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Bringing aerial laser scanning archaeology to the deep learning era

Vladyslav Sydorov

03/12/2024, Symposium Agorantic 2024

École française d'Extrême-Orient (EFEO)

Our team

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Exploring complexity in archaeological landscapes using LiDAR & deep learning

Director	Supervisor	Co-director	PhD	PhD	Partner
					
Damian Evans	Christophe Pottier	Vladyslav Sydorov	Adam Wijker	Yohann Perron	Loïc Landrieu
EFEO	EFEO	EFEO	EFEO	EFEO/ENPC	ENPC

Traces of perishable architecture

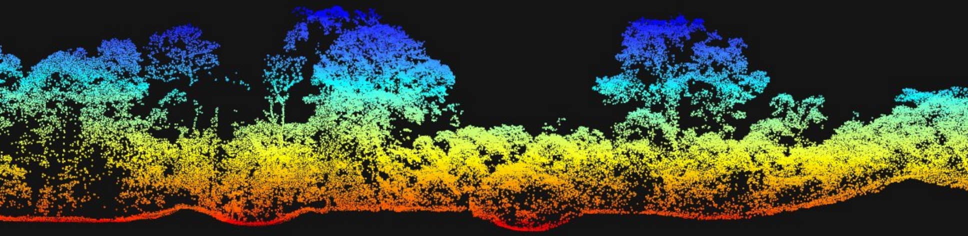
Faint topography changes

Remains obscured by vegetation

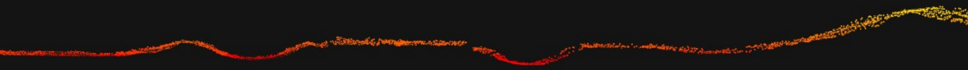
Aerial LiDAR

Aerial LiDAR: Canopy penetration

Aerial LiDAR: Dense 3D point cloud

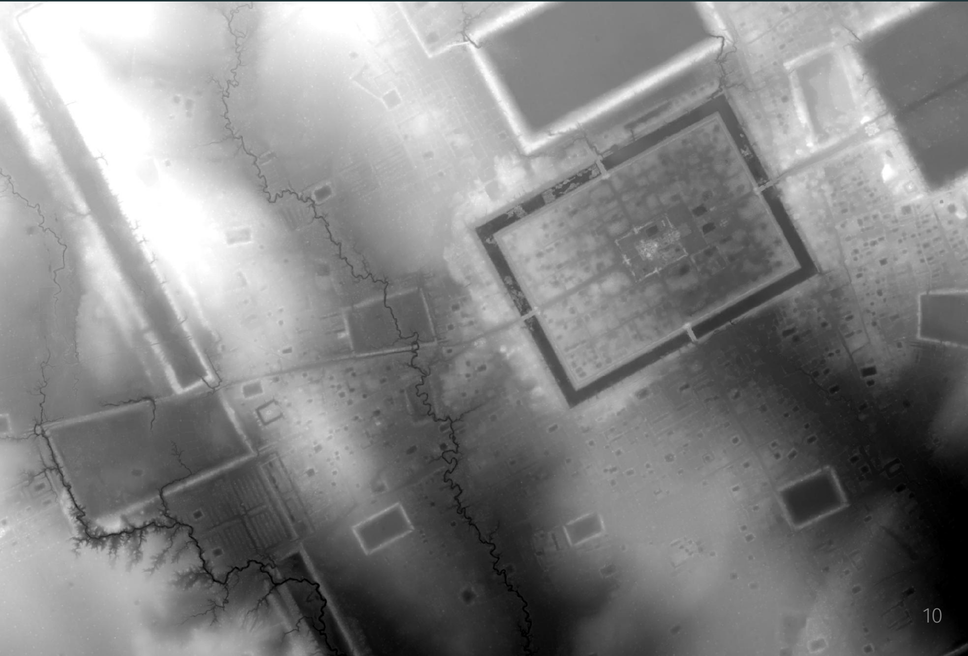


