Mapping RWH with remote sensing – update on degraded land model

Aug 2023

Overarching goals and context of degraded land (glacis/non-glacis) model

The goal of the glacis/non-glacis model is to produce a landscape factor to constrain analyses for our overarching objectives of measuring adoption and benefits of RWH techniques. Specifically, farmers are expected to only adopt RWH on land that is glacis. In addition, a glacis /non-glacis model on its own could also provide a general tool that would be accessible to government and other agencies to monitor changes in degraded land with minimal resources. It can also serve as an outcome for measuring impacts of RWH adoption.

The overarching objectives of the remote sensing are as follows:

1. **Objective 1) detect demi-lunes remotely:** We have developed a model able to detect new demilunes with around 80% accuracy using Sentinel and PlanetScope (3m) data, as described here. Adding glacis predictions as an input could improve the accuracy of this model. It would also help constrict the search area for high-resolution imagery that would be needed in a two-stage approach to achieve very high levels of precision in identifying demi-lunes.
2. **Objective 2) detect benefits of RWH** (e.g. increased crop yield (increased NDVI or other vegetation index) or resistance to drought (increased moisture in soil)). With Sentinel-2 data, we observed an increase in NDVI in locations following demilune construction, however this simple pre-demilune (2017) vs post-demilune (2018) analysis is not enough to establish causality because 2018 was wetter than 2017. We developed a model comparing demilune fields to non-demilune fields, but, without information on degraded lands, this is a biased comparison because non-demilune fields are often on non-degraded lands and thus biased toward higher production. The glacis/non-glacis model will allow us to conduct this same diff-in-diff analysis with more balanced matching and thus assess whether improvements were seen in demilune fields compared to fields also on degraded lands but without demilunes.

We will use the glacis/non-glacis model described below to refine our previous analyses for the 2017 RCT and prepare similar analyses for the scale-up project.

Glacis/non-glacis model summary:

The goal of this exercise was to build a Random Forest (RF) model that predicts the location of degraded, glacis land.

- Training and validation data for the model include field boundaries labeled as “glacis” or “non-glacis” that were collected during the January 2023 baseline field survey, along with “other” non-agricultural landcover polygons that were digitized referencing USGS/USAID landcover maps.
- Remote sensing data from Sentinel-1, Sentinel-2, and Shuttle Radar Topography Mission (SRTM) were extracted within these field boundaries and used to train and validate the model based on their “glacis” or “non-glacis” labels. Wall-to-wall surface predictions, i.e. a glacis/non-glacis classification map was created by applying the trained model on raster images of these same remote sensing predictive features.

Field Data:

- The baseline field survey includes coordinates of boundaries for 3,233 glacis fields and 1,033 non-glacis fields.[1]
- This training data only includes information about land currently used for agriculture. To teach the model what "other" non-agricultural landcover types look like, sample polygons were digitized around other predominant landcover types (ponds/lakes, wetlands, built up, rocky outcrops, passage) on high-resolution imagery[2], while cross-referencing USGS/USAID landcover maps (courtesy of Gray Tappan) around the Takieta, Gouchi, and Wacha communes.
- For each model, 75% of the training samples (by field, or polygon, and stratified by class) were used in the training set, and the remaining 25% of samples were held out as the validation set.

RS Imagery:

RS predictive features were created from three sensors:

1. Sentinel-1[3] Synthetic Aperture Radar (SAR) was included to capture land surface/soil information.
2. Sentinel-2[4] imagery was included to capture the effects of glacis land on agricultural productivity and vegetation vigor.
3. Shuttle Radar Topography Mission (SRTM)[5] topographic features (elevation, slope) were included to capture information related to water availability.

RF Predictions:

- Using the standard predict function, the model assigns discrete class labels based on the class that the majority of decision trees in the Forest predict.
- Alternatively, the predict-probability[6] function with a user-defined threshold assigns a pixel to the glacis field class, i.e. 1, if its continuous glacis-probability raster value is greater than the threshold value, or the grouped (non-glacis field with "other" non-ag) class, i.e. 2, if it is below.

