A prototype for automated crop boundary delineation with a focus on rice paddy fields

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Output 3.2

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Changelog

Issue	Changes	Delivered
1.0	Initial version	23.07.2024

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1 Introduction

This document, Technical Report Output 3.2, provides a quantitative and qualitative assessment of the results obtained from the final prototype using the geodatabases of crop boundary polygons where reference data were available. First, the experimental setup used to test the model is presented in order to show the training, test and validation sets defined to assess the performance of the developed prototype. Then, the results obtained on the test set are reported.

2 Experimental Setup

Figure 1 **s**hows the experimental setup used to generate crop boundary delineation results. The spatial distribution of the training, validation, and test tiles are depicted in blue, yellow, and green, respectively. In addition, the Sentinel-2 image and the corresponding reference boundaries are displayed for one tile.

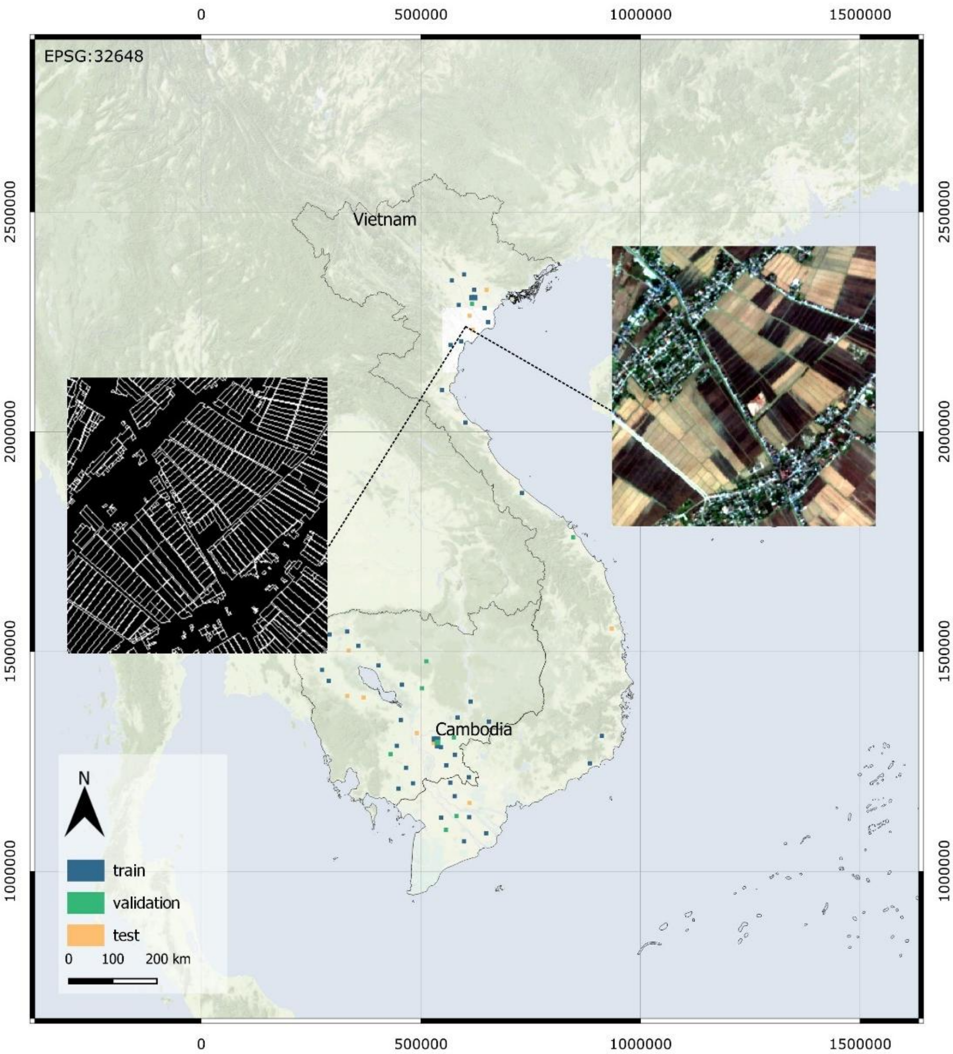


Figure 1 Spatial distribution of the training, validation, and test tiles shown in blue, yellow, and green, respectively. For one tile, the Sentinel-2 image and the corresponding reference boundaries are displayed.

Table 1 shows the number of tiles, the number of field polygons, and the average crop field size present in the training, validation, and test sets. The reference boundaries are manually digitized resulting in 318,088 and 120,913 field polygons in Cambodia and Vietnam, respectively.

	N. of tiles	**N. of Polygons**	**Avg. Crop Field Size (m^2)**
Training	43	304,777	2,920
Validation	9	83,066	2,385
Test	10	51,158	4,042
Total	62	439,001	2,950

Table 1. Number of tiles, field polygons and average crop size for the training, test and validation set in the considered experimental setup.

3 Experimental Results

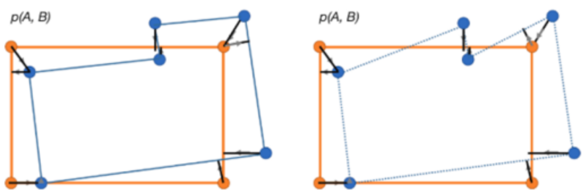
This section provides an overview of the results obtained on 10 Sentinel-2 tiles that have been used to assess the performance of the network, i.e., the test set that is spatially disjoint from the training set. Both a qualitative and quantitative evaluation of the results obtained is provided. To assess the accuracy, we considered the: (1) Precision, (2) Recall, (3) F1-Score, and (4) Polis metrics [2]. The *Precision* metric assess the correctly identified crop boundaries with respect to all the crop boundaries delineated (true and false). The *Recall* metric evaluates the correctly identified crop boundaries with respect to all the pixels that should have been identified as crop boundaries (the area crop boundaries present in the scene). The *F1-score* metric provides a single score that balances both precision and recall in one number. Finally, the *Polis metric* accounts for the shape of the outline. In particular, this metric accounts for shape and accuracy differences between the reference polygons and the predicted ones (i.e., low values indicates high similarity). Figure 2 shows how to compute these metrics.

