An investigation of the synergistic use of Sentinel-1 and Sentinel-2 data for wetland classification: a case study from Greece

Andromachi Chatziantoniou[1]*, George P. Petropoulos[2], Emmanouil Psomiadis[1]

(1) Department of Natural Resources Management and Agricultural Engineering, Agricultural University of Athens, Greece
(2) Department of Geography and Earth Sciences, University of Aberystwyth, SY23 2EJ, United Kingdom

AGRICULTURAL UNIVERSITY OF ATHENS
ΓΕΩΠΟΝΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

PRIFYSGOL ABERYSTWYTH UNIVERSITY

*Author of correspondence: andromachi.chatz@gmail.com

1. INTRODUCTION

Developing accurate and robust techniques for **mapping and monitoring changes wetland ecosystems** is of crucial importance in water resources management. The recent launch of EO instruments such as that of the Sentinels series from the European Space Agency (ESA) opens up new opportunities for exploring the development of techniques that will allow improving our ability to map wetland ecosystems from space. This **study aims** at evaluating the use of **Sentinel 1 Synthetic Aperture Radar (S1 SAR) & Sentinel 2 (S2) data** combined with the advanced classification algorithm **Support Vector Machines (SVMs)** for mapping a typical wetland ecosystem in Greece.

The **study objectives** were: (1) to evaluate the **performance of SVMs classifier** in combination with S2 data, and, to assess the **added value** of (2) the use of **S1 data**, (3) the use of Principal Component Analysis (**PCA)** and Minimum Noise Fraction (**MNF)** transformations and (4) the use of **Grey Level Co-occurance Matrix (GLCM)** to the classification accuracy.

2. STUDY SITES & DATASET

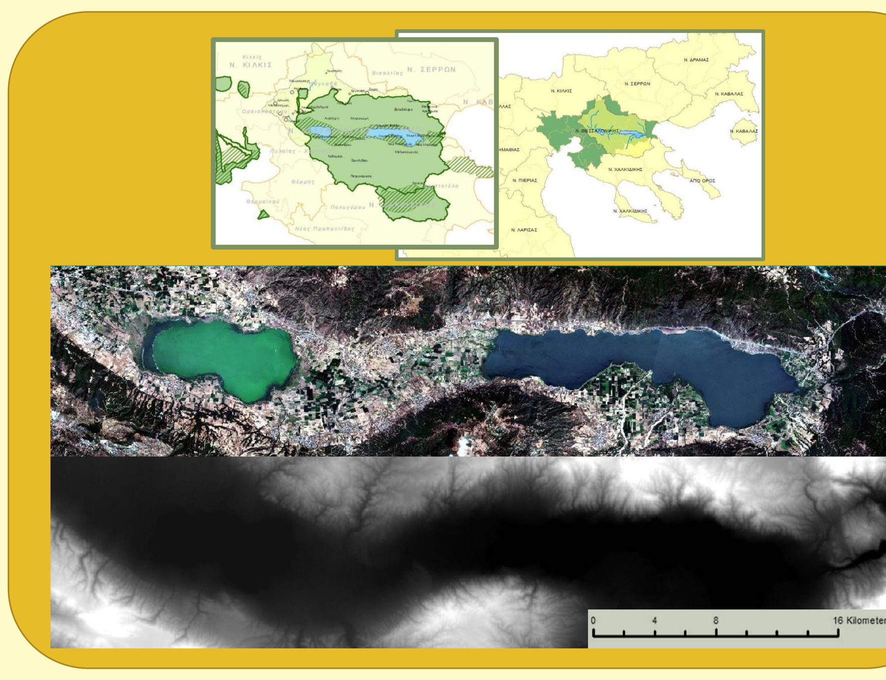
The National Park of Koronia and Volvi lakes is one of the most important Ramsar wetlands of Greece. A large number of plants (aquatic and terrestrial), animals, birds and fish reproduce, nest, feed and rest in the wetland habitat. The wetland is protected by numerous national and international conventions and is also included in the European ecological network of protected sites "NATURA 2000" **[4].**

Datasets:

- **Sentinel 2** MSI images acquired on 02.08.2016 and 28.01.2016 at processing level 1C*
- **Sentinel 1** SAR SLC image acquired on 02.08.2016*
- **SRTM** DEM 1arcsec (v2)

*provided free of charge via ESA's Sentinels Scientific Data Hub (https://scihub.copernicus.eu/)

All data are in the WGS84 reference system and UTM projection, zone 34. The software used for data processing was SNAP 5.0.0 and ENVI 5.1.



