are separately evaluated in the workflow for shadow detection as described in the preceding sections.

To better compensate for inherent errors and potential vegetation growth over time, use of an additive factor was evaluated and applied to the tree CHMs. Specifically, the following were tested: (1) original canopy height, (2) canopy height + 1 m, (3) canopy height + 2 m, and (4) canopy height + 3 m. This was also combined with the SCL-urban-water and SCL-forest layer adaptive thresholds for a total of 20 combinations to evaluate against the ground-truth points.

### 3.5. Correction of tree and terrain shadow-afflicted pixels

After identifying the shadow-afflicted pixels in the preceding step, and selecting the most accurate approach, a correction workflow is then applied to rectify the shadow-afflicted pixels. For shadow correction, several machine learning models are trained and tested on hyperlocal training data (i.e. only on the image of interest) which offers geographic flexibility (Lasko and O'Neill, 2023; Pelta et al., 2022; Venter et al., 2020). Each model undergoes hyperparameter tuning as described in a subsequent section. Additionally, the use of a novel shadow-

**Table 2**

Input geospatial datasets used as model features for correcting the shadow-afflicted pixels.

| Sensor/Asset                      | Original Resolution | Dataset Description                                                | Additional Information                                                                                                                      |
|-----------------------------------|---------------------|--------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| World Cover Land Cover            | 10 m                | Annual land cover type                                             | One hot encoded categorical class                                                                                                           |
| Sentinel-1 SAR                    | 10 m                | VV, VH backscatter                                                 | Ascending and Descending node average for 2 weeks pre and post Sentinel-2 acquisition date                                                  |
| Sentinel-1 SAR                    | 10 m                | VV & VH Annual Standard Deviation                                  | Terrain-corrected Sigma Nought Backscatter (dB)                                                                                             |
| Sentinel-1 SAR (Texture)          | 10 m                | VH GLCM Variance                                                   | 5 × 5 pixel window                                                                                                                          |
| Sentinel-2 MSI (Shadow-afflicted) | 10 m                | Near-IR, Red, Green bands                                          | Dependent variable.                                                                                                                         |
| Sentinel-2 MSI (Texture)          | 10 m                | Near-IR Annual 75th percentile GLCM Variance                       | 7 × 7 pixel window                                                                                                                          |
| Sentinel-2 MSI                    | 10 m                | Near-IR and NDVI 75th and 25th annual percentiles Slope and Aspect | Computed from 1 year cloud-masked time series                                                                                               |
| NASADEM/ SRTM DEM                 | 30 m                |                                                                    | Resampled to 10 m grid.                                                                                                                     |
| Shadow-Independent Focal Layer    | 200 m               | 25th, 50th, 75th, 90th percentiles from Near-IR band               | Percentile for a given pixel obtained using 200 m (20 cell) neighborhood on Near-IR band with shadows nullified/ Excluded from computation. |
| Shadow-Independent Focal Layer    | 500 m               | 25th, 50th, 75th, 90th percentiles from Near-IR band               | Percentile for a given pixel obtained using 500 m (50 cell) focal neighborhood on Near-IR band with shadows nullified.                      |
| Tree and terrain shadow layer     | 10 m                | Binary shadow layer                                                | Used to ensure shadowed pixels are excluded from the training set                                                                           |
| Sentinel-2 SCL                    | 60 m                | Cloud, no data, cloud shadow                                       | Used to exclude these pixels from the training set                                                                                          |

independent focal layer is evaluated for enhancements to shadow-correction accuracy. Ultimately, the approach seeks to maximize accuracy, and minimize model fit and prediction times to ensure accuracy and scalability. A highly accurate, but very slow to fit or predict model is not all that useful in this case, which would hamper efforts to conduct this correction at regional scales.

For correction of shadow-afflicted pixels, first an equalized stratified random sample is generated on the World Cover V2 dataset separately for each site with 20,000 samples. World Cover contains 11 classes, but some classes are missing or minimally present in the scene (i.e. permanent snow, lichen and moss are not present in any scene). To overcome this, the shrubland and grassland categories were merged prior to sampling, and missing classes were ignored. The equalized stratified random sample points enable a balanced set of training data to be used for fitting and evaluating the machine learning models across the test sites (Lasko et al., 2021; Olofsson et al., 2014). It should be re-iterated that the models are generated separately for each image.

### 3.6. Input features for shadow correction

Input layer values are extracted to the random sample points to serve as features in the machine learning models. Table 2 displays the layers evaluated in this study. Models are developed for each of the dependent variables of interest from a shadow-afflicted Sentinel-2 image from a



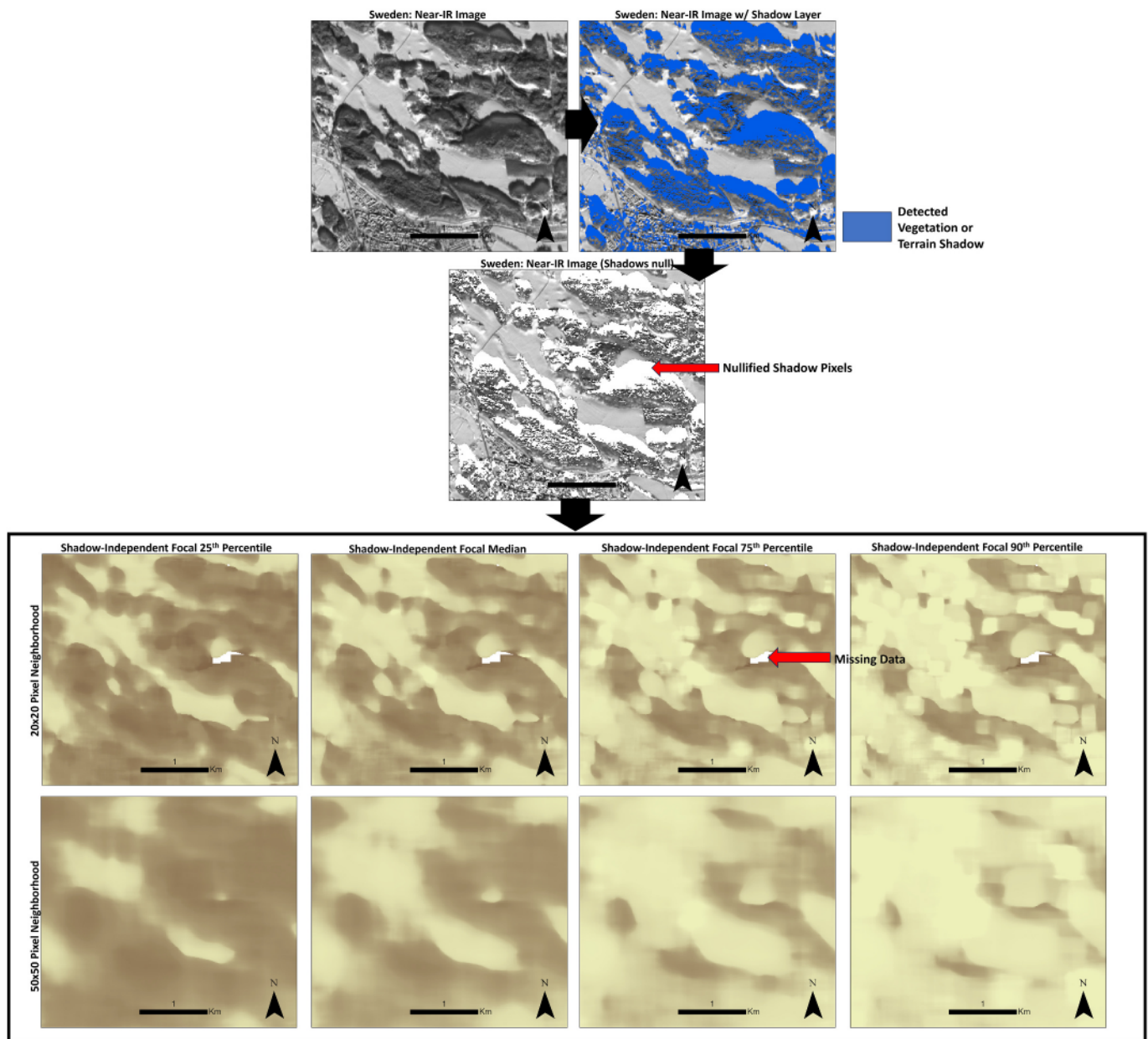


Fig. 4. Workflow to create the 8 different shadow-independent focal layers used as model features for shadow correction.

date near the winter solstice: (1) Near-IR band, (2) red band, (3) green band, and (4) NDVI. For each model, the accuracy is evaluated with 20% of the equalized stratified random sample points which were withheld from the training data. The accuracy is evaluated with and without a novel shadow-independent focal layer, which is described in a proceeding section.

The input features shown in the Table 2 are described in further detail in appendix A.3.

### 3.7. Shadow-independent focal layers

Considering the tenement of geography that close things are often closely related, a layer is created, representing pixel values adjacent to shadowed areas, which are likely to have similar values. For this, it starts with the near-infrared band and uses the shadow layer to nullify (mask out) shadow pixels. Then, the same for cloud and cloud shadow pixels using the SCL. With this modified near-infrared layer, it applies a focal algorithm which computes 25th, median, 75th, and 90th percentiles for

every pixel within a) a 20 cell by 20 cell diameter (200 m total), or b) a 50 by 50 cell diameter (500 m total), for a total of 8 geospatial data layers which are used in the machine learning models (Hodgson, 1998). The window size was selected to ensure that they are larger than typical tree shadows observed (200 m), and typical steep mountain shadows observed (500 m) so as to enable a smoothing effect where adjacent unshadowed pixels can influence the machine learning algorithm. Prior studies have applied similar window sizes with success in related domains (Lasko et al., 2024; Ozkan and Demirel, 2021). A visualization of the workflow is shown in Fig. 4. As shown, the 200 m size results in occasional missing data due to large shadows, thus the coarser resolution layers can add value here. Various machine learning model frameworks can still make predictions with partial missing data (i.e. XGBoost, LightGBM). Subsequently, the 500 m layer has minimal missing data pixels and thus provides additional predictive insight in certain examples of missing data. The ML models are evaluated with and without these shadow-independent focal layers.

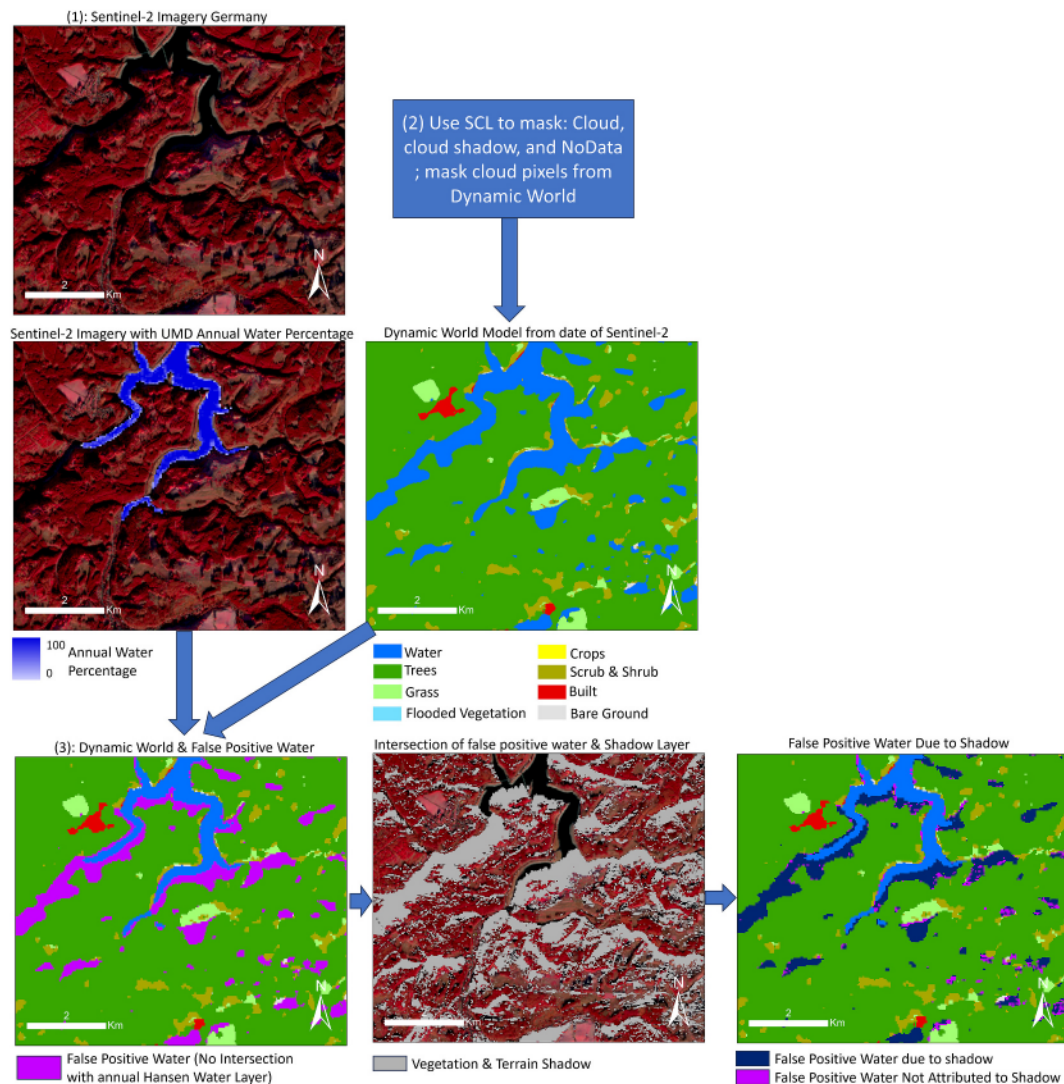


Fig. 5. Workflow for evaluating false positive water in the Dynamic World land cover product attributed to tree and terrain shadows. Water was the only observed error due to shadows.