Line-level metric – *PoLiS* $= p(A,B) = \frac{1}{2q}\sum_{a_j \in A} \min_{b \in \partial B} \| a_j - b \| + \frac{1}{2r}\sum_{b_k \in B} \min_{a \in \partial A} \| b_k - a \|$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1 - score = 2 \times \frac{Precision\ x\ Recall}{Precision + Recall}$$



PoLiS distance between predicted crop A (orange) and reference crop (blue) marked with a black line

Figure 2 Accuracy metrics considered to evaluate the results obtained.

3.1 Qualitative Results

This section provides an overview of the results obtained from the qualitative viewpoint. The crop boundary maps of the are presented by reporting the Polis values together with deep learning model output (boundary score), true colour composition of the Sentinel-2 monthly composite, and the reference crop field boundaries highlighted in red and overlayed on top of the Very High resolution (VHR) google basemap images. The lower the Polis values (i.e., yellow and dark colours), the better the delineation of crop boundaries from a geometric point of view. From the results obtained, most of the outlined crops have a good correspondence with the manually digitized reference polygon.

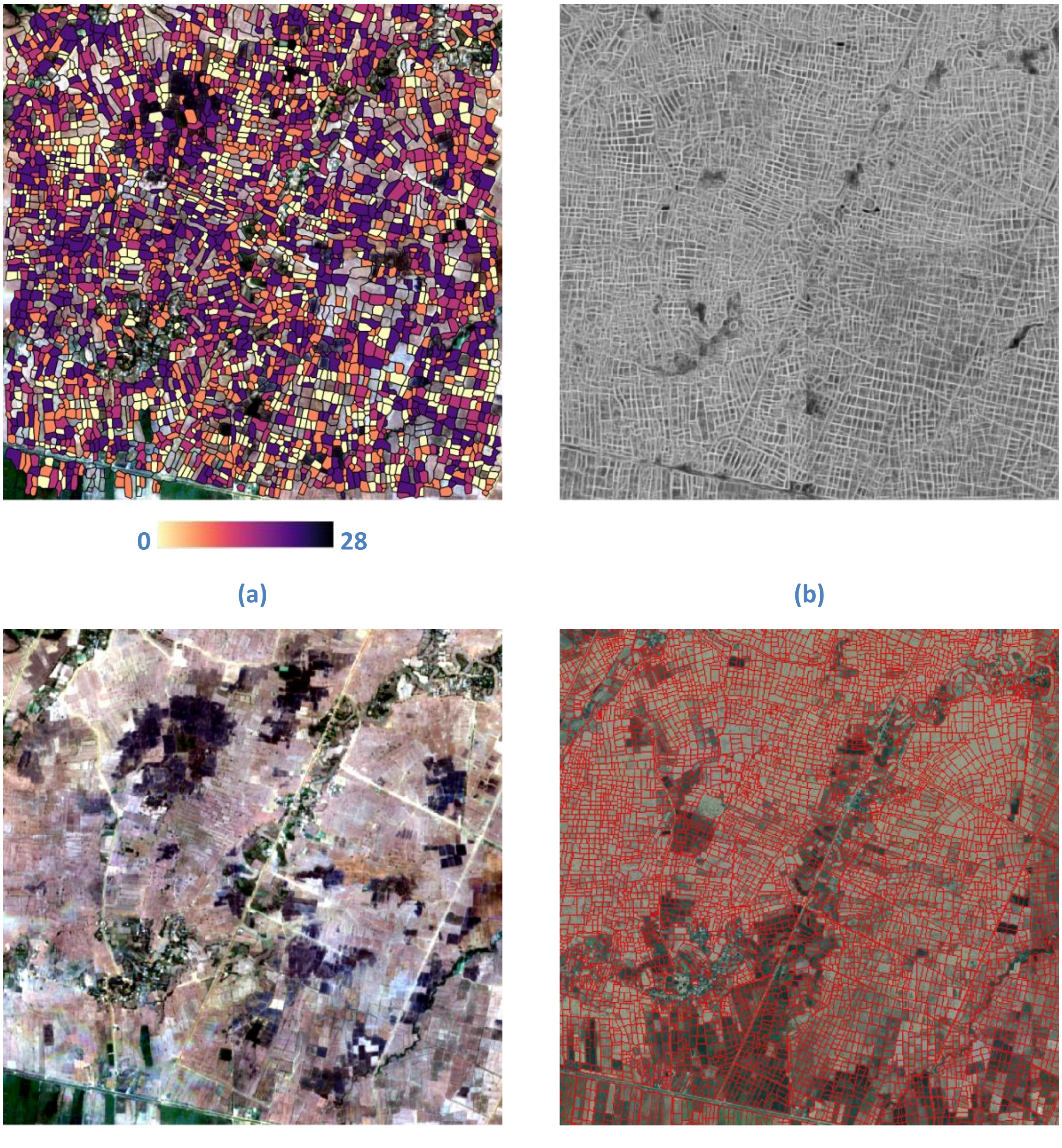
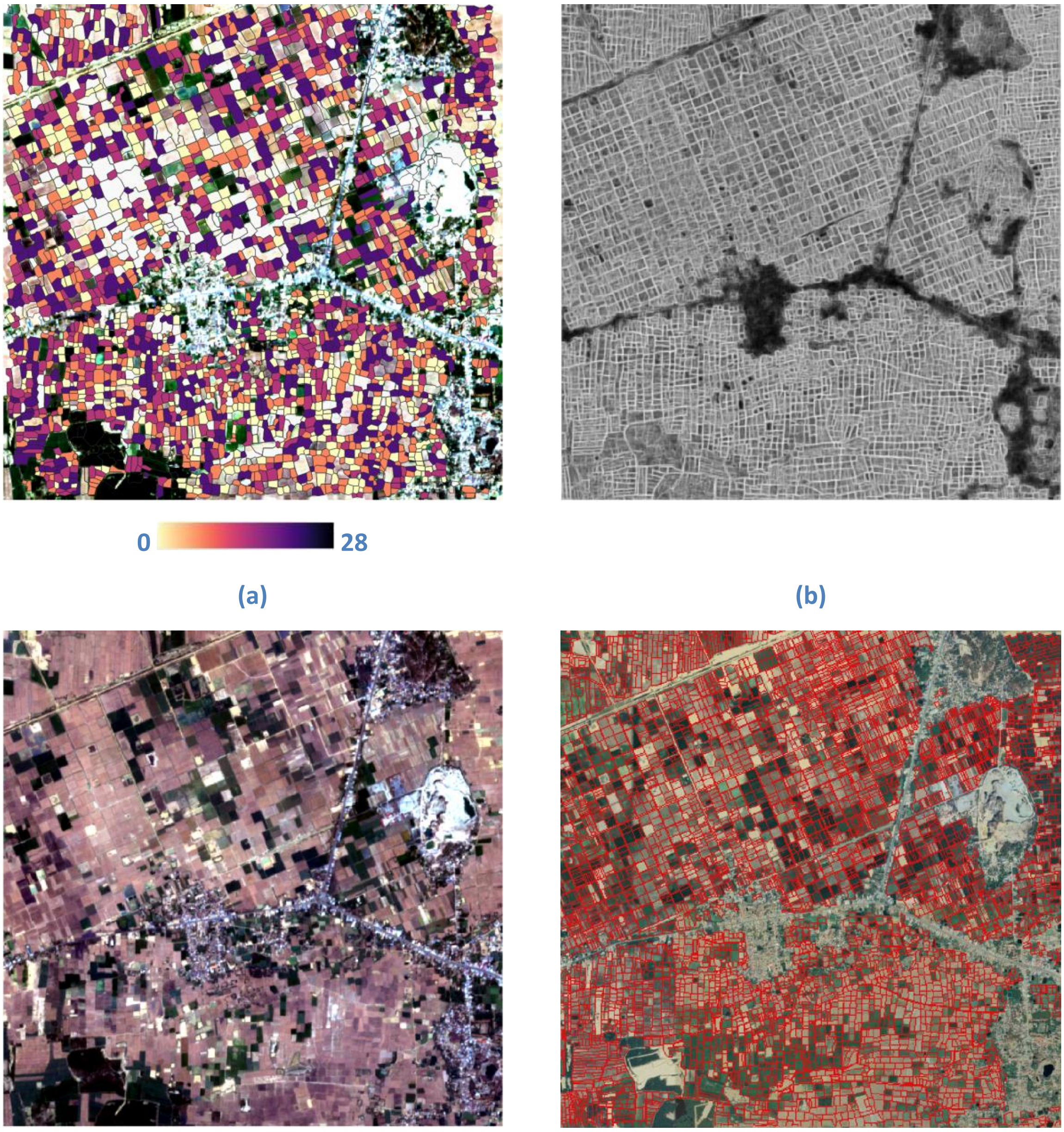