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[1] Quality check: Any fields with conflicting answers regarding the glacis status of a field were removed: For each glacis field, respondents must have answered at least 1 for Q3_2 (How many of these fields have the glacis even on one part?), as well as 1 for Q3_3 (Is this a glacis or non-glacis?) and 1 for the verification question Q3_5 (does this field have 'glacis'?). Non-glacis fields must have answered 2 for Q3_3 and 0 for Q3_5. Other data cleaning included deleting misplaced points from field polygon, and splitting overlapping fields down the middle to remove double-sampling.

[2] Image interpretation: 0.5cm Maxar imagery from ESRI basemap and 3m Planet monthly mosaics were the main high-resolution images referenced. Rocky outcrops may look greenish but in the Planet's false-color-composite, vegetation appears bright red and rocky outcrops (not vegetated) still appear gray. To distinguish seasonal wetlands, a waterbody may look dry in the Planet monthly mosaics during March, and either have standing water or much more lush vegetation (signaling a marshy wetland) during October, after much of the rain. Town centers often include trees and more vegetation mixed with the housing structures. Most built samples were collected from the Zinder region, which has an airport with larger, pure areas of asphalt and larger structures without vegetation intermixed.

[3] Sentinel-1 processing: Raw Sentinel-1 dual-polarization (VV+VH) images from two months during the slack agricultural period (when crop shouldn't interfere with the backscatter signal) were downloaded from EE API. These images have had an orbit file, border noise removal, terrain correction, and speckle filtering applied, before transformation from linear to db scale for export. A focal filter was applied to these four images to smooth, or reduce the effect of "speckles" common in SAR imagery.

[4] Sentinel-2 processing: Sentinel-2 monthly cloud-free reflectance bands were created from the median value of Sentinel-2 cloud- and shadow-masked images for each acquisition in a given month during the growing season. Sentinel-2 monthly cloud-free reflectance bands from four months during the growing season were processed and downloaded using Earth Engine (EE) API. Table 1 shows the Sentinel-2 bands with their corresponding pixel size. Table 2 shows the VIs used, their formula, and description of what each specializes in measuring.

[5] The two topographic features, 30m NASA STRM digital elevation model (DEM) and slope raster (derived from the DEM), were downloaded from EE.

[6] Method description: The "predict-probability" function saves a continuous confidence probability for each class. Then, a glacis confidence threshold is applied, where for each sample the majority class is assigned, unless two conditions are met: First, intending to minimize FNs, if the predicted class is not glacis but the glacis probability is higher than the threshold, that sample is assigned to the glacis class; Second, to alleviate glacis overprediction, if the predicted class is glacis but its probability is less than the threshold, then the sample is assigned to the "other" class with the second-highest probability.

Accuracy Metrics:
The following accuracy metrics are guiding the iterative process of (1) adding or removing "other" non-ag landcover classes and additional "other" polygon samples, (2) feature selection, (3) assigning an appropriate glacis-probability threshold, and (4) hyperparameter tuning:

- Overall accuracy (OA) – total number of correctly classified validation pixels divided by the total number of validation pixels – for overall model assessment
- Confusion matrix - with producer's accuracy (PA)[7] and user's accuracy (UA[8]) – for individual class recall and precision accuracy assessment
- The glacis class PA, complement of error of omission or false-negative (FN) rate – for glacis class recall
- Qualitatively, classification rasters for the 20km x 20km processing grids throughout the study area were saved and visually inspected by cross-referencing the training and high-resolution imagery.

Robustness Testing:
Stability Over Time: To assess how generalizable the model is over time, one model was created using all 82 features from April 2022-2023, and another model was created using the same features from the previous year's (2021-2022) remote sensing imagery[9].
Cross-Validation: To assess the stability of model predictions when training samples are randomized, the training/validation (T/V) partition[10] was randomly generated 10 times and 10 different models were created from each T/V split, trained using 82 (12 Sentinel-1, 68 Sentinel-2, and 2 topographic) features, and finally accuracy metrics were assessed for the 10 TV model predictions.