3. METHODOLOGY (1) preprocessing (2) training and validation samples selection (3) SVMs parameters optimization (4) classification (5) accuracy assessment

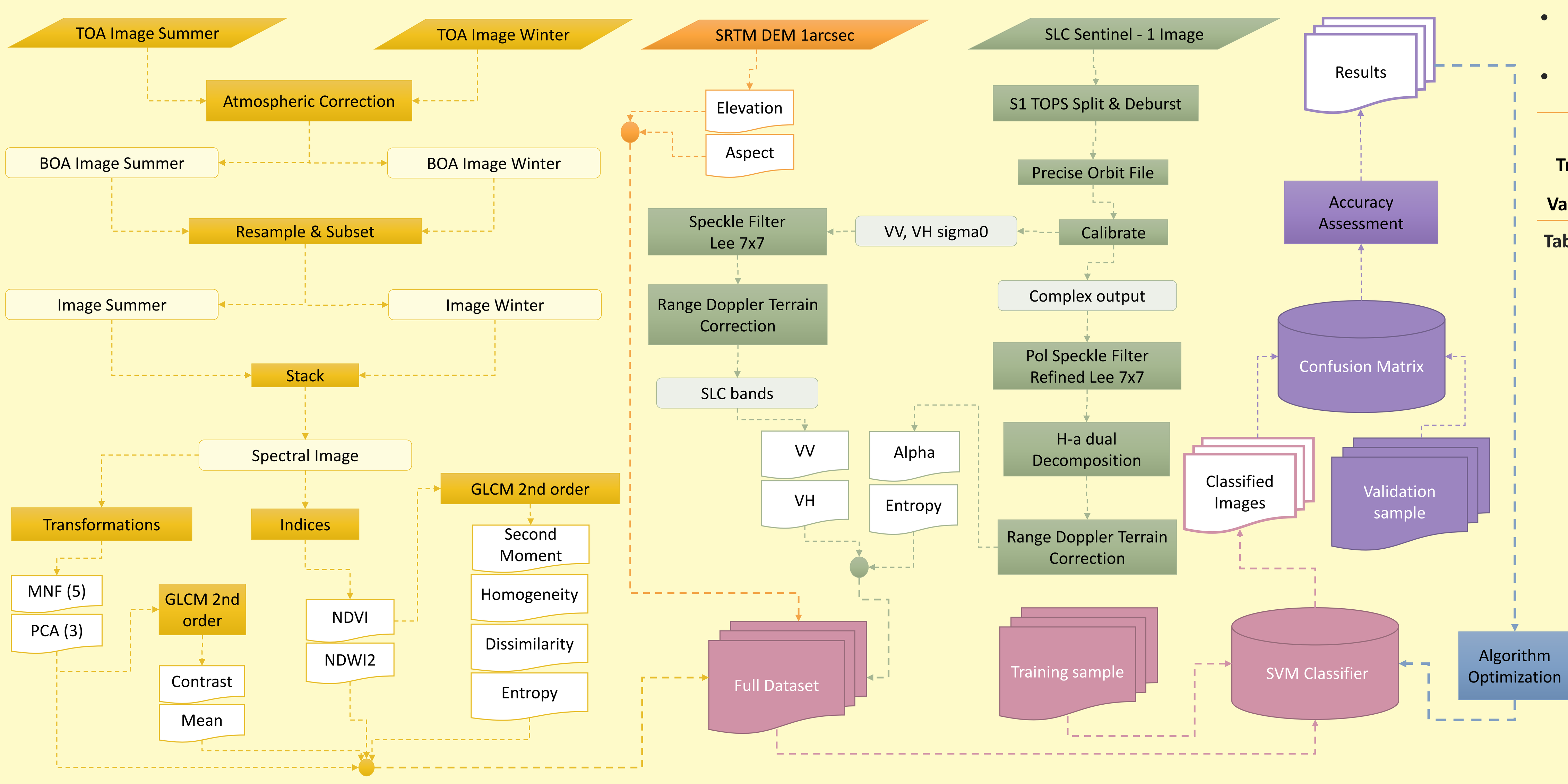


Figure 1: *Flowchart of the methodology implemented in this study*

- **Atmospheric correction** applied in SNAP to convert the Top-of-Atmosphere reflectance values (TOA) to corrected Bottom-of Atmosphere reflectance values (BOA).
- Implemented **indices**: **1**. NDVI= (NIR-R)/((NIR+R) **2**. NDWI2=(NIR-G)/((NIR+G)