Aerial LiDAR: Stripping vegetation points

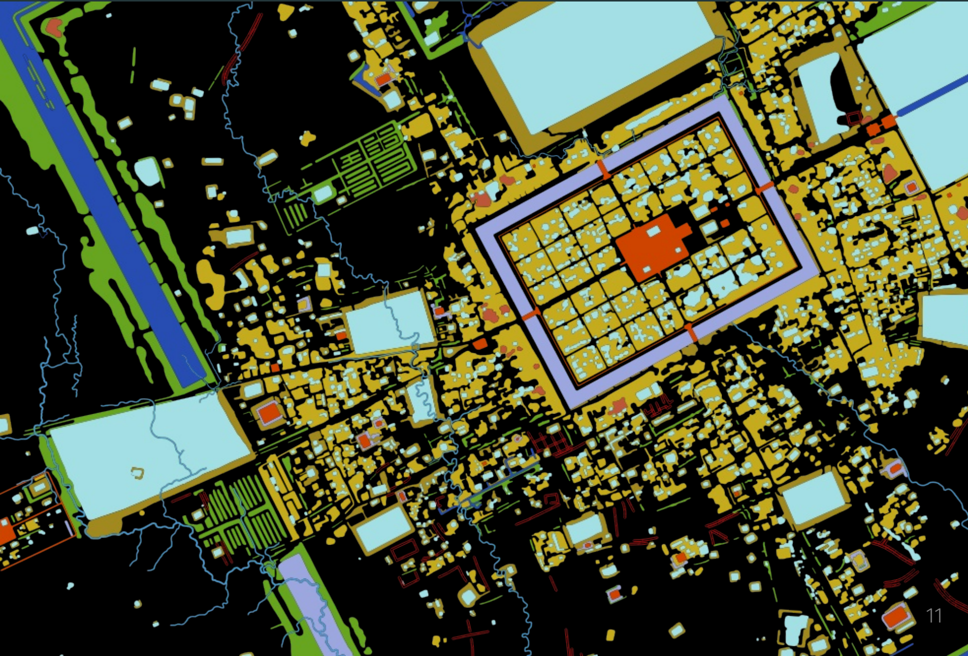


Modality: Satellite

Modality: LiDAR terrain model

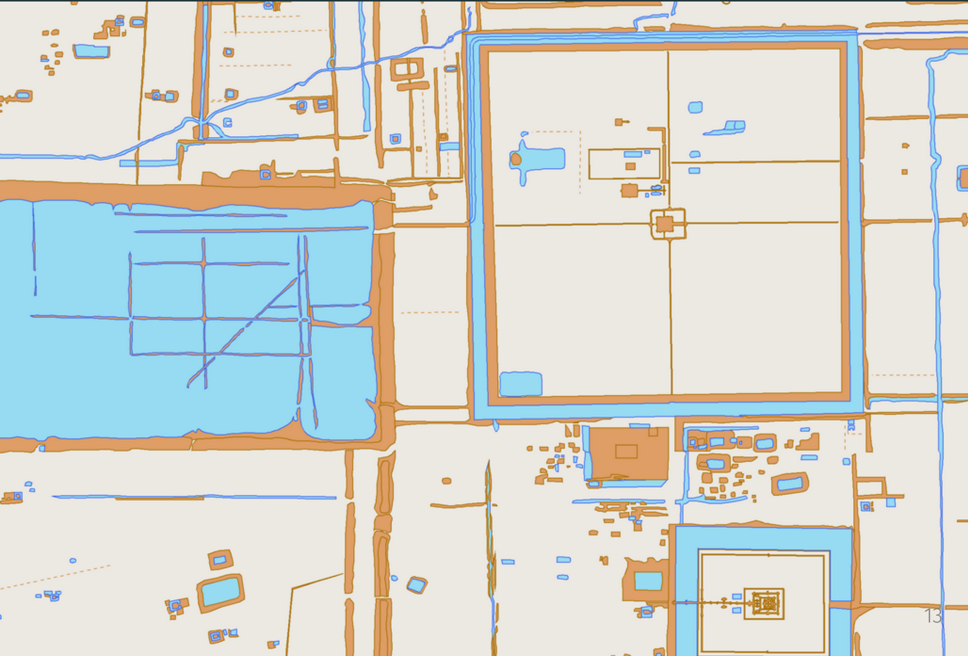


Modality: LiDAR-guided feature polygons

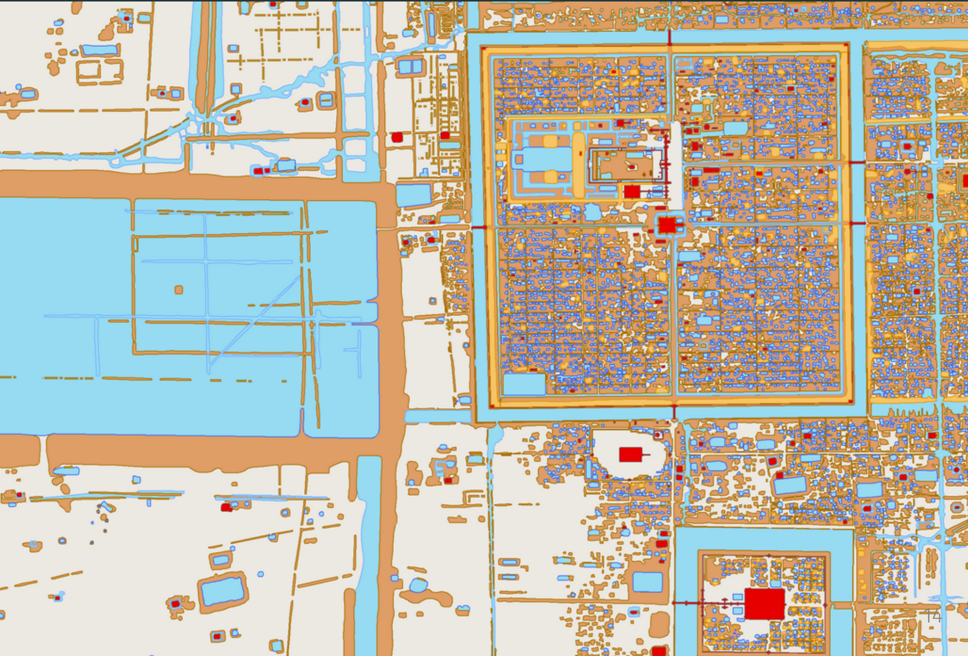


Cambodia. Angkor campaign, 2012-2020: satellite

Cambodia. Angkor campaign, 2012–2020: before

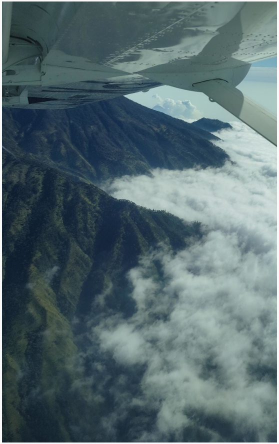


Cambodia. Angkor campaign, 2012-2020: after

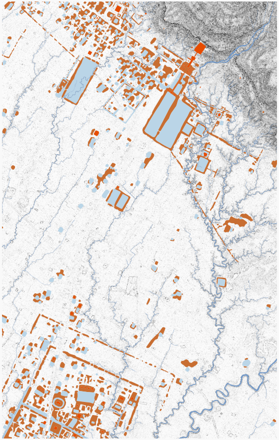


archaeoscape.ai axes

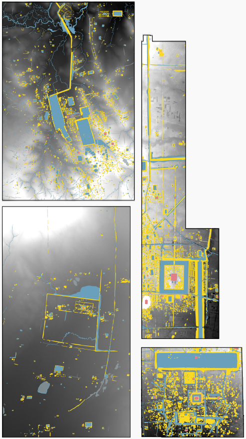
Acquire data



Interpret & Analyse



Aggregate & share

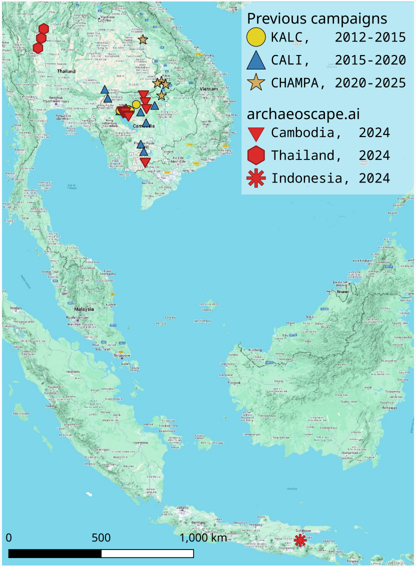


Acquiring data

Region of interest

Previously

- Focus: Khmer heartlands
- Laos foray with CHAMPA
- $\sim$ 6500 km^2 over 12 years



Previously