- All confusion matrix tables from cross-validation robustness testing. Between all versions, OA ranged from 83%-89% and Glacis PA from 93-94%. At the 70% threshold, OA ranged from 84%-88% and Glacis PA ranged from 86%-89%. Increasing the threshold lowered Glacis PA but increased "other" classes (as the model was no longer overpredicting glacis). A smaller range in accuracy between the 10 iterations would be ideal and signify a model that is mode robust to random variation.

Feature Selection:
Reducing the number of predictive features can help improve model reproducibility, reduce time spent processing, and decrease data volume.

1. RF's feature importances, gini importance (decrease in node impurity) and permutation importance (decrease in accuracy), were run on these 10 random T/V splits to determine if a handful of features were consistently ranked among the most important features.

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[7]Producer's Accuracy (row % correct): complement of Omission Error. For each class, how often real features on the ground are correctly classified on the map. In the table, PA for each class = the # of correctly classified validation pixels for a given class / the total number of validation pixels for that class (row total).
[8] User's Accuracy (row % correct): complement of Commission Error. For each class, how often features on the map will actually be present on the ground. In the table, UA for each class = the # of predicted pixels that were actually that class / total # of pixels that were predicted to be that class.
[9] Time robustness results: Quantitatively, OA and glacis error of omission were similar. Qualitatively, some areas of dense pockets of "glacis" and "non-glacis" predictions remained the same, but predictions more often changed near the edges of these clusters. Comparing majority predictions from 2023 to 2022, 80.28% of the pixels remained the same, 9.22% of the classified pixels changed from "non-glacis" to "glacis", and 10.5% of the pixels changed from "glacis" to "non-glacis". From the 2023 to 2022 probability predictions assigned at a 60% confidence threshold, 84% of the pixels remained the same, 8.86% changed from "non-glacis" to "glacis", and 7.14% changed from "glacis" to "non-glacis".
[10] T/V split: 75% Training, 25% Validation, stratified by class

- No wavelength band, VI, or time of year was clearly most important, but elevation was consistently ranked in the top 5. Among Sentinel-2, features using NIR and SWIR bands in the middle of the growing season ranked most important. Among the Sentinel-1, features with the additional speckle-reducing smoothing filter applied were most important.

2. A correlation matrix with all Sentinel-1 and Sentinel-2 features throughout the year showed that SAR backscatter features, reflectance bands, and VIs contained highly redundant information, especially for VIs of adjacent months (i.e. Oct NDVI & Nov NDVI), and adjacent band wavelengths of a single date (i.e. Nov SWIR1 & Nov SWIR2).
    - To reduce the amount of features in a reproducible way that minimizes the amount of information lost, a 58-band model was created using Sentinel-2 reflectance bands from two months (June, Oct) during the growing season and VIs for every other month during the growing season, assigning VIs that use same bands to a different month whenever possible. Two Sentinel-1 dates during the dry season (December & February) with the smoothing filter were included, along with Elevation and Slope.

Takeaways:

Reducing the number of features to the 10 top ranked from the 10 T/V splits, overall accuracy decreases compared to models with more bands, and each T/V split's prediction raster shows more variation from other T/V splits. This illustrates that the consistently top ranked features from Gini and Permutation importances do not adequately capture characteristics of the landscape that can differentiate glacis from non-glacis land.

Confusion matrix accuracy assessments for a RF model using 82 remotely sensed features and the "predict" majority and "predict probability" + glacis proba% threshold model predictions can be seen in Table 3. The standard 82 feature model predicts glacis holdout samples with 93% PA but a lower UA, at 87%. This high PA illustrates that few glacis samples are missed, but the lower UA indicates that many other samples from other classes are also being classified as glacis, i.e. the model is overpredicting glacis. To minimize glacis overprediction, increasing the glacis prediction threshold to 60% increases UA to 92% (lowering glacis overprediction) and lowers PA to 88% (increasing missed glacis). Considering all classes together, OA remains at 89%.