### 3.8. Shadow correction machine learning models

Using the input features and the 20,000 training points, several ensemble regression models separately trained and evaluated for each site, and the results aggregated across snow and non-snow images. Evaluation focused on: Extra Trees, Random Forest, XGBoost, and LightGBM algorithms from the sklearn, LightGBM, and XGBoost libraries (Pedregosa 2011; Chen and Guestrin, 2016; Ke et al., 2017). Hyperparameter optimization tested different values for the `n_estimators`, `max_depth`, `max_features`, `learning_rate`, `subsample`, `min_samples_split` as shown (Table A.1). Any remaining parameters were left at defaults. These parameters were selected as they tend to be most impactful (Huang and Boutros, 2016; Ørebæk and Geite, 2021; Probst et al., 2019).

In addition to ensemble-based regression models, accuracy is tested for 3 different deep learning algorithms designed for performance on tabular data by leveraging the Autogluon tabular framework which automates data preparation, model tuning, cross-validation, and early stopping and has models optimized for tabular data, as is the case in this manuscript (Erickson et al., 2020). The following Algorithms were evaluated: RealMLP, PyTorch Feed-Forward Neural Network, and Fastai neural network with details described in the Appendix A.2.

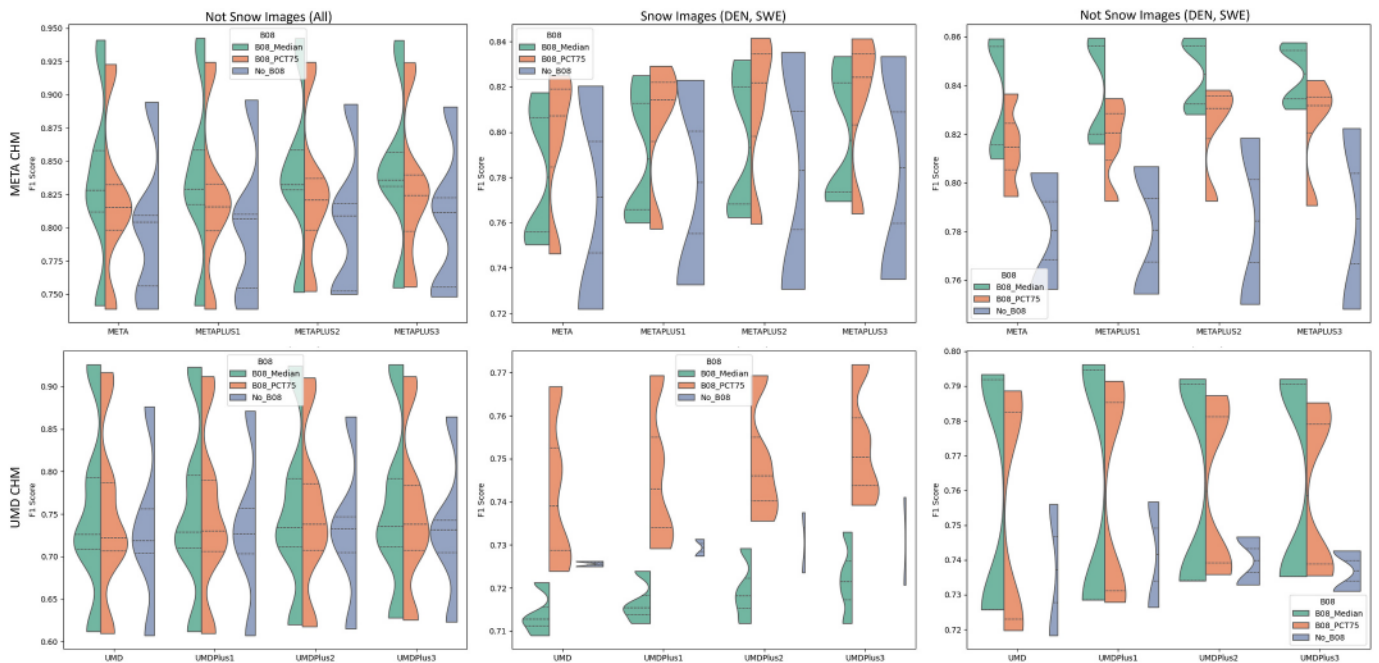
### 3.9. Accuracy assessment of shadow correction

The shadow correction is evaluated for the Near-IR, red, green, and NDVI from Sentinel-2 by using 20% of the 20,000 points which were withheld from model training. There is an approximately equal number of points per land cover type. Because shadow-afflicted pixels have inherently low pixel values, it is not possible to evaluate the accuracy directly on shadowed pixels. Instead, for testing purposes the correction algorithm is applied to all non-shadow pixels, with synthetically designated validation pixels as shadow. The MAE is reported, which is a basic metric that is robust to outliers and more interpretable than Mean Squared Error (MSE) (Willmott and Matsuura, 2005). The equation is below:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

To compensate for the measuring accuracy with synthetically designated shadow pixels, boxplots are produced as described in the next section, to compare the original spectral values in non-shadow and shadow pixels against the shadow-corrected reflectance values for the same. An accurate result would expect the corrected shadow reflectance values to be spectrally-similar to the original non-shadow reflectance values.





**Fig. 6.** F1-score distributions for the shadow layers separated by snow images and non-snow images, showing the accuracy change when using the 2 different adaptive thresholds or no adaptive threshold (blue line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

### 3.10. Comparison of this approach against standard topographic correction methods

Traditional terrain radiometric correction models which apply illumination correction based on DEM slope, local incidence angles, and other factors were compared against this study. Specifically, C-correction and the gamma correction model were compared (Gu and Gillespie, 1998; Richter et al., 2009). These semi-empirical methods use a DEM with slope, aspect, and solar angles to compensate for shadow pixels. The distribution of values for each of these correction methods are visualized in boxplots to show the difference between corrected and uncorrected pixels for each image, and they are compared further with the approach from this study. An accurate result would have the corrected shadow pixel value distribution closely resemble the uncorrected, non-shadow pixels in the original image. Before generating the distribution plots, the ocean and cloud pixels are masked out, and the most accurate shadow layer from this study is used to separate the plots into shadow and non-shadow pixels.

### 3.11. Assessing land cover map errors due to tree and terrain shadows

Shadows cast by trees or terrain lead to inherent errors in downstream products derived from satellite imagery, such as land cover type. This is especially prevalent in land cover models which are primarily based on a single date of imagery, as opposed to a time series. The Dynamic World product is globally produced and one of the most well-known land cover products that falls into the single image category which is why it was selected for evaluation. However, it is expected that the errors would be present in other land cover mapping approaches which do not rely on an annual time series.

The workflow for evaluation of errors is shown in Fig. 5. Accordingly, Sentinel-2 imagery is selectively acquired over two sites where major errors were observed: (1) Göttingen, Germany from 2021 to 12-20, and (2) Iwate, Japan from 2022 to 11-15. The Sentinel-2 SCL was used to mask out cloud, cloud shadow and no data pixels from the Dynamic World product. Because the Dynamic World product has issues with underestimated cloud masking, additional manual masking was

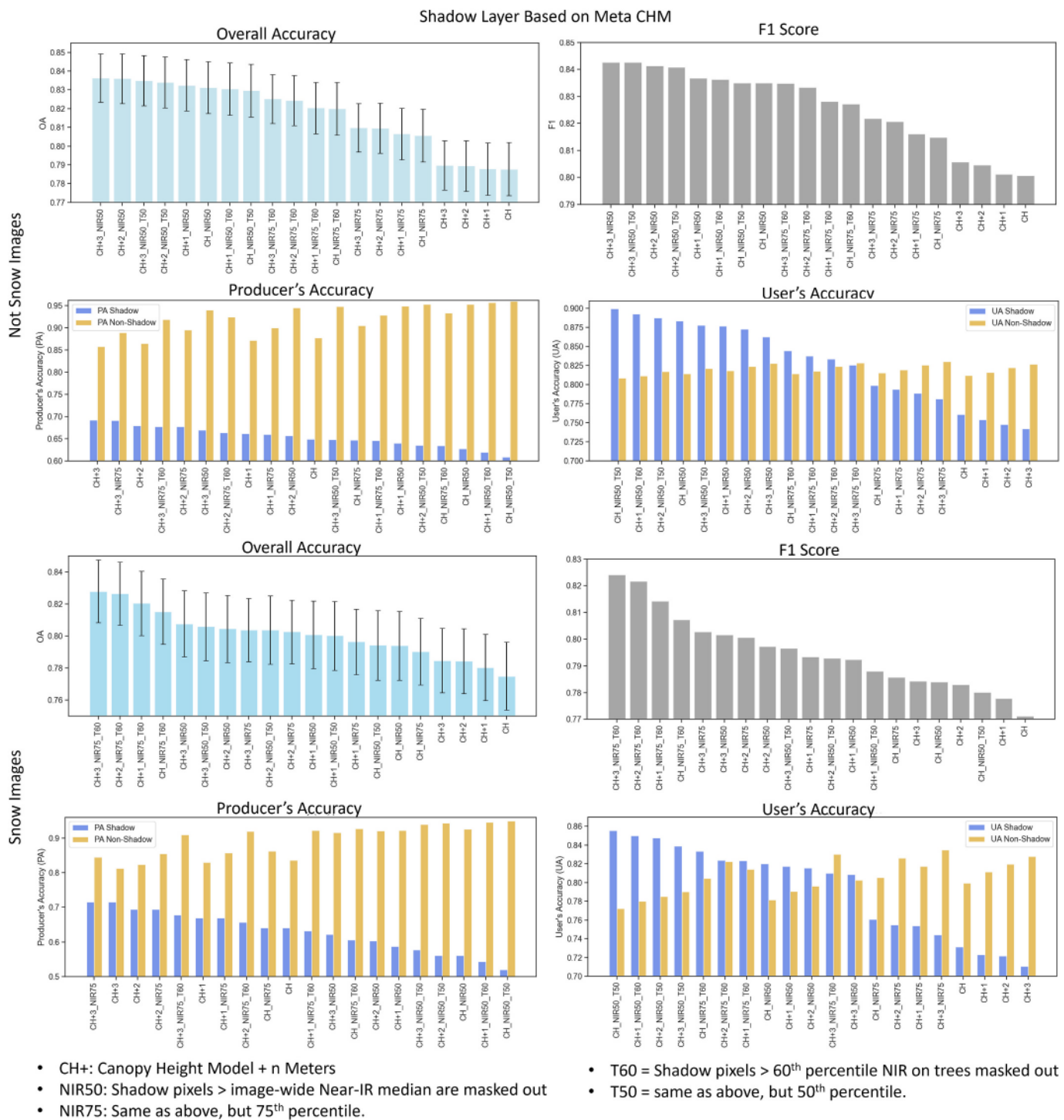
performed where applicable. Subsequently, the UMD annual water percentage layer was selected for the corresponding year of each Sentinel-2 image. This layer is considered highly accurate at mapping surface water and uses a time series of images which minimizes impacts from shadows (Pickens et al., 2020). Then, the water layer is intersected (water % > 0) with the Dynamic World layer (water class only) to compute the overlapping pixels. If a pixel was not labeled as water in the UMD layer, then it was considered as false positive water. Subsequently, these false positive water pixels were intersected with the shadow layer from this manuscript, to determine an approximate attribution of false water pixels due to shadow. Error analysis was limited to water as it was the only land cover type error observed due to shadow error.

## 4. Results

### 4.1. Tree and terrain shadow detection

For the creation of the tree and terrain shadow layer, we evaluated the use of the UMD CHM and the META CHM layers with and without the SCL-urban-water and SCL-forest adaptive thresholding applied. We aggregated the results by snow-covered images (2 – Denmark and Sweden) and non-snow covered images (5 – Denmark, Japan, New Zealand, Sweden, United Kingdom). Fig. 6 contains a breakdown of the variation in F1-scores shown for the META and UMD CHMs with the different possible adaptive threshold combinations evaluated. In both snow and non-snow scenes for UMD and META approach, the highest accuracy groups used CHM + 3 (i.e. an additive factor of 3 m applied to the tree CHM). The accuracies varied by about 5% for META CHM non-snow, 8% for META snow, and 2% for UMD not snow, and 6% for UMD snow scenes indicating that tuning these parameters is important.

The most accurate shadow layer used the META CHM with an additive factor 3, and adaptive threshold of Near-IR median (image wide), which means that pixels above those values are labeled as non-shadow. The overall accuracy was 83.6% ( $\pm 1.6\%$ ), F1-score was 84.3%, shadow user's accuracy was 86.3%, shadow producer's accuracy was 66.9%, not shadow user's accuracy was 82.8% and not shadow producer's accuracy was 94.0%. The shadow model without adaptive thresholding has a



**Fig. 7.** Accuracy metrics for the shadow detection layers created using the META CHM, including use of adaptive threshold and additive factors on the CHMs.

