living planet symposium | BONN 23–27 May 2022

TAKING THE PULSE OF OUR PLANET FROM SPACE

MACHINE LEARNING BASED APPROACH FOR SATELLITE DETECTION OF POTENTIAL NEW ARCHAEOLOGICAL SITES LINKED TO THE MOBILITY OF PREHISTORIC GROUPS IN THE EGYPTIAN WESTERN DESERT

Alessia Brucato, Nicola Masini, Giuseppe Scardozzi, Giulio Lucarini

D2.12.1 Cultural and Natural Heritage – 1
Room H2-02

26/05/2022

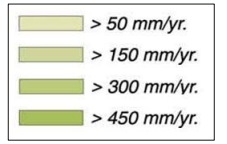
SUMMARY

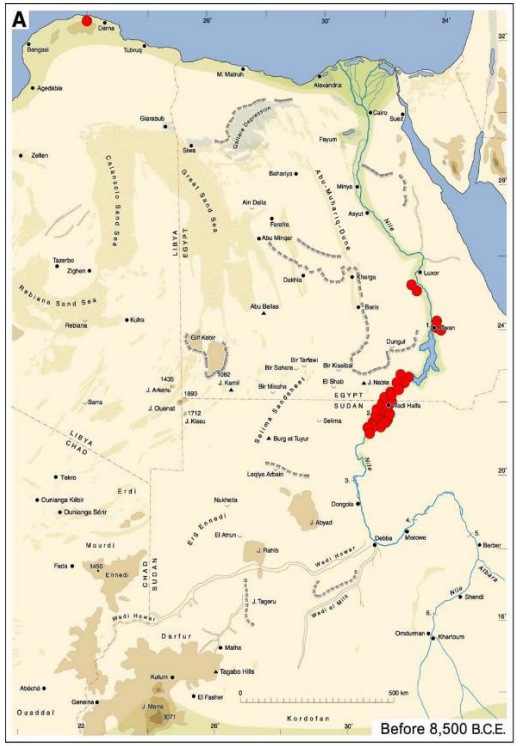
- ENVIRONMENT
- ARCHAEOLOGICAL CONTEXT
- WORKFLOW
- PLATFORMS
- PARAMETERS
- IMAGE PROCESSING
- ALGORITHMS
- REFERENCES

INTRODUCTION | MATERIALS | METHODS | RESULTS | CONCLUSIONS

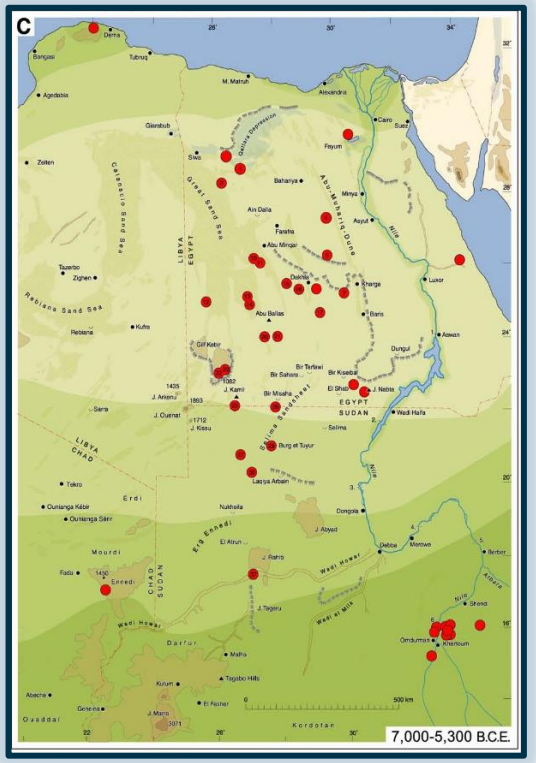
- ENVIRONMENT
- SITES
- SLAB STRUCTURES
- DATASET
- IMAGERY
- PRELIMINARY RESULTS

Holocene climatic sequence of the Eastern Sahara
(Kuper, Kröpelin 2006)

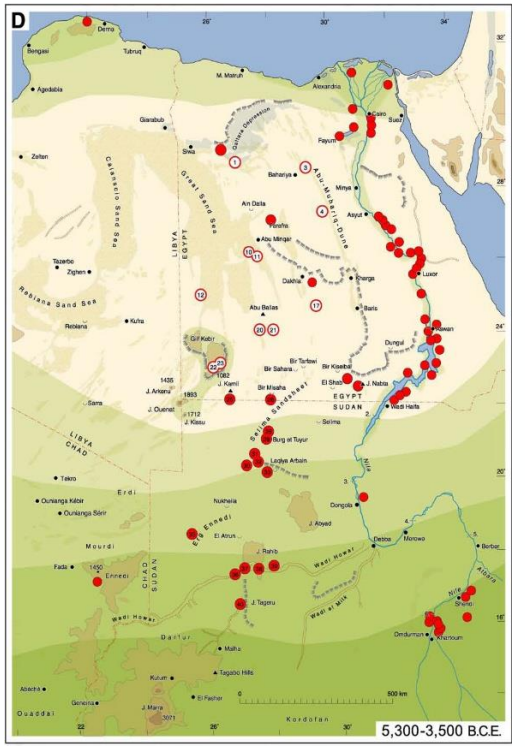




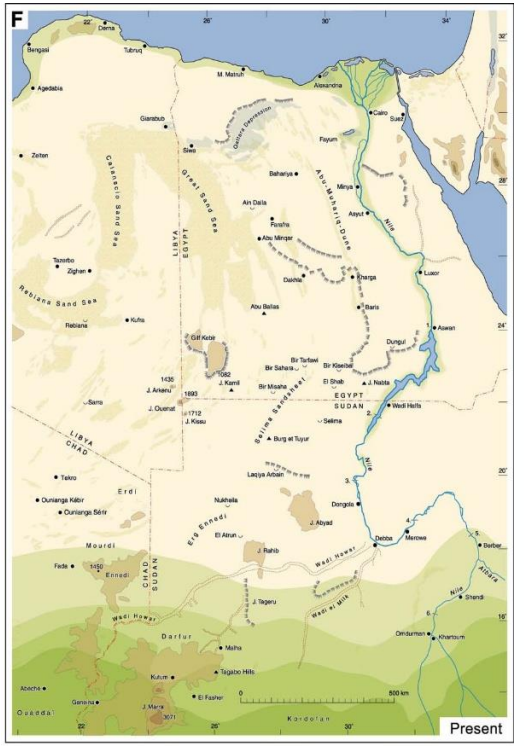
Before 8500 BC



7000-5300 BC



5300-3500 BC



Today

INTRODUCTION

Early Wadi el Obeiyid A

6600-6100 cal. BC

- **Increased Sedentism**
- Structured hearth pits
- *Steinplätze* hearths

Sites: Hidden Valley IIIA, El Bahr

Late Wadi el Obeiyid A

6100-5700 cal. BC

- **Semi-permanent settlements**
- First slab structures
- Structured hearth pits

