ECTI Transactions on Computer and Information Technology
Journal homepage: https://ph01.tci-thaijo.org/index.php/ecticit/
Published by the ECTI Association, Thailand, ISSN: 2286-9131

Fine-Grained Land Segmentation for Climate Change Impact Assessment: Leveraging the DeepGlobe Dataset with Advanced AI-driven Geospatial Analysis Techniques

Soukaina El Maachi[1], Rachid Saadane[2], Mohamed Wahbi[3] , Abdellah Chehri[4] and Abdelmounaim Badaoui[5]

ABSTRACT

As our planet experiences unprecedented heat waves, ice melting, and a steady rise in average temperatures, the unmistakable impact of global climate change is apparent. This environmental crisis has been recognized as the “greatest global health threat of the twenty-first century,” urging the international community to take action. In response to this urgent call, nations worldwide have come together to address the challenges posed by climate change. The Paris Agreement and the Sustainable Development Goals are beacons of hope, signifying the collective commitment to a sustainable future. In this paper, we suggest land segmentation using deep learning to solve modeling and monitoring environmental phenomena as a way in which Artificial Intelligence could benefit the current efforts toward climate change mitigation endeavors. Using the DeepGlobe dataset, we suggest a deep learning-based method for land segmentation in this study to shed light on the impacts of climate change on land cover. We use the DeepGlobe dataset, which comprises high-resolution satellite images classified into several types of land cover. To execute pixel-level land segmentation and automatically extract complicated spatial information from the imagery, our suggested methodology utilizes a deep convolutional neural network architecture. By using the DeepGlobe dataset to train the model, we can take advantage of its broad coverage and variety of land cover classes, improving the model’s capacity to generalize across multiple geographical regions. By monitoring and modeling the impacts of global climate change on agriculture, water resources depletion, and coastal erosion. We conclude that by allowing for more specialized and efficient land use management, conservation, and restoration measures, artificial intelligence can help in the fight against climate change.

Article information:

Keywords: Climate Change, Artificial Intelligence, Smart Agriculture, Remote Sensing, Water Resources, Coastal Erosion, Sustainable Development, Satellite Imagery

Article history:
Received: February 2, 2023
Revised: May 1, 2023
Accepted: August 10, 2023
Published: December 16, 2023 (Online)

DOI: 10.37936/ecti-cit.2023174.251544

1. INTRODUCTION

As our planet experiences unprecedented heatwaves, ice melting, and a steady rise in average temperatures, the unmistakable impact of global climate change is apparent. This environmental crisis has been recognized as the “greatest global health threat of the twenty-first century,” urging the international community to take action. In response to this urgent call, nations worldwide have come together to address the challenges posed by climate change. The Paris Agreement and the Sustainable Development Goals are beacons of hope, signifying the collective commitment to a sustainable future. These landmark initiatives emphasize the urgent need to adopt eco-friendly practices, promote human development, and safeguard our precious biosphere for generations to come. Through international cooperation, the world is uniting in a shared endeavor to combat climate change and its far-reaching consequences [1]. This collective effort reflects the unwavering determina-

[1,2,3] The authors are with SIRC-LAGES-EHTP Hassania School of Public Works, Casablanca, Morocco, E-mail: soukaina.elmaachi.cedoc@ehtp.ac.ma, saadane@ehtp.ac.ma
[4] The author is with Dep. Math. and Computer Science Royal Military College. Kingston, Canada E-mail: chehri@rmc.ca
[5] The author is with LASTIMI-EST University Mohamed V. Sale, Morocco, E-mail: abadaoui est@yahoo.fr