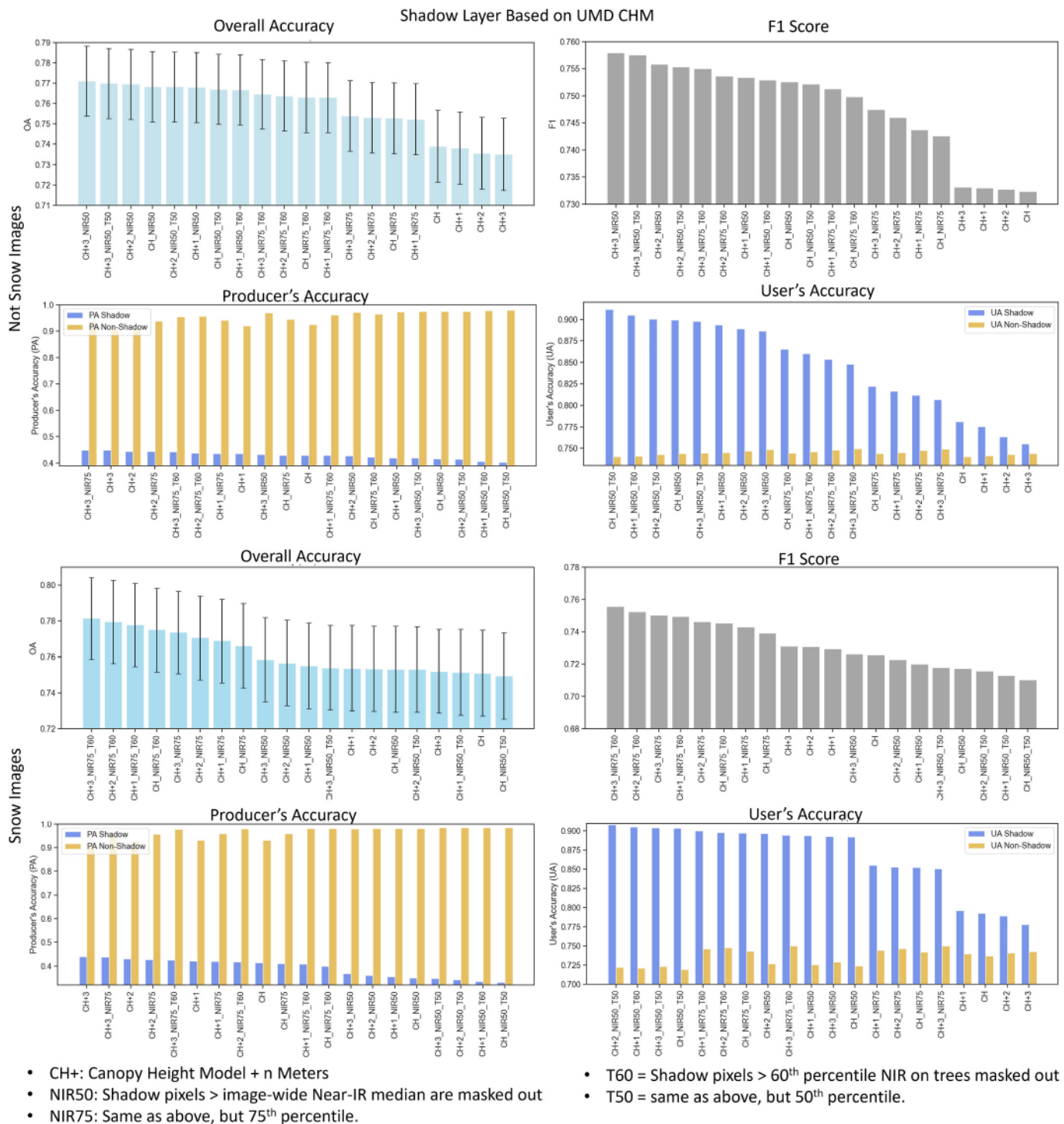
lower F1-score (80.6%) and overall accuracy (79.0%) indicating that these enhancements offered about a 4% increase in overall accuracy. For the snow images, the most accurate combination used an additive factor of 3, adaptive threshold of Near-IR 75th percentile (image-wide), and 60th percentile (trees only). The overall accuracy for snow images was 82.8% ( $\pm 2.1\%$ ) and F1-score (82.4%). When directly compared against the non-snow Denmark and Sweden images overall accuracy average (85.1%  $\pm 2.1\%$ ) and F1-score (84.7%), we did not find a significant difference in accuracy between the snow and non-snow images. The accuracy metrics are shown for all tested combinations in Fig. 7.

For the approach using the UMD CHM, the same non-snow

combination of thresholds yielded the highest overall accuracy at 77.1% ( $\pm 1.6\%$ ), F1-score (75.8%), shadow user's accuracy (88.7%), shadow producer's accuracy (43.4%), not shadow user's accuracy (74.8%), and not shadow producer's accuracy (97.0%). This overall accuracy was about 6% lower than the META-based approach. For the snow images, the most accurate combination used the same parameters as the META snow scenes. The overall accuracy was 78.1% ( $\pm 2.1\%$ ) and F1-score (75.5%). This indicated that there was not a significant difference between the UMD CHM snow scenes and non-snow scenes. The accuracy metrics are shown for all tested combinations in Fig. 8.

Maps of the shadow layers derived from the approaches with the





**Fig. 8.** Accuracy metrics for the shadow detection layers creating using the UMD CHM, including use of adaptive threshold and additive factors with the CHMs.

UMD CHM and Meta CHM are shown in Fig. 9. Within the Denmark images and UK image, the biggest differences are observed where the UMD CHM generally does not detect small spatial area shadows (i.e. from small groups of trees), whereas the META CHM detects many more of these. This is likely due to the spatial resolution differences between the two datasets (i.e. 1 m vs 30 m). The approach with the META CHM also better detects shadows cast by trees onto other trees within a forest. Both products appear to accurately capture larger, more prominent shadows. The green pixels indicate that a large amount of bright pixels are removed from the adaptive thresholding process. This helps to compensate for the additive offset factor and inherent height errors in

the data sources.

As seen from Fig. 9, after modifying the original shadow layer (i.e. shadow layer derived from CHM + 3 m), the barcharts indicate a reduction in the percentage of shadow in the image after the adaptive thresholds are applied (i.e. META\_Modified, UMD\_modified). For Sweden, an almost 8% reduction in area is observed, which likely reduced a substantial area of false positive shadow pixels. This figure also demonstrates that tree and terrain shadows occupy a substantial portion of land surface area in these images. The lowest land surface area was observed in the Japan site (8.4% of area was shadow), and the highest was observed in the Sweden snow image (31.0% of area was shadow)

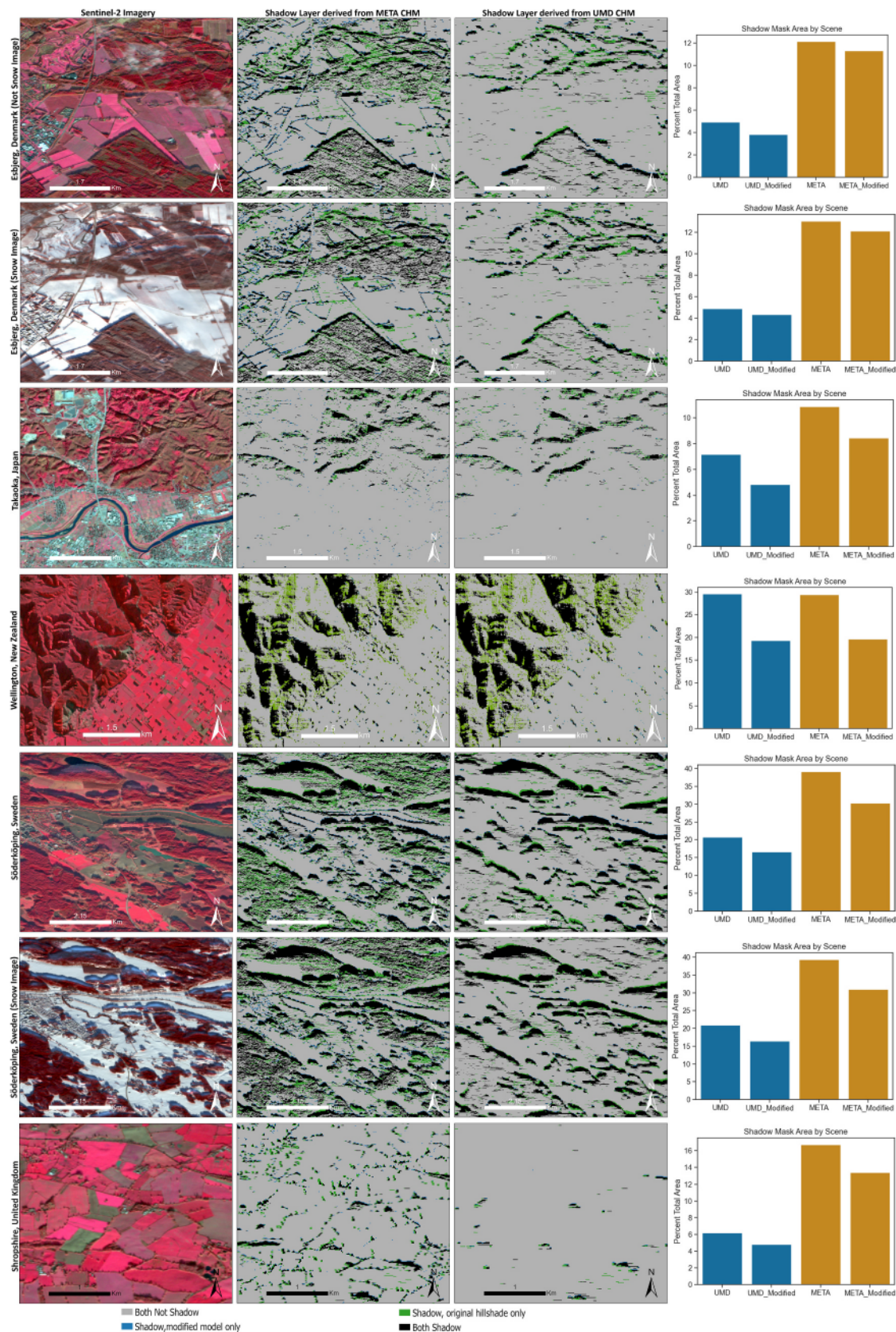


Fig. 9. Spatial comparison of shadow layers with and without adaptive threshold. Barcharts of shadow area per each Sentinel-2 granule.



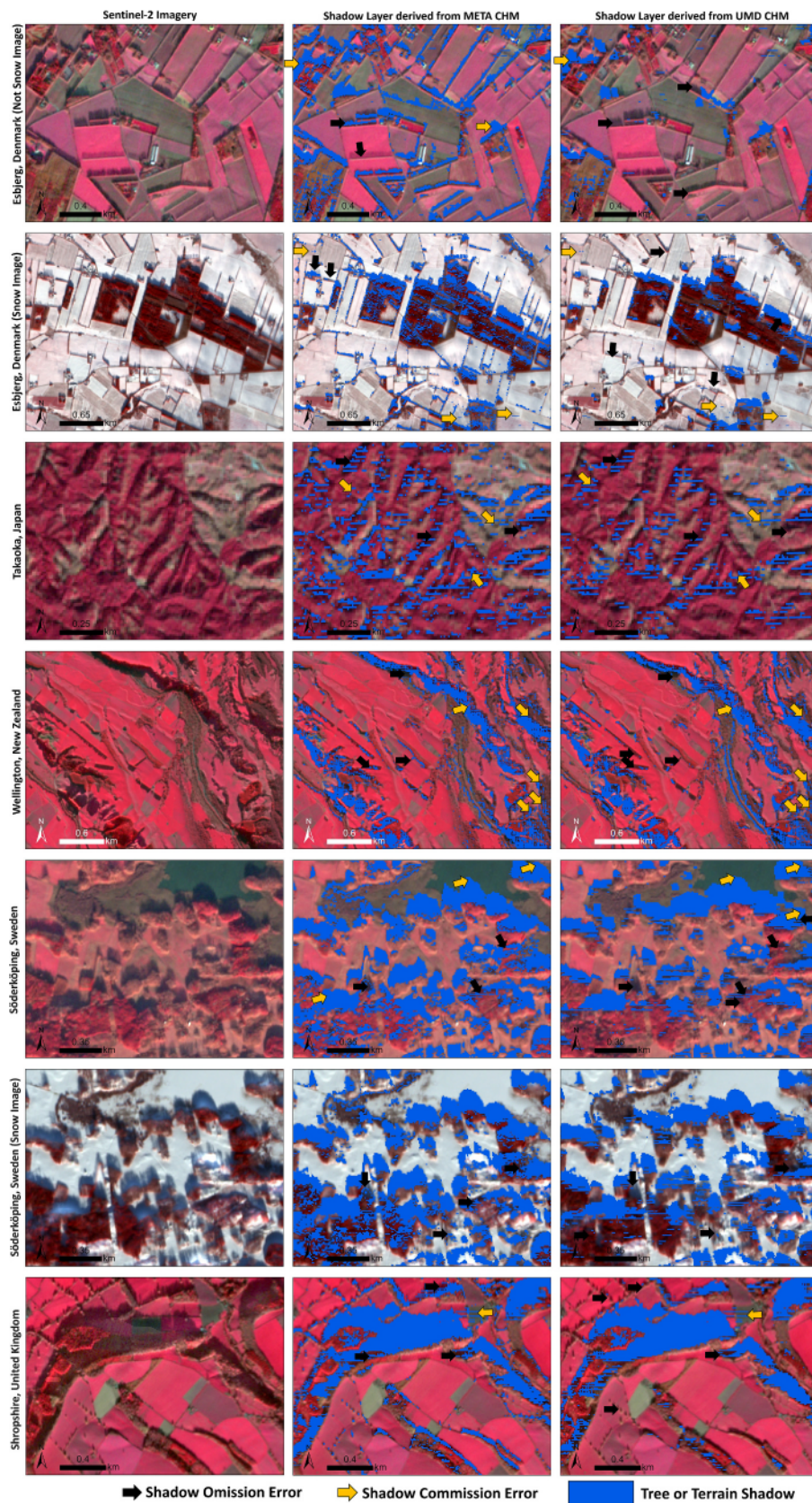


Fig. 10. Example locations of shadow layer errors for each study image.



**Table 3**

Model metrics and hyperparameters for the ensemble machine learning models for shadow correction. Note that the MAE is derived from the withheld sample validation data and is slightly different than reported in fig. 12, which is based on the entire image MAE.

| Model                                         | MAE<br>NIR | R-<br>Squared | Train<br>Time (s) | Predict<br>Time (s) | N<br>Estimators | Max<br>Depth | Max<br>Feats | Min samples<br>split | Learning<br>rate | subsample | Num<br>leaves |
|-----------------------------------------------|------------|---------------|-------------------|---------------------|-----------------|--------------|--------------|----------------------|------------------|-----------|---------------|
| <b>Most accurate model</b>                    |            |               |                   |                     |                 |              |              |                      |                  |           |               |
| Extra Trees                                   | 412.0      | 0.817         | 28.8              | 5593.0              | 500             | 100          | 15           | 2                    | N/A              | N/A       | N/A           |
| XGBoost                                       | 414.0      | 0.814         | 4.2               | 132.8               | 500             | 10           | N/A          | N/A                  | 0.025            | 0.8       | N/A           |
| LightGBM                                      | 415.3      | 0.813         | 1.4               | 354.3               | 750             | 100          | N/A          | N/A                  | 0.025            | N/A       | 75            |
| Random<br>Forest                              | 420.9      | 0.810         | 11.1              | 914.4               | 100             | 100          | 10           | 2                    | N/A              | N/A       | N/A           |
| <b>Best combination of speed and accuracy</b> |            |               |                   |                     |                 |              |              |                      |                  |           |               |
| LightGBM                                      | 419.3      | 0.810         | 0.4               | 65.7                | 100             | 10           | N/A          | N/A                  | 0.075            | N/A       | 1000          |
| XGBoost                                       | 420.4      | 0.810         | 1.0               | 47.2                | 100             | 10           | N/A          | N/A                  | 0.05             | 0.8       | N/A           |
| Extra Trees                                   | 449.3      | 0.793         | 1.2               | 368.0               | 100             | 10           | 15           | 2                    | N/A              | N/A       | N/A           |
| Random<br>Forest                              | 434.0      | 0.800         | 9.0               | 341.4               | 100             | 10           | 15           | 2                    | N/A              | N/A       | N/A           |

**Table 4**

Metrics for the tabular deep learning models used for shadow correction.

| Model           | MAE   | pred_time_test | Fit_time (s) | PredTimeImage |
|-----------------|-------|----------------|--------------|---------------|
| NeuralNetFastAI | 431.0 | 0.100          | 25.6         | 185.7 s       |
| NeuralNetTorch  | 429.6 | 0.091          | 54.1         | 129.9 s       |
| RealMLP         | 439.7 | 0.157          | 161.8        | 313.8 s       |

and non-snow image (30.4%). This is expected because the Japan site was at the lowest latitude evaluated and the Sweden site was at the highest latitude evaluated. The other sites percentages can be interpreted from the barcharts. Overall, across the 7 images, the average shadow area was 18.2% ( $\pm 1.0\%$ ).