Figure 3: Crop boundary delineation results obtained in Tile 12 (Cambodia): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.



(c) (d)

Figure 4: Crop boundary delineation results obtained in Tile 16 (Cambodia): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

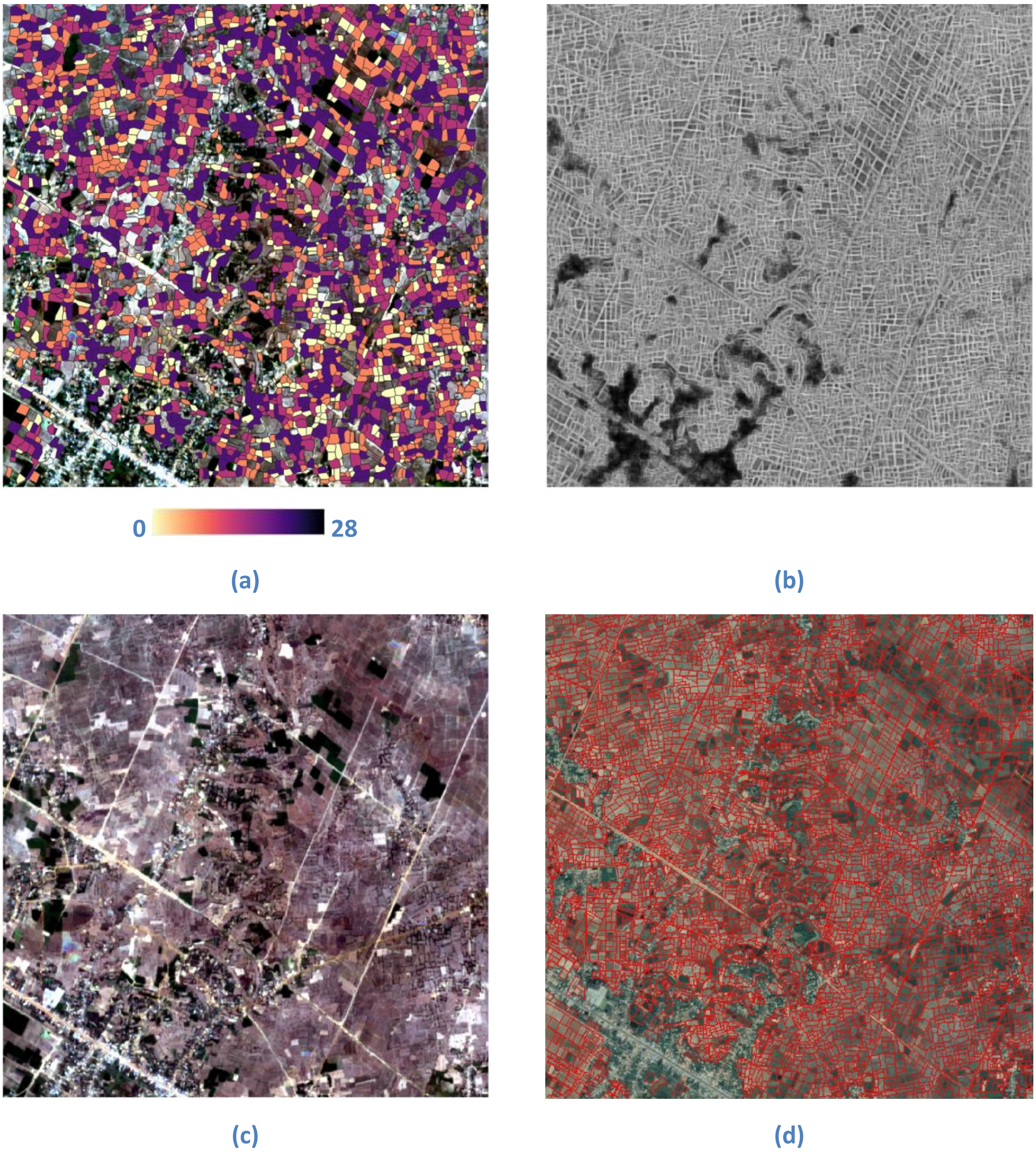
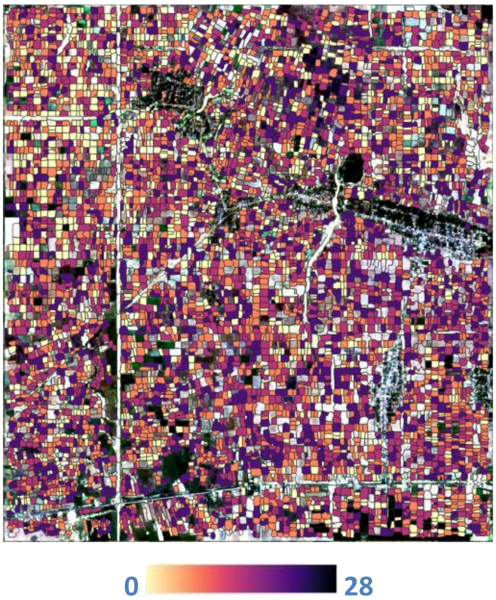
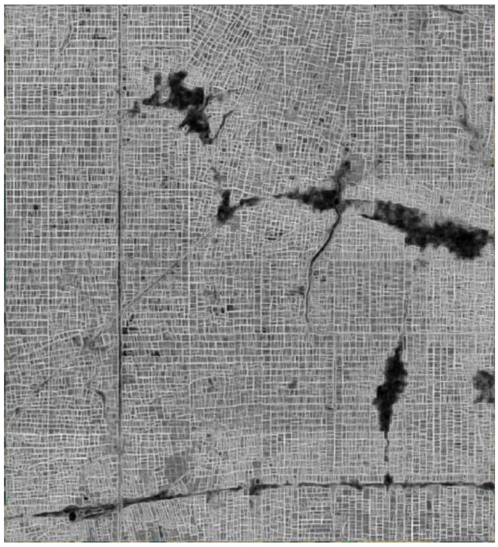