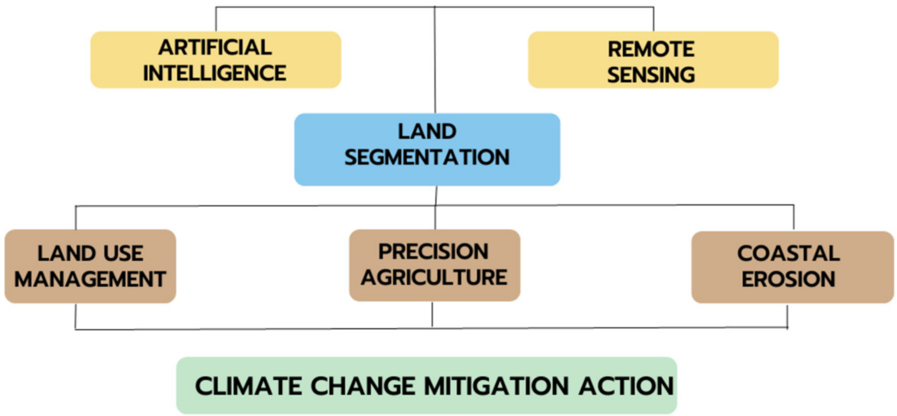

Fig. 1: *Paper outline.*

tion to steer our planet toward a greener, more resilient future, where environmental preservation and human well-being go hand in hand. As the journey unfolds, the world's determination to tackle climate change continues to grow, illuminating a path toward a better and more sustainable world for all. However, the effects of climate change can be resolved or mitigated with the aid of artificial intelligence applications, especially considering the significant contribution that big data analytics and learning systems in the cloud are making to developing new intelligent services. It is now possible to collect data more accurately and in real-time, thanks to the proliferation of standards, open-source software and hardware and inexpensive sensors [2]. Accurate land segmentation is essential for comprehending the implications of climate change since it has a major impact on patterns of land cover. This work uses the DeepGlobe dataset and deep learning algorithms to segment the land using the DeepGlobe dataset. The DeepGlobe dataset is a vast array of high-resolution satellite images classified according to types of land cover. With a focus on land segmentation problems, it was specifically curated to support research and development in the fields of computer vision and remote sensing. The dataset offers a large and varied collection of imagery that spans numerous geographical areas and types of land cover. Understanding the connection between land cover changes and climate change can help develop efficient solutions for climate change adaptation and mitigation.

1.1 Organization:

This paper discusses the potential of artificial intelligence (AI) to mitigate the impacts of climate change on agriculture and coastal erosion. The focus is on applying deep learning techniques to perform land segmentation for improved monitoring of agricultural and coastal areas. The paper's structure is as follows: Section 2 introduces climate change in the context of the UN's sustainable goals. Section 3 presents projects that have been implemented worldwide to mitigate the effects of climate change through the raw use of sensors. Section 4 presents the incorporation of AI in sustainable development driven by technological advancements. Section 5 provides an overview of remote sensing and its contribution to understanding climate systems and fluctuations. In Section 6, we propose a deep learning algorithm for land segmentation, utilizing the DeepGlobe dataset known for its suitability in fine-grained land segmentation and climate change analysis. We compare this approach to state-of-the-art projects discussed in Section 3, aiming for better land monitoring and management to mitigate climate change effects. The paper concludes in Section 7, summarizing its key find ings and contributions.

2. CLIMATE CHANGE

Over the very recent history of the planet, our species has rapidly transformed from being one of the millions of species on Earth to being the species that is singularly changing the whole world to suit its own needs. Scientists now refer to humanity's fluence during this time as the "great acceleration" since this planetary alteration has been so quick and profound. Leading climate scientist James Hansen of the National Aeronautics and Space Administration and three other senior researchers testified to a US Congressional committee in 1988. He was confident that the warming trend in Earth's temperature observed at the time was caused by the accumulation of carbon dioxide and other "greenhouse" gases and not by natural variation [3]. Hansen was criticized at the time and subsequently for his "adventurous" interpretation of climate data. Still, the attention that accompanied his speech reflected a decade of growing concern about climate change's geopolitical implications. A Lancet editorial on health and the "greenhouse effect" was released in less than a year. In 1989, two more academic articles on climate change and health were also published. The 1989 ed-