- Focus: Khmer heartlands
- Laos foray with CHAMPA
- $\sim$ 6500 km^2 over 12 years

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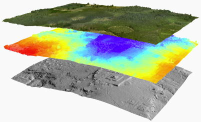
- Focus: rainforest civilisations
- Sukhothai: Siamese & Khmer
- East Java: a longer shot
- $\sim$ 900 km^2 in 2024

Phases of the LiDAR campaign

I. Aerial acquisition

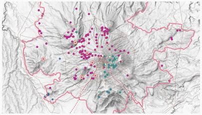
- Scoping: parameters designation, surveys
- Flight ops: acquire points, photos

II. Point cloud analysis



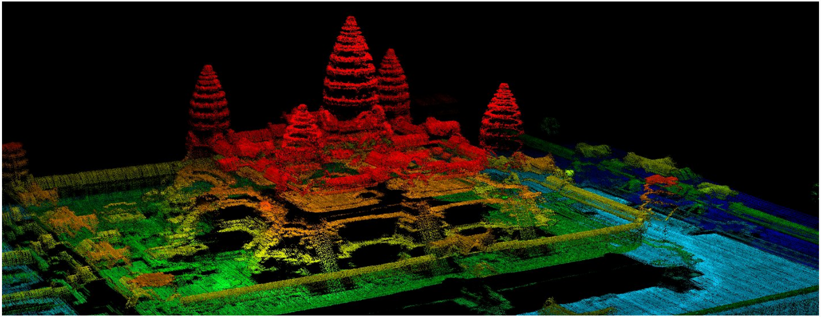
- Points processing: de-noise, classify
- Producing 2D imagery (DTM & derived)
- Feature interpretation and delimitation

III. Archaeological follow-up



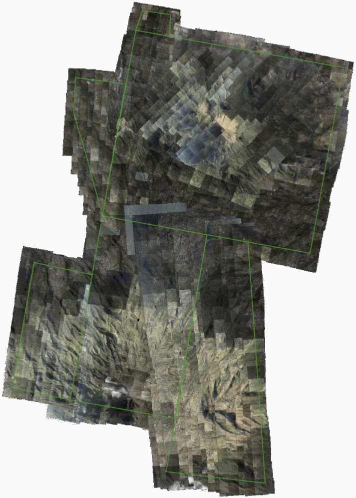
- Local authority engagement, collaboration
- Field verification and mapping
- Synthesis & dissemination