Accuracy assessments for a RF model using 58 remotely sensed features and the "predict" majority and "predict probability" + glacis proba% threshold model predictions can be seen in Table 4. The standard 58 band model (with less Sentinel-1 and Sentinel-2 band dates) also predicts glacis holdout samples with 93% PA. The lower UA at 80% shows that the model is heavily overpredicting glacis. By increasing the glacis prediction threshold to 60%, this yields more balanced glacis PA and UA class accuracies (85% & 88%) while keeping the OA similar at 86-87%. Compared to the 82 feature model with 60% threshold predictions, glacis PA and OA decreased 3% and 2%, respectively. This illustrates that the 58 feature model largely captures the same glacis-related landscape characteristics as the 82 feature model. The top of Figure 1 shows a processing grid's majority prediction and grouped predictions at a 60% glacis probability threshold and the bottom of Figure 1 shows predictions for the 53 20km x 20km processing grids that contain field data from the scale-up RCT's 2023 baseline survey and the 2021 field census.

Limitations:

- The model is overpredicting glacis[11] based on a 20-40% estimate of glacis land in the study area.
- Inaccuracies to the model primarily stem from RS inputs[12] and training field labels[13].
- Accuracy assessment from the validation set tells a story about how the model performs in the areas where there are training samples, so it's difficult to truly assess how the model generalizes and performs in areas where there are little to no samples for a given class.

Next Steps:

This glacis prediction model may be used with the past RCT's data to add matching (based on a fields' glacis status[14]) to the diff-in-diff analysis (where RWH benefits have been measured pre- and post-demilune adoption). Figure 2 shows the glacis vs non-glacis classification raster overlaid with the old RCT's field boundary data collected in 2021.

This glacis prediction model may be used in the upcoming scale-up RCT to

- Assess where rainwater harvesting (RWH) techniques are more likely to be implemented, referencing this model's predicted glacis land, and
- Remotely sensed features used from this model specifically related to vegetation productivity (i.e. October Sentinel-2 NDMI1) may be used as baseline measurements in assessing RWH benefits once adoption does occur.

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[11]The model is also likely overpredicting glacis landcover because there are other types of non-agricultural landcover (i.e. steppe, savannah) that we can't generate reliable training samples for. Gray Tappan maps don't cover enough of our study area and steppe/savannah look too similar to the agricultural classes (i.e. glacis and non-glacis) in high-resolution Maxar and Planet imagery, so we can't collect training samples for those classes at a high enough confidence in order to feed the model highly accurate training data about what those classes look like.

[12]Limitations of RS inputs: Improperly masked clouds (high reflectivity) and shadows (low reflectivity) may affect the median reflectance value of a given pixel. SAR speckling, edge-effects.

[13]Limitations of field labels: Glacis land is often considered degraded on a continuous scale, i.e. having various degrees of degradation, whereas the training data used in this model were binary labels of glacis, or not. Based on the survey's line of questioning, this was also based on the farmer's definition of glacis, so the edge-cases of similarly slightly-degraded fields may have been labeled as "glacis" or "non-glacis" field samples, depending on the farmer. Additionally, the survey asked if even part of a field was glacis, so it's possible that only a small fraction of a field labeled "glacis" had glacis land. Because pixels from the entire field were extracted, these "glacis" samples may contain pixels of both glacis and not-glacis land all under the glacis label.