Sites: Hidden Valley Village III, IIA, Sheikh el Obeiyid Village

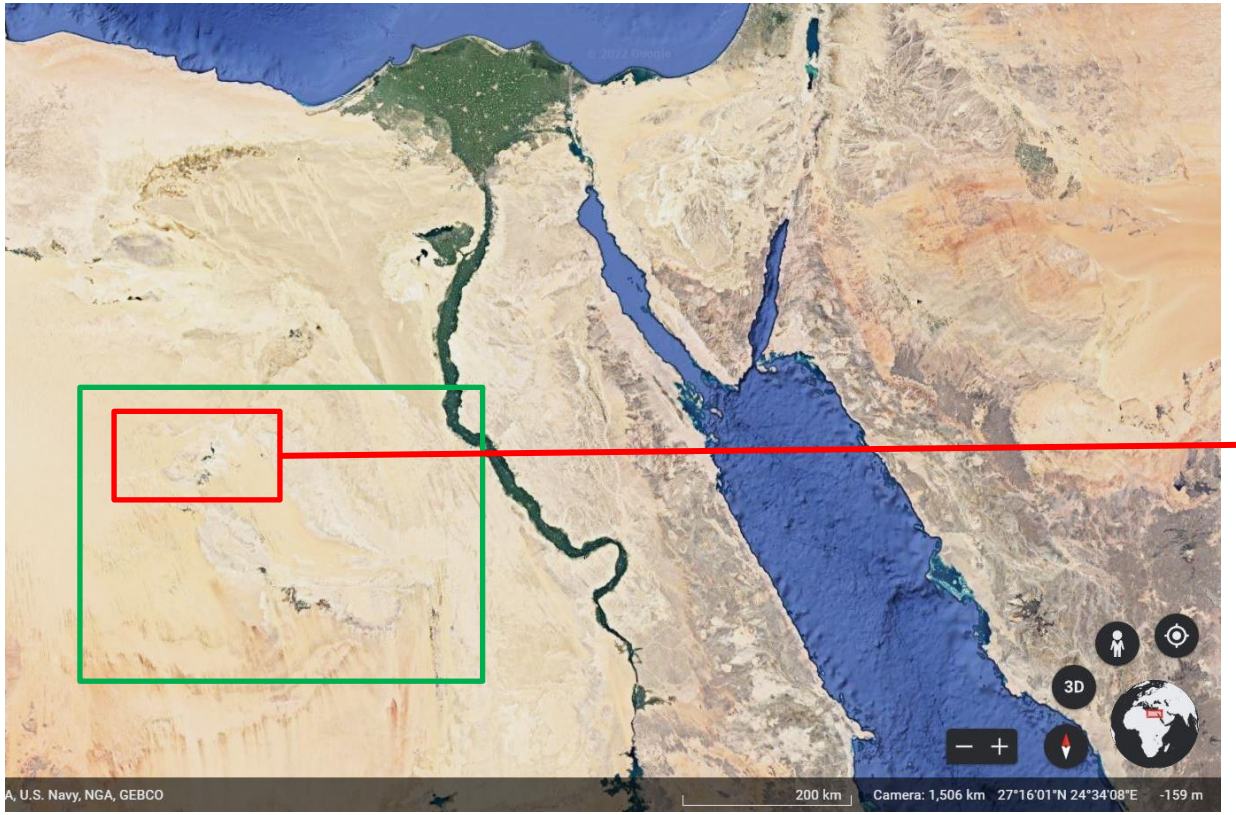
Wadi el Obeiyid B

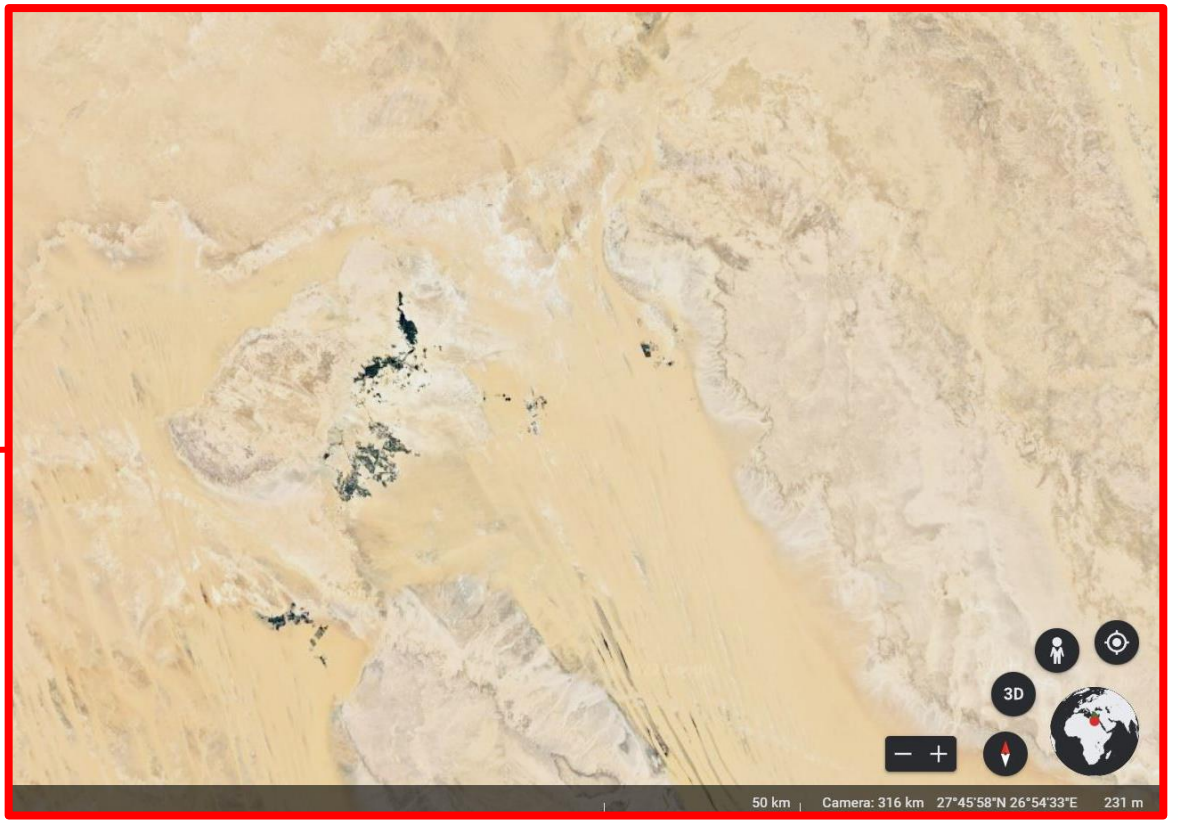
5600-5200 cal. BC

- **Seasonal movements**
- Slab structures
- *Steinplätze* hearths

Sites: Hidden Valley II, El Bahr – Bir el Obeiyid

Oases of the Egyptian Western Desert
Farafra Oasis





INTRODUCTION

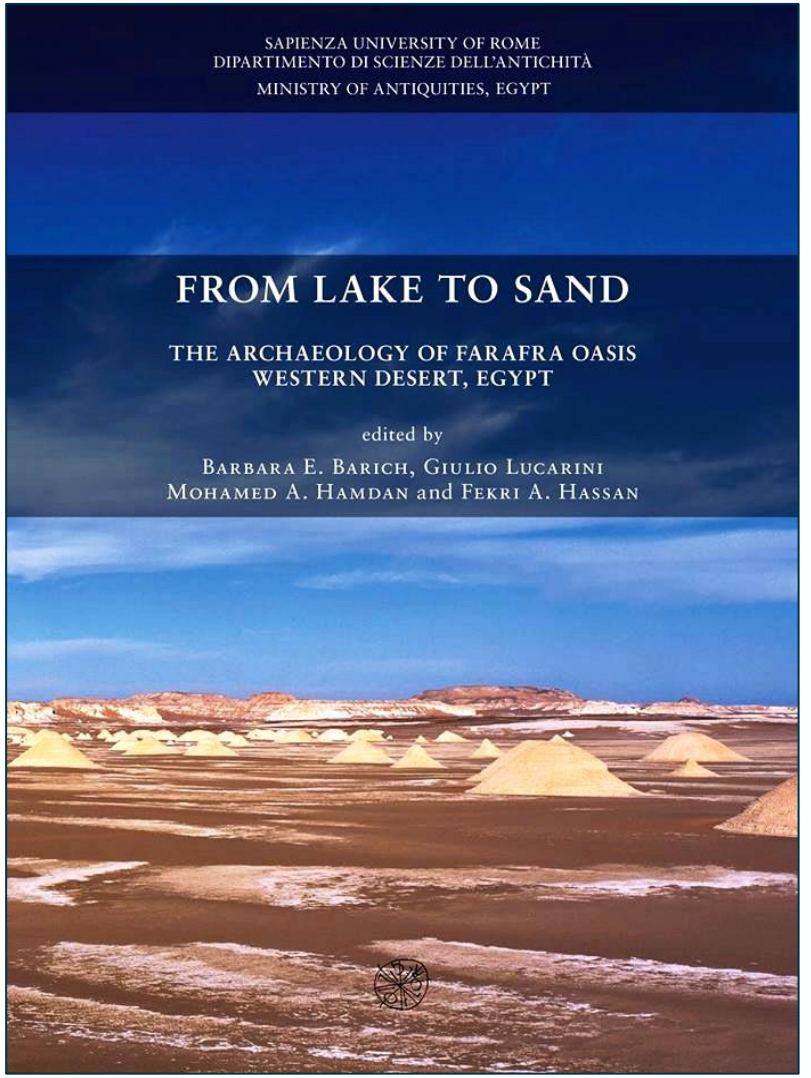
Farafra Oasis Prehistoric Project

Co-directors: Barbara E. Barich, Giulio Lucarini

Egypt, since 1986

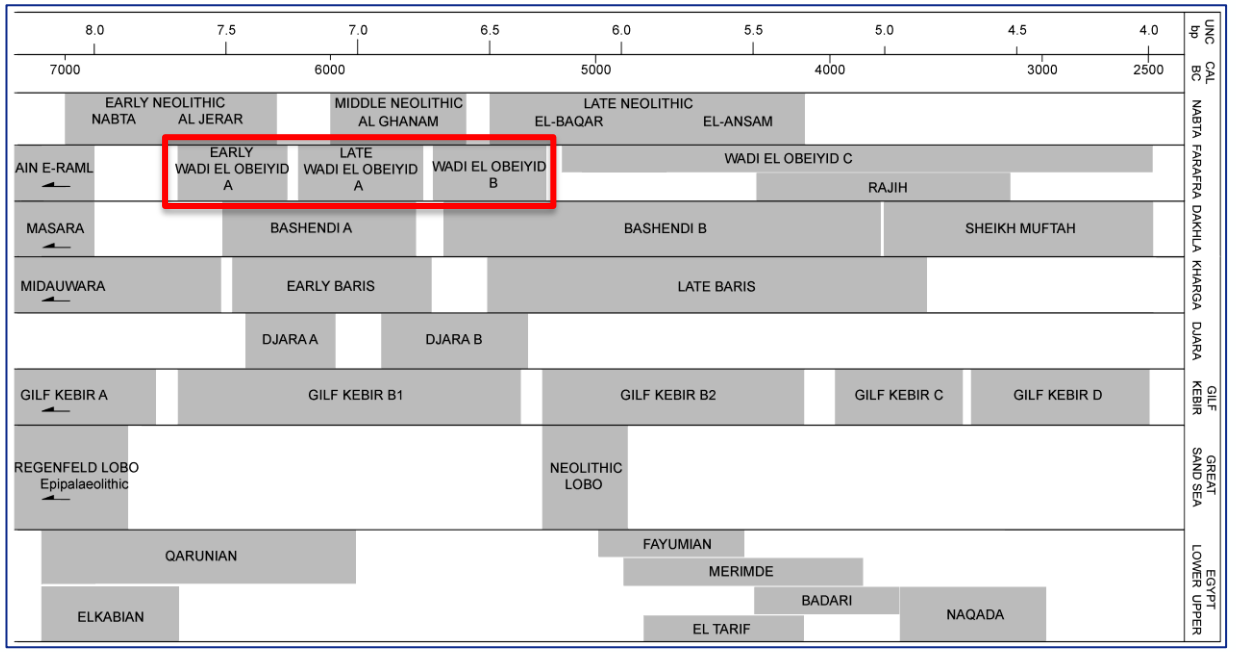
https://www.ismeo.eu/portfolio_page/italian-archaeological-mission-to-the-farafra-oasis-western-desert-egypt/

ISMEO



INTRODUCTION

Mid Holocene Wadi el Obeiyid A-B
6600-5200 BC
Foragers/herders



Date BP	Unit	Palaeoenvironment			Climate	Archaeology
		North	Basinal	South		
< 4500		Desert wind erosion and aeolian deposit accumulation	Desert wind erosion and formation of yardangs and aeolian deposits accumulation		Hyper arid	(?)
5000 to 6000	V	Wadi activity and colluviums	Playa basinal silt deposition (wadi fed playa)		Moist	Late Neolithic artifacts, hearths and ostrich eggshells
ca 6000	IV	Wind blown accumulation with few torrential floods	Dryness of the playa, wind deflation and phytogenic dune accumulation		Arid	Final occupation of the Neolithic village
6000 to 7000	III	Beach sand and gravel and at least 10 high stand lake	Playa basinal silt deposition (wadi fed playa)	accumulation of lee dune barrier on the shadow of the sandstone hills	Wet	Neolithic occupations at the Hidden Valley village, stone structures, flint implements, ostrich eggshell
ca 8000	II	Wind blown accumulation and alluvial and colluvial activity	Sheet wash and slope wash accumulation in the basin (wash playa)		Frequent dry	Hearths
> 8000	I	Wadi activity, sand and gravelly beach few high stand lakes and colluvium	Playa basinal silt deposition and few alluvial activity (wadi fed playa)	(?)	Wet	Final Palaeolithic (LSA) on top of lower plateau