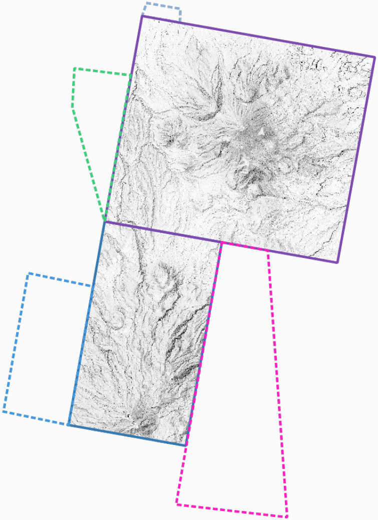
Cambodia 2024: 12 locations, UAV



Thailand 2024: Sukhothai Historical Park, plane

Indonesia 2024: East Java, plane





Data analysis and interpretation

Archaeological mapping

Figure 1: LiDAR-derived topography, Vat Phou, Laos

Archaeological mapping: manual

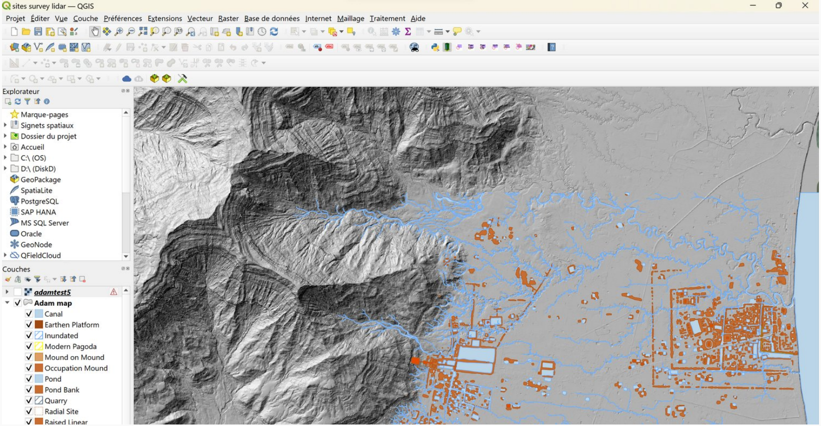


Figure 2: Preliminary mapping in QGIS, Vat Phou, Laos

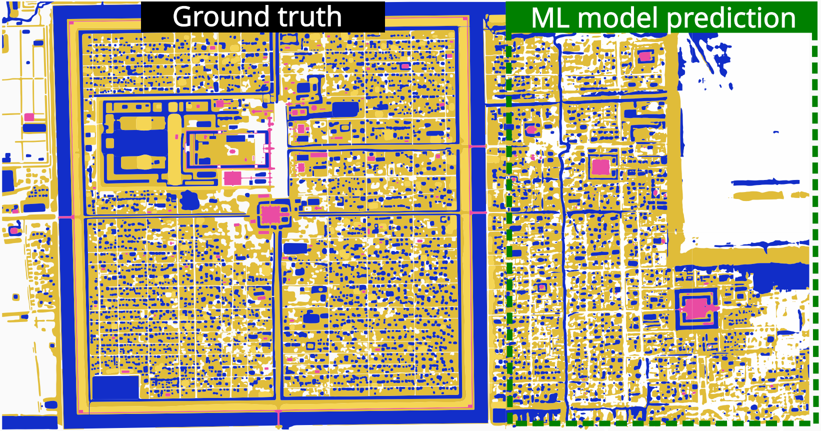
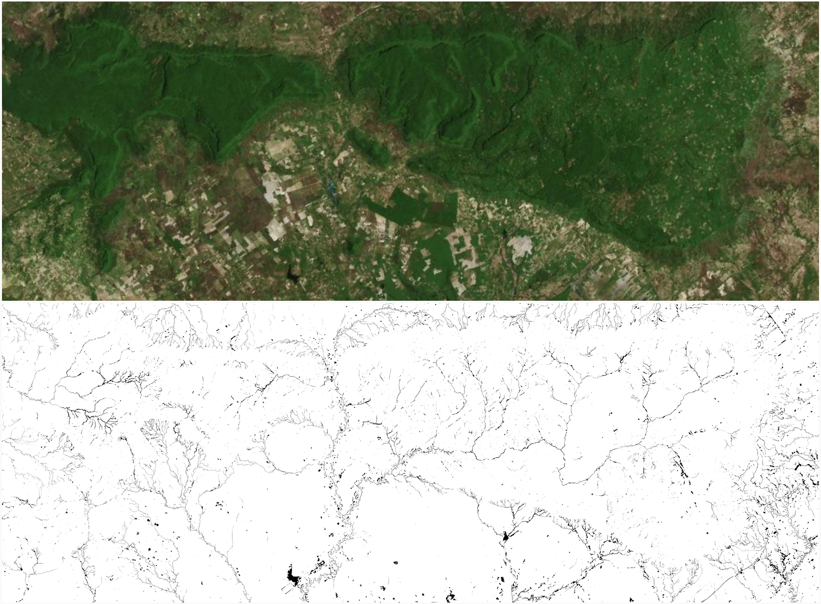


Figure 3: DeepLabv3 baseline predictions in Angkor, Cambodia

ML applications: river network delineation



ML applications: looting hole identification

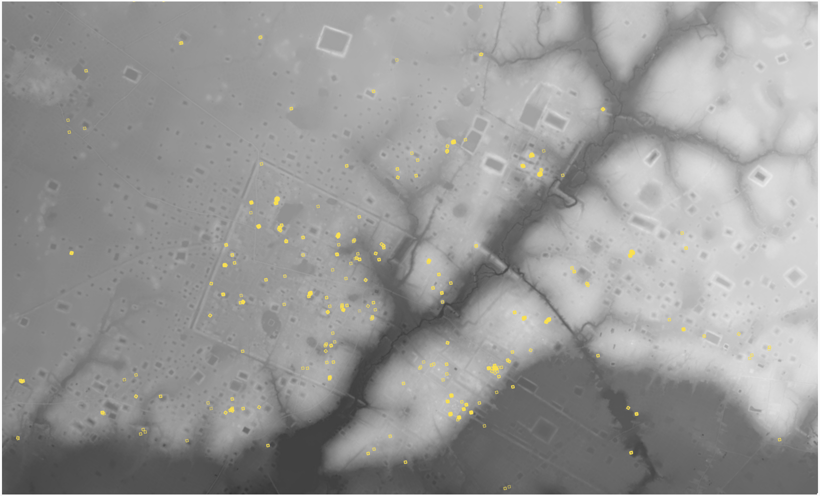
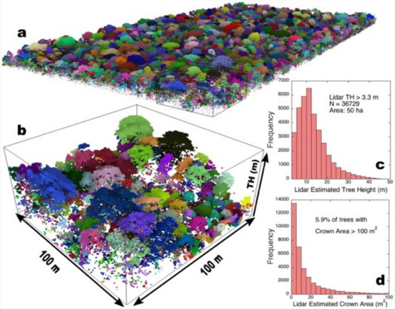