	marshes	swamps	forest	shrubs	crops	sand	soil	urban	water
Training	857	681	2741	853	1457	1188	1493	1862	2856
Validation	200	120	550	170	300	200	300	370	570

Table 1: *Training and validation points for each class*

LULC Classes	Class description
Crops	No - wetland class, healthy and high yield arable farming land
Water	Wetland class, exposed surface water
Urban	No - wetland class, impervious surfaces, urban fabric, roads, industrial facilities
Forest	No - wetland class, mixed forest with trees from medium to large size
Shrub	No-wetland class, long or short grass species, sparse trees and bushes
Sand	No - wetland class, exposed lake, river or estuarine bed, coarse sand
Soil	No - wetland class, bare land, very low or no vegetation
Marshes	Wetland class, aquatic plants that is either emerge, submerge or floating in water
Swamps	Wetland class, aquatic forest or shrubs

Table 2: *Description of selected LULC classes*

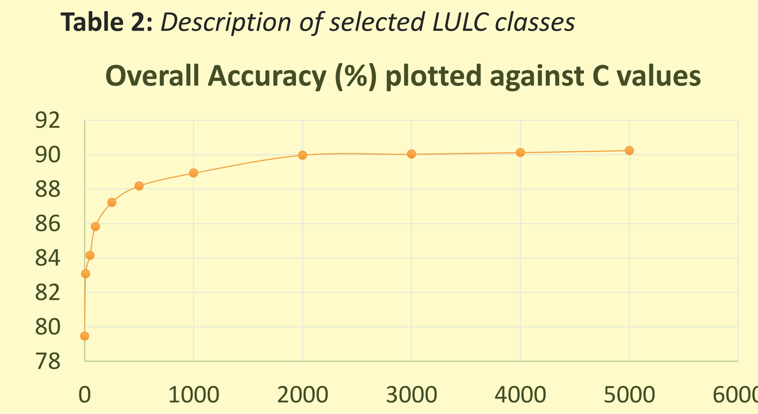
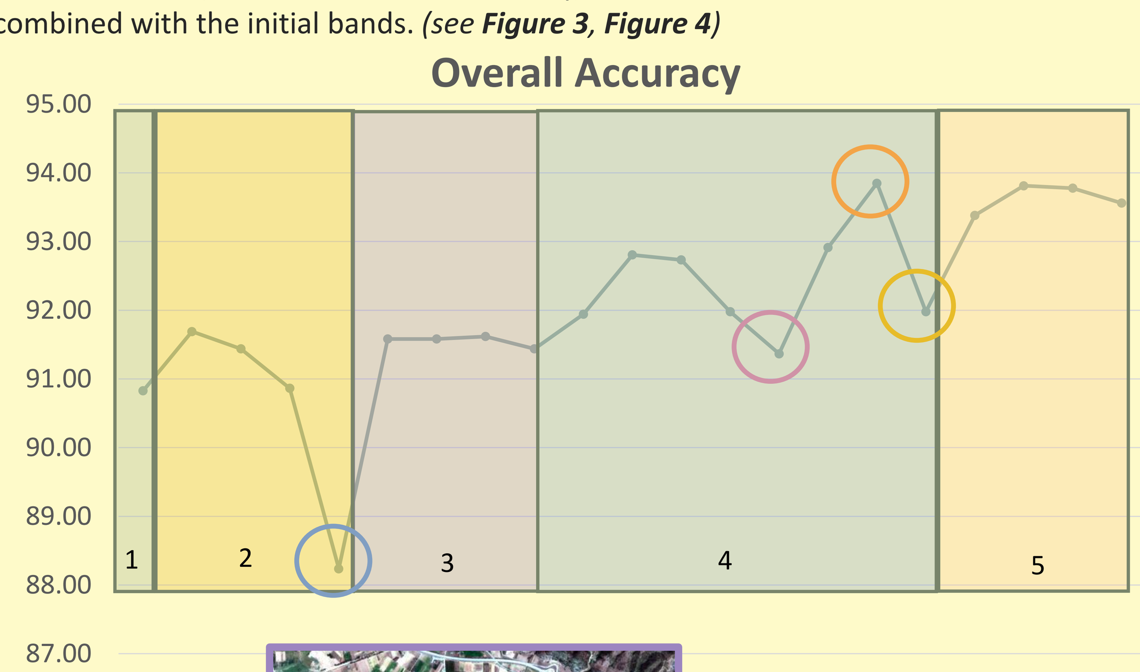