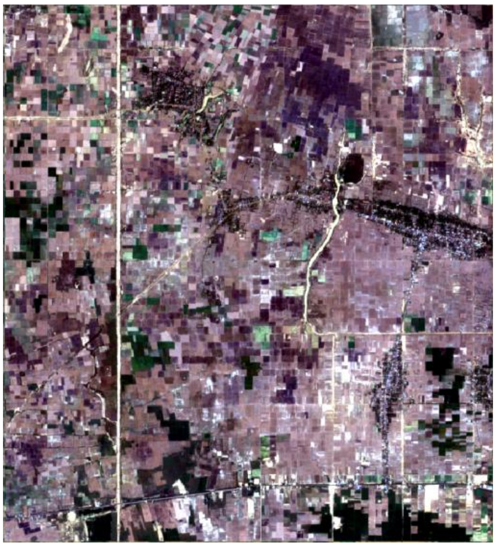
Figure 5: Crop boundary delineation results obtained in Tile 8 (Cambodia): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.



(a)



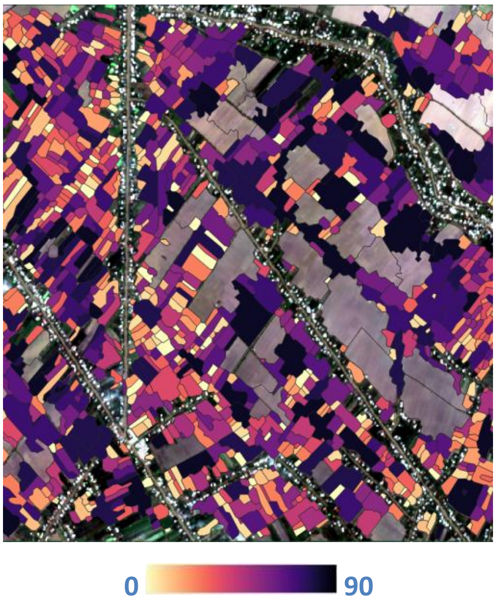
(b)



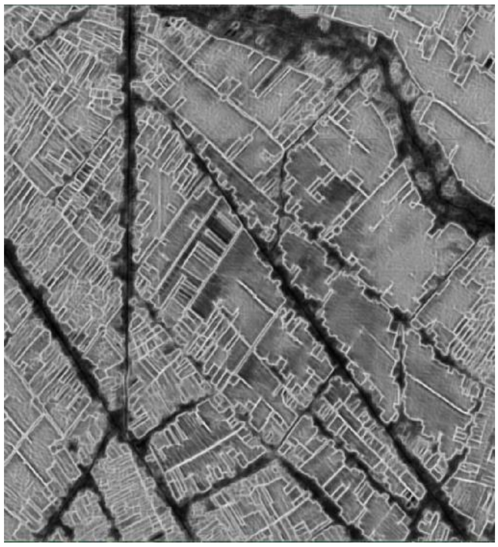
(c)

(d)

Figure 6: Crop boundary delineation results obtained in Tile 58 (Cambodia): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.