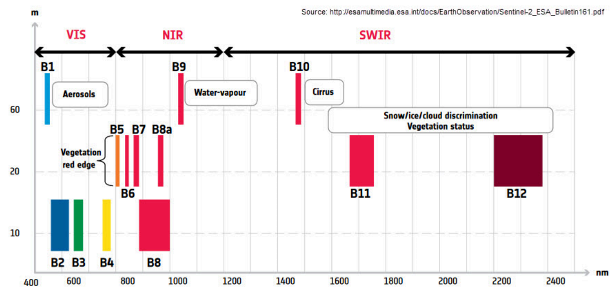
[14] This glacis prediction model was trained using glacis status field data from January 2023 and imagery from 2022-2023. Measuring the benefits of demilunes on fields in 2018, grouped by glacis status from 2023 assumes that glacis fields in 2023 were still glacis in 2018 (i.e. not a degraded field within 5 years), and that non-glacis fields in 2023 were still non-glacis in 2018 (i.e. not a restored field). Literature suggests that around three years after demilune adoption, the land should be restored from glacis to non-glacis status. To test this, landcover classes will be extracted from fields with demilunes in 2018. If demilunes created in 2018 succeeded in restoring the land, the 2023 glacis classification should predict those fields with demilunes in 2018 to be "non-glacis".

Appendix:

RF Imagery

Table 1: Sentinel-2 reflectance bands (below) were cloud-masked and monthly median reflectance features were used to create monthly VI features

Sentinel-2 band: Name	Wavelength	Spatial resolution
B2: Blue	490nm	10m
B3: Green	560nm	10m
B4: Red	665nm	10m
B6: Red-edge	740nm	20m
B8: NIR (near infrared)	842nm	10m
B8A: Red-edge	865nm	20m
B11: SWIR1 (short wave infrared)	1610nm	20m
B12: SWIR2	2190nm	20m



RF Imagery

Table 2: Sentinel-2 vegetation indices used in the model, for each cloud-free monthly mosaic

Vegetation Index (VI)	Formula	Description
NDVI	$\frac{NIR-RED}{NIR+RED}$	Green biomass (vigor, density, and health). Differentiates between soil and vegetation. Saturates at high density.
EVI2	$\frac{2.5*(NIR-RED)}{(NIR+6*RED-7.5*BLUE+1)}$	Green biomass (vigor, density, and health). Corrects for atmospheric condititions. Doesn't saturate at high density.
MSAVI2	$\frac{2*NIR+1-sqrt((2*NIR+1)^2-8*(NIR-RED)))}{2}$	Green biomass (vigor, density, and health) at low density. Minimizes soil sensitivity.
NDWI	$\frac{Green-NIR}{GREEN+NIR}$	Monitor slight changes in water content of the water bodies. Sensitive to built structures.
NDMI1	$\frac{NIR-SWIR1}{NIR+SWIR1}$	Vegetation moisture, leaf water content (with SWIR1). The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content.
NDMI2	$\frac{NIR-SWIR2}{NIR+SWIR2}$	Vegetation moisture, leaf water content (with SWIR2). The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content.

RF Accuracy

Table 3: Confusion matrix from the 82 feature model used for robustness testing: ***majority prediction*** (top)[15], and ***60% glacis class threshold prediction*** (bottom) *[16]* emphasize the Glacis class PA, Glacis class UA, and OA

	82 bands			PRED (columns)					
	majority	Glacis field	NOT Gla	Dense veg	Built	Water	Wetland	Rock	Passage	PA
VAL row	Glacis field	65045	4066	44	21	0	27	95	36	93.81
	NOT Gla	6341	21863	10	0	0	1	0	1	77.48
	DenseVeg	150	1	2563	9	0	183	16	0	87.71
	Built	1033	126	6	1756	0	13	1	0	59.83
	Water	0	0	0	1	2967	177	0	0	94.34
	Wetland	620	18	397	754	0	17858	0	0	90.89
	Rock	588	0	181	30	0	0	13588	0	94.45
	Passage	492	436	0	0	0	0	0	8024	89.63
	UA	87.58	82.47	80.07	68.30	100.00	97.80	99.18	99.54	<u>89.38</u>
										<u>OA</u>