Fig. 10 visualizes omission and commission errors for shadows for each of the 7 study images. In the Denmark sites, omission errors commonly were due to small or narrow clusters of trees which were not accurately detected. Some shadows were overestimated as well, and were not effectively compensated for with the adaptive thresholding. The Denmark snow site shows some false positive shadows which are due to errors in the SRTM DEM. The same can be observed over a section of the Japan site where a striping pattern of horizontal false positive shadow can be observed as indicated in the arrows. The Sweden not-snow site has several large shadows which are overestimated, however, they are not overestimated in the snow image. This is likely due to the shadows over the laker having darker spectral values than the frozen lake. The UK site has a combination of mixing shadows likely due to error in the CHMs, and various false positive shadows attributed to errors in the SRTM DEM as seen with the horizontal striping.

#### 4.2. Tree and terrain shadow correction

The most accurate shadow layer was used for applying the shadow correction algorithms. After evaluating the random forest, LightGBM, Extra Trees, XGBoost, RealMLP, PyTorch Feed-Forward Neural Network, and Fastai Neural Network, we found the most accurate to be the Extra Trees algorithm with a mean absolute error of 412.0 for the Near-IR band and R-squared of 0.817. Additional parameters for this model and the other ensemble models are shown in Table 3. This model had a slow training time (26.4 s) and an incredibly slow prediction time for the entire image (5593 s), which is much too slow to be usable. However, the LightGBM algorithm offered a slightly lower error rate (MAE = 419), but with a 0.4 s training time and 65 s entire image prediction time making it more usable for broader scale studies. The XGBoost model had slightly lower accuracy and with a 47.2 s entire image prediction time. It should be noted that these training and prediction times are generated from a laptop with a 6 core i7 processor and 16gb ram without use of a graphics card. Speeds would be variable

based on resources. The predictions were applied to the entire image for testing purposes, but in practice prediction time would be faster as it would only be applied to shadow-afflicted pixels.

The deep learning correction algorithms are shown in Table 4. They had slightly lower accuracies with the PyTorch Feed Forward Neural Network offering an MAE of 429.6 with 54 s training time, but still a slower prediction time for the entire image as compared to the ensemble models. The deep learning models leveraged an 8GB NVIDIA Cuda-enabled GPU for training and prediction, and this time would be substantially sped up with improved resources. The other algorithms such as RealMLP and fastai neural network were slightly less accurate as shown. It is important to note that the deep learning model accuracies could be improved, but the model fit time for tuning parameters would be too lengthy for practical application in a hyperlocal model.

With the most accurate and efficient model being the tuned LightGBM model, we used this to evaluate the utility and impact on accuracy of the shadow-independent focal layers. Accordingly, when the shadow-independent layers are used in the regression, the MAE for the Near-IR band averages 440, however without these layers the MAE is substantially higher at 691. The most dramatic difference is for the Denmark snow site with a decrease from MAE = 325 to MAE = 1042 without the layers. Thus, the shadow-independent focal layer is important for the regression model, and more important in some scenes than in other scenes. However, for the New Zealand site, negligible improvement was observed.

Fig. 11 visualizes the MAE for the LightGBM shadow correction algorithm by land cover type, and by whether or not the shadow-independent layer is used. Nearly every land cover type has lower MAE when the shadow-independent focal layer is used, excepting shrubland in the Japan image, which occupied less than 1% of land surface area. Generally, low errors were observed over cropland and sparsely vegetated land cover types, which often are afflicted by the shadows.

Fig. 12 (a,b,c,d,e,f) contains maps of the LightGBM model output for each of the 7 images. The top-right sub-image contains the model predictions applied only to shadowed pixels, the middle row shows prediction using the shadow correction model for the entire image using a) all input features, and b) all except the shadow-independent focal layer. The bottom row represents the MAE for the Near-IR band as applied to all pixels. It should be noted that the correction algorithm was applied to shadow areas with a with an additional 1 pixel buffer, to compensate for shadow underestimation.

Fig. 12b: Shadow correction for shown for Denmark not-snow image subset.

Fig. 12c: Shadow correction for shown for the Japan image subset.

Fig. 12d: Shadow correction for shown for the New Zealand image subset. Note that this is the one scene where the shadow-independent



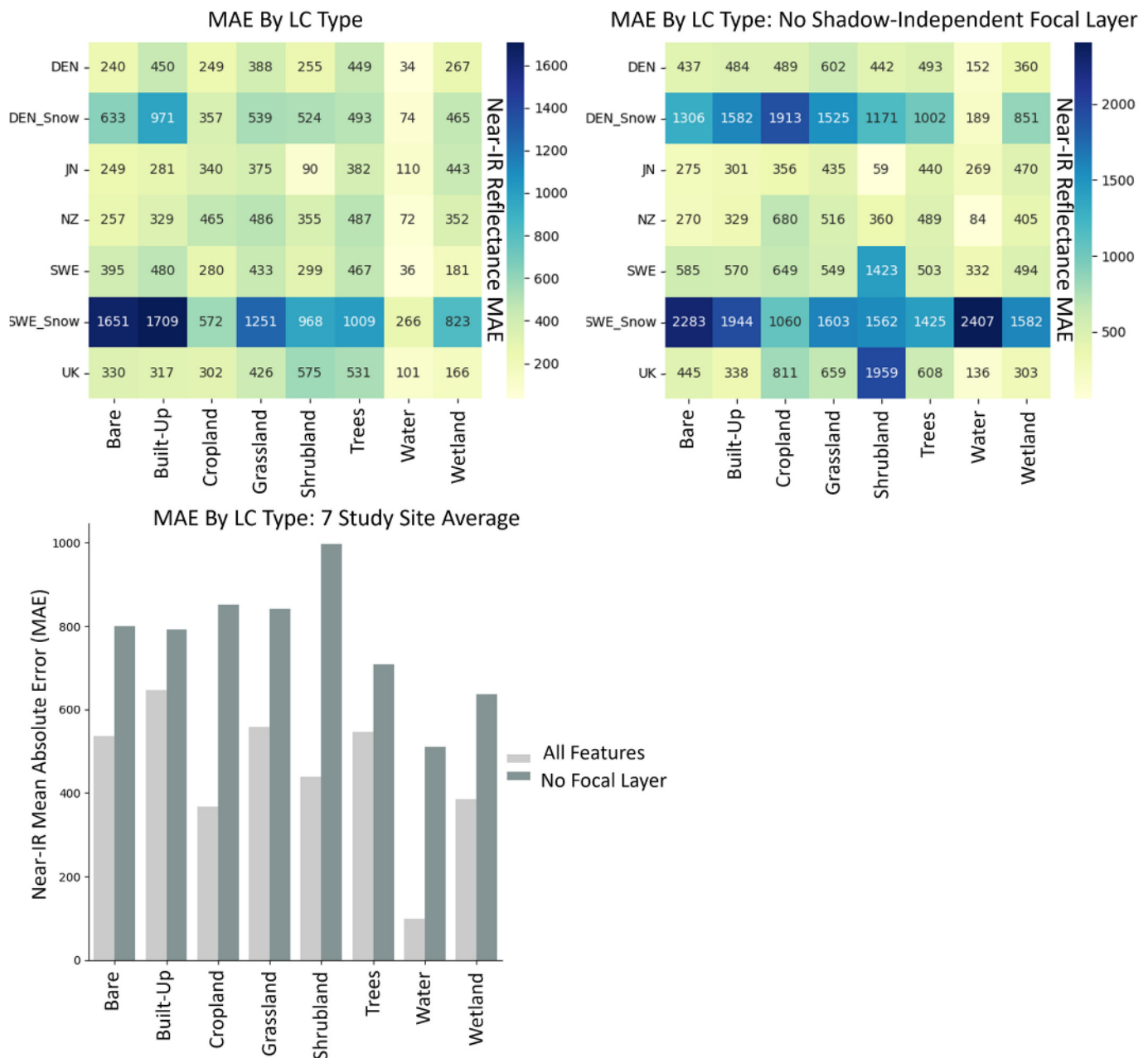


Fig. 11. Near-IR MAE by WorldCover land cover type shown for each of the 7 images. The Left-side shadow correction model used all input features for model training, right-side excluded the shadow-independent focal layers. The bottom figure visualizes the average for all tested images.

focal layer yielded negligible improvement.

Fig. 12e: Shadow correction for shown for the Sweden snow image subset.

Fig. 12f: Shadow correction for shown for the Sweden not-snow image subset.

Fig. 12g: Shadow correction for shown for the UK image subset.

The MAEs are provided for all dependent variables (near-IR, red, green, and NDVI) in Fig. 13, which also displays bar charts of the image mean and standard deviations to show that in all cases, the MAEs are less than the image-wide standard deviation and mean. This suggests that because the MAEs for most sites (except the Sweden snow image) are low relative to the standard deviation, unsystematic errors are likely relatively low, indicating generally strong model performance (Robeson and Willmott, 2023). The figure shows that for each image, the MAEs are reduced when using the shadow-independent focal layer. Interestingly, a substantial improvement in accuracy is observed for the Denmark snow

image when using the layer. We attribute this to the image broadly covered by a very thin layer of snow which was likely penetrated by the SAR sensor and this bias was likely reflected in the model. The same was not observed in the Denmark non-snow image, which helps to support this theory. Across all 7 sites we observed an MAE of 0.037 for NDVI, 440 for Near-IR, 302 for red band, and 259 for green band. For separation by snow and non-snow images the MAEs were: NDVI (0.027 snow vs 0.046 not snow), Near-IR (747 snow vs 318 not snow), red (696 snow vs 144 not snow), and green (603 snow vs 122 not snow).

#### 4.3. Comparison of shadow correction with other topographic correction methods

The topographic correction methods are compared against the tree and terrain shadow correction approach from this study using boxplots to compare between shadow, and non-shadow pixels for the Near-IR

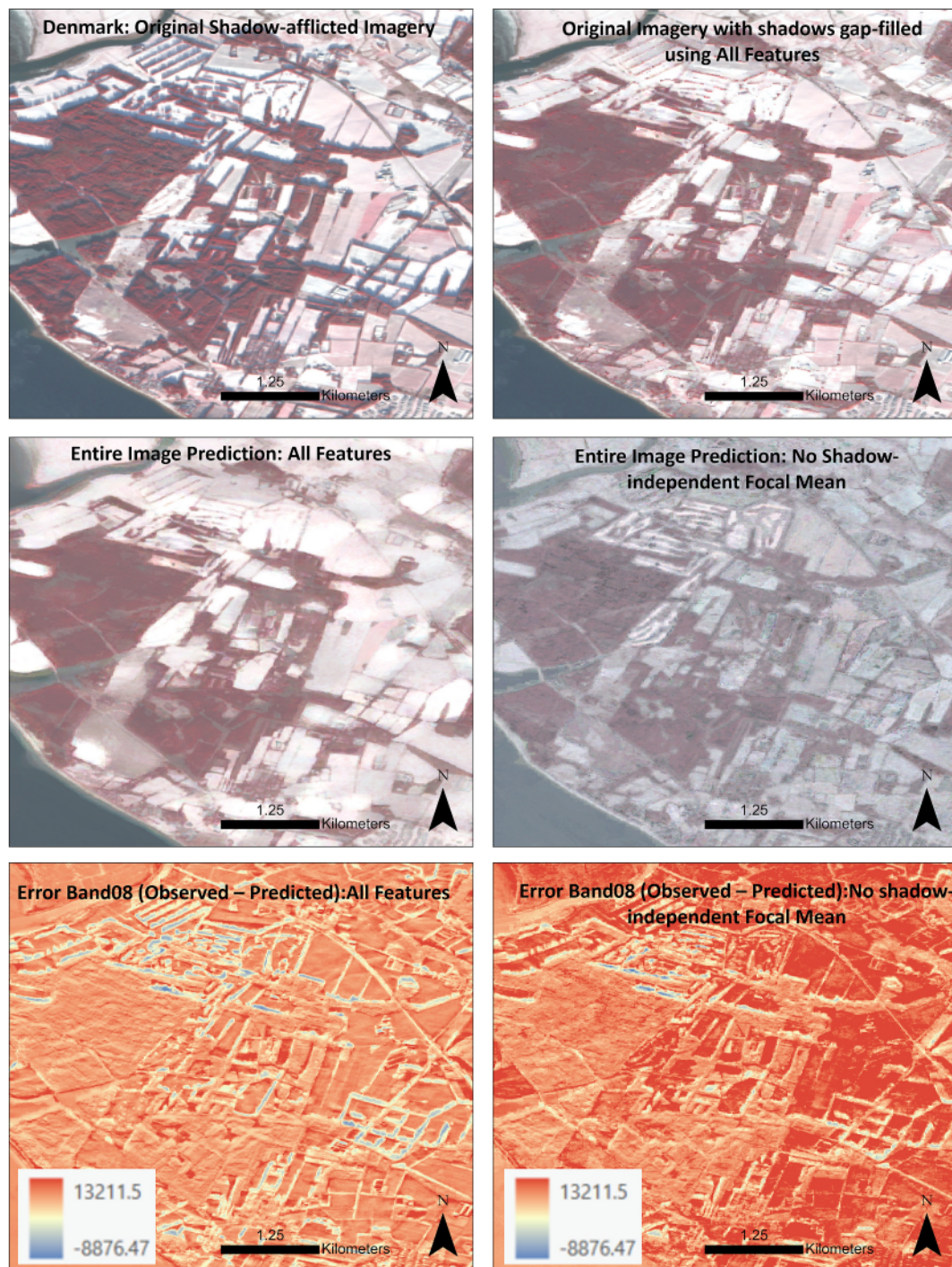


Fig. 12. a: Shadow correction and MAE for most accurate model shown for Denmark image subset.

band. The plots are shown for each site in Fig. 14. The plots are separated by land cover class using the WorldCover product, including visualization of all land cover types, followed by the two most commonly shadow-afflicted land cover types from this study of trees and grassland/shrubland/cropland. The figure shows good agreement between the boxplots generally, however, this study has lower performance over the Japan study site. Generally, there is good agreement between the shadow-corrected pixel values, and uncorrected non-shadow pixels values produced in this study. The C-factor and Gamma results are generally had only minor improvements to reflectance values, excepting the two Sweden sites where Gamma correction

resulted in modestly improved values. Interestingly, in New Zealand the shadow pixel values were decreased during correction, this is a known artifact that can occur with c-factor correction in self-shadowed, steep terrain where diffuse light is most prevalent.