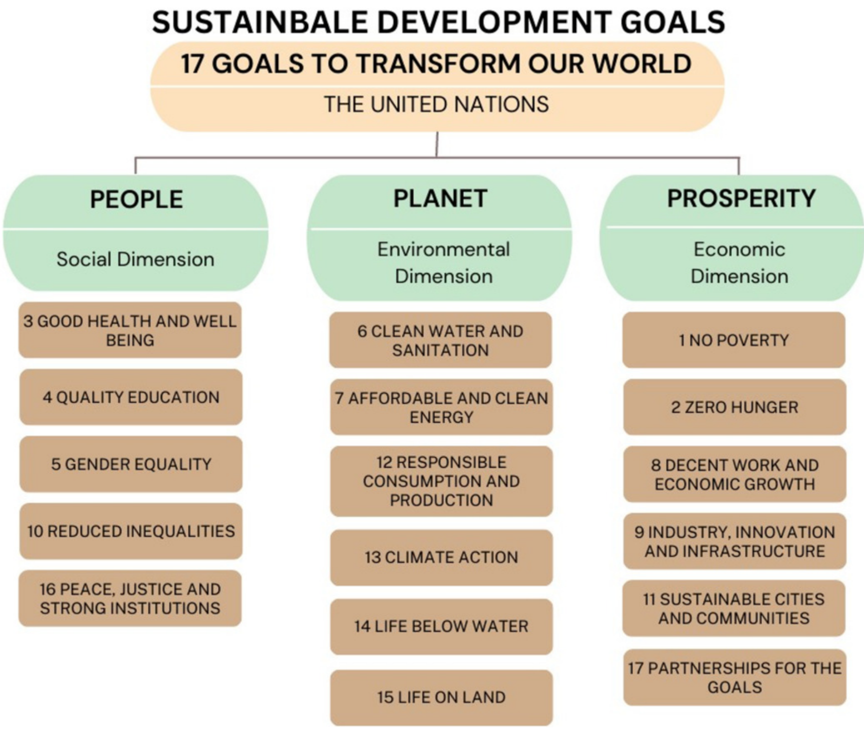

Fig.2: *Social, environmental, and economic dimensions of SDGs [5].*

itorial specified that "global warming, increased ultraviolet flux, and higher levels of tropospheric ozone will reduce crop production, with potentially devastating effects on world food supplies. Malnutrition might become commonplace, even among developed nations, and armed conflicts would be more likely as countries compete for a dwindling supply of natural resources" [3]. Climate change was finally named the "greatest global health threat of the twenty-first century," according to a Lancet and University College London Institute for Global Health Commission paper published in 2009, which called it the "largest global health threat of the twenty-first century".

2.1 Climate Change at the Heart of International Green Efforts

The international community established an ambitious agenda for going green, promoting human development, and preserving the biosphere with the adoption of the Paris Agreement and the Sustainable Development Goals (SDGs) illustrated in Fig.2. However, to be effective, it must be implemented to integrate climate policy with more fundamental sustainable development goals. A common vision for advancing a sustainable economy, society, and environment is embodied in the 17 Sustainable Development Goals (SDGs) outlined in the UN 2030 Agenda. [4] Accordingly, governments have begun collaborating through international initiatives and assessing performance concerning the SDGs on social, environmental, and economic levels [3].

2.2 Climate Change Impact on Agriculture

The demand for food products is predicted to dramatically increase as the world population increases from 1.8 billion in 2009 to 4.9 billion in 2030 [7][13]. In the Mediterranean region, agriculture is the sector that contributes the most to overall water abstractions. Due to altered weather patterns and the ensuing biophysical repercussions, the agriculture industry is, on the one hand, directly impacted by climate change [8]. On the other hand, over a quarter of anthropogenic greenhouse gas (GHG) emissions are attributable to land use, including agriculture, forestry, and other activities. As such, reducing agricultural emissions is essential to achieving the goals of the international community on climate change [8].

2.3 Climate Change Impact on Coastal Erosion

Another significant environmental shift is the relative rise in sea level since it indicates an increase in the demand for sediment, which, if unmet, leads to a coastal retreat. Erosion ensues when higher sea levels allow waves to break closer to the coast and send more wave energy to the shoreline [9]. Current predicted sea-level changes estimate a rise of up to 0.6 m by 2100 [10]. The Regional Seas Program (RSP) was founded by the United Nations Environment Program (UNEP) in 1974 to coordinate regionally based efforts to safeguard the maritime environment. The first UNEP project created under the RSP was the Mediterranean Action Plan (MAP), which served as a template for other waters worldwide [11]. Hence, managing coastal areas is a must and necessitates a systematic and comprehensive approach to mitigate the impacts of coastal erosion.

3. RELATED WORK AND LITERATURE REVIEW:

Using scientific and engineering techniques to prove ecological conditions is the focus of the comprehensive environmental monitoring and management field. Understanding how to monitor, simulate, and regulate ecological processes efficiently is a vital concern. In this section, we provide initiatives implemented in the IoT field to combat climate change impacts [6].

3.1 An Integrated System for Regional Environmental Monitoring and Management Based on the Internet of Things [6]

In [6], a novel Intelligent Information System (IIS) has been developed for regional environmental monitoring and management, built on the framework of the Internet of Things (IoT). The IIS architecture consists of four layers: Perception Layer, Network Layer, Middleware Layer, and Application Layer.

The Perception Layer facilitates data collection. The Network Layer ensures data transmission and interconnections, often employing short-range wireless networks. The Middleware Layer decomposes complex systems into simpler components. Lastly, the Application Layer is responsible for storing, processing, and sharing environmental data using cloud and e-science platforms.