	82 bands			PRED (columns)					
	60%	Glacis field	NOT Gla	Dense veg	Built	Water	Wetland	Rock	Passage	PA
VAL row	Glacis field	61404	7348	108	92	0	157	115	110	88.56
	NOT Gla	4197	23976	18	6	0	10	6	3	84.97
	DenseVeg	14	13	2664	21	0	194	16	0	91.17
	Built	443	187	8	2270	0	25	2	0	77.34
	Water	0	0	0	1	2967	177	0	0	94.34
	Wetland	196	36	423	777	0	18213	0	2	92.70
	Rock	62	14	184	47	0	0	14080	0	97.87
	Passage	131	504	0	0	0	0	0	8317	92.91
	UA	92.41	74.74	78.24	70.63	100.00	97.00	99.02	98.64	<u>89.54</u>
										<u>OA</u>

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[15] The standard majority predictions qualitatively and quantitatively showed an over-prediction of glacis land: Glacis class accuracies showed unbalanced high PAs (high recall) yet low UAs (low precision), such that many "other" classes were predicted as glacis. Visually, the classification rasters were mostly blanketed as glacis predictions, much higher than the 20-40% estimate over the study area.

[16] With predict-probability's output glacis-probability raster, Decreasing the threshold to ~30% would yield very high glacis PA (low FN rate), but would also highly over-predict glacis (high FP rate). Increasing the threshold to ~60% - 70% resulted in less samples being predicted as glacis, lowering the glacis PA (inc FN rate) but increasing the glacis UA (dec FP rate). The overprediction of glacis in the majority classification rasters also suggests that a higher threshold % is appropriate for this training set.

RF Accuracy

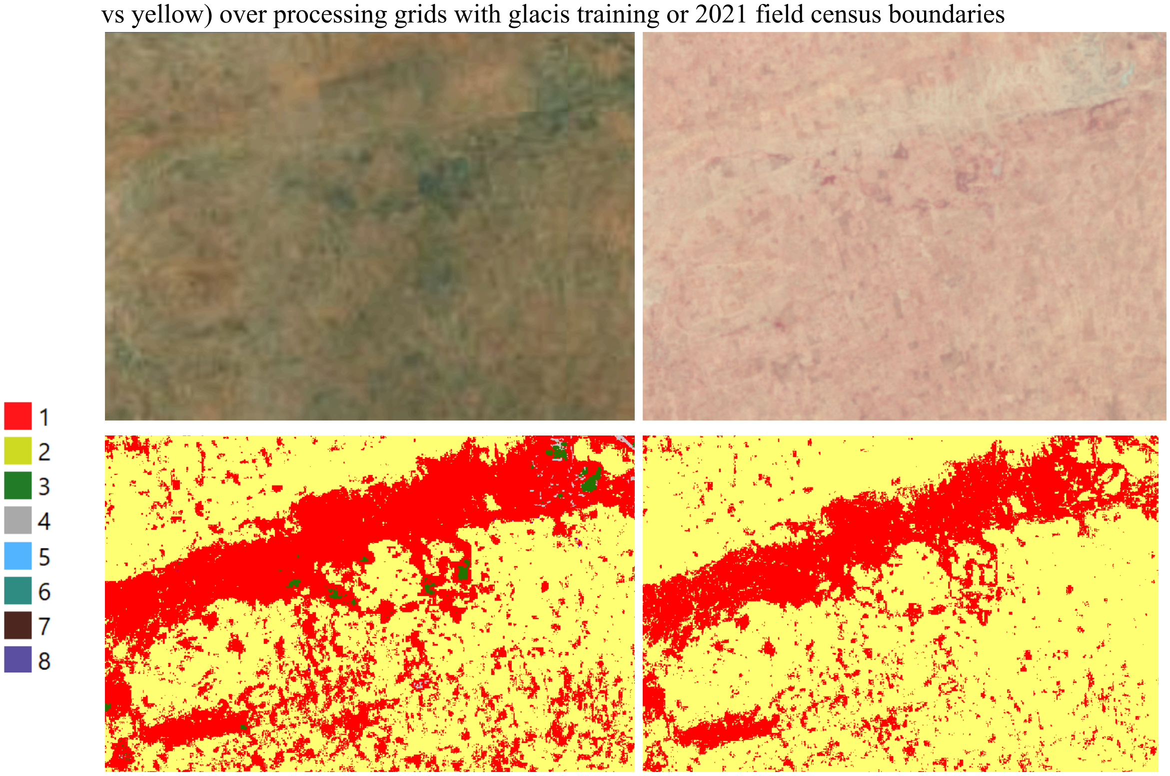
Table 4: Confusion matrix from the 58 band model with selected uncorrelated bands: ***majority prediction*** (left), and ***60% glacis class threshold prediction*** (right) emphasize the Glacis class PA, Glacis class UA, and OA