#### 4.4. Dynamic world land cover errors attributed to seasonal tree and terrain shadow

As a selective case study, we located two Sentinel-2 images where water errors were prominent and appeared to be caused due to terrain and tree shadow. They were the Göttingen, Germany, and Iwate, Japan



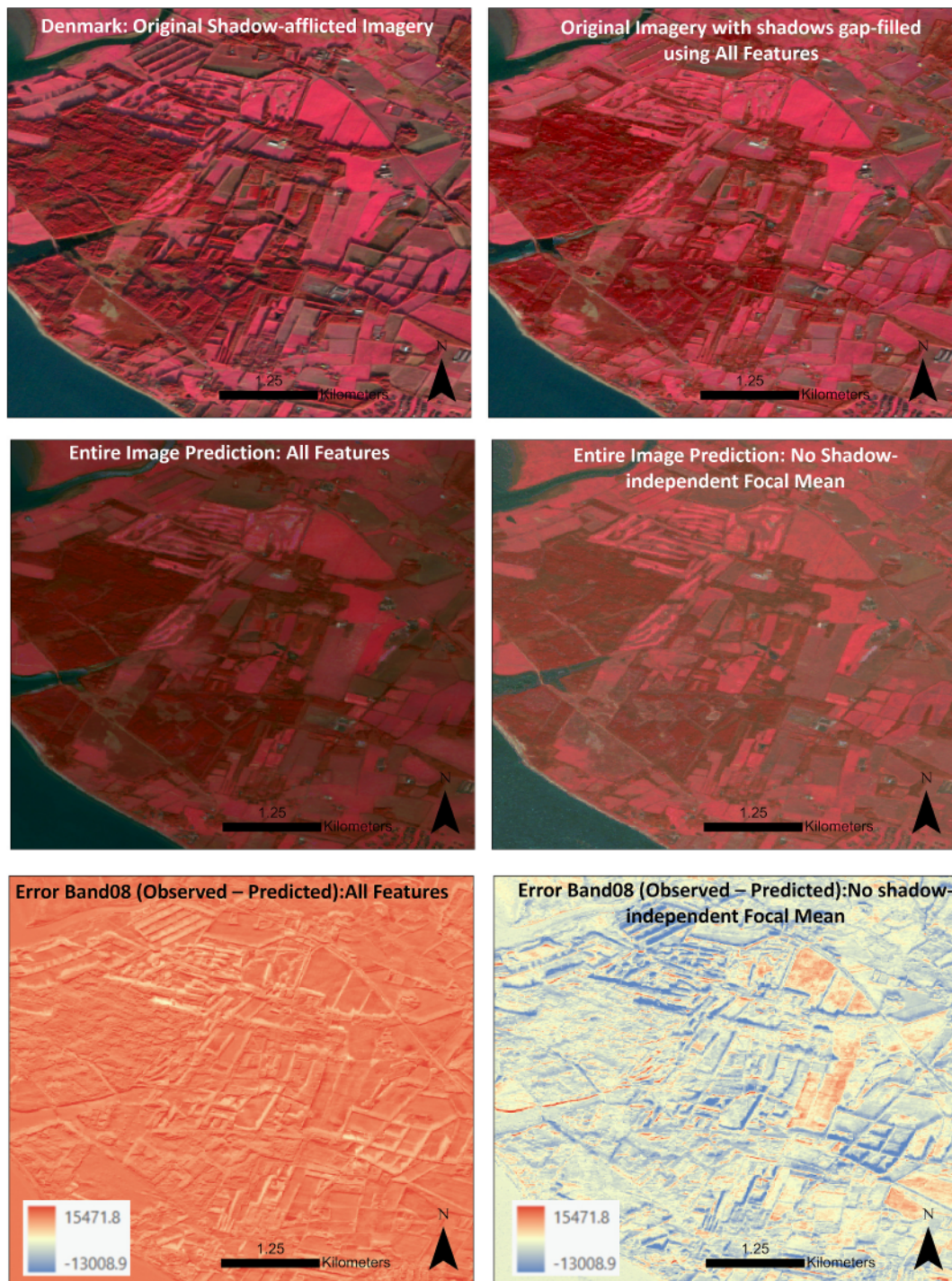


Fig. 12. (continued).

acquired on the dates as mentioned in the methods. Accordingly, after computing the shadow layer and following the approach for identifying false positive water, we then computed to the total area occupied by false positive water in these Sentinel-2 granules. A subset of the input image and the Dynamic World layer are shown in Fig. 15. The arrows highlight tree and terrain shadows which are falsely mapped as surface water. However, most of the water visible in these images is false water due to shadow.

For Iwate, Japan, 9.2% of the surface area was tree or terrain shadow. We identified 18.6% of Dynamic World water pixels were false water, directly attributed to tree and terrain shadow. For the Göttingen, Germany image, 12.4% of surface area was detected as tree or terrain

shadow, and we identified 10.1% of Dynamic World water pixels were false positive water due to tree or terrain shadow.

## 5. Discussion

Our results for shadow detection produced a physical-based approach which is computationally efficient and has a reasonable overall accuracy of 83.6% ( $\pm 1.4\%$ ) for all non-snow images, 82.8% ( $\pm 1.8\%$ ) for snow images (Denmark and Sweden), and 85.1% ( $\pm 2.1\%$ ) for non-snow images (Denmark and Sweden), indicating the non-snow approach may be slightly more accurate, but cannot be conclusively determined due to the overlapping confidence interval ranges. The



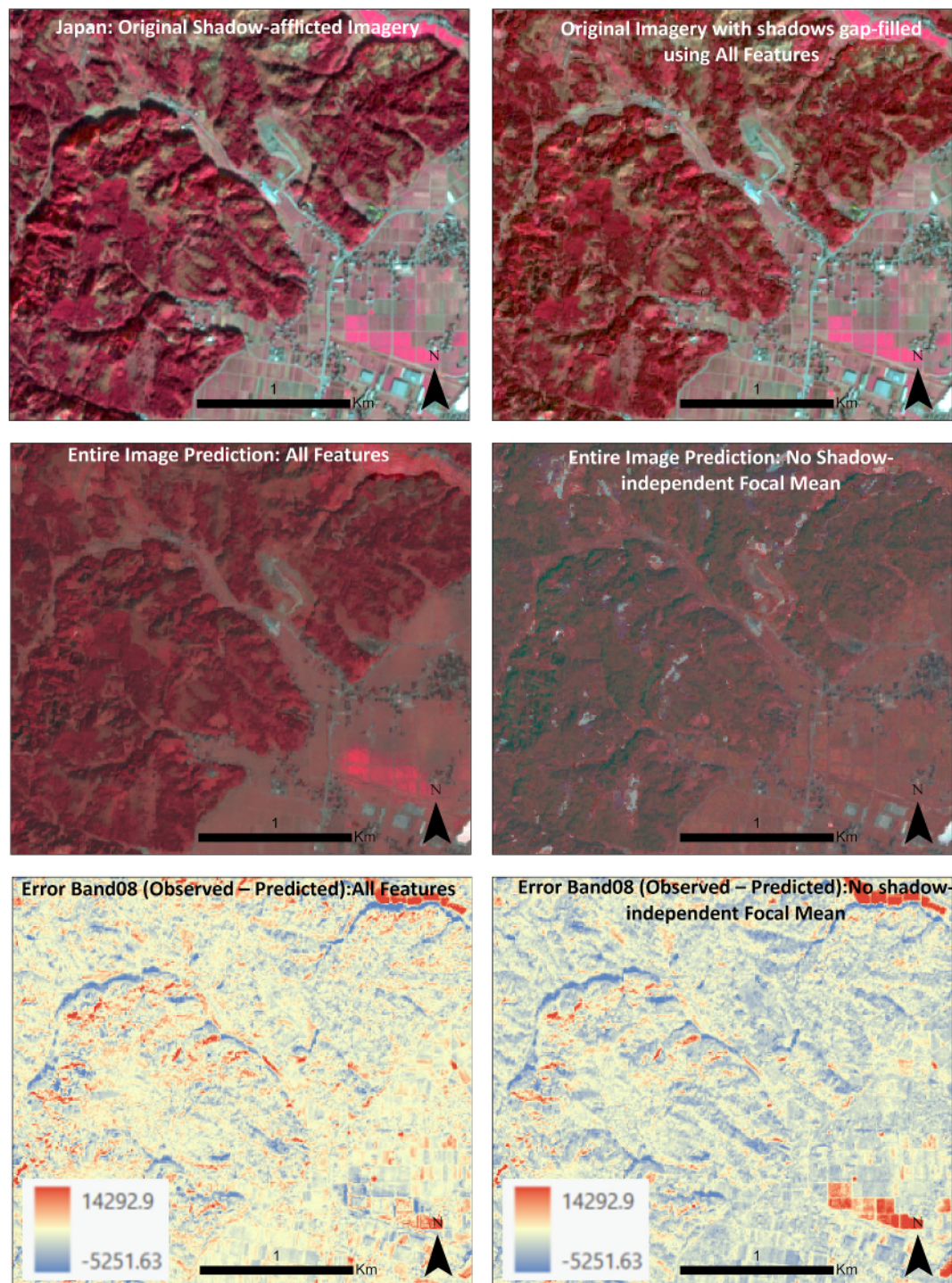


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shadow detection model had a strong user's accuracy, but lower producer's accuracy, indicating that it could be improved to overcome shadow omission errors, which are largely attributed to DEM resolution and artifacts, hillshade algorithm artifacts, and CHM errors including omission of younger trees and narrow clusters of trees. Tree and terrain shadows were found to occupy a surprising amount of area in these images, accounting for between 8% and 30% of surface area in the images, with a 7-image area average of 18.0% ( $\pm 1.0\%$ ) based on the Meta CHM. This substantial area indicates that mitigation of shadow effects must be considered in remote sensing studies conducted at moderate-to-high latitudes, especially if current approaches are not

effectively mitigating these shadows. These effects could lead to drastic errors in products such as land cover, as we had shown in the Dynamic World product, but also more wide-reaching in other derivative studies related to vegetation health, biomass, gross primary productivity, and more. However, it should be cautioned that radiance related applications like albedo should be avoided with this shadow correction approach. Prior research has not yet characterized how prevalent this combination of tree and terrain shadows are across different geographies. Through our shadow correction approach leveraging multi-source imagery, including multitemporal SAR, DEM, etc. we demonstrated gap-filling of shadows. This approach included a novel shadow-independent



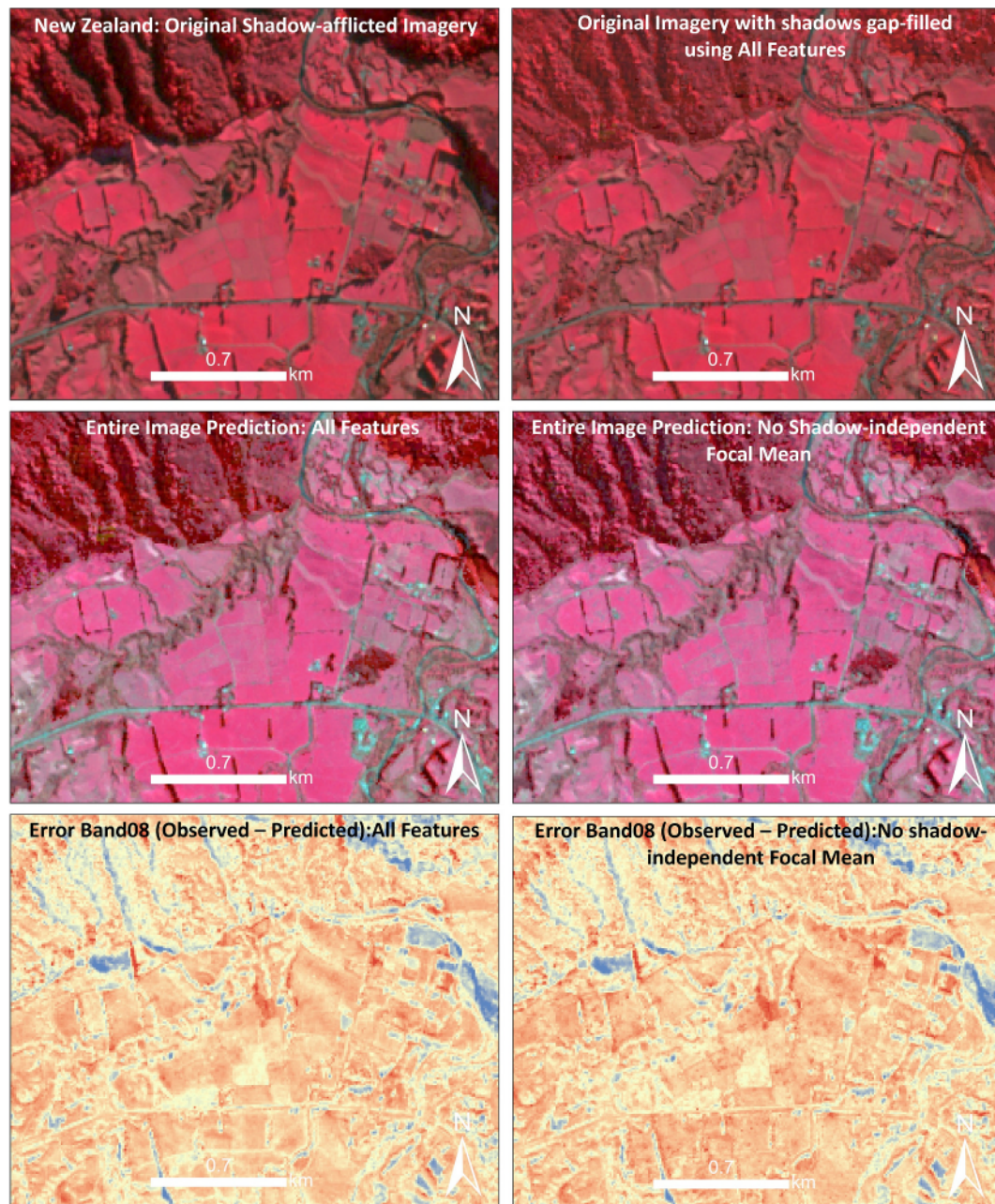


Fig. 12. (continued).

focal layer, which yielded  $MAE = 440$  for near-IR vs  $MAE = 691$  for near-IR without the shadow-independent focal layer.