Mohamed A. Hamdan

INTRODUCTION

Mid Holocene Wadi el Obeiyid A-B
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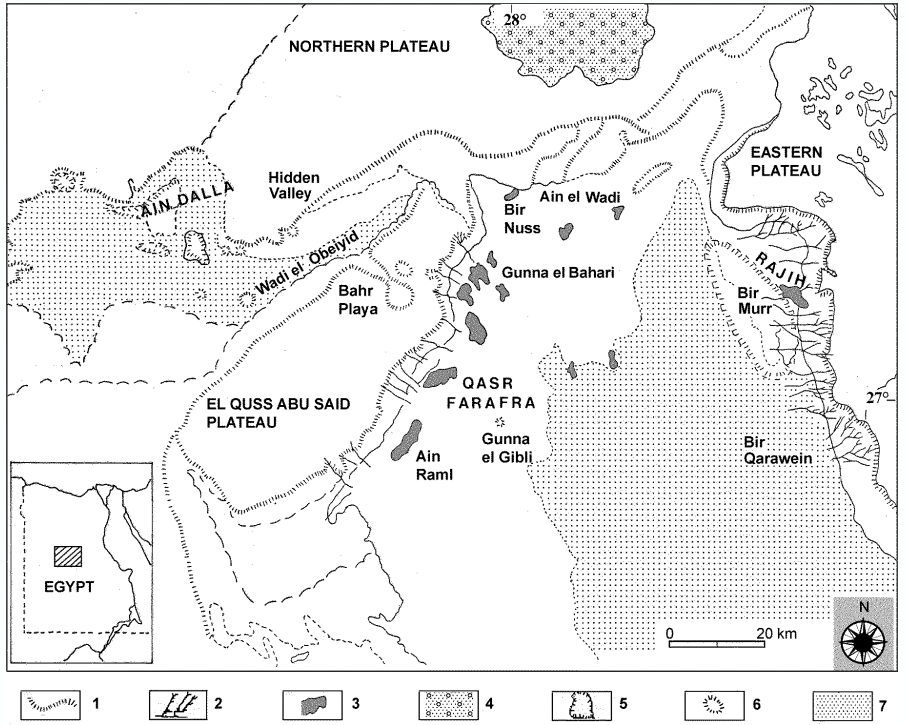
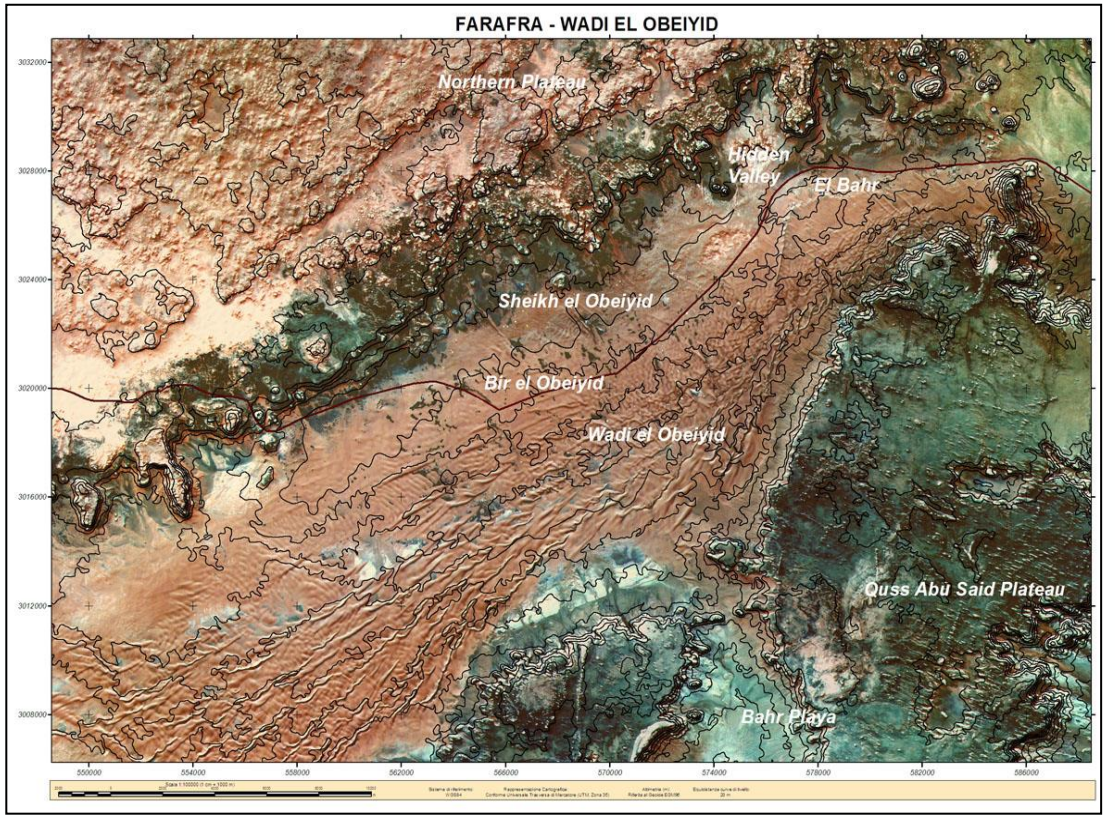
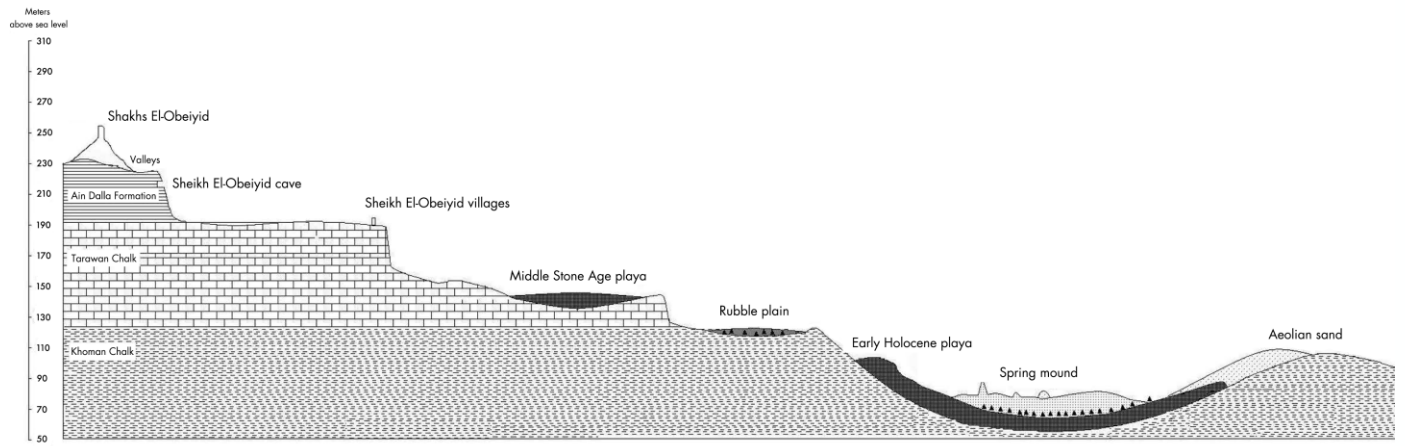