(a)



(b)

(c)

(d)

Figure 7: Crop boundary delineation results obtained in Tile 56 (Vietnam): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

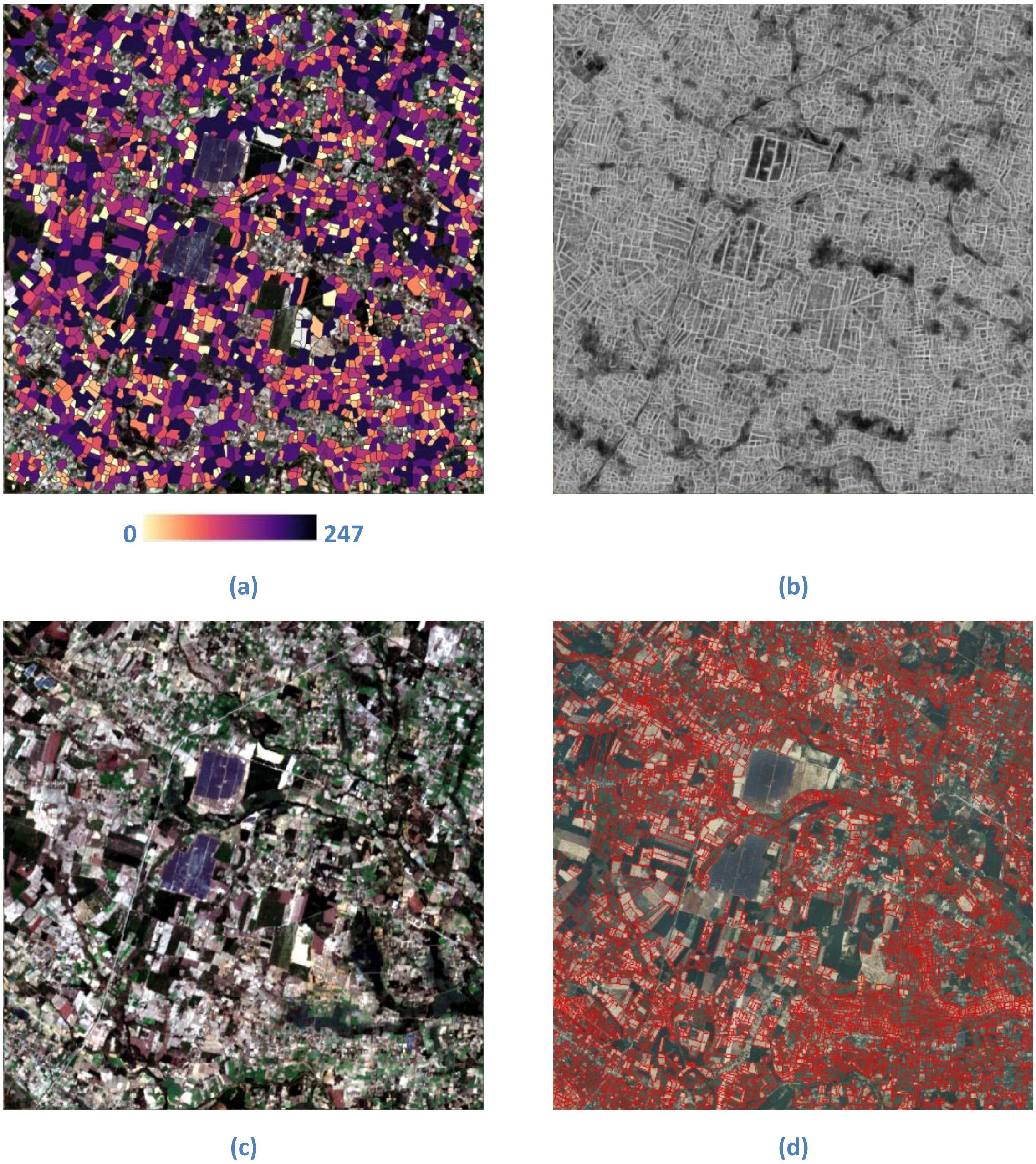


Figure 8: Crop boundary delineation results obtained in Tile 46 (Vietnam): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