Since there are not yet algorithms produced which detect tree and terrain shadows using satellite-derived imagery, direct comparison with other study results is difficult. However, there are some similar studies which can be compared. First, for shadow layer detection, [Aboutaleb et al., 2019](#) used a UAS image with 4 different methods to produce tree shadow maps. Accordingly, the overall accuracies ranged from 84.1% to 90.4% with the most practical approach for international implementation, as in our study, being those with the 84.1% accuracy (unsupervised classification); and 86.4% (physical-based model). These values are similar to our multi-site accuracies of 83.6% for non-snow images (5 total images) and 82.8% for snow images (Denmark and Sweden); and 84.3% for non-snow images (Denmark and Sweden). It is difficult to directly compare due to different validation schemes. [He et al., 2022](#) produced an all-source shadow layer which included vegetation shadow, building shadow, etc. The study used a robust adaptive

unsupervised approach with particle swarm optimization and the result attained accuracy for vegetation shadow in a single image ranging from 86% to 96%, which is higher than this manuscript's accuracy, but the model may not be easily transferable to other sites. [Zhang et al. 2020](#) created a robust all-source shadow layer which was trained on over 70 image chips of NAIP imagery across the U.S.A. The resulting overall accuracy for their most accurate model was 90.6%, which is higher than this manuscript's accuracy. However, the approach is more computationally intensive and on higher spatial resolution imagery. [Wang et al., 2024](#) applied a similar approach using solar position geometry and a matting method to detect the shadows of all sources with around 90% overall accuracy.

For the correction of tree and terrain shadows, we compare against several studies which corrected for varying types of shadows. [Wen et al. 2015](#) achieved an RMSE of about 84 for the near-IR band of Landsat 8 for all-source shadow correction using an approach that mimics the values of nearby spectrally-similar features. This error rate is substantially



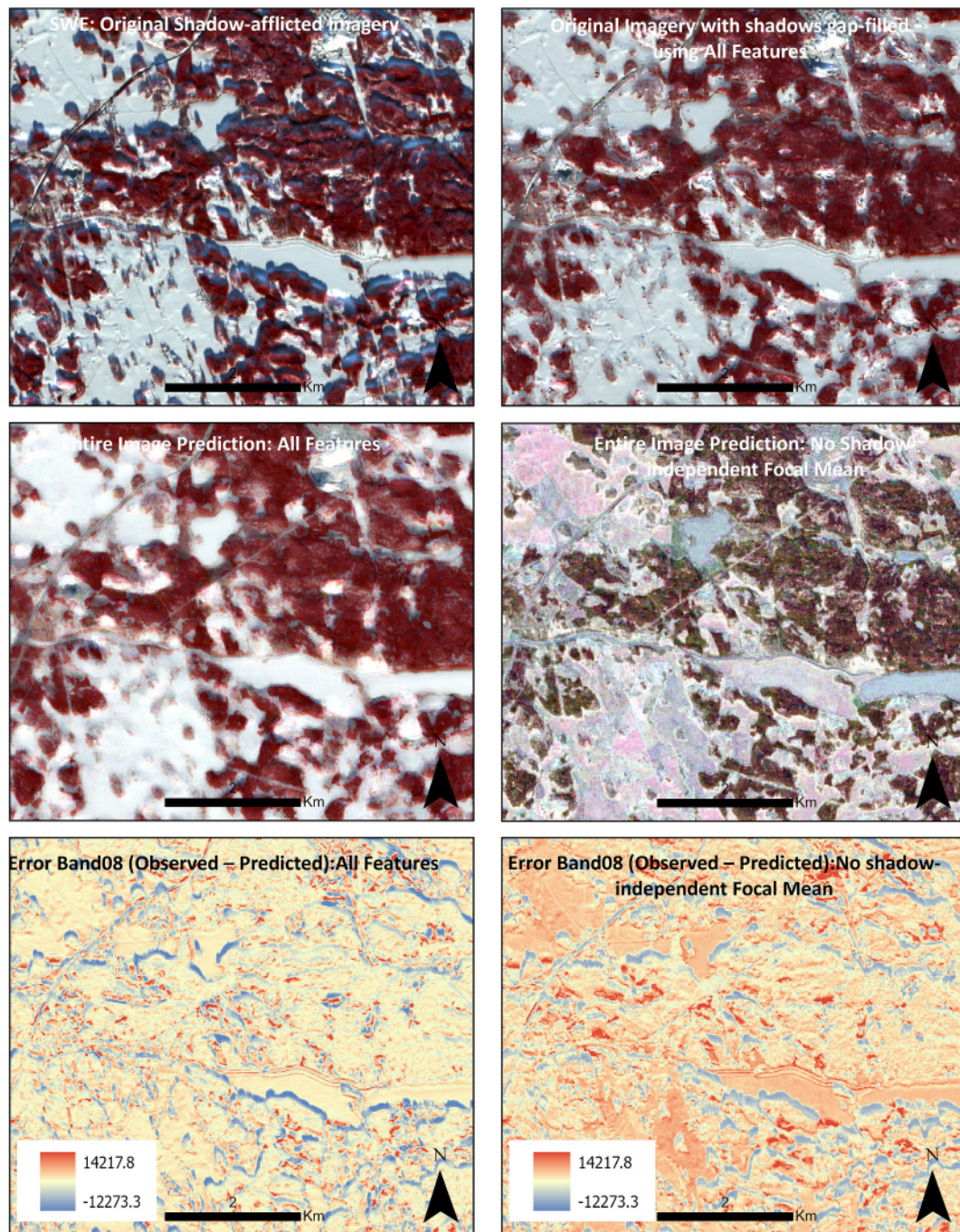


Fig. 12. (continued).

better than that of this manuscript, however, the practical generalizability of this method is questionable as implementation within heterogeneous landscapes could lead to spectral mismatch and more substantial errors. Han et al. 2020 noted an RMSE percentage ranging from about 18% to 60% across 3 different images for the RGB components for the correction of shadows in high resolution imagery, which was generally more in line with our study which a mean-normalized MAE of about 18.5% averaged across Near-IR, Red, and green bands. Lasko et al. 2022 achieved an MAE of 0.078 for NDVI for cloud-shadow gap filling for a single scene, that accuracy was lower than this manuscript's MAE of 0.037. There have been additional studies which achieved relatively high accuracy metrics typically with normalized errors around 3–20% using deep neural networks or radiative transfer models (Chi et al., 2024; Jiang et al., 2022; Li et al., 2022a; Luo et al., 2023).

There are several limitations to consider in this study. While we used robust accuracy assessment and sampling guided by the literature (Olofsson et al., 2014; Congalton and Green 2019), our analysis was limited to 7 globally-distributed images due to the time required to manually delineate ground-truth points. However, this analysis focused on moderate-to-high latitude areas and can be considered representative of diverse geographies within the northern and southern hemisphere, including Japan, Sweden, Denmark, New Zealand, and the United Kingdom. While the sites evaluated snow and non-snow conditions, they were temporally limited to winter months to capture peak shadow times. However, shadow detection accuracy could be different for other seasons. The shadow detection approach has some inherent errors which are difficult to overcome. For example, the tree height layers are produced for a fixed year (i.e. 2020). Considering that tree heights and



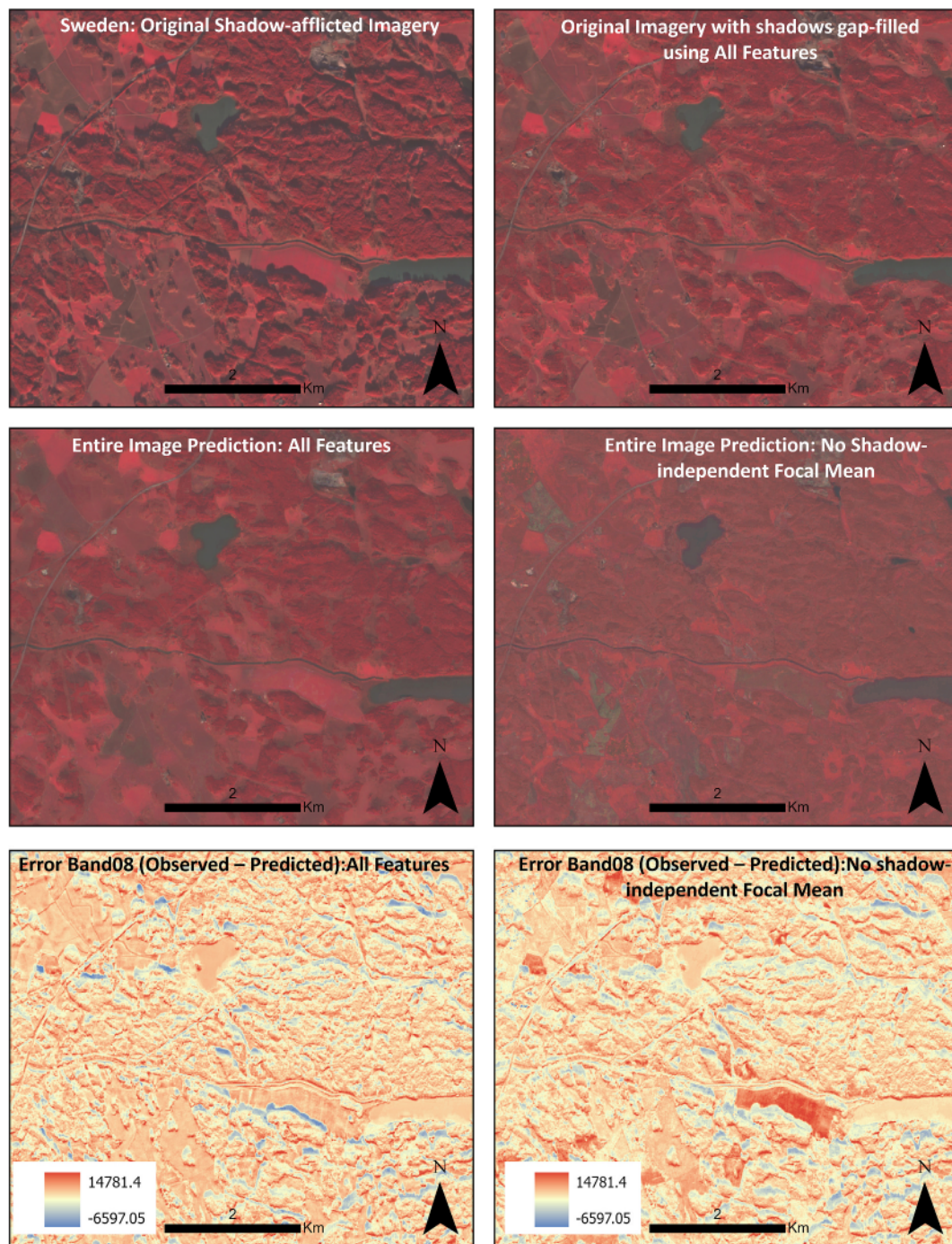


Fig. 12. (continued).

extent can change over time, the method could be improved if more frequent tree height layers become available. However, to compensate for growth of trees we included the additive factor evaluation, and to compensate for tree decline we included the adaptive thresholding method, both of which combined were found to improve the overall accuracy. The tree height layers lacked field validation, which leads to uncertainty. Next, the UMD tree height layer had a 30 m resolution, which made it inherently impossible to detect shadows from smaller clusters of trees, thus leading to higher shadow omission errors.