Figure 2: For the SVM classification, the RBF kernel function was used. The γ value was kept as suggested, *1/number of features*. After several tests, the optimum C value was found at 2000. From a C value of 1, overall accuracy was rapidly rose up to 500 before beginning to plateau off at 2000

4. RESULTS

- Accuracy assessment was carried out on the basis of the **overall accuracy (OA)** and **kappa (K)** statistics. In addition, each class accuracy was evaluated separately using User's and Producer's accuracy (UA, PA) and **mapping accuracy (MA)**. The detailed error matrix was also computed for each of the classification images as it allowed evaluating the UA and PA accuracy for each of the information classes included in our classification scheme.
- Five datasets were created and the **different scenarios** were tested
  (1) S2 bands ***(2)*** Transformations added value ***(3)*** SAR added value ***(4)*** GLCM added value ***(5)*** Multiseasonal approach added value
- The **best results**, in terms of overall accuracy, were achieved with the addition of **texture** information (GLCM analysis) and, also, when a **multiseasonal** approach was attempted. The transformed components seem to increase the overall accuracy only when they are combined with the initial bands. *(see **Figure 3, Figure 4**)*



$$MA = \frac{\text{Pixels of } X_{correct}}{\text{Pixels of } X_{correct} + \text{Pixels of } X_{omission} + \text{Pixels of } X_{commission}}$$

- Only B,G,R,NIR of the original bands and MNF C2, C5, PC3
- Only SAR Alpha and Entropy
- Mean MNF C2, C5 added to GLCM
- Aspect added

Figure 3: *(left)* Classification overall accuracy (OA) for the different scenarios represented by coloured areas. Each scenario includes 4-5 trials.

Figure 5: *(below) Classified image, version 2.4.7. Includes original S2 bands, PC1-3, MNF C1-5, NDVI, NDWI2, VH σ⁰, GLCM NDVI bands: Homogeinity, Dissimilarity, Entropy, Second Moment, GLCM MNF bands: Mean MNF C2, Mean MNF C5*