To validate the system, it utilized multisource datasets, including 50 years of meteorological data, prediction data of air temperature and precipitation, and ten years of Modis's datasets. The findings revealed a global warming trend, with the mean annual air temperature rising by 1.24°C over the past 50 years.

3.2 An Open Source and Low-Cost Internet of Things enabled Service for Irrigation Management [12]

This project introduces LoRaWAN, which combines long-range communication, low power consumption, and secure data transmission. The primary goal of this project is to improve irrigation management techniques by enabling real-time computation of crop water demand using soil and weather data. A Weather Station for monitoring meteorological variables and a Field Station for measuring soil moisture and applied water were used[12][14]. The LoRaWAN network server, based on Pycom LoPy 1.0, transmits data that can be programmed in MicroPy- thon. The gateway platform comprises a concentrator iC880A, a Raspberry Pi, a preconfigured SD- card, and an aluminum housing [12]. For managing and visualizing the collected data, an open-source solution was employed, enabling real-time analysis and visualization of incoming telemetry. Farmers can access the irrigation management service through a web application connected to the LoRaWAN server and the application backend system deployed on the public cloud. This project was piloted for three years in citrus farming in Sicily, to optimize irrigation practices and promote sustainable water usage.

3.3 Coastal Monitoring System based on Social Internet of Things Platform [9]

This study presents a coastal monitoring system designed to address the challenges of coastal erosion on the island of Sardinia, Italy. The system comprises a beach unit and a sea unit, each equipped with sensors to capture essential environmental data. The beach unit captures images for crowd detection and measures parameters like air temperature, humidity, wind direction, strength, and UV radiation. On the other hand, the sea unit measures water parameters such as temperature, pH, and wave motion.

With this coastal monitoring system, Italy aims to strike a balance between tourism management and protecting its valuable coastal ecosystems.[9]

Many studies have been conducted to achieve better land monitoring without entirely relying on sensors and using artificial intelligence with remote sensing instead. Tzepkenlis et al. [29] propose an efficient deep-learning method using Sentinel imagery. Puttinaovarat et al. [30] present a 2014 study using artificial neural networks and thematic layers. Boonpook et al. [31] focus on deep learning for land use classification with Landsat 8 imagery. These works highlight the progression from traditional techniques to modern deep learning approaches in land cover analysis, and showcasing the importance of different satellite data sources.

In the next section, we discuss artificial intelligence's potential considering modern-day technological advancements.

4. ARTIFICIAL INTELLIGENCE

Artificial intelligence uses computer power combined with large datasets to simulate the human brain's problem-solving flow and decision-making abilities. Machine learning and deep learning are subfields of AI that employ algorithms trained on data to produce predictions or classifications and provide insights. AI has several advantages, including the automation of repetitive jobs and enhanced decision-making. AI incorporation in sustainable development comes because of vast and varied technological advancements namely:

- Access to Opensource Technology: Open-source AI is defined as an artificial intelligence technology that is publicly available for commercial and non-commercial use under various open-source licenses. Datasets, prebuilt algorithms, and ready-to-use interfaces are all part of open-source AI.

- Open-source datasets: Data is the catalyst of novation. Data is used to train AI software, and the training and test data in open-source AI are both freely available. According to IBM, 2.5 quintillion bytes of unstructured data are created every day. Access to AI solutions instead of building them from scratch.
- Open-source algorithms: They are usually accessible as open-source algorithm libraries that can be used as-is, trained with open-source or enterprise data, or tweaked to make customized AI applications.
- Access to Computing Power: Data storage capacity increases in perfect sync with computational capability. There is almost a direct relationship between decreasing data storage prices and increasing data storage capacity. There is more room to innovate and build innsophisticated applications with the convenience and ability to store vast amounts of data.

5. REMOTE SENSING:

5.1 Remote Sensing: An overview

The term “remote sensing” describes the capturing of data and information about a phenomenon and a region without coming into direct touch with it. In-situ observation can be substituted with it.[15] [23]

The development of high-resolution optical satellite photography creates new opportunities for tracking changes on the surface of the world. When compared to aerial images, this data has the benefit of being practically universally available and, occasionally, having more spectral channels [16].

5.2 Benefits of Remote Sensing:

Areas that are difficult for people to get to or to approach without being noticed can be usefully revealed by aerial photos [19]. Aerial picture data is used in many different businesses, including land inventory, vegetation monitoring, and environmental assessment.