As for shadow correction, considering that shadowed pixels contain inherently darker than normal spectral values, it was impossible to evaluate the method directly on shadow pixels without in situ measurements with advanced equipment. Instead, we evaluated the method

by synthetically considering random non-shadow pixels in the image as shadow. It is important to consider that this may lead to inconsistencies as shadowed pixels have different illumination conditions with primarily diffuse skylight, among other factors. To partially address this issue, the distribution of values were compared between original non-shadowed and corrected shadow pixels using boxplots. The shadow-independent focal layer neighborhood window sizes could further be evaluated and optimized to enhance accuracy, however, the results found the use of these layers as-is, still yielded substantially improved accuracy. For shadow correction accuracy, additional hyperparameter tuning could be undertaken to further refine accuracy; the deep-learning algorithm accuracies would likely be similar or better than the ensembles with substantially longer training time. For attribution of false



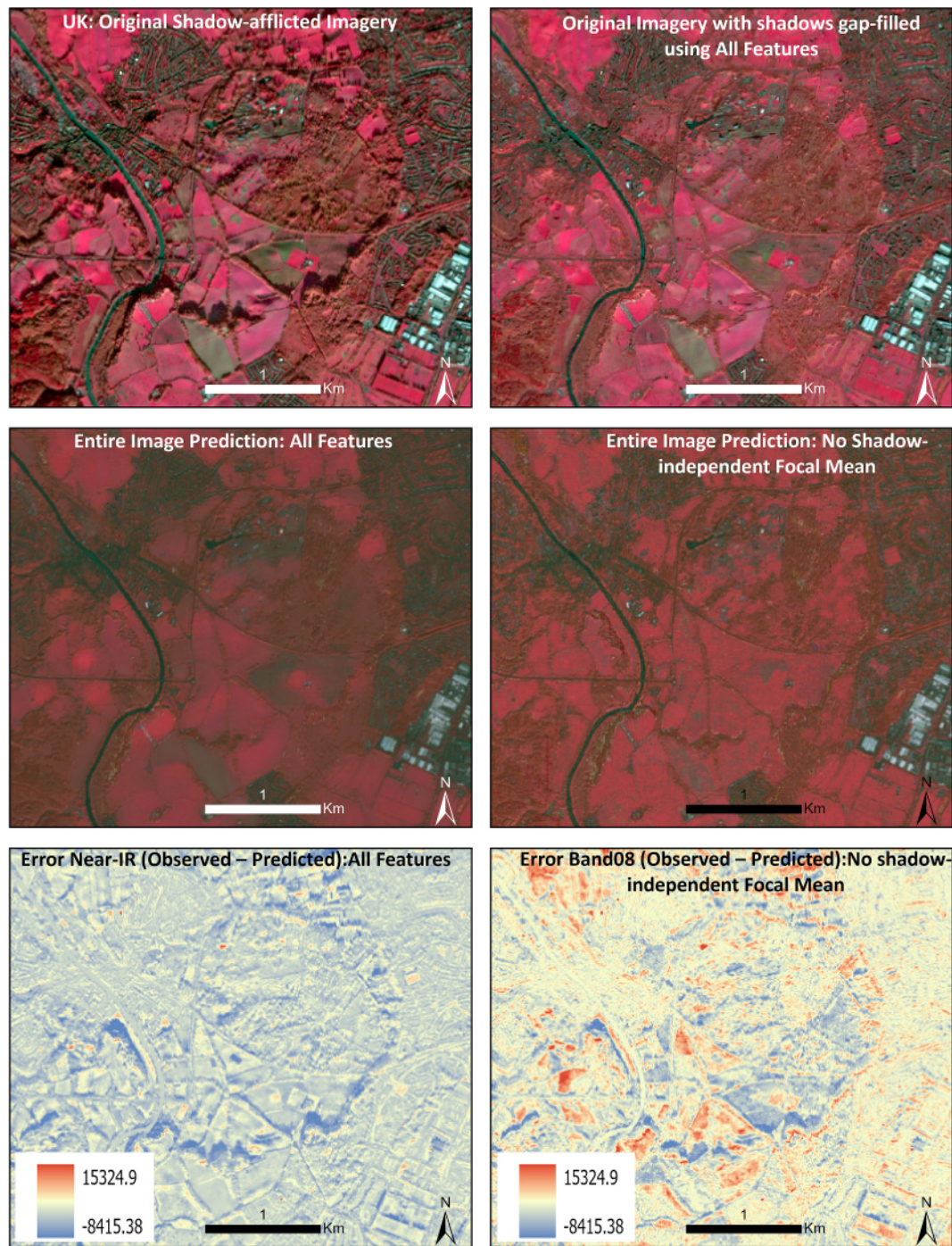


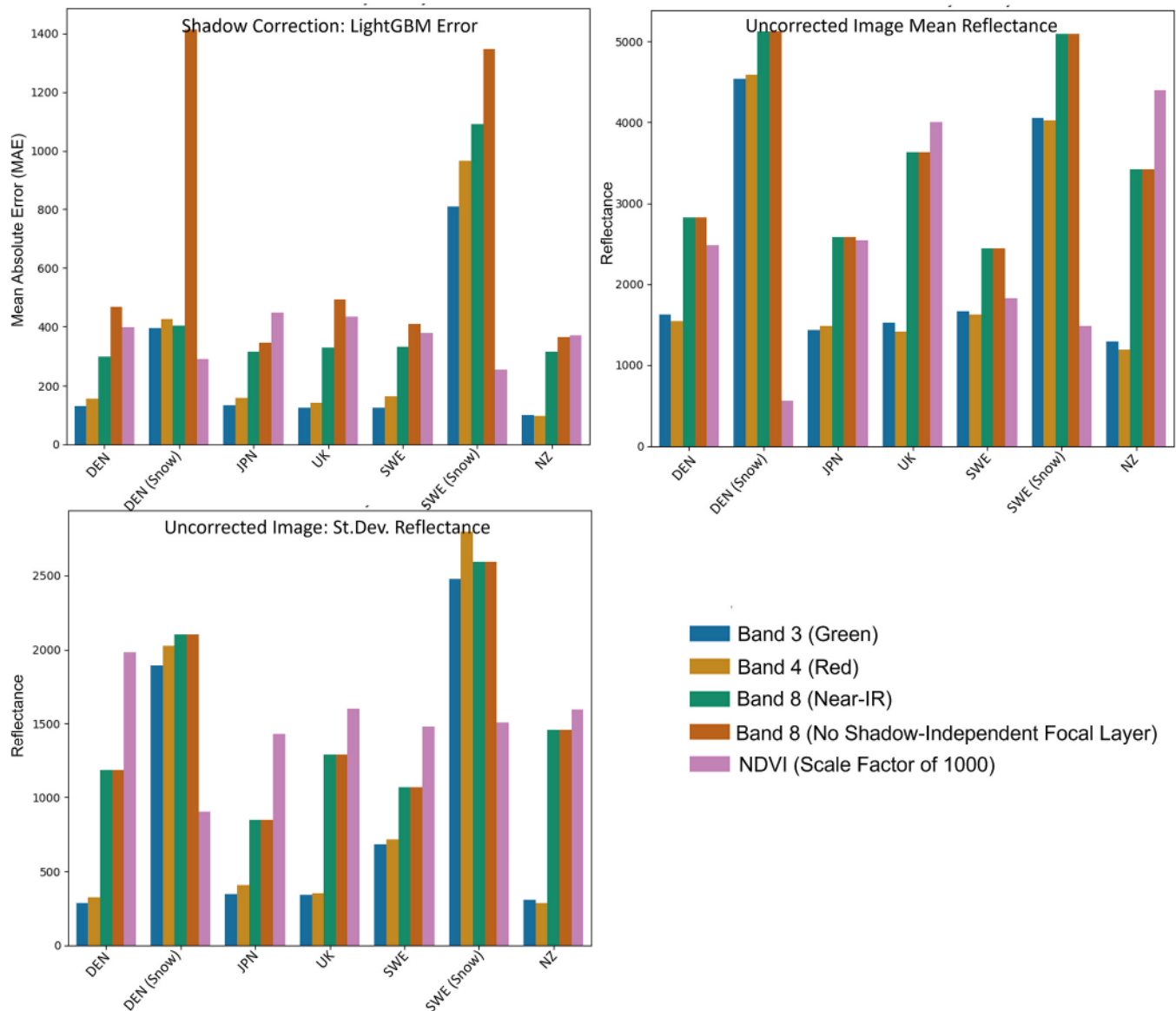
Fig. 12. (continued).

positive water due to cast shadows as detected in Dynamic World, it is important to consider that the spatial resolution of the UMD water layer is 30 m and Dynamic World is 10 m, resulting in some likely missing pixels in the UMD layer for small water features and edges, which would likely bias the error slightly. On the same, it should be reiterated that the land cover errors were tested on only 2 case study locations for the purpose of highlighting the need for shadow correction in the context of land cover classification. It was not an exhaustive evaluation. For these scenes, shadow errors exclusively observed as water pixels, thus the analysis focused on false positive water attributed to shadows.

The broader implications of this research show that tree and terrain shadows represent a sizeable proportion of winter images in high latitude imagery (between 8 and 30% for tested sites), suggesting the

importance of shadow correction, and highlighting case study examples on resultant errors in land cover products. For updated practical applications, inclusion of shadow layers in machine learning classification and regression models related to biophysical parameters would likely yield improved results, as these errors have been observed in various studies (Alavipanah et al., 2022). Further, topographic correction models (Richter et al., 2009; Soenen et al., 2005) could be refined based on the findings of this study, to also include tree CHMs, which are now widely available, for improved topographic correction which would include tree shadow effects. Further, for approaches such as the C-factor, Gamma, or SCS + C (Gu and Gillespie, 1998; Richter et al., 2009), the tree and terrain shadow layer could mask out these shaded pixels when building topographic regression models. A core novelty of this





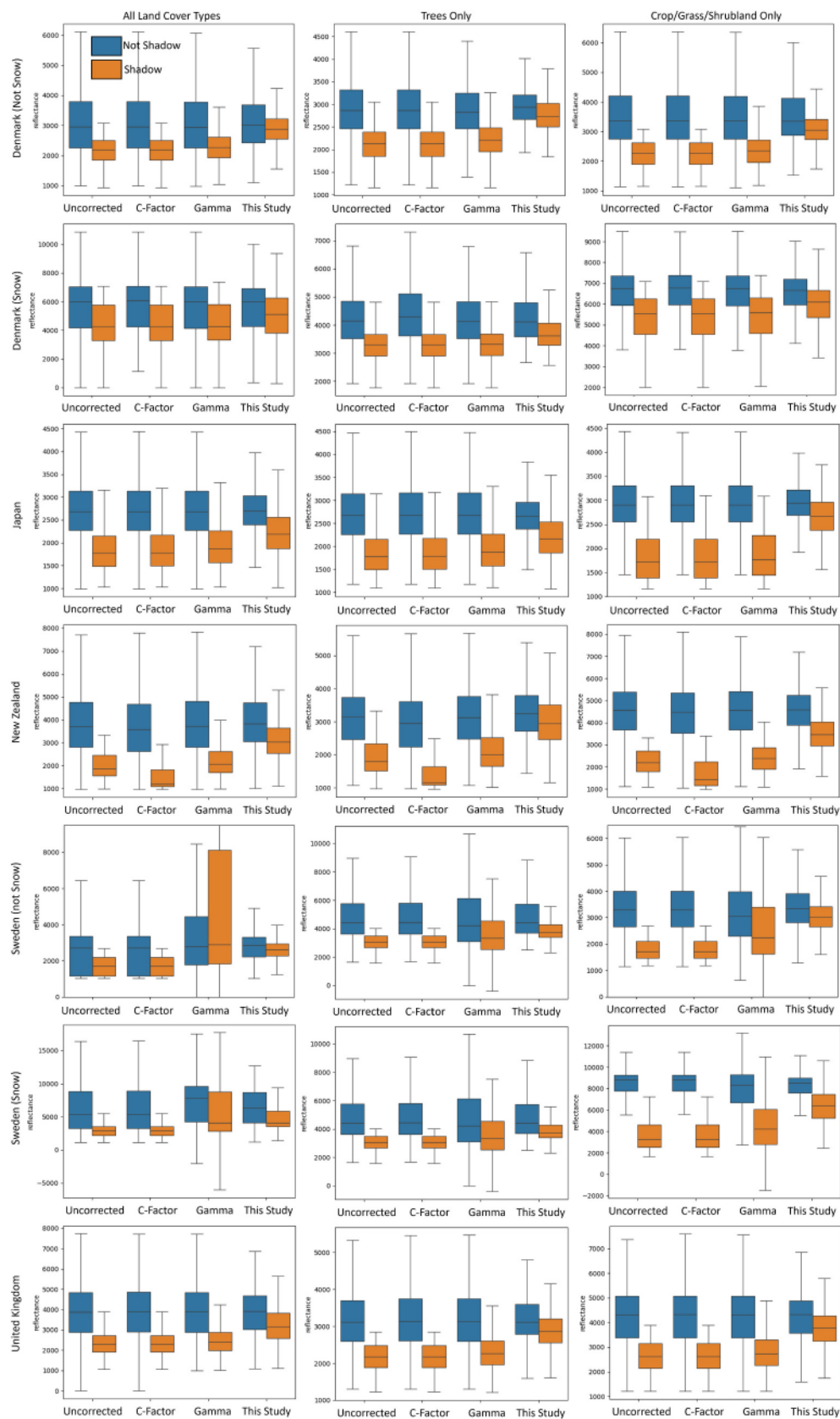
**Fig. 13.** Left: Mean Absolute Error (MAE) of shadow correction for each band tested, as well as for when the shadow-independent focal layer was excluded when tested on band-08. Center: original Sentinel-2 image-wide reflectance mean, and left: original Sentinel-2 image-wide reflectance standard deviations. For all sites, the MAE is below the mean and standard deviation.

manuscript is that the shadow approach can be characterized as a system-integration-oriented approach where shadow detection and correction are coupled. Traditional topographic correction models (Richter et al., 2009; Soenen et al., 2005) do not incorporate a separate shadow identification step. Further, these approaches attempt to correct original pixel values based on sun geometry and DEM characteristics. Whereas, this manuscript uses multi-source data fusion to predict the shadowed-spectral value with an ML model, as opposed to adjusting the original value by a scaling factor. Thus, the methods are related to those applied in data gap filling manuscripts such as cloud gap-filling.