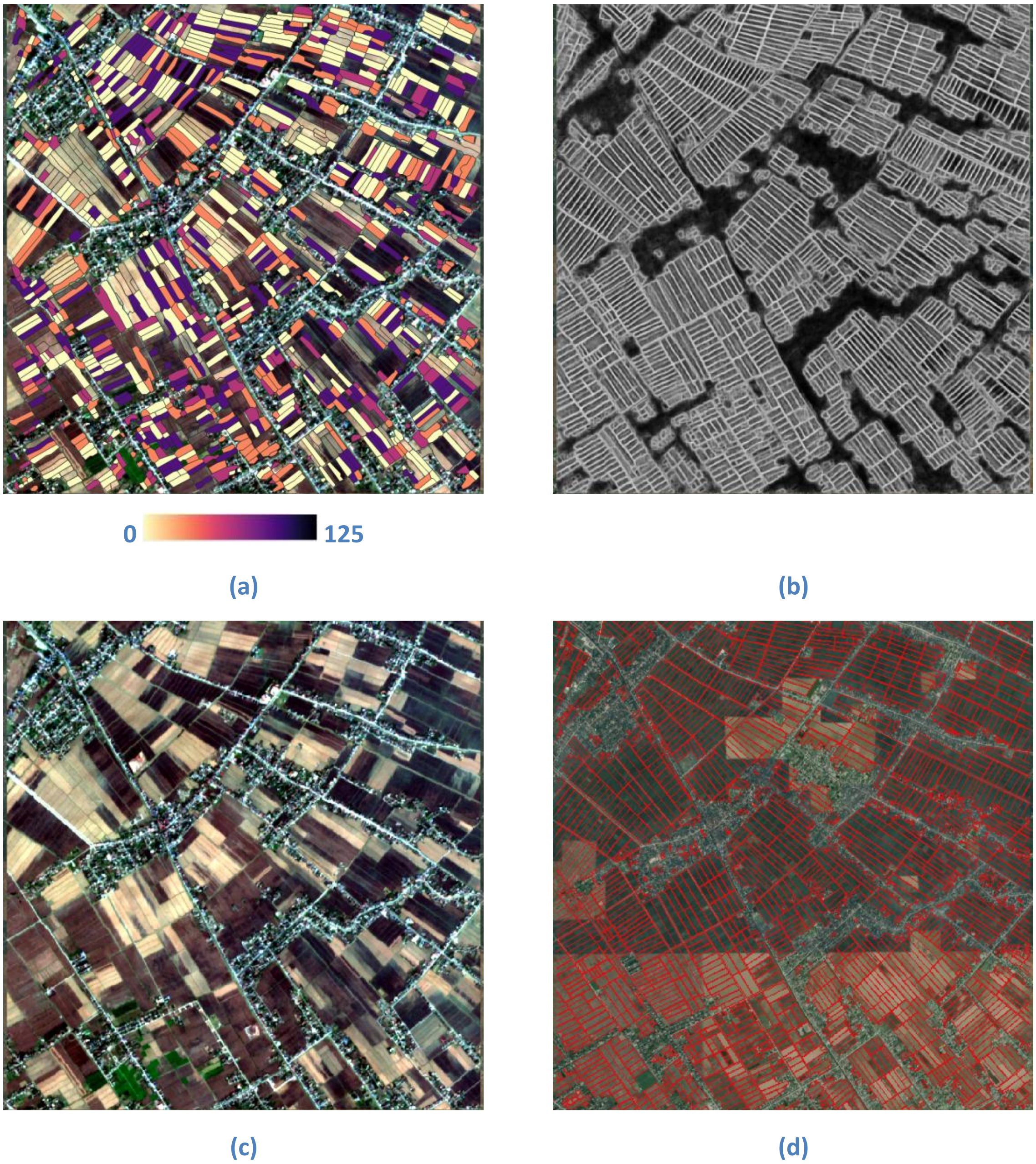


Figure 9: Crop boundary delineation results obtained in Tile 30 (Vietnam): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

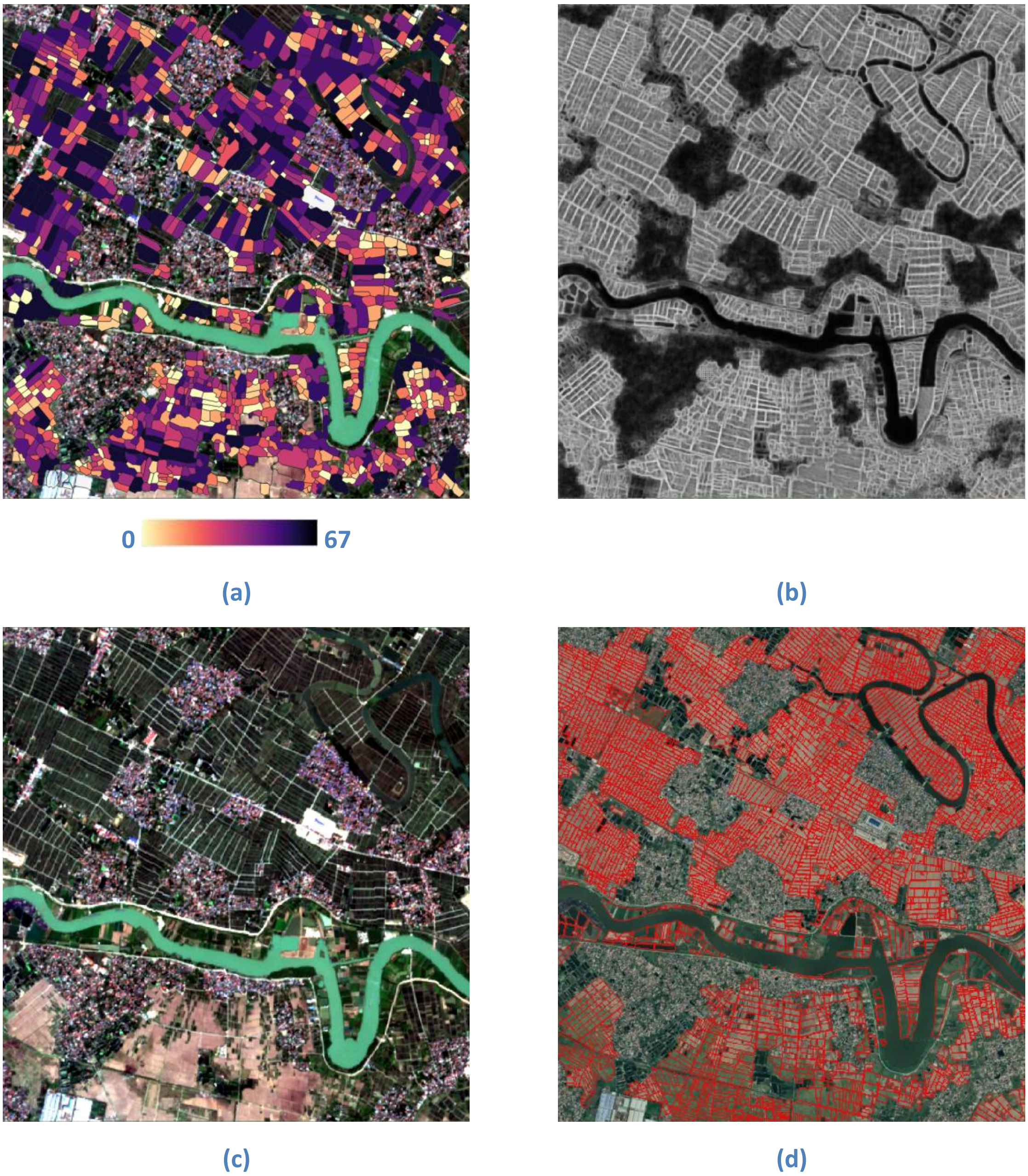


Figure 10: Crop boundary delineation results obtained in Tile 27 (Vietnam): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