Figure 4: Looted sites in Sambor Prei Kuk, Cambodia

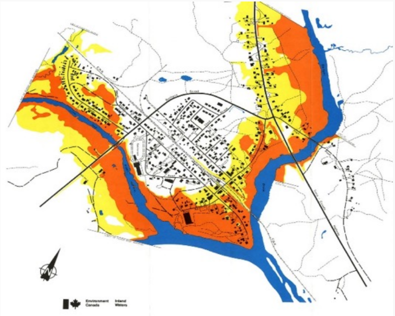
The long tail of archaeology adjacent applications

Biodiversity



- Plant identification
- Biomass estimation[1]

Social



- Land use analysis
- Flood risk maps[2]

[1] Lidar detection of individual tree size in tropical forests. Ferraz et al.

[2] `https://www.esa.int/ESA_Multimedia/Images/2006/05/Flood_risk_map_of_Badger`

Aggregation and dissemination

Coverage: 7500 km^2 over 12 years

country	years	campaign	$\sim km^2$
Cambodia	2012-2015	KALC	400
Cambodia	2015-2020	CALI	2000
Thailand	2016-2017	Phanom Rung	200
Laos	2020-2025	CHAMPA	4000
Cambodia	2020-2024	archaeoscape.ai	60
Thailand	2024	archaeoscape.ai	600
Indonesia	**2024**	**archaeoscape.ai**	**220**

Table 1: EFEO's LiDAR campaigns in Southeast Asia.

Coverage: 7500 km² at a glance

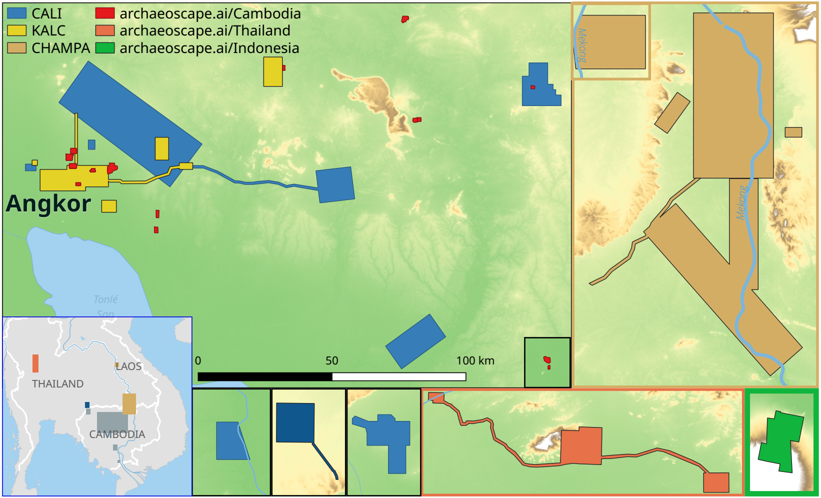


Figure 5: Total area coverage of the campaigns.

Coverage: challenges

Proper data consolidation

- Interpretation requires archaeological context
- Field data, historical maps, surveys, inventory
- Temporal aspect: environment evolves (and erodes)

Integration is complicated

- Heritage management rests with local stakeholders.
- Important: data sovereignty and safety.
- Open data not yet embraced in archaeology.

No such thing as free storage

- Data get lost, corrupted!
- CC0 license not always applicable
- Terrabytes of data - difficult

WebGIS platform. Open source, restricted data.

Why?

- Integration of multiple modalities
  - Different imagery types, historical maps
  - Inventory and location of existing sites
- Access to the latest data in the field
- **Responsible** collaboration across researcher groups

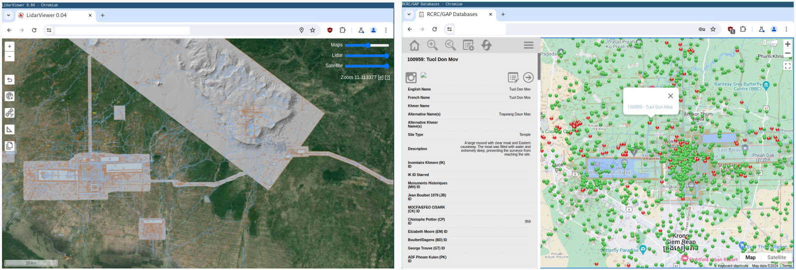


Figure 6: Web platform under development

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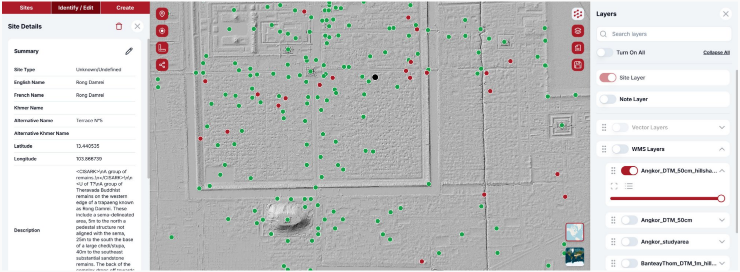

Figure 6: Web platform under development

ML dataset: No geo-referencing required!