Ulisse Fabiani

MATERIALS - ENVIRONMENT

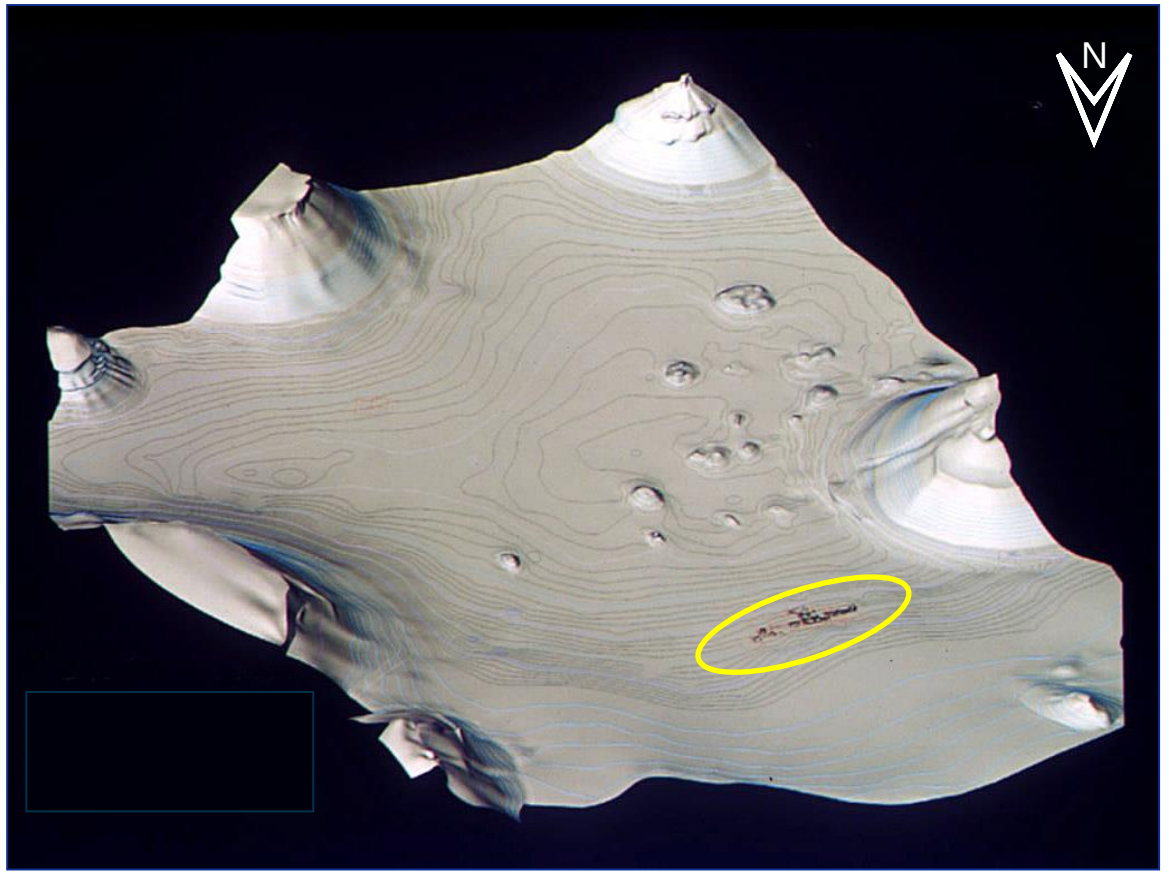


Wadi el Obeyid Northern Plateau

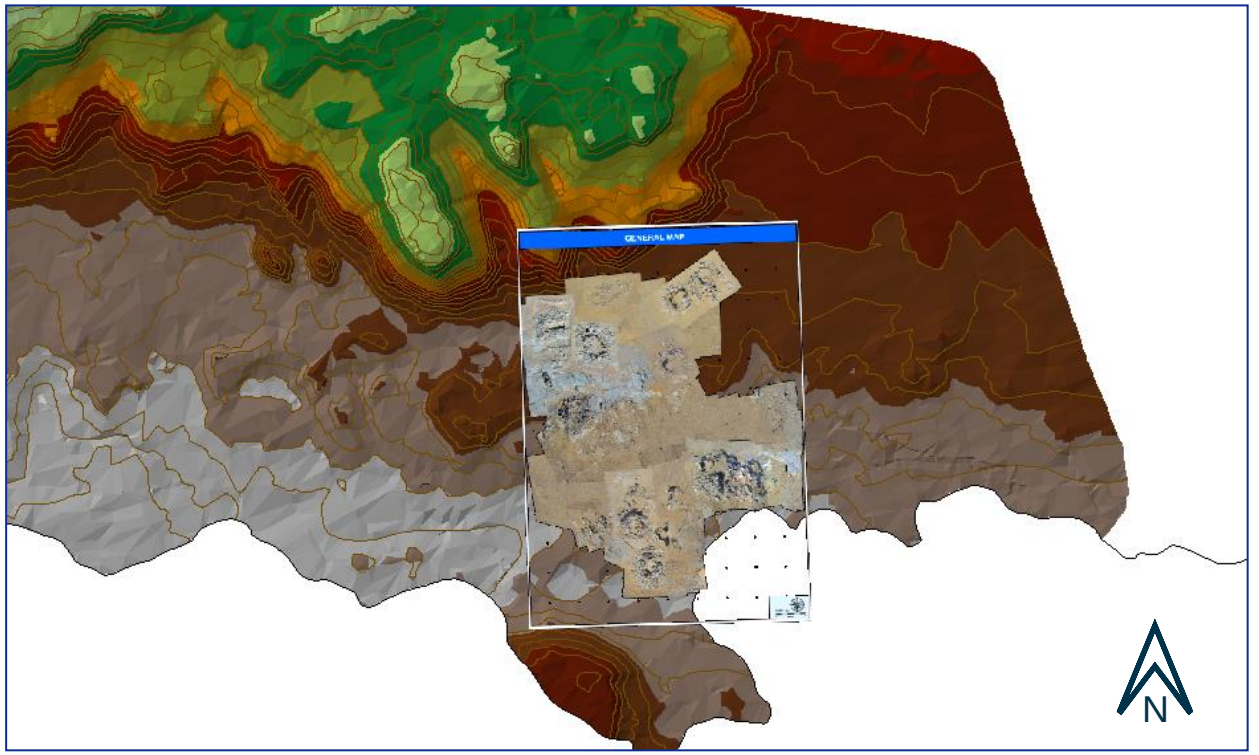
Mohamed A. Hamdan

MATERIALS - ENVIRONMENT

Hidden Valley basin and village



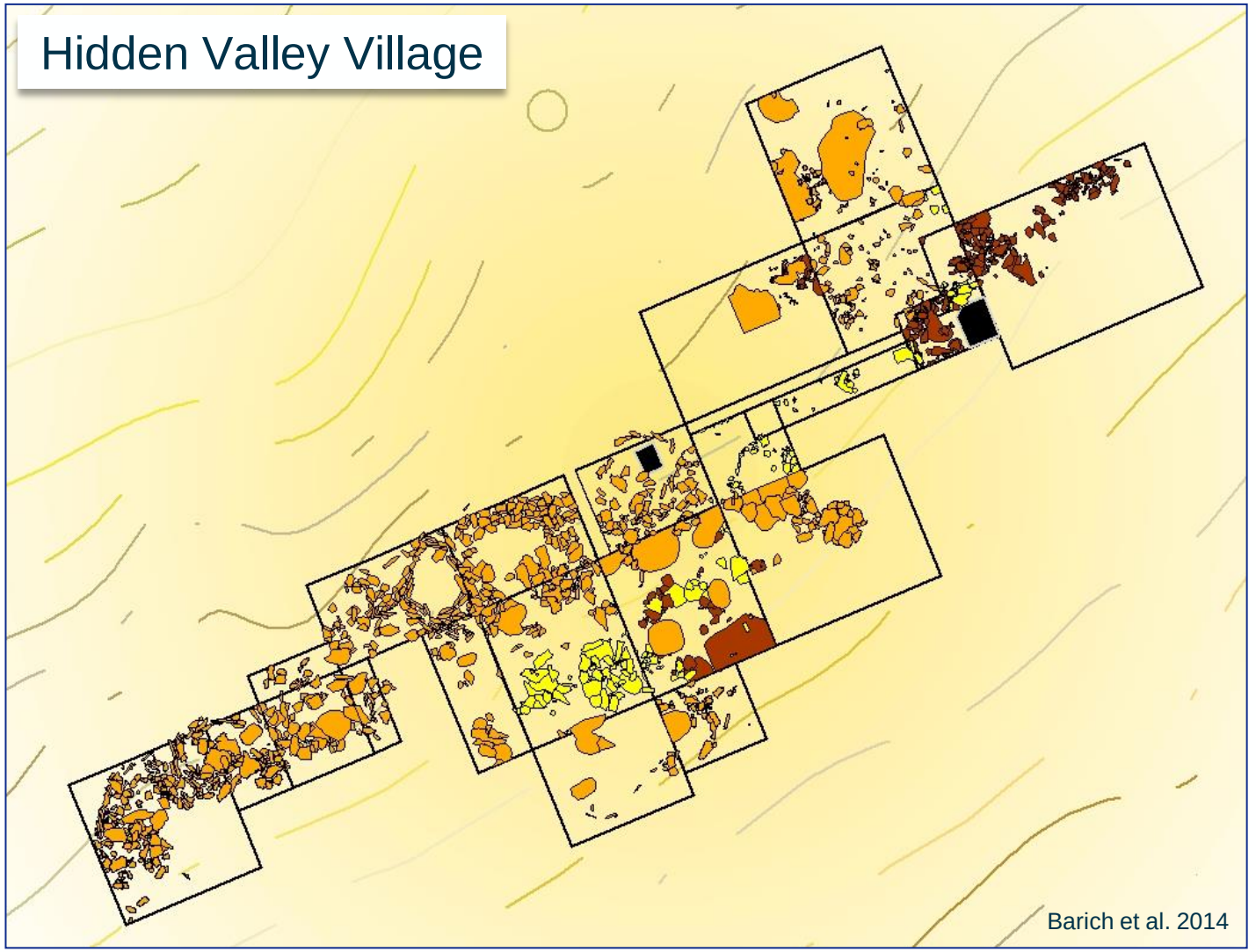
Sheikh el Obeiyid Village



Ulisse Fabiani

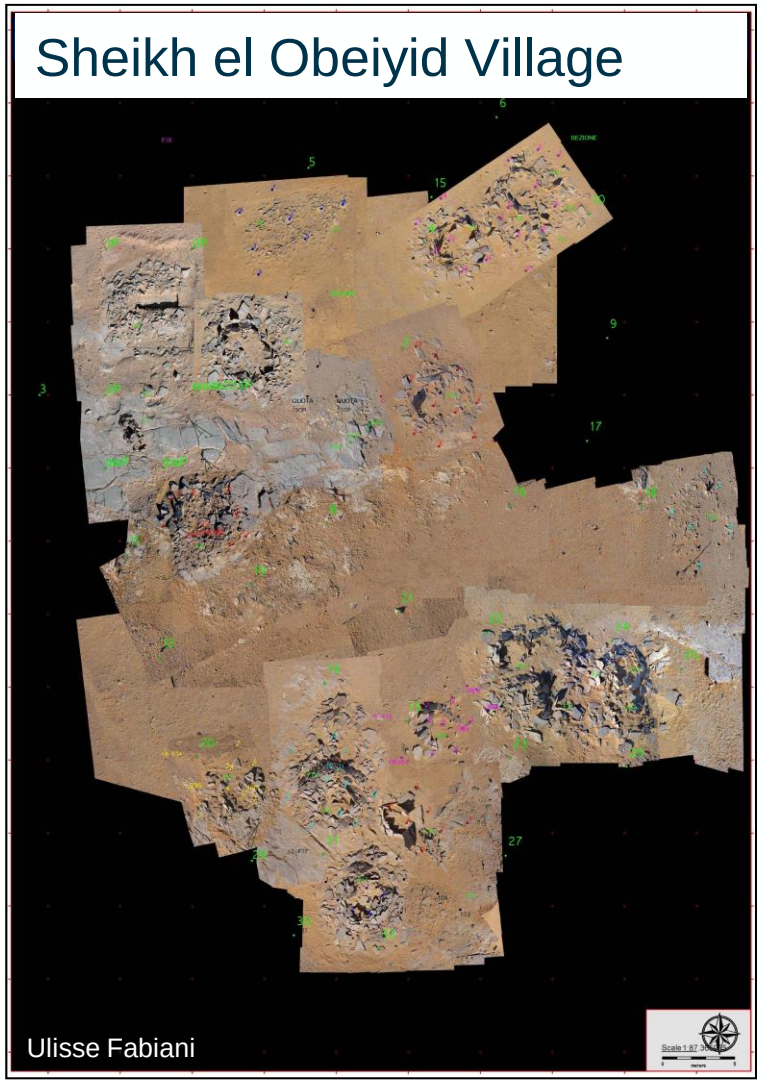
MATERIALS - SITES

Hidden Valley Village



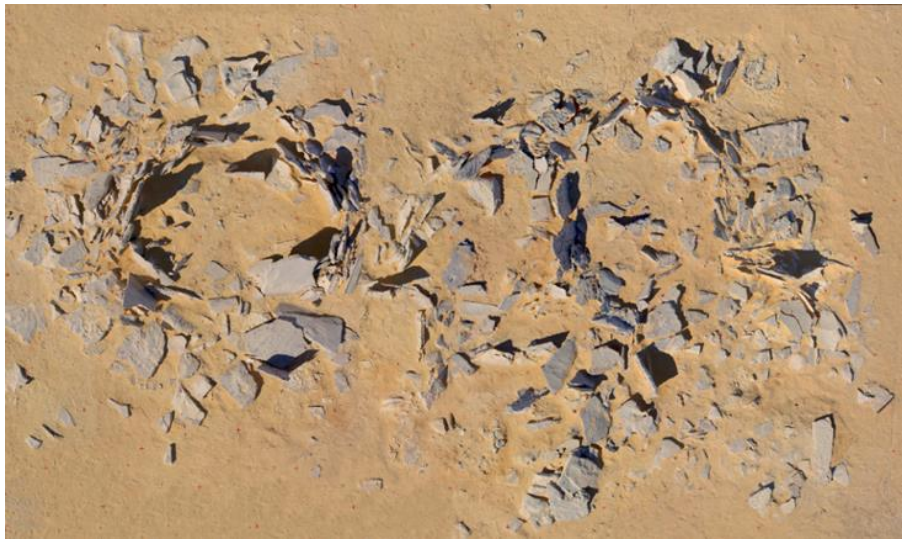
Barich et al. 2014

Sheikh el Obeiyid Village



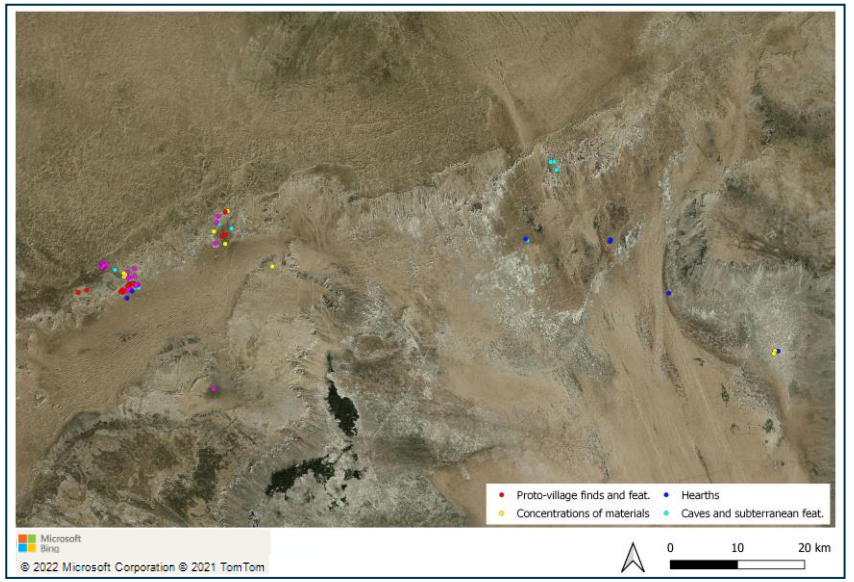
Ulisse Fabiani

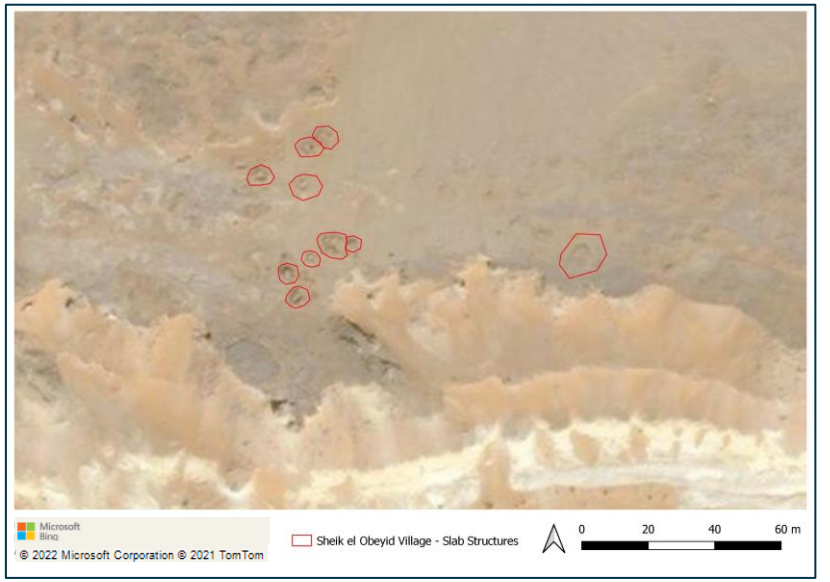
MATERIALS – SLAB STRUCTURES

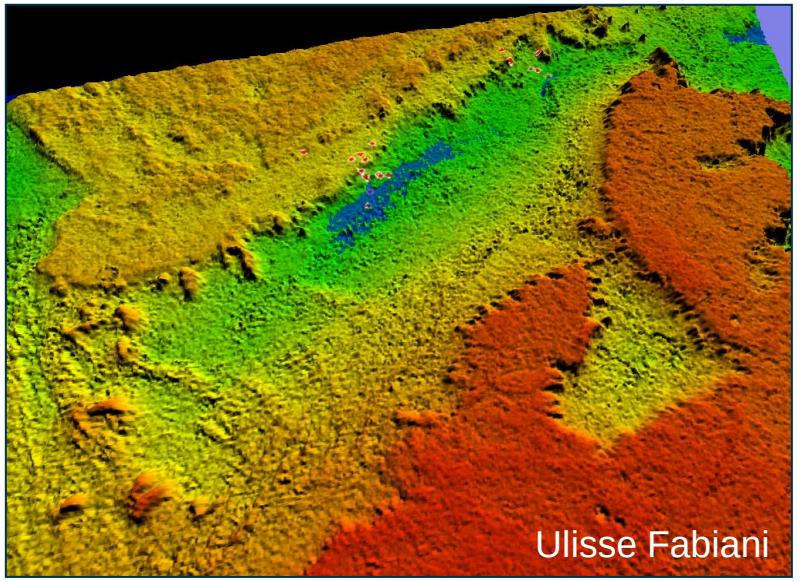


Fabrizio Galeazzi

MATERIALS – DATASET







DATASET

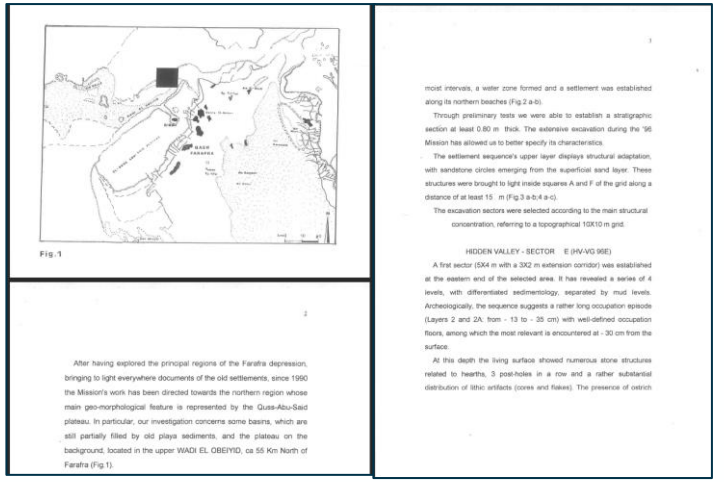
Publications and Reports

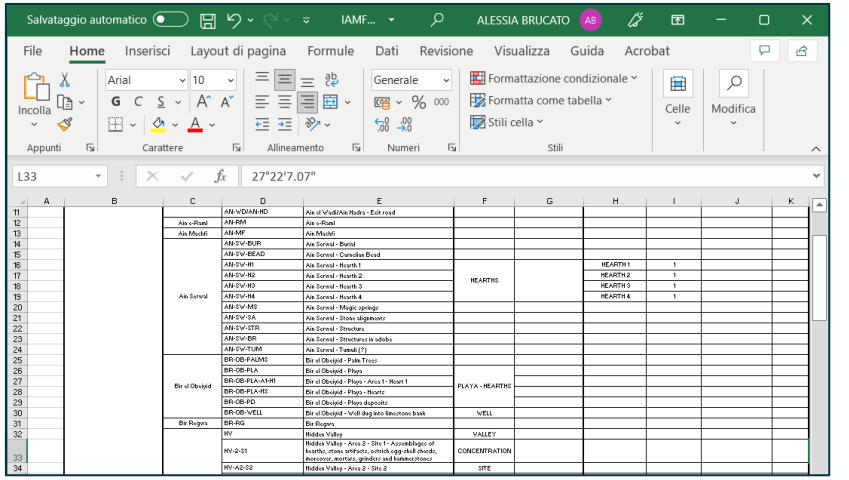
Database

Graphic, photo and 3D documentation

DEM

GIS





MATERIALS - IMAGERY

SATELLITE IMAGERY

Corona KH-4B

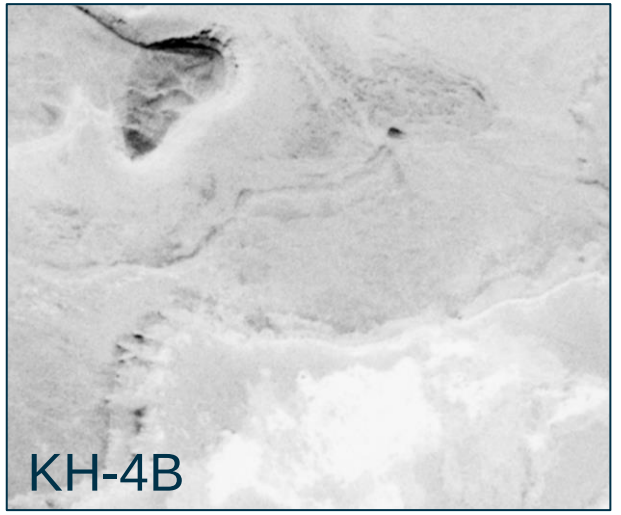