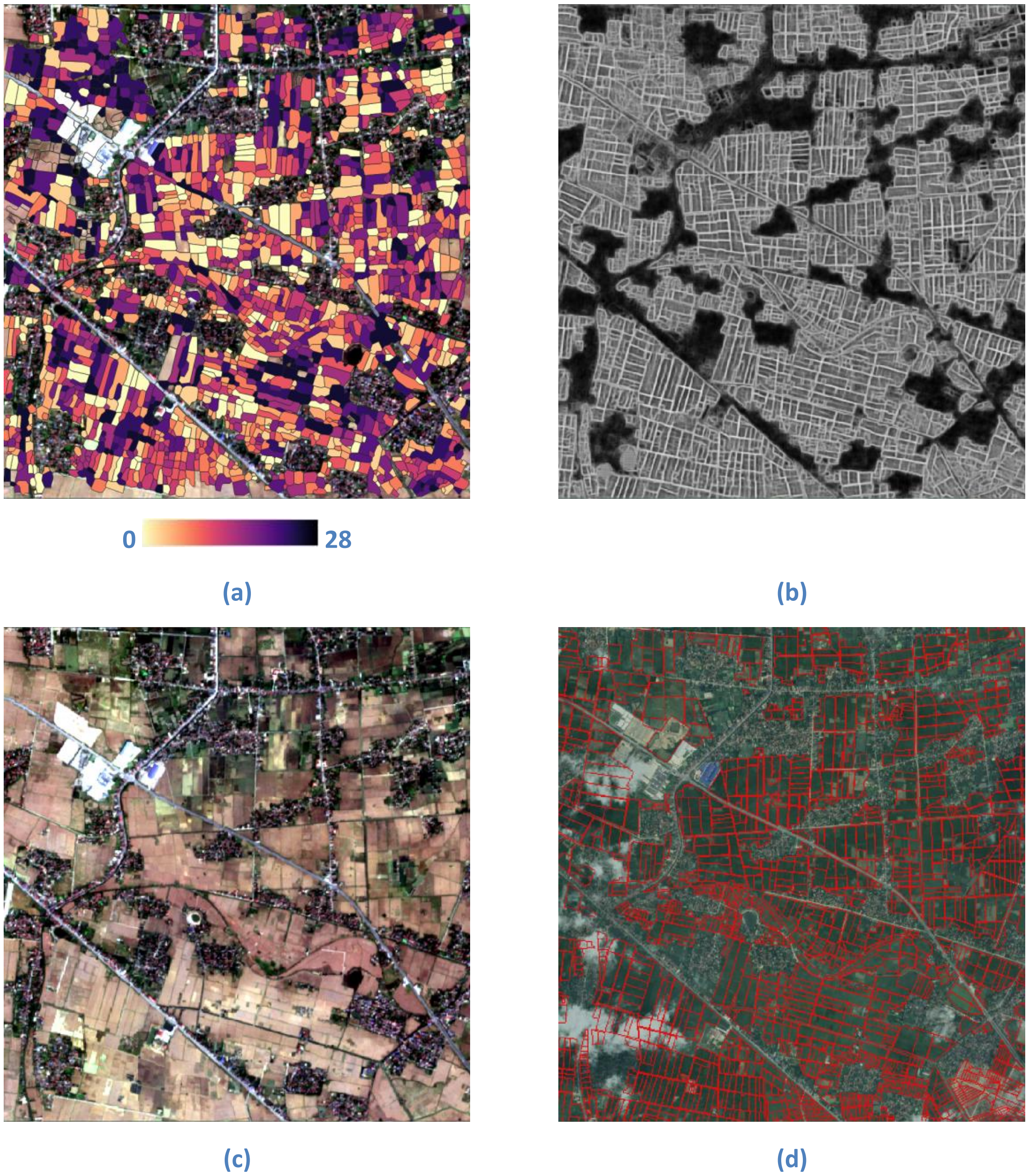


Figure 11: Crop boundary delineation results obtained in Tile 26 (Vietnam): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