Archaeoscape: Bringing Aerial Laser Scanning Archaeology to the Deep Learning Era

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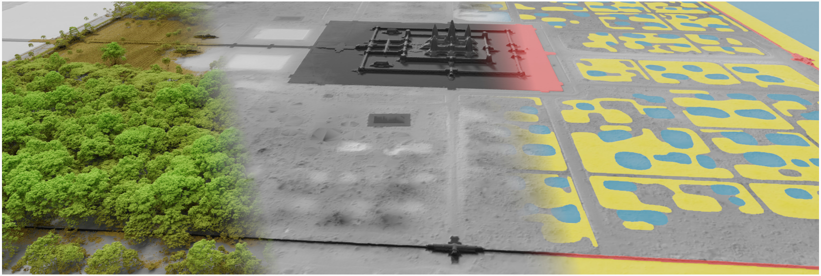
Abstract

Airborne Laser Scanning (ALS) technology has transformed modern archaeology by unveiling hidden landscapes beneath dense vegetation. However, the lack of expert-annotated, open-access resources has hindered the analysis of ALS data using advanced deep learning techniques. We address this limitation with Archaeoscape (available at https://archaeoscape.ai), a novel large-scale archaeological ALS dataset spanning 888 km^2 in Cambodia with 31,141 annotated archaeological features from the Angkorian period. Archaeoscape is over four times larger than comparable datasets, and the first ALS archaeology resource with open-access data, annotations, and models.

We benchmark several recent segmentation models to demonstrate the benefits of modern vision techniques for this problem and highlight the unique challenges of discovering subtle human-made structures under dense jungle canopies. By

ML dataset for LiDAR archaeology

Dataset: quick overview



What it is

- Largest open-access ML dataset for LiDAR archaeology
- 888 km^2 with 31,141 mapped features
- Focused on Khmer civilization

Khmer civilisation

- 6th to 15th centuries
- Longstanding urban tradition
- Cambodia, Laos and Thailand

Time and place

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Large-scale features

- Temple complexes
- Hydraulics! (reservoirs, canals)

Time and place

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Large-scale features

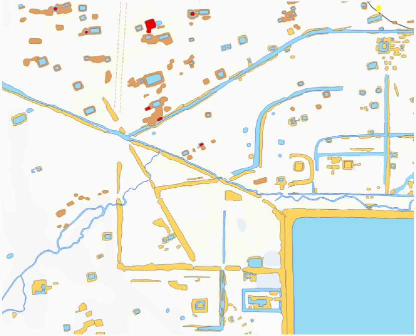
- Temple complexes
- Hydraulics! (reservoirs, canals)

Hidden traces

- Perishable structures
- Earthen features are eroded
- Difficult to see on the ground

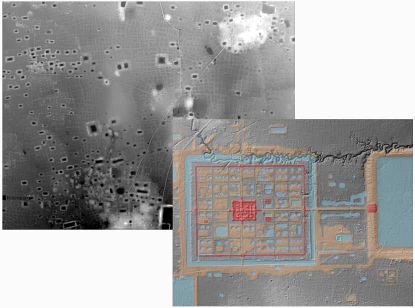
Mapping Angkor

- Timeline: from 2015 to now
- Builds on pre-lidar mapping methodology by Pottier (1999) and Evans (2007)
- Typology: temple sites, earthen features, and water features



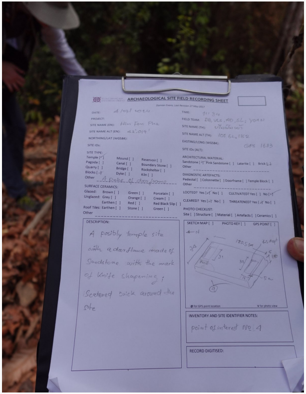
Annotation process

- Very high feature density, complex archaeological landscapes
- Each feature manually traced in ArcGIS/QGIS
- Products: DTMs, hillshades, SLRMs and orthophotos