Examples of remote sensing applications that are also connected to practices for coping with climate change include:

• natural resource management;

• management of agricultural practices, such as land use, land conservation, and soil carbon stock;

• tactical forest fire-fighting operations in real-time decision support systems;

• monitoring of land cover and its changes over various temporal and spatial scales, even after a disaster event; and

• better informing decision-makers.[23]

For instance, the most significant issues in hydrometeorology are monitoring and forecasting extremely severe agricultural droughts. Numerous severe droughts in the twenty-first century seriously harmed global and local crop production. Technologies for agricultural drought monitoring and forecasting are urgently required to reduce drought hazards. That is when remote sensing is proper. In [21], To track and forecast agricultural droughts in North Africa, researchers used an ecohydrological land data assimilation system (LDAS), which can simulate soil moisture and leaf area index (LAI) through assimilation of microwave brightness temperature data into a land sur- face model (LSM). Using LAI and LDAS-calculated soil moisture, it is possible to track national crop failures in Morocco, Algeria, and Tunisia, which are indicated by drops in the country’s total wheat production. For Morocco, Algeria, and Tunisia, the correlation between the simulated LAI and the country’s wheat production is strong (r = 0.70, 0.65, and 0.72, respectively). LAI and agricultural droughts can be reliably predicted with a 2-3 month lead time using seasonal meteorological forecasts based on general circulation models (GCMs). This drought propagation, which encompasses both hydrological and ecological processes, should be carefully monitored to provide pertinent information to decision-makers, farmers, pastoralists [20], and others amid a drought. Inter-national Satellite Land Surface Climatology Project 2 soil data and the Food and Agricultural Organization global dataset [22], were used to make an initial estimation of the model’s unknown soil and vegetation parameters. The data’s accessibility on a global scale makes it possible to create topographic databases for almost any area of the planet. It can, therefore, assist numerous businesses to increase their output and quality of work, whether it is for military objectives, disaster relief, or prevention.[16]

Remote sensing has recently been employed to enhance our comprehension of the climate system and its fluctuations. It allows for the monitoring of the Earth’s surface, oceans, and atmosphere at various spatiotemporal scales, allowing for the observation of the climate system and the investigation of climate-related processes or long-term and transient events. Performing a visual inspection and manually digitizing aerial photographs are the significant components of the feature extraction process used to create a GIS. The primary approach for generating geographic data is still this, although manually extracting or identifying features requires much work and effort.

To create automated systems that analyze this data and perform valuable activities, the vast amount of data generated by remote sensing can be put into machine learning models. The most helpful data are those that have been labeled since supervised learn-

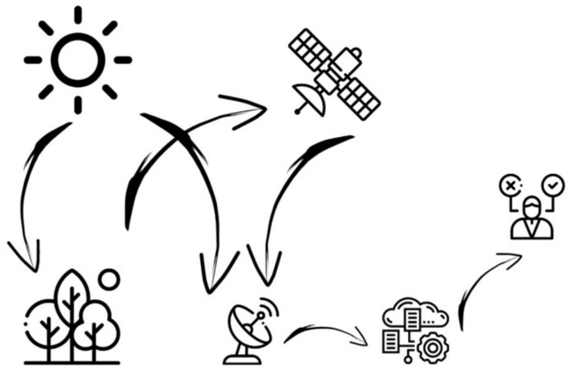

Fig.3: Diagram of Elements of a Remote Sensing System [25].

Fig.4: Aerial sensor systems to detect and classify objects on Earth by using propagated signals.

ing can use them to address a wide range of issues. [18]

6. LAND SEGMENTATION USING DEEP LEARNING:

6.1 Land segmentation: An overview

Any long-term landscape planning projects dependent on present and previous land usage must include credible land cover or habitat maps. High spatial resolution habitat maps covering broad areas will provide direction for land-use management, particularly in locations where sustainable management of natural resources is a goal. We provide a computational method for automatically identifying ecosystems using aerial photography. Ultimately, by prioritizing land uses and assessing habitat services, this technique could be utilized to support specialists, policymakers, and decision-makers who support sustainable agroecology.[17]

These maps are typically constructed from aerial or satellite photographs with the land category, such as meadows, fields, or hedges, annotated by a human expert. Even for geomatics experts [17], with the high image resolution of up to 10 cm/pixel and the skilled hand and eye precision, this task is arduous and prone to misunderstandings. Additionally, it takes a long time to complete: human expert needs 48 hours to annotate a 4 km^2 aerial image with a 50 cpi resolution.