	58 bands			PRED: cols					
VAL row	***majority***	Glacis field	NOT Gla	Dense veg	Built	Water	Wetland	Rock	Passage	PA
	Glacis field	72567	5017	33	12	0	61	97	113	93.15
	NOT Gla	9539	24419	132	10	0	23	1	33	71.49
	DenseVeg	1394	0	6112	98	0	490	23	1	75.29
	Built	1027	218	11	11422	0	6	235	1	88.41
	Water	0	0	0	1	1268	191	0	0	86.85
	Wetland	1195	22	298	1830	0	29858	34	0	89.83
	Rock	2203	0	29	20	0	72	19448	0	89.33
	Passage	1804	189	0	0	0	1	13	7295	78.42
	UA	80.87	81.76	92.40	85.28	100.00	97.25	97.97	98.01	86.69
										OA

	58 bands			PRED: cols					
VAL row	***60%***	Glacis field	NOT Gla	Dense veg	Built	Water	Wetland	Rock	Passage	PA
	Glacis field	66893	9773	125	113	0	488	182	326	85.87
	NOT Gla	5763	28083	166	26	0	38	15	66	82.22
	DenseVeg	158	40	6654	375	0	851	39	1	81.97
	Built	427	424	18	11755	0	8	284	4	90.98
	Water	0	0	0	1	1268	191	0	0	86.85
	Wetland	376	72	367	1833	0	30546	40	3	91.90
	Rock	928	18	31	43	0	113	20638	1	94.79
	Passage	899	395	0	1	0	7	29	7971	85.69
	UA	88.67	72.37	90.40	83.09	100.00	94.74	97.23	95.21	87.40
										OA