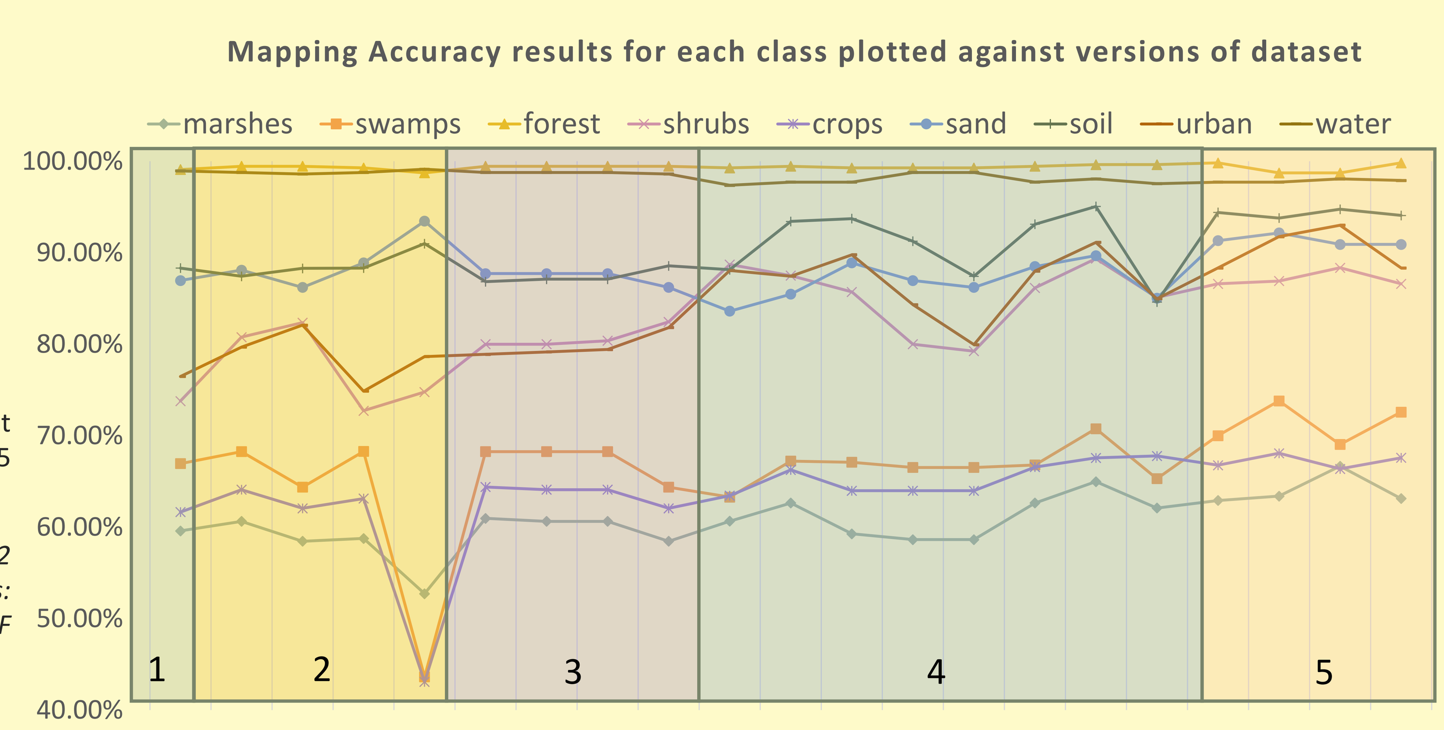
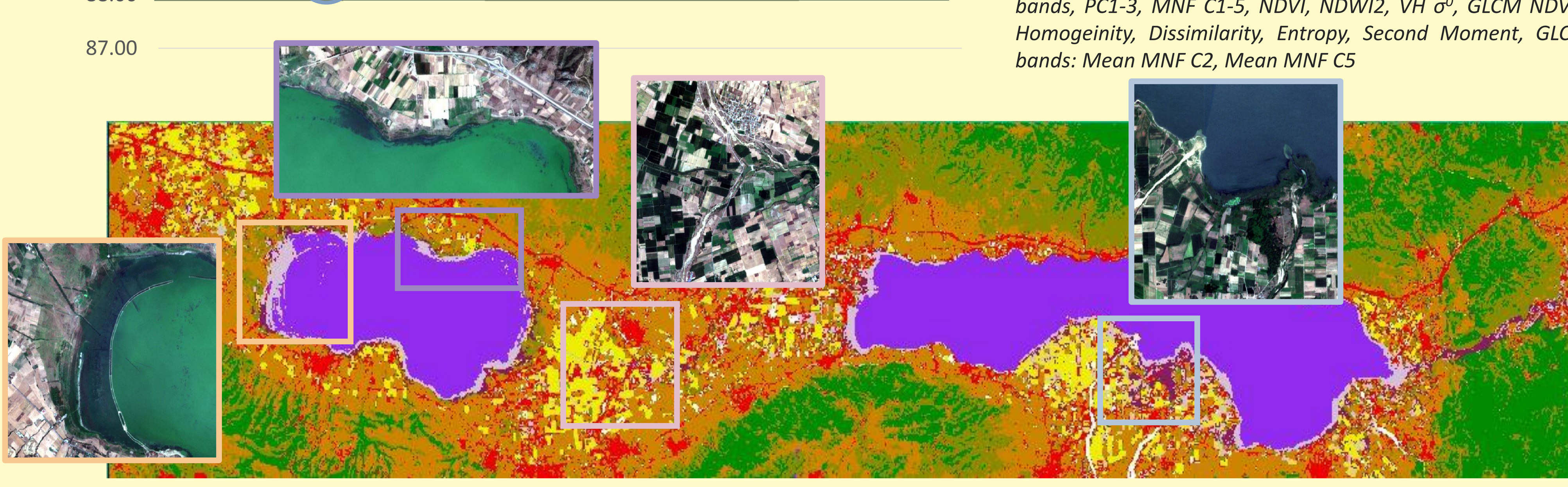