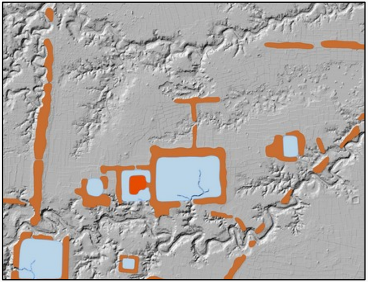


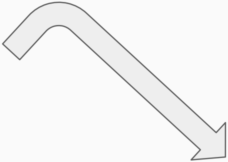
Ground verification

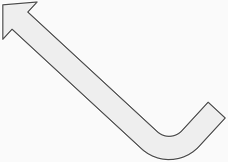
Ground verification



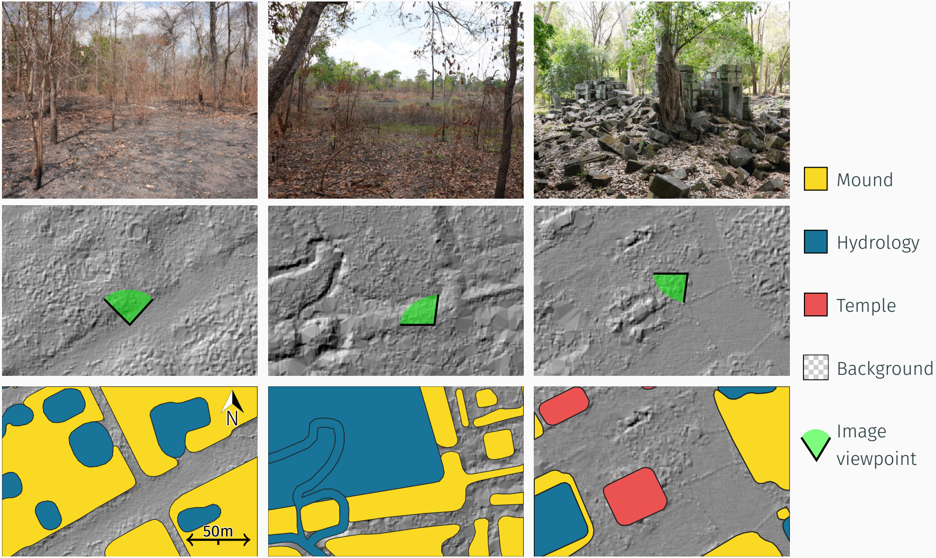
Ground verification







Main classes



(a) Occupation mound (b) Pond bank (c) Collapsed temple

Whole dataset at a glance

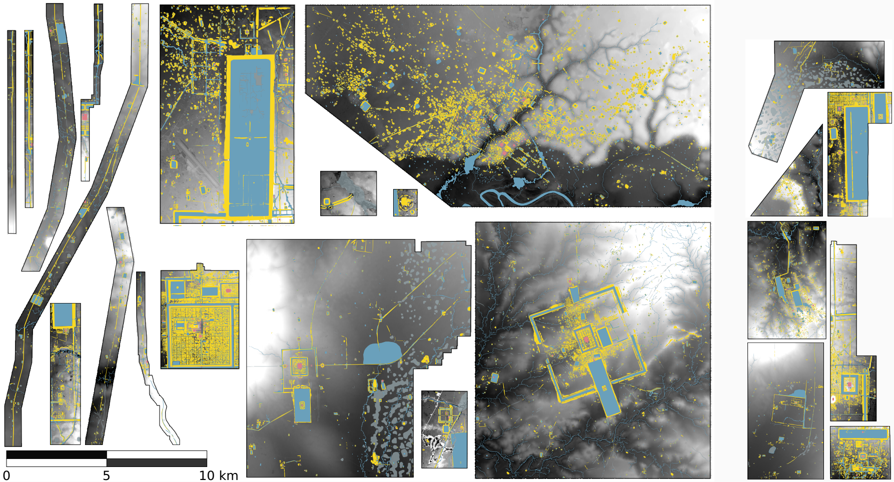


Figure 8: Archaeoscape ML benchmark

Comparison to existing

	open-access	hi-res RGB	location	extent in km^2	resolution in meters	number of instances
Arran[1]	✔	✗	United Kingdom	25	0.5	772
Litchfield[2]	✗	✗	USA	50	1	1,866
Puuc[3]	✗	✗	Mexico	23	0.5	1,966
AHN[4]	✗	✗	Netherlands	81	0.5	3,553
AHN-2[5]	✗	✗	Netherlands	437	0.5	3,849
Connecticut[6]	✗	✗	USA	353	1	3,881
Dartmoor[7]	✗	✗	United Kingdom	12	0.5	4,726
Pennsylvania[8]	✔	✗	USA	4	1	4,376
Uaxactun[9]	✗	✗	Guatemala	160	1	5,080
Chactún[10]	✗	✗	Mexico	230	0.5	10,894
Archaeoscape (ours)	✔	✔	Cambodia	**888**	0.5	**31,411**

[1] https://github.com/ickramer/Arran [2] Suh et al. 2021 [3] Zhang, Ringle, and Willis 2024 [4] Verschoof-van der Vaart et al. 2020 [5] Fiorucci et al. 2022 [6] Vaart et al. 2023 [7] Gallwey et al. 2019 [8] Carter, Blackadar, and Conner 2021 [9] Bundzel et al. 2020 [10] Somrak, Džeroski, and Kokalj 2020

Comparison to existing

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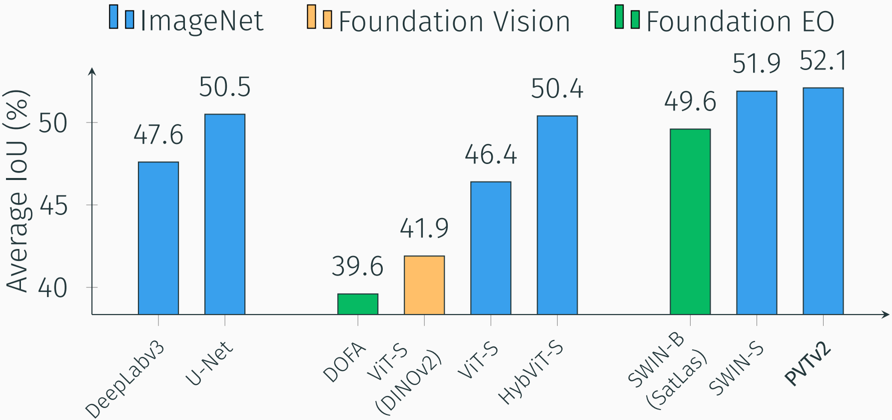
Our Archaeoscape dataset

- Inputs: 50cm DTM, orthophotos
- Target: Semantic segmentation (Mound, Water, Temple, BG)
- 4X area, 6X annotations than comparable