Deep learning has recently been used to solve various computer vision-related issues, including picture classification, object segmentation, and semantic segmentation. Additionally, convolutional neural networks (CNNs), a type of deep learning technology, have drawn much interest for their ability to identify objects in satellite photos. [26]

Deep learning and other contemporary AI technologies can be used to automate and support processes that have historically been handled by humans in several sectors of natural science. Today, high-quality data in large quantities that are updated regularly are provided by remote sensing. In contrast to other sources, such as aerial photography, which are of higher quality but are produced more expensively and in smaller quantities, these data are quickly produced and accessible to the public. [18]

To achieve semantic segmentation for roads and buildings from satellite images, several semantic segmentation models based on deep learning techniques such as fully convolutional networks (FCNs), Deeplabv3, UNet...etc. In this section, we use UNet as an architecture to segment land coverage.

6.2 UNET:

Convolutional networks are frequently employed for classification tasks in which the output of an image is a single class label. The desired output, or the assignment of a class label to each pixel, should incorporate localization in many visual tasks, particularly in precision agriculture image processing. This model has been introduced in [27], and is a network and a training technique that makes heavy use of data augmentation to better use the given annotated samples. The architecture comprises a symmetric expanding path that permits exact localization and a contracting path to capture context. The u-net is a convolutional network architecture for quick and accurate image segmentation. So far, it has exceeded the previous best technique (a sliding-window convolutional network) for segmenting neural structures in electron microscopic stacks for the ISBI challenge. It won by a vast proportion the Cell Tracking Challenge at ISBI 2015 and the Grand Challenge for Computer-Automated Detection of Caries in Bitewing Radiography, which are the two most challenging categories of transmitted light microscopy (Phase contrast and DIC microscopy).

Fig.6 shows the network architecture in detail. It comprises an expanded path on the left and a contracting path on the right (right side). The contracting path adheres to the standard convolutional network architecture. Two 3×3 convolutions (unpadded convolutions) are applied repeatedly, and after each one, a rectified linear unit (ReLU) and a 2×2 max pooling operation with stride two are applied for down-sampling. We quadruple the number of feature channels with each downsampling step.

6.3 Dataset:

The DeepGlobe dataset is a collection of labels and satellite images created for deep learning-based geospatial image analysis tasks. It was developed in the context of the DeepGlobe Challenge, a competition that aims to enhance cutting-edge approaches to geospatial image processing.

The DeepGlobe dataset comprises three components:

- Road Extraction: This dataset includes road networks' labels and high-resolution satellite imagery. The objective is to develop models reliably extracting road networks from satellite photos.
- Building Extraction: This collection includes high-resolution satellite imagery with building footprint labels. The objective is to develop models that can precisely extract building footprints from satellite photos.
- Land Cover Classification: This dataset contains multi-spectral satellite imagery and labels of land cover classes. The goal is to train models that can accurately classify land cover types, such as forests, water bodies, and urban areas.

In this paper, we use the latter, which is The Land Cover Classification Track in DeepGlobe's 2018 Challenge, as the source of the dataset, which was obtained via Kaggle [28] and collected by DigitalGlobe's satellite. Fig.7 provides examples of images from the dataset with their corresponding ground truth images.

The training data for Land Cover Challenge contains 803 satellite imagery in RGB, size 2448×2448. 2448×2448 is too large for our model, so we applied data augmentation and divided the images into smaller patches. Each image has a 50cm pixel resolution. The dataset contains 171 validation and 172 test images with no masks. We create a test dataset by combining the original validation and test images, dividing the training dataset, and selecting a section for validation with masks. Each satellite image comes with a mask image for land cover annotation. The mask is a RGB image with seven classes of labels, using color-coding (R, G, B) as follows:

Urban land: 0,255,255 - Man-made, built-up areas with human artifacts (can ignore roads for now are hard to label)

Agriculture land: 255,255,0 - Farms, any planned (i.e, regular) plantation, cropland, orchards, vineyards, nurseries, and ornamental horticultural areas; confined feeding operations.

Rangeland: 255,0,255 - Any non-forest, non-farm, green land, grass

Forest land: 0,255,0 - Any land with x

Water: 0,0,255 - Rivers, oceans, lakes, wetlands, ponds.

Barren land: 255,255,255 - Mountain, land, rock, desert, beach, no vegetation

Unknown: 0,0,0 - Clouds and others

An example of our dataset is shown in Fig.6.