Figure 4: *(right)* Classification mapping accuracy (MA) results for each Class for all scenarios representedby colored areas. Each scenario includes 4-5 trials.

- Very high accuracies were achieved in forest and water classes most likely due to the use of NDVI and NDWI2 indices and the information on elevation.
- Adequately high accuracies were achieved in soil, sand, urban and shrubs classes. This was likely due to their low spectral separability. While the image was acquired in mid-summer, the presence of moisture is significantly low on the ground which can lead to high reflectance values and, thus, confusion between artificial surfaces and natural surfaces with no or limited vegetation (soil, sand, shrubs).
- Medium accuracies were achieved in crops, marshes and swamps classes. Classes with high humidity and dense healthy vegetation are difficult to be distinguished. Information on elevation did not help in this case, because most of the agricultural land lies at the same altitude as aquatic vegetation near the lakes. An object-based method could likely improve the classification accuracy on these classes.



5. DISCUSSION & CONCLUSIONS

In overall, results exemplified the appropriateness of the Sentinel imagery combined with the SVMs in obtaining a mapping of the wetlands area.

- The **transformed components (PC1-3, MNF C1-5)** **increased** the overall accuracy **~1%** only when they were combined with the original S2 bands.
- **MNF** slightly **outperformed PCA** in the results **(~4%)**.
- The implementation of **SAR data** did not increase the overall accuracy significantly, but **increased the separability** between some classes *(crops, swamps, marshes).*
- The highest accuracies **(up to 93.85%)** achieved with the addition of information on the **texture (GLCM analysis).** This **also improved the individual accuracies** for some classes *(i.e. soil class maximum ~8%).*
- The **multiseasonal approach** seems to **improve the classification of vegetation classes** *(especially crops)* and it would be useful to be further investigated.

This study aimed to investigate ***the synergistic use of Sentinel spectral and SAR data*** as well as the ***additional information derived from them***, combine with ***contemporary algorithms*** to assist ***wetland management***. This investigation is of considerable scientific and practical value, as it strengthens evidence on the ***suitability of synergistic use of Sentinel data*** for improving our ability to understand better Earth's physical process and physical environment. Yet, to our knowledge, the use of ***contemporary classification algorithms*** (e.g. Support Vector Machines) combined with ***Sentinel*** imagery ***has not been adequately investigated so far***. In this context the use of other classifiers (e.g. decision trees, object-based) would be interesting to be investigated combined with multi-seasonal imagery, as could also potentially assist in improving thematic information extraction accuracy.

5. REFERENCES

[1] Kavzoglu, T. and Colkesen, I. (2009). A kernel functions analysis for support vector machines for land cover classification. International Journal of Applied Earth Observation and Geoinformation, 11(5), pp.352-359. **[2]** Manandhar, R., Odeh, I. and Ancev, T. (2009). Improving the Accuracy of Land Use and Land Cover Classification of Landsat Data Using Post-Classification Enhancement. Remote Sensing, 1(3), pp.330-344. **[3]** Munyati, C. (2004). Use of Principal Component Analysis (PCA) of Remote Sensing Images in Wetland Change Detection on the Kafue Flats, Zambia. Geocarto International, 19(3), pp.11-22. **[4]** Perivolioti T., Mouratidis A., Doxani G., Bobori D. (2016). Monitoring the water Quality of Lake Koroneia using long time – series of multispectral satellite images. ESA Living Planet Symposium 2016, Prague. **[5]** Zhang, Y., Zhang, H. and Lin, H. (2014). Improving the impervious surface estimation with combined use of optical and SAR remote sensing images. Remote Sensing of Environment, 141, pp.155-167.