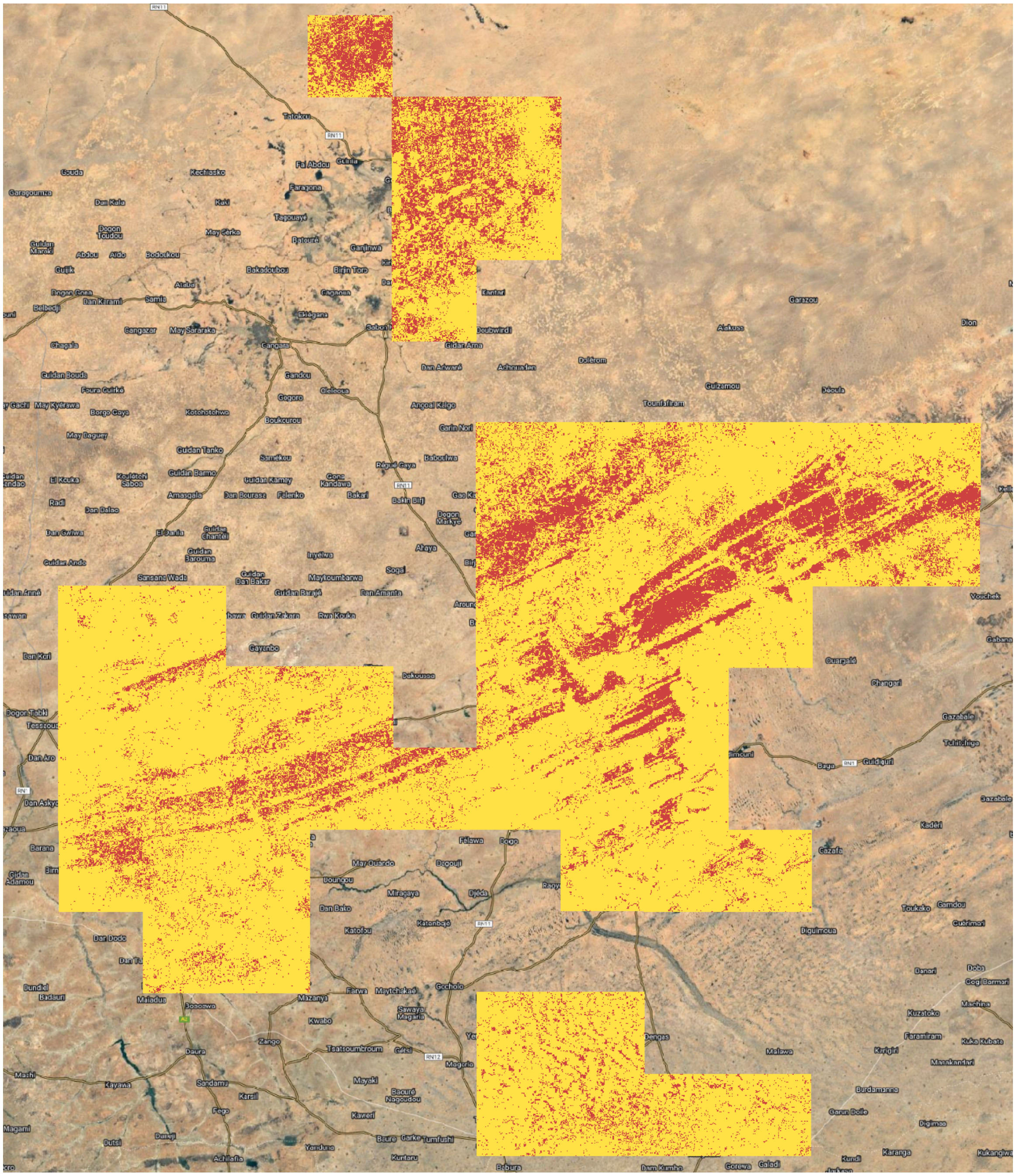
RF Surface Predictions

Figure 1: Top Left: High-resolution Maxar satellite imagery, Top Right: Planet Nov 2022 false-color composite[17], Middle Left: Glacis landcover predictions[18], and Middle Right: "Glacis" vs "Non-glacis" (red vs yellow) grouped predictions at a 60% threshold for a single processing grid. Bottom: "Glacis" vs "Non-glacis" predictions (maroon vs yellow) over processing grids with glacis training or 2021 field census boundaries



[17] Planet normalized analytic monthly monitoring false-color composite (NIR, red, green bands loaded into red, green, blue color channels) highlights vegetation in red

[18] Legend class names: 1: Glacis, 2: Non-glacis, 3: Dense vegetation, 4: Built Up, 5: Pond/lake, 6. Wetland, 7. Rocky, 8. Passage



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Kechiasko
Garagoumsa
Dan Kulu
Kuki
May Sarkin
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Bakadoubou
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Samia
Gangara
Gandou
Gogoro
Boukourou
Garazou
Dion
Dolérom
Guizamou
Djoula
Tourafiram
Gidar Arna
Baboufwa
Soga
Bakin Birji
Afaya
Inyelwa
Dan Amanta
Rwa Kouka
Gayenbo
Dakoussa
Dan Kori
Dogon Tabki
Tessaoua
Dan Aro
Dan Askya
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Katofou
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Doba
Machina
Faramiram
Kuka Kubata
Kangiri
Budamanna
Digimsa
Karanga
Kukangiwa
Dan Kumbo
Gorewa
Gadadi
Kuzaloko

Next Steps: Glacis predictions with 2021 field census data

Figure 2: “Glacis” vs “Non-glacis” (maroon/green) classification raster with the past RCT’s 2021 field census boundaries