The overall methodology we followed:

1- Download DeepGlobe aerial data.
2- Load data.
3- Data augmentation and image preprocessing
4- Select the adequate network model.
5- Train data
6- Test on the validation dataset.
7- Tune parameters and hyperparameters of the model where necessary until a better performance is achieved
8- Repeat steps 6 and 7 until we reach the best result
9- Use the final trained model and test it on the test data

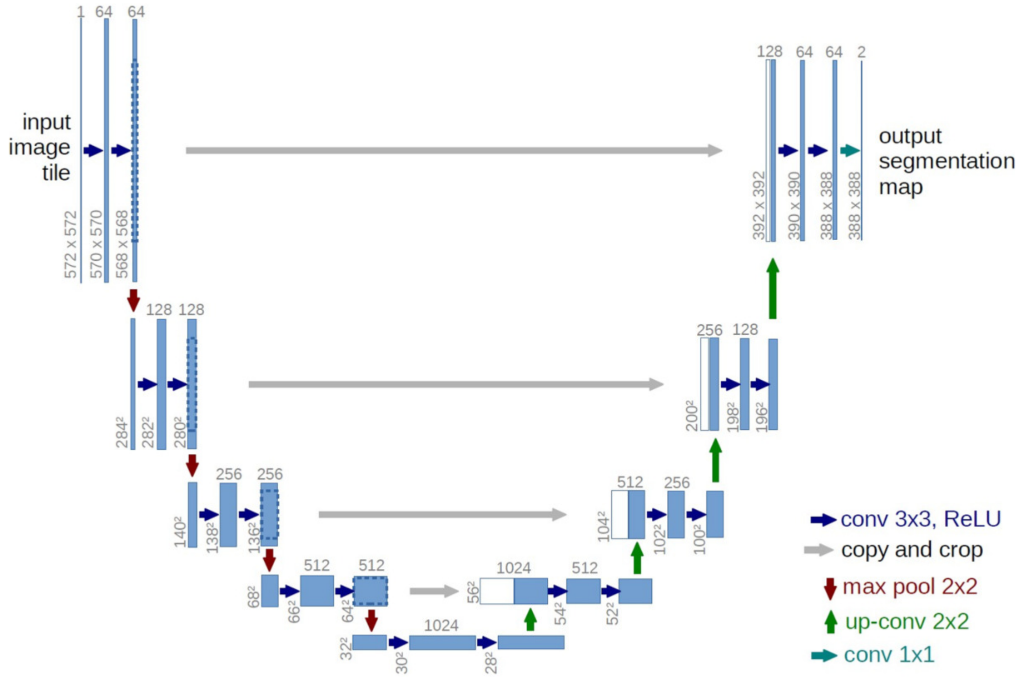

Fig.5: *U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations. [27].*

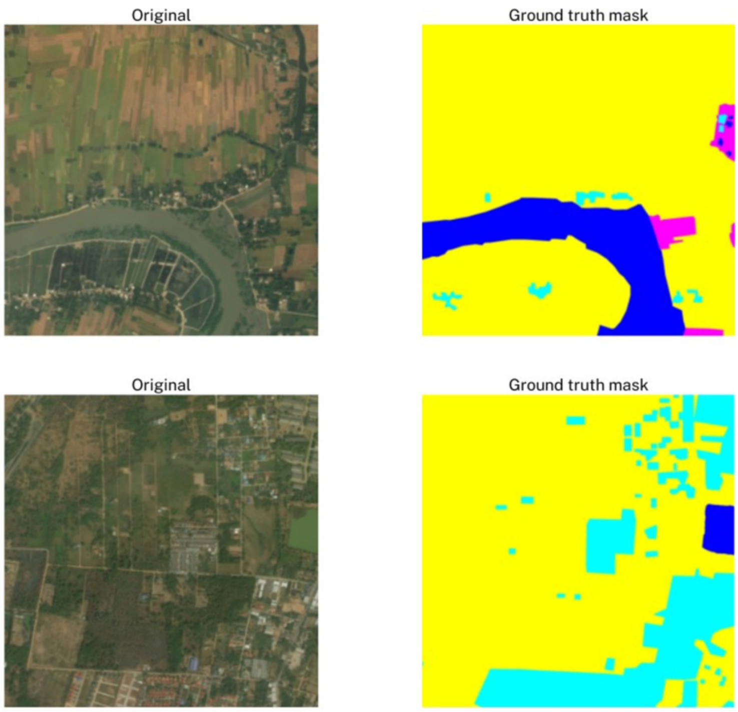

Fig.6: *Examples of the land cover dataset: on the left is the image, and on the right is the ground truth mask.*