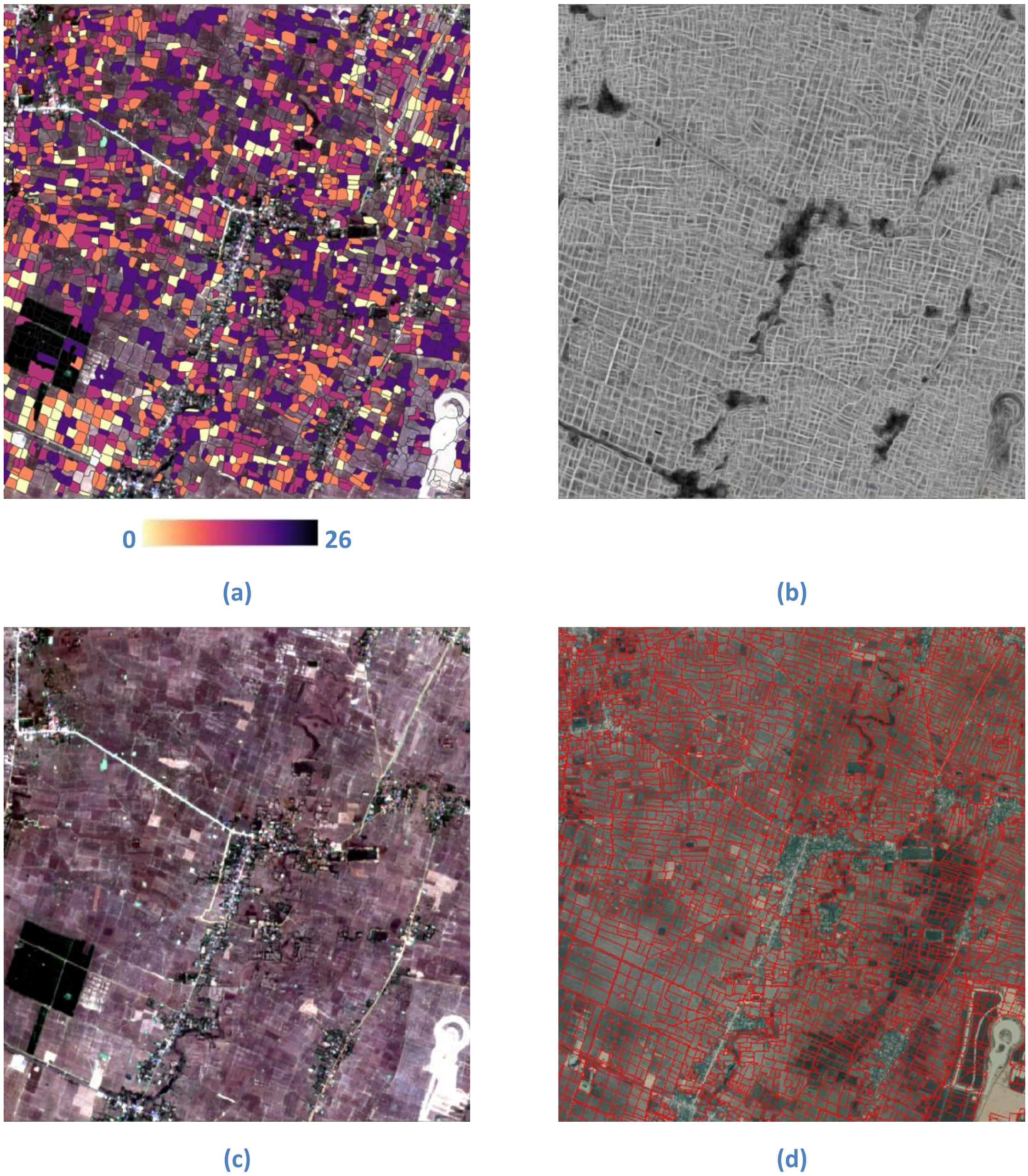


Figure 12: Crop boundary delineation results obtained in Tile 21 (Cambodia): (a) boundary predictions from the U-Net associated with the Polis values, (b) the deep learning model output (boundary score), (c) true color composition of the Sentinel-2 monthly composite, and (d) reference crop field boundaries highlighted in red and overlayed on top of VHR google images.

3.2 Quantitative Results

Table 2 provides a comprehensive overview of the performance metrics, including precision, recall, F1-score, and polis metrics, computed across the entirety of the test set, as well as specifically for the sample plots situated in Cambodia and Vietnam. These quantitative assessments are aligned with the qualitative findings presented in the previous section. Notably, the results reveal that the delineation of crop boundaries demonstrates consistency and accuracy across both regions, regardless of the varying crop conditions observed in Cambodia and Vietnam. This consistency suggests that the methodology employed for crop delineation is effective and reliable, demonstrating its applicability across diverse agricultural landscapes even thought the spatial resolution of the considered satellite data is 10m.

		Precision	Recall	F1-score	Polis (m)
Cambodia	8	0.50	0.34	0.40	19.30
	12	0.55	0.39	0.46	17.10
	16	0.57	0.37	0.45	21.51
	21	0.43	0.34	0.38	23.85
	58	0.53	0.39	0.45	17.66
Vietnam	26	0.45	0.41	0.43	33.42
	27	0.45	0.22	0.30	34.99
	30	0.59	0.43	0.50	29.86
	46	0.38	0.24	0.30	29.02
	56	0.35	0.21	0.26	39.91
Overall		0.48	0.33	0.39	26.66

Table 2. Field boundary prediction performances obtained on the test set in terms of Precision, Recall, F1-Score and Polis (m). The results are reported per tile and across the whole test set.

4 Summary and Conclusion

The technical report presented, Output 3.2, provided an overview of the crop boundary detection results obtained from both the qualitative and quantitative viewpoints. The results obtained by the prototype are the ones achieved in the test set made up of 10 tiles, evenly distributed between Cambodia (5 tiles) and Vietnam (5 tiles).

The prototype model achieved similar performance in the two countries, with an average F1 score of 0.36 and an average polis metric of 33.44 meters in Vietnam, compared to 0.42 and 19.88 meters in Cambodia, respectively. These outcomes are consistent with the overall metrics, which indicate an average F1 score of 0.39 and an average polis metric of 26.66 meters.

It is important to remark that these assessments are conducted on a test set that ensures statistical reliability, comprising tiles unseen by the model during training and validation and spatially distinct from the training and validation regions. Given the 10-meter spatial resolution of the Sentinel-2 data and the typical size of crop field areas in the study region, these results are promising for both countries.

In summary, the findings suggest that (1) the proposed deep learning based prototype effectively addresses the delineation of crop boundaries in Cambodia and Vietnam, and (2) Sentinel-2 data can be used for establishing a national-scale geodatabase of crop boundaries on an annual basis. However, transitioning the prototype into an operational system requires further activities, with key steps outlined as follows:

[1] **Complete Automation**: Automating the entire processing chain to improve the post-processing steps, which are crucial for the crop boundary delineation results.

[2] **Integration with Existing Initiatives**: Integrating the proposed workflow with existing rice crop area information from initiatives such as AFSIS activities and INAHOR (or similar rice crop monitoring systems) enhances the synergy between crop boundary detection and rice crop area detection workflows, facilitating comprehensive agricultural monitoring.

[3] **Multi-Year Crop Boundary Delineation**: Conducting multi-year experiments to assess spatial inconsistencies arising from applying the workflow to annual Sentinel-2 data is imperative. Tailored solutions must be devised to ensure continuous updates to crop boundaries, thereby maintaining the relevance and accuracy of the geodatabase over time.

References

[1] Persello, Claudio, et al. "AI4SmallFarms: A Data Set for Crop Field Delineation in Southeast Asian Smallholder Farms." *IEEE Geoscience and Remote Sensing Letters* (2023).

[2] Zhao, Wufan, Claudio Persello, and Alfred Stein. "Building outline delineation: From aerial images to polygons with an improved end-to-end learning framework." ISPRS journal of photogrammetry and remote sensing 175 (2021): 119-131.