Benchmark results

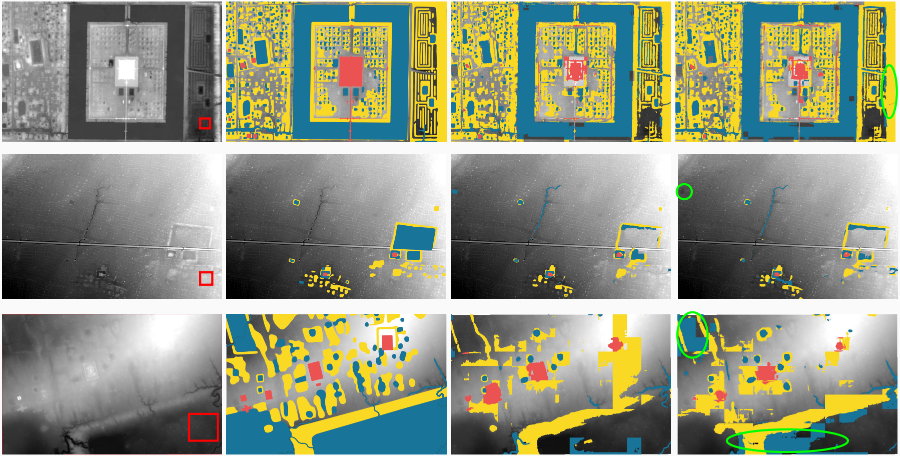
	Backbone	pre-training	input size	IoU avg	IoU temple	IoU hydro	IoU mound	IoU bkg	OA
CNN	U-Net[a]	ImageNet1K	224	50.5	33.3	32.7	48.6	87.6	88.2
	DeepLabv3[b]	ImageNet1K	224	47.6	19.8	35.9	47.5	87.2	87.8
ViT	ViT-S[c]	ImageNet21K	224	46.4	18.5	33.3	46.6	87.0	87.5
	ViT-S[c]	DINOv2	224	41.9	14.5	26.1	40.9	86.2	86.7
	ViT-B[d]	CLIP	224	30.3	3.4	15.8	30.3	83.1	83.4
	ViT-B[d]	LAION2B	224	32.4	2.8	14.4	28.2	84.3	84.6
	ViT-L[e]	ScaleMAE	224	30.4	0.0	16.0	22.8	82.7	82.8
	HybViT-S[c]	ImageNet21K	224	49.5	28.8	34.0	47.9	87.5	88.1
HViT	SWIN-S[c]	ImageNet21K	224	51.0	30.9	35.0	50.5	87.7	88.3
	PCPVT-S[c]	ImageNet1K	224	51.7	**33.4**	35.0	50.6	88.0	88.5
	PVTv2-b1[c]	ImageNet1K	224	**52.1**	32.3	**36.4**	**51.4**	**88.2**	**88.7**
	U-Net[a]	ImagineNet1K	512	52.8	31.8	39.7	50.7	89.1	89.6
	PVTv2[c]	ImagineNet1K	512	52.2	28.3	38.0	53.0	89.4	89.9

Benchmark results



- Foundation models do not generalize
- Hierarchical models perform best
- Key is large context/receptive field

Qualitative results

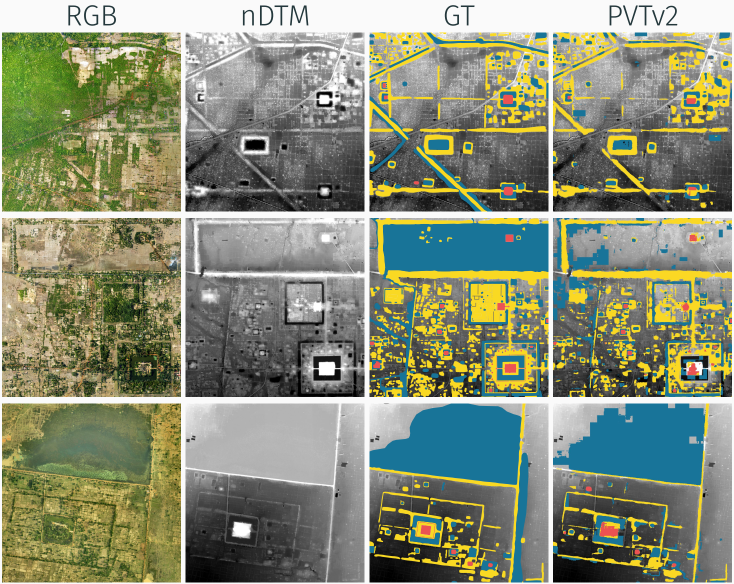


Input ALS | Ground truth | U-Net-224 | PVTv2-224

Modalities

	Backbone	pre-training	IoU					OA
			avg	temple	hydro	mound	bkg	
RGB+E	U-Net	ImageNet1K	50.5	**33.3**	32.7	48.6	87.6	88.2
	ViT-S	DINOv2	41.9	14.5	26.1	40.9	86.2	86.7
	PVTv2-b1	ImageNet1K	**52.1**	32.3	36.4	**51.4**	<u>88.2</u>	<u>88.7</u>
RGB	U-Net	ImageNet1K	51.2	28.8	**37.8**	49.8	**88.3**	**88.9**
	ViT-S	DINOv2	36.6	10.4	19.4	31.5	85.2	85.6
	PVTv2-b1	ImageNet1K	49.9	27.8	35.1	48.5	<u>88.0</u>	<u>88.5</u>
E	U-Net	ImageNet1K	34.2	1.5	22.7	29.3	83.2	83.2
	ViT-S	DINOv2	29.0	1.6	12.6	20.1	81.6	81.4
	PVTv2-b1	ImageNet1K	33.9	6.0	20.6	27.0	82.0	33.9

Modalities (Qualitative)



Thank you!

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