Hexagon KH-9

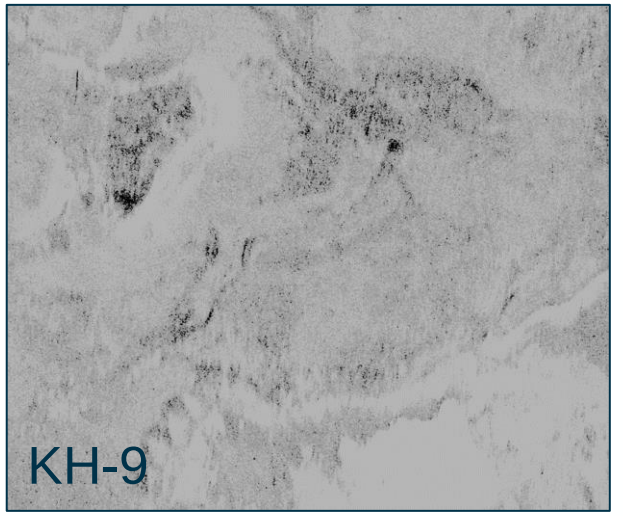
Sentinel 2

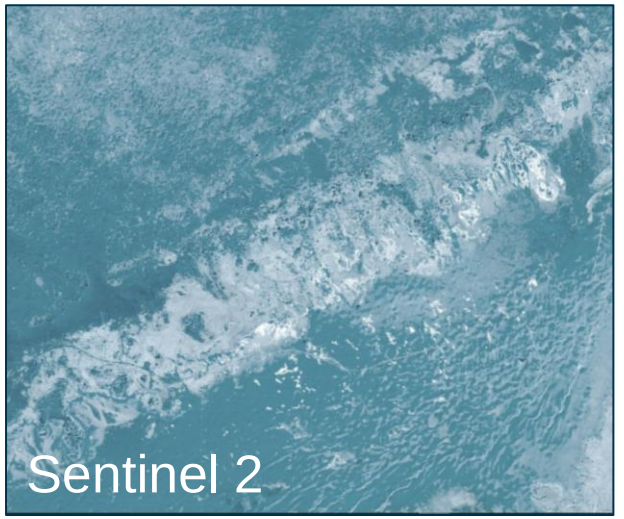
RGB, NIR, SWIR1, SWIR2

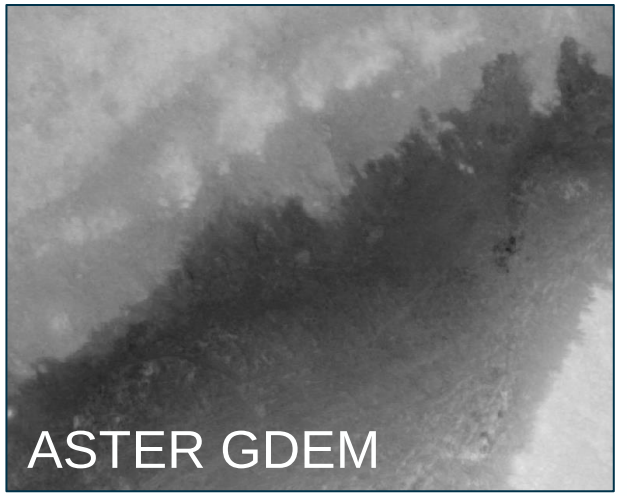
ASTER GDEM

(COSMO SkyMed, TanDEM-X)









METHOD - WORKFLOW

DATABASE AND FILTERS

Archaeological proxies

Surface parameters

MULTI-TEMPORAL MULTI-SENSOR AGGREGATES

Composite files of different satellite images, bands, times of recording and computations

ALGORITHMS

Linear Discriminant Analysis [1]

ALFEA method [2]

Lisa Geary C Spatial Auto-correlation [2]

Unsupervised Isodata Classification [2]

Segmentation [2]

Random Forest Classifier [1]

Convolutional Neural Network [3, 4]

GEE AND GIS

Composite files processing and calculation

Final results vectorization

Final results comparison

Distribution analysis

Archaeological analysis

1. *Orengo et al. 2020*
2. *Lasaponara et Masini 2018*
3. *Albawi et al. 2017*
4. *O'Shea et Ryan 2015*
5. *Costanzo et al. 2021*