## 6. Conclusion

This study developed an approach to detect winter tree and terrain shadows from satellite imagery as demonstrated using Sentinel-2 10 m imagery. The approach leveraged a DEM, tree CHM, solar angles, a hillshade model, and an adaptive threshold correction, which provided a lightweight algorithm that is scalable to broad geographic regions as evaluated across 7 globally distributed images. The average accuracy

across snow and non-snow images was approximately 83.2% ( $\pm 1.6\%$ ). The results indicated using the META CHM yielded higher accuracy than the Landsat-based UMD CHM, likely due to spatial resolution differences. To correct the shadow-afflicted pixels, we presented a workflow using a variety of input features including multitemporal SAR, image textures, and a novel shadow-independent focal layer with both XGBoost and LightGBM tuned models yielding similar accuracy and prediction time capabilities (MAE = 440 for Near-IR). The MAE for NDVI (0.037), red band (301), and green band (259) were all substantially below image reflectance mean and standard deviation, indicating a robust model. The deep learning algorithms were tuned within the Autogluon framework, and had slightly lower accuracy than the ensemble regressors. We found the shadows impact satellite-derived products and demonstrated examples from 2 case study images with Dynamic World land cover model over Germany and Japan. Findings indicated between 10.1% and 18.6% of water pixels were erroneous due to tree or terrain shadow in these 2 images. Lastly, the analysis found that tree and terrain shadows occupied between 8% and 30% of area across the 7 study images, with an average of 18.0% ( $\pm 1.0\%$ ), indicating



**Fig. 14.** Boxplots comparing topographic correction methods in shadowed and non-shadowed pixels.



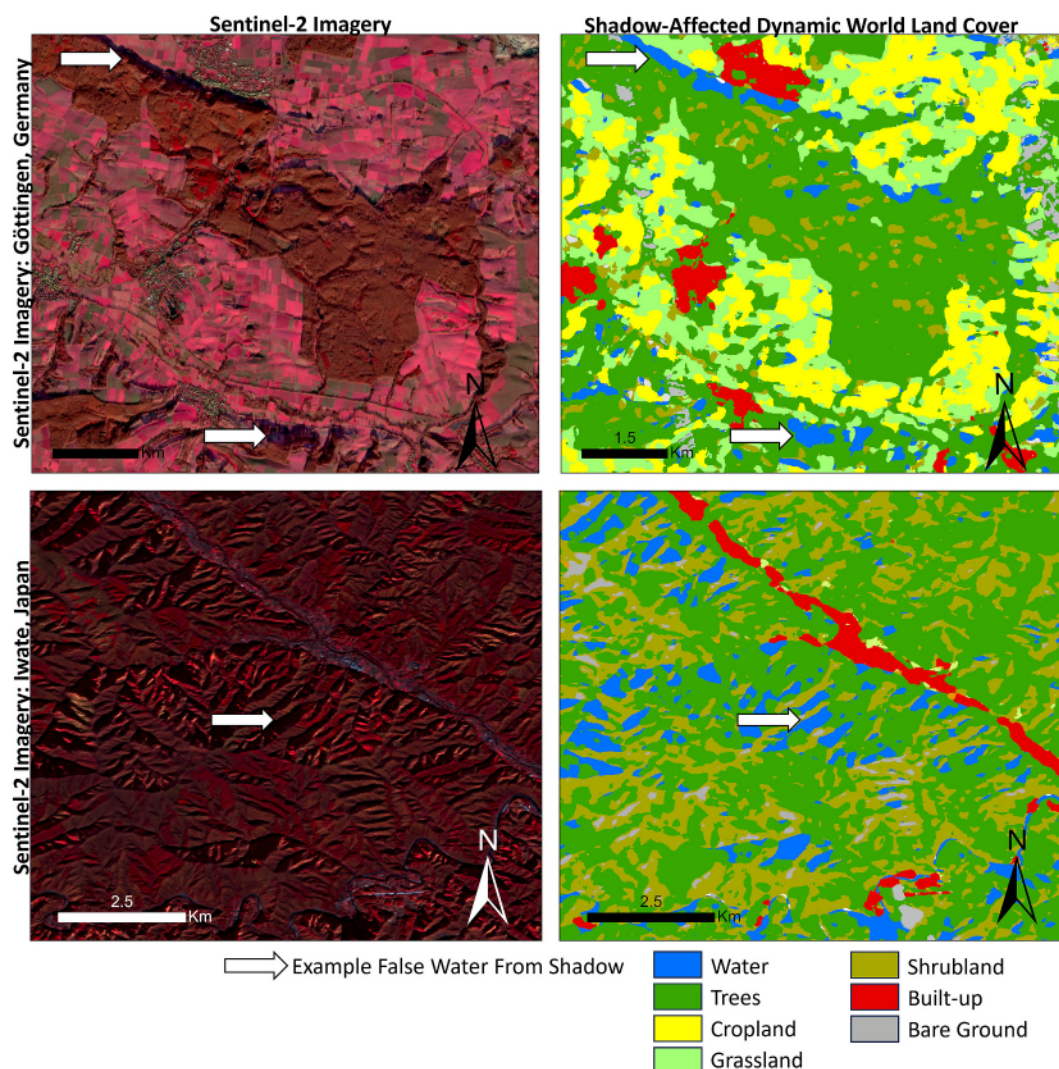


Fig. 15. Examples of False positive surface water attributed to tree or terrain shadow on the Dynamic World land cover product.

that these winter shadows are very important to consider for mitigation when conducting environmental monitoring studies with satellite imagery in moderate-to-high latitude during months when shadows are prominent (i.e. winter solstice time and adjacent months). Ultimately, the use of tree and terrain shadow layers could lead to improved outcomes in topographic models (Richter et al., 2009), and the correction of tree and terrain shadows generally could lead to improvement in modeling of biophysical parameters, including land cover.

#### CRediT authorship contribution statement

**Kristofer Lasko:** Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Caleb G. Pan:** Writing – review & editing, Visualization, Validation, Formal analysis. **Sean P. Griffin:** Writing – review & editing, Validation, Funding acquisition.

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#### Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: (Kristofer Lasko, Caleb G. pan, and Sean P. Griffin report financial support was provided by US Army Engineer Research and Development Center Geospatial Research Laboratory.)

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## Appendix A. Appendix

### A.1. Shadow Correction Ensemble Model Hyperparameters

The ensemble machine learning model hyperparameters were tuned based on attempting all value combinations shown in Table A.1. The tested models included random forest, extra trees, LightGBM, and XGBoost.

**Table A.1**

Ensemble model hyperparameters and values used for tuning the shadow correction models. N/A is added if that parameter is not tuned or available for the given model.

| Model         | n_estimators    | Max_depth           | Max_features | Min_samples_split | Learning_rate                 | Num_leaves                  | Subsample_rate |
|---------------|-----------------|---------------------|--------------|-------------------|-------------------------------|-----------------------------|----------------|
| Random Forest | 100,250,500,750 | 10,25,50,75,100,500 | Sqrt,10,15   | 2,10              | N/A                           | N/A                         | N/A            |
| Extra Trees   | 100,250,500,750 | 10,25,50,75,100,500 | Sqrt,10,15   | 2,10              | N/A                           | N/A                         | N/A            |
| LightGBM      | 100,250,500,750 | 10,25,50,75,100,500 | N/A          | N/A               | 0.01, 0.025, 0.05, 0.075, 0.1 | 15,30,45,60,75,125,250,1000 | N/A            |
| XGBoost       | 100,250,500,750 | 10,25,50,75,100,500 | N/A          | N/A               | 0.01, 0.025, 0.05, 0.075, 0.1 | 15,30,45,60,75,125,250,1000 | 0.5, 0.8, 1    |

### A.2. Shadow correction deep learning models and parameters

The shadow correction deep learning models and parameters tested are described here. Specifically, the RealMLP algorithm which uses token mixing and offers performance in line with CNNs (Holzmüller et al., 2025), Fastai-tabular which is based on the PyTorch neural network framework, but offers automation of training and tuning with layer freezing and discriminative learning rates (Howard et al. 2020), and third a PyTorch Feed-Forward Neural Network (Paszke et al., 2019). For tuning of each algorithm, we used a random search function with the “medium\_quality” preset and a time-out of 10 min per image for training. The medium preset provides a reasonable balance between training and prediction time; and accuracy. For RealMLP; it considers GELU/RELU activations; a small random range of num\_layers; and moderate range of hidden\_size parameter with varied dropout. For fastai and the pytorch neural network; it tests different layer dropout patterns; embedding dropouts; and layers as well as learning rate; epoch size and batch size with varied regularizations. More detail is available (Erickson et al., 2020). From this testing, we then report the most accurate model and associated fit time and prediction time based on the 20% validation data that is withheld from training. It is essential to consider that accuracy could likely be improved by performing longer model tuning, but because the models are trained separately per image, this is practically infeasible.

The deep learning algorithms were evaluated using a computer with 16GB DDR4-2666 MHz SDRAM, NVIDIA GeForce RTX2060 with 8GB GDDR6 memory, 9th Gen Intel Cor i7-9750H and a 512GB NVMe SSD. The ensemble models were applied without GPU-acceleration or parallel processing when predicting the imagery. The process of predicting shadow pixels could be sped up using Dask and rioarray with windowed output image writing. However, already the processing should be fast and require minimal optimization, since our fastest average prediction time was around 60 s for all pixels in a Sentinel-2 image. In practice, a researcher would only correct shadow pixels (approximately 18% of pixels in the image), this would likely result in an unoptimized prediction taking under 20 s per subset image.

### A.3. Shadow correction input features

This sections described in more detail the data layers used for shadow correction. The layers include: (1) World Cover Land Cover version 2; this layer was one-hot-encoded to represent the categorical class in a binary manner; (2) Sentinel-1 C-band VV and VH polarization backscatter in Sigma Nought dB units; this image was an average of the ascending and descending node acquisitions from approximately 2 weeks before the Sentinel-2 image and 2 weeks after the Sentinel-2 image to ensure reduction of radar shadow and noise; (3) Sentinel-1 C-band VV and VH annual standard deviation computed from both ascending and descending nodes for 6 months before and 6 months after the Sentinel-2 image of interest; (4) Grey-level Co-occurrence matrix (GLCM) variance derived from the Sentinel-1 SAR VH (2) with a  $5 \times 5$  pixel window and 64 quantization levels from a probabilistic quantizer (Hall-Beyer, 2017); (5) GLCM variance derived from Sentinel-2 annual 75th percentile composite using the same parameters except for a  $7 \times 7$  pixel window. The annual composite was used to ensure shadows were not present in the texture. (6) Sentinel-2 annual 25th and 75th percentile composites for Near-IR (Band-08) and NDVI computed from 1 year of cloud-masked imagery containing less than 10% cloud cover (note exclusion of 25th percentile input for New Zealand site due to steep and seasonally-persistent mountain shadows); (7) NASADEM/SRTM DEM provided at 30 m spatial resolution and resampled to 10 m in alignment with Sentinel-2; from this dataset we derived slope and aspect to use as input features; (8) Shadow-Independent Focal Layer: computed from the Near-IR band as described in the methods; 8 total focal inputs are included with one at 500 m resolution and another at 200 m resolution; (9) tree and terrain shadow layer: the shadow layer produced earlier in this study is included to filter out shadow pixels from the training set. Since land surface under shadow has reduced reflectance, inclusion of these pixels in the model would result in propagation of errors; (10) the Sentinel-2 SCL is used to filter out the medium and high probability clouds, cloud shadow, and no data pixels from the training set.

### A.4. Comparison of shadow correction methods

Traditional topographic correction methods incorporate solar angles with DEMs for radiometric correction of imagery. The C-factor method is based on the cosine of the solar zenith angle with a c-parameter created from a regression model between pixel radiance and solar illumination angle, whereas gamma correction normalizes pixel values using sun-terrain geometry (Gu and Gillespie, 1998; Richter et al., 2009). Accordingly, these two topographic correction methods were visually compared against the approach from this study for visual comparison in the New Zealand image. The boxplots of value distributions were presented in Fig. 14 of the results section for all 7 images. Fig. A.4 contains the original near-IR band and each of



the shadow correction methods tested. Note that C-factor made some improvements in partially-occluded shadows, while gamma made more improvements in deep shadow. A striping effect can be observed due to the SRTM DEM resolution. The shadow-correction from this study appeared to substantially reduce shadow effects for the visualized area.

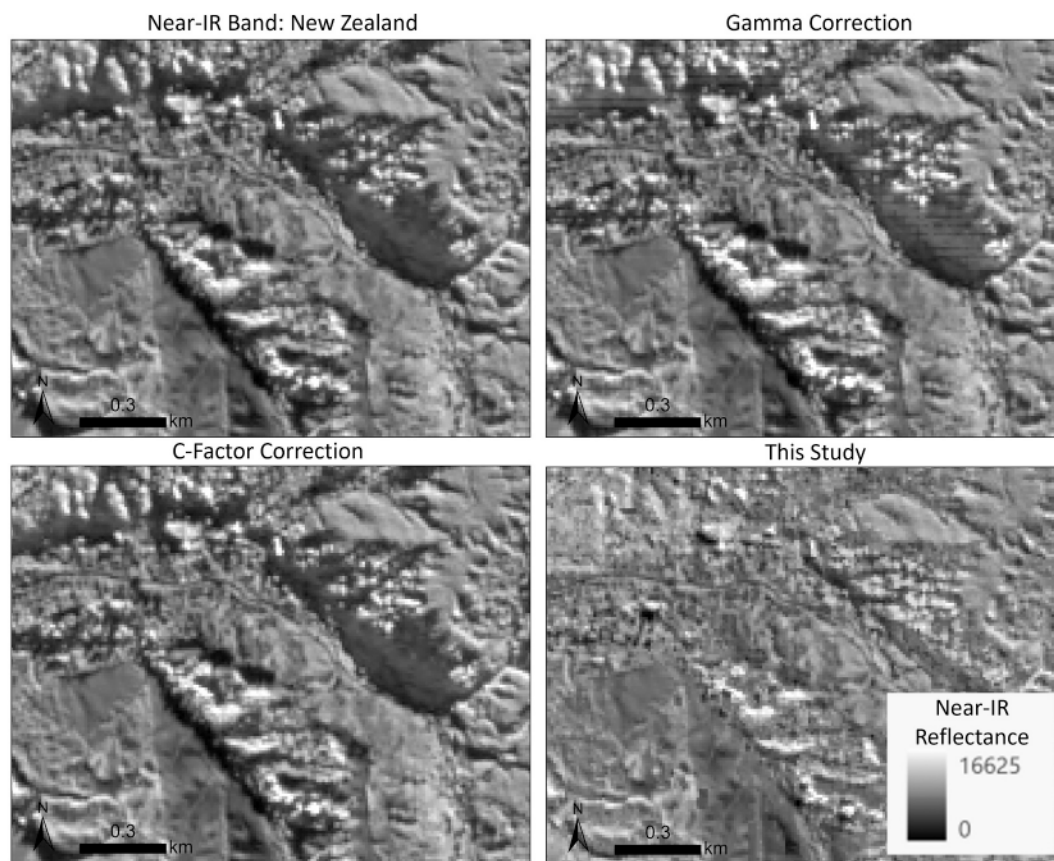


Fig. A.4. Visualization of two topographic correction methods (C-factor and Gamma) with the original Near-IR image and the shadow correction method from this study shown for a subset of the New Zealand image.

## Data availability statement

All data was acquired from public repositories as described in the methods section. The code and products are available at: <https://doi.org/10.5281/zenodo.18717889>.

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