METHODS – PLATFORMS

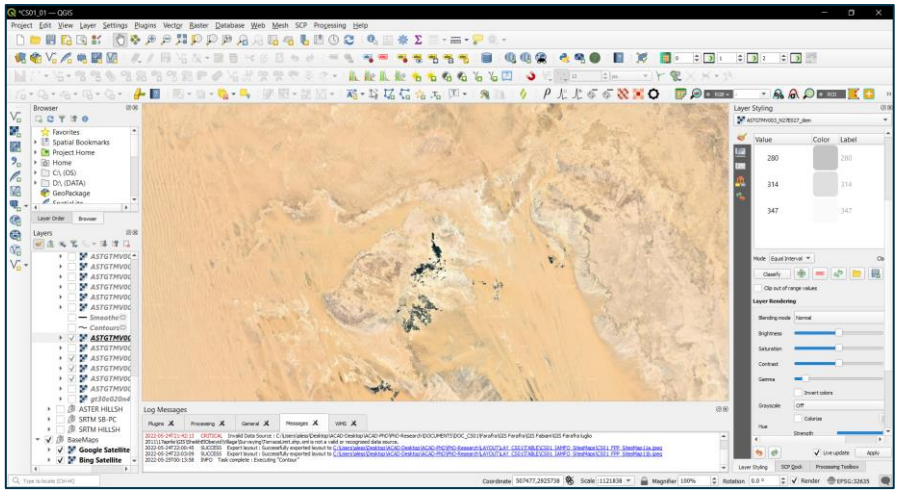
PLATFORMS

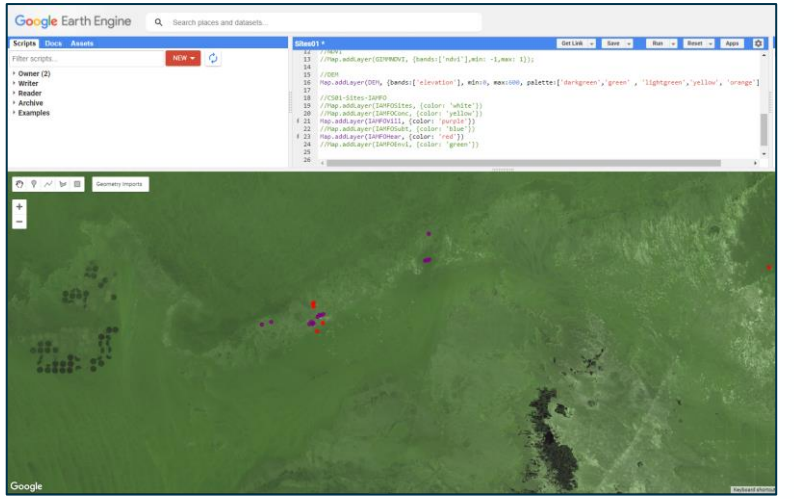
GIS

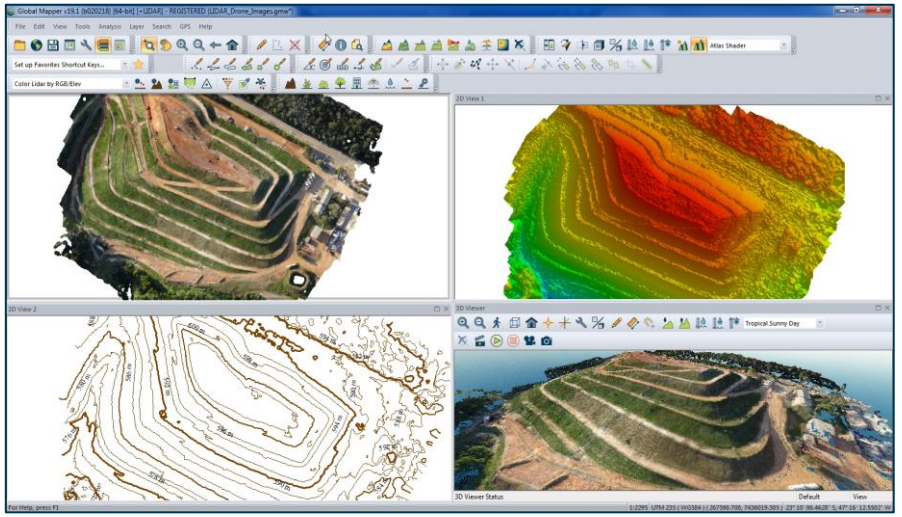
GEE

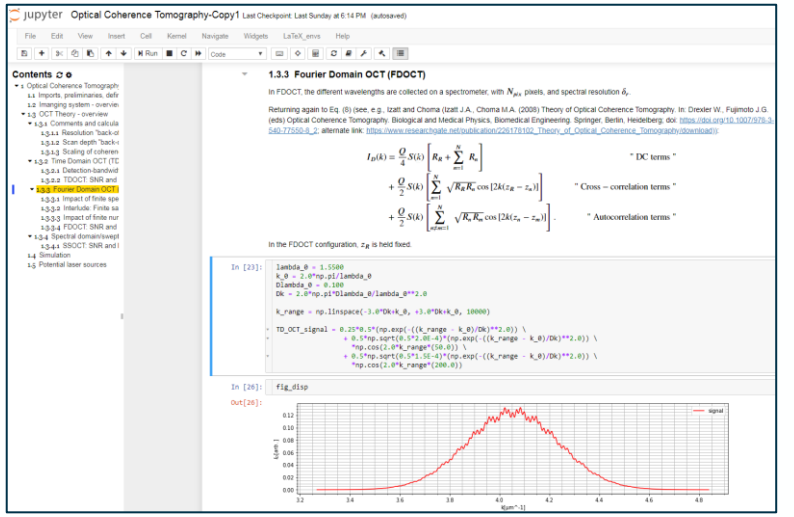
Global Mapper

Code editors









METHODS - PARAMETERS

ARCHAEOLOGICAL PROXIES

Shadow marks

Feature morphology

Feature orientation

Construction materials

Environmental hotspots

Archaeological hotspots

Spectral signatures

SURFACE PARAMETERS

Surface roughness

Surface discontinuity

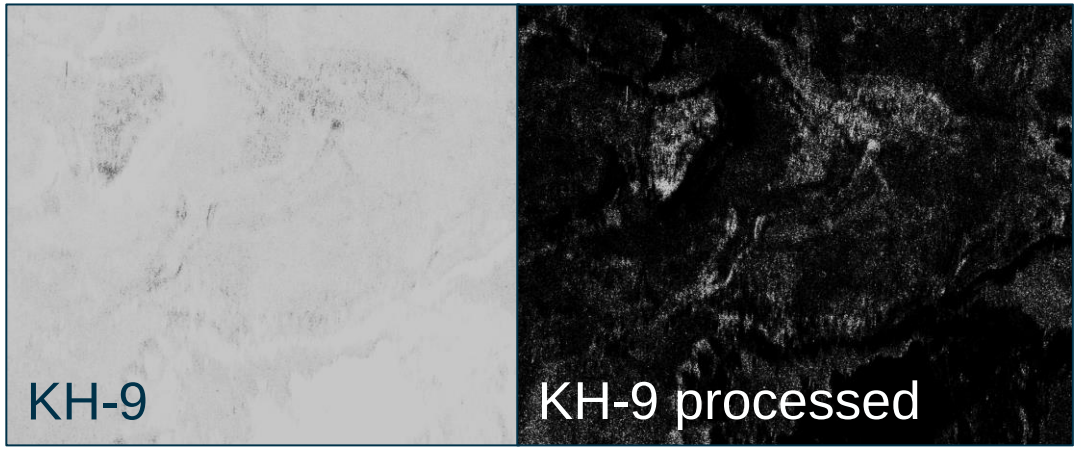
Paleo and modern topography,

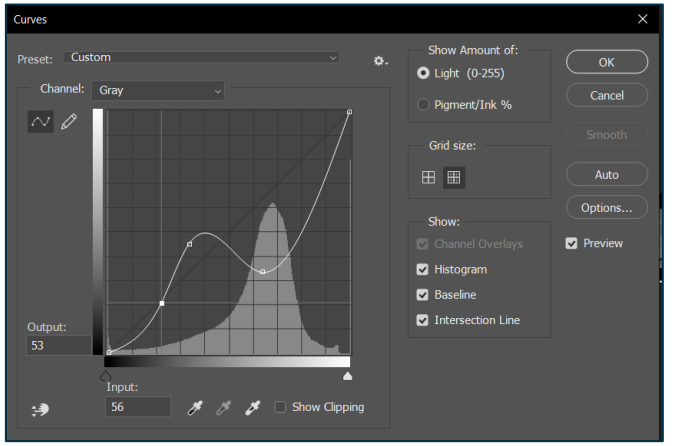
hydrography and climatology

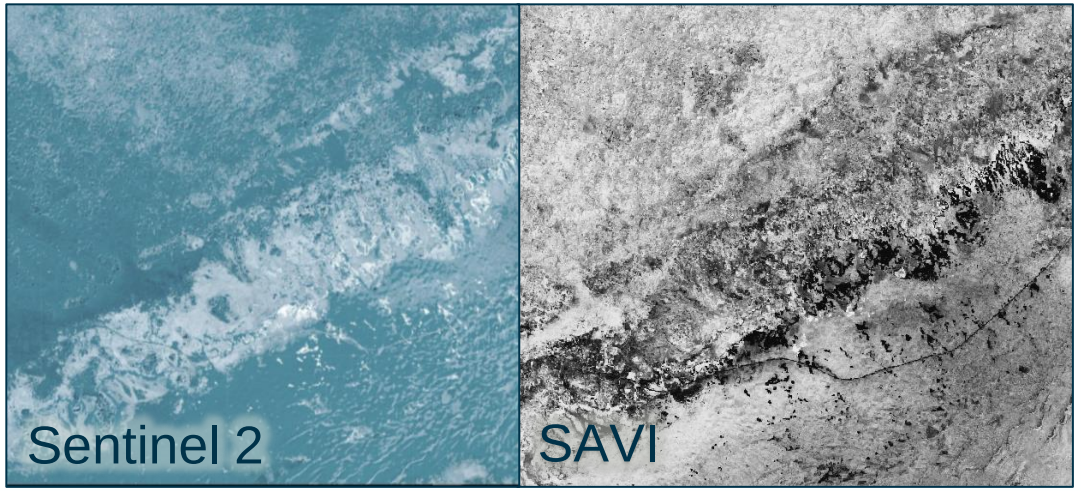
Electric conductivity of the soil

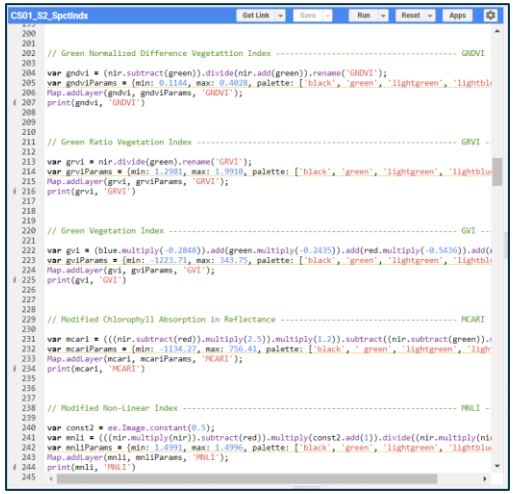
Moisture content percentage

METHODS – IMAGE PROCESSING









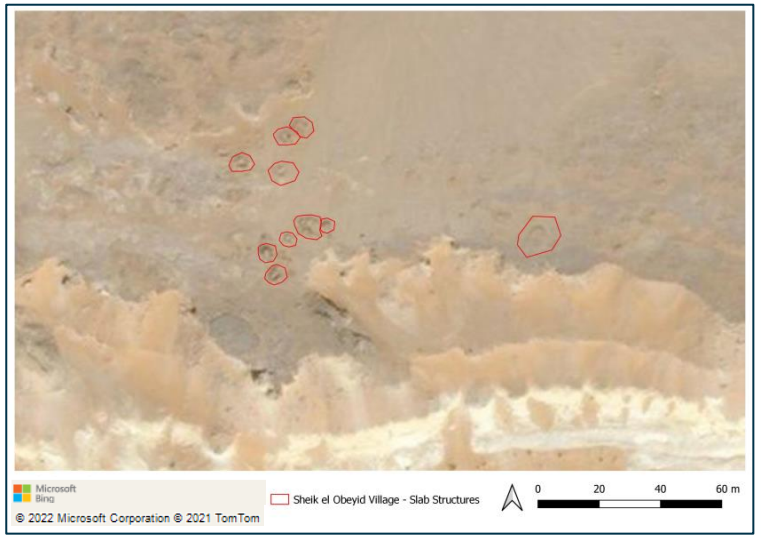
PROCESSES

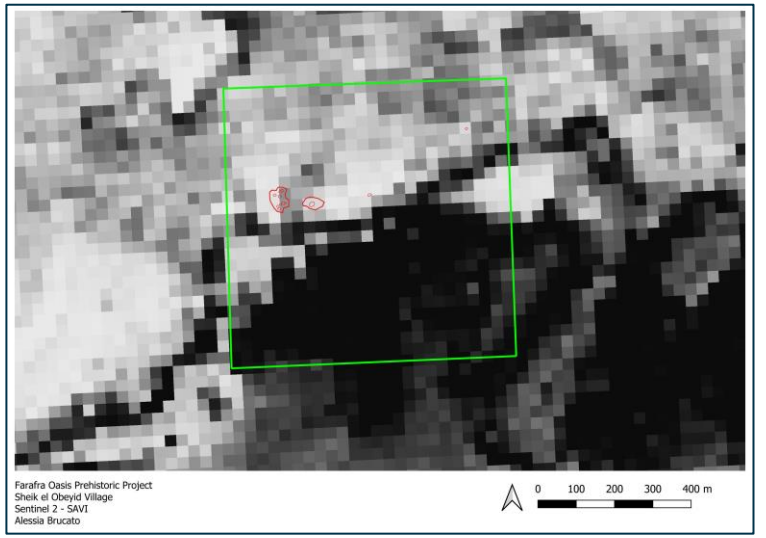
Color Curves calibration and noise reduction

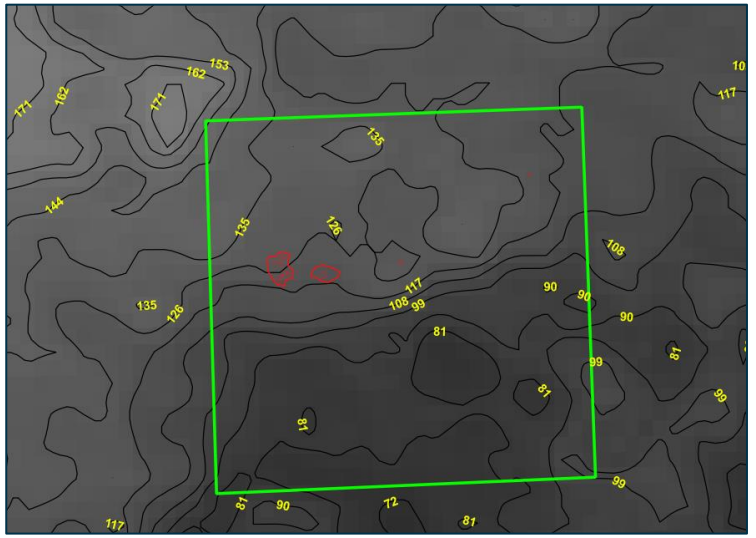
Spectral Indices calculation

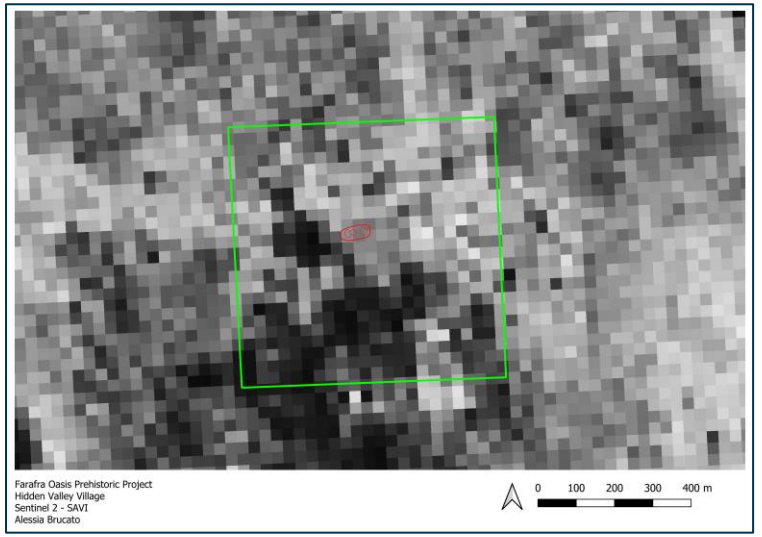
(Mean, PCA)

METHODS – IMAGE PROCESSING









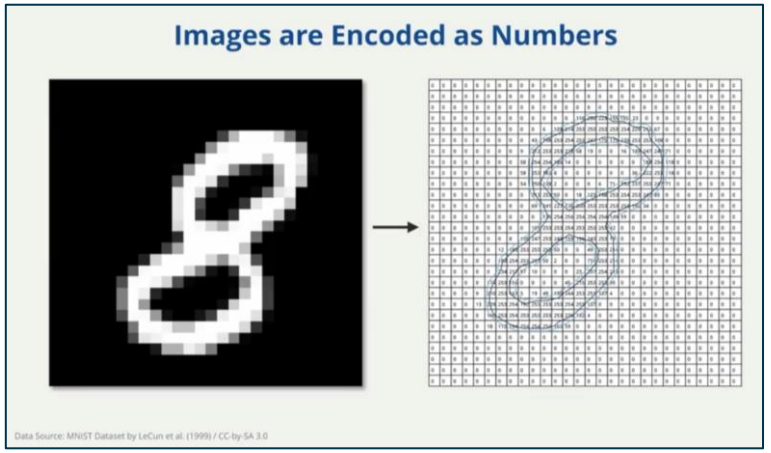
Multitemporal Multisensory Overlapping Composites

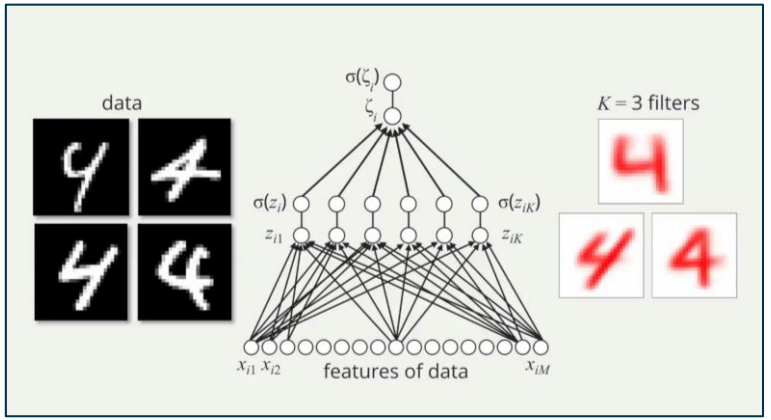
+

Training vectors for ML:

- Slab Structures
- Proto-villages
- Surroundings

METHODS - ALGORITHMS





Convolutional Neural Network
Multiclass Perceptron

```
class Net(nn.Module):
    def __init__(self):
        super().__init__() # just run the init of parent class (nn.Module)
        self.conv1 = nn.Conv2d(1, 32, 5, padding=2) # input is 1 image, 32 output channels, 5x5 k
        self.conv2 = nn.Conv2d(32, 64, 5, padding=2) # input is 32, bc the first layer output 32
channels, 5x5 kernel / window
        self.conv3 = nn.Conv2d(64, 128, 5, padding=2)


        self.fc1 = nn.Linear(128*25*25, 512) #flattening.
        self.fc2 = nn.Linear(512, 2) # 512 in, 2 out bc we're doing 2 classes (dog vs cat).

    def convs(self, x):
        # max pooling over 2x2
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv3(x)), (2, 2))

        return x

    def forward(self, x):
        x = self.convs(x)
        x = x.view(-1, 128*25*25)  # .view is reshape ... this flattens X before
        #x = torch.flatten(x, start_dim = 0)
        x = F.relu(self.fc1(x))
        x = self.fc2(x) # bc this is our output layer. No activation here.
        return F.softmax(x, dim=1)


net = Net()
print(net)
device = torch.device("cuda:0")
#device = torch.device('cpu')
net.to(device)
if REBUILD_DATA:
    dogsvcats = DogsVSCats()
    dogsvcats.make_training_data()

training_data = np.load("training_data.npy", allow_pickle=True)
print(len(training_data))
```

```
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```
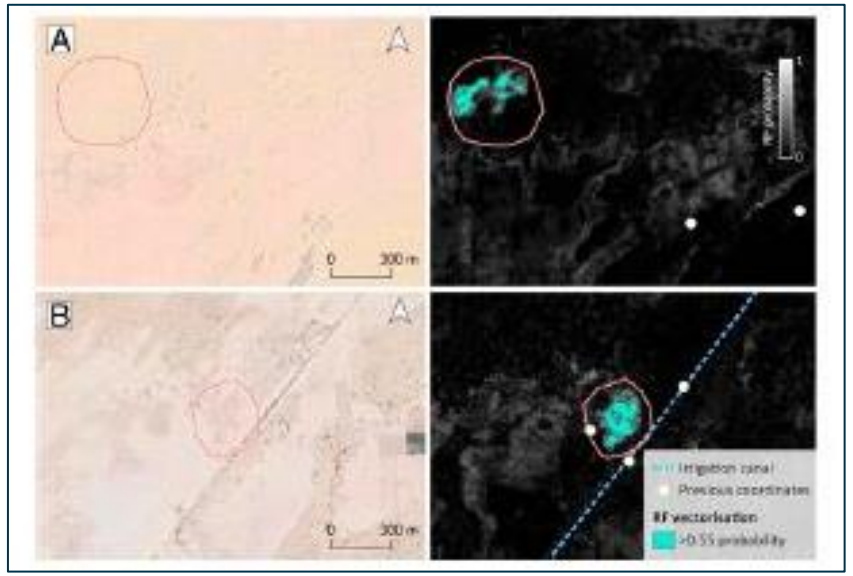

L. Carin , D. Carlson, T. Dunn, K. Liang, Introduction to Machine Learning, Duke University, Coursera

PRELIMINARY RESULTS



H.A. Orengo et al. 2020

The preliminary results of this study

1) are currently being collected and checked within a relational database and a GIS through Error Rate with Cross-Entropy Validation;

2) will enrich the existing archaeological datasets about the hunter-gatherer/early herder groups populating the EWD during the Early and Mid-Holocene;

3) will provide essential information about the human mobility patterns between the Eastern Sahara and the Nile Valley during the same period, shedding new light on the contribution of these communities to the emergence of the Egyptian late prehistoric and Predynastic cultures.

CONCLUSIONS AND FUTURE PROSPECTS

This study will offer an effective approach to overcome many difficulties of ground-based surveys, especially in Egypt where, after 2015, access to the EWD was reduced and denied by the Egyptian Authorities due to security and safety concerns.

In fact, despite the efforts of several international research groups to identify and assess the distribution of these features, right now it is impossible to bring to light new sites or study the known sites via traditional ground-based surveys.

The application of a remote, automated, precise, and cost-effective methodology for feature detection and analysis will help the archaeological research overcome these obstacles and open new lines of investigation.

REFERENCES

- S. Albawi , T.A. Mohammed, S. Al Zawi , Understanding of a Convolutional Neural Network , in 2017 International Conference on Engineering and Technology (ICET), 2017, DOI: 10.1109/ICEngTechnol.2017.8308186
- M. Amani , A. Ghorbanian , S.A. Ahmadi , M. Kakooei , A. Moghimi , S.M. Mirmazloumi , S.H.A. Moghaddam , S. Mahdavi , M. Ghahremanloo , S. Parsian , Q. Wu , B. Brisco , Google Earth Engine Cloud Computing Platform for Remote Sensing Big Data Applications: A Comprehensive Review , in IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing , 13, 2020
- B.E. Barich, G. Lucarini, M.A. Hamdan, F.A.Hassan, From Lake to sand. The Archaeology of Farafra Oasis, Western Desert Egypt, Monography 2014, ISBN: 978887145207
- R. Bennett, D. Cowley, V. De Laet , The data explosion : Tackling the taboo of automatic feature recognition in airborne survey data , in Antiquity 2014, 88, 896 905.
- I. Berganzo-Besga, H.A. Orengo, F. Lumbreras, M. Carrero-Pazos, J. Fonte, B. Vilas-Estévez. 2021. "Hybrid MSRM-Based Deep Learning and Multitemporal Sentinel 2-Based Machine Learning Algorithm Detects Near 10k Archaeological Tumuli in North-Western Iberia" Remote Sensing 13, no. 20: 4181. https://doi.org/10.3390/rs13204181
- J. Casana , Regional scale archaeological remote sensing in the age of big data. Automated site discovery vs. brute force methods in Advance in Archaeological Practice , 2(3), 222 233. doi:10.7183/2326 3768.2.3.222
- M.J. Harrower , J. Schuetter , J. Mccorriston , P.K. Goel , M.J. Senn , Survey, Automated Detection , and Spatial Distribution Analysis of Cairn Tombs in Ancient Southern Arabia. In Mapping Archaeological Landscapes from Space , in Mapping Archaeological Landscapes from Space 2013, 259 268, DOI: 10.1007/978 1 4614 6074 9_22
- K. Kvamme , An examination of automated archaeological feature recognition in remotely sensed imagery . In Computational Approaches to Archaeological Spaces ; Bevan , in Computational Approaches to Archaeological Spaces , 2020; pp.53 68.
- R. Lasaponara , N. Masini, Space Based Identification of Archaeological Illegal Excavations and a New Automatic Method for Looting Feature Extraction in Desert Areas , in Surveys in Geophysics 2018, 39, 1323 1346, https://doi.org/10.1007/s10712 018 9480 4
- R. Lasaponara, N. Abate and N. Masini. 2022. “On the Use of Google Earth Engine and Sentinel Data to Detect “Lost” Sections of Ancient Roads. The Case of Via Appia” IEEE Geoscience and Remote Sensing Letters 19, no. 3001605: 1-5. https://doi.org/10.1109/LGRS.2021.3054168.
- G. Lucarini. 2011. “Il Paesaggio Antico di Sheikh el Obeiyid (Farafra). La Playa e il Villaggio tra Tecnologia e Aspetti Simbolici” Scienze dell'Antichità 17: 45-60. Permalink: http://digital.casalini.it/3086888
- N. Masini, R. Lasaponara , Sensing the Past from Space: Approaches to site detection . Sensing the Past , in Geotechnologies and the Environment, 2017, 16, 23 60, https://doi.org/10.1007/978 3 319 50518 3_2
- N. Masini, R. Lasaponara , Recent and Past Archaeological Looting by Satellite Remote Sensing: Approach and Application in Syria , in Remote Sensing for Archaeology and Cultural Landscapes 2020, 123 137, https://doi.org/10.1007/978 3 030 10979 0_8
- H.A. Orengo, F.C. Conesa , A. Garcia Molsosa , A. Lobo, A.S. Green, M. Madella , C.A. Petrie , Automated detection of archaeological mounds using machine learning classification of multisensor and multitemporal satellite data , in Proceedings of the National Academy of Science of the United States of America , PNAS 2020, 117, 31, 2020, pp. 18240 18250
- K. O'Shea, N. Ryan , An Introduction to Convolutional Neural Networks , in ArXiv e prints , 2015, DOI: arXiv:1511.08458 [cs.
- L. Rayne , J. Bradbury, D. Mattingly, G. Philip, R. Bewley , A. Wilson, From Above and on the Ground: Geospatial Methods for Recording Endangered Archaeology in the Middle East and North Africa , in Geosciences 2017, 7, 100, 1 31, doi:10.3390/geosciences7040100
- D. Tapete , F. Cigna, Donoghue , D.N.M., Looting marks ’ in space borne SAR imagery : Measuring rates of archaeological looting in Apamea (Syria) with TerraSAR X Staring Spotlight , in Remote sensing of environment , 178, 42 581

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Thank you