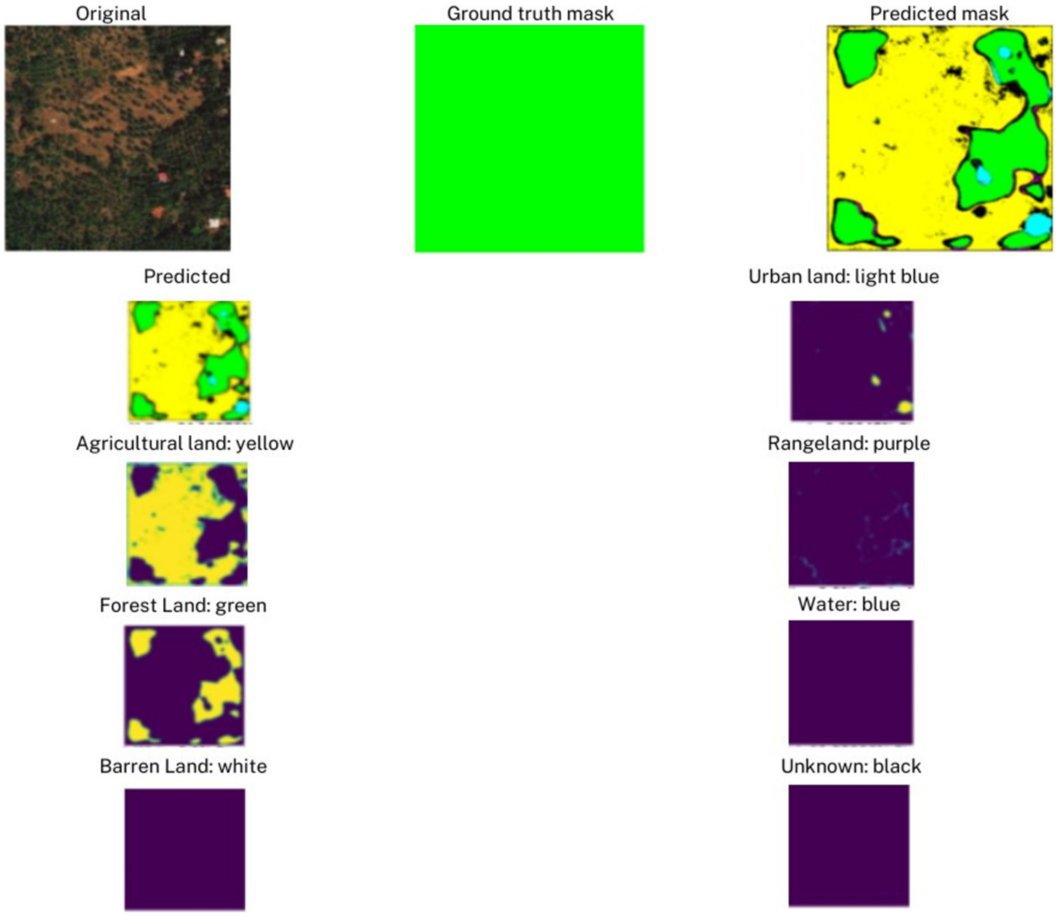

Fig. 7: *Sample predictions vs. ground truth masks in validation data for UNet.*

6.4 Metrics:

- We use the dice coefficient, a measure of overlap between two masks, in our case ground truth and the predicted mask. 1 indicates a perfect overlap while 0 indicates no overlap. The overlap between the expected mask and the ground truth is measured by the dice coefficient. While the network aims to maximize the dice coefficient, employing it directly as a loss function can produce promising results because it was built to perform well with class-imbalanced data.

- It cannot rule over the smaller segmentation class since it does not consider the background class. The result of the dice coefficient is a score between [0,1], where 1 represents a perfect overlap. So, (1-DSC) is a loss function that can be utilized.

- We use Precision and Recall as extra metrics for the model's ability to classify FP and FNs.

- The Adam optimizer, which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments, with an initial learning rate lr = 1e-5. The unet was trained and evaluated by the data sets containing seven objects classes (i.e, urban land, agriculture land, range land, forest land, water, barren land, unknown).

- Samples in train: 723
- Samples in validation: 80
- Samples in the test: 343
- The experiments were implemented using the public platform TensorFlow and run on Google collaboratory with one GPU (Tesla T4).

6.5 Results and discussion:

In this section, we analyze the results of training for U-Net. Fig. 7 and Fig. 8 include input images and the ground truth, and illustrate the results of training for the UNet model. Each object is colored differently (e.g., green pixels designate forest, blue designate water, etc). Training lasted 8 hours, with four batches and 100 epochs. Results are shown in Table 1.

Table 1: *Validation Metrics and Values.*

Validation Metrics	Values
Dice Coefficient Loss	0.0950
Dice Coefficient	0.9050
Precision	0.8992
Recall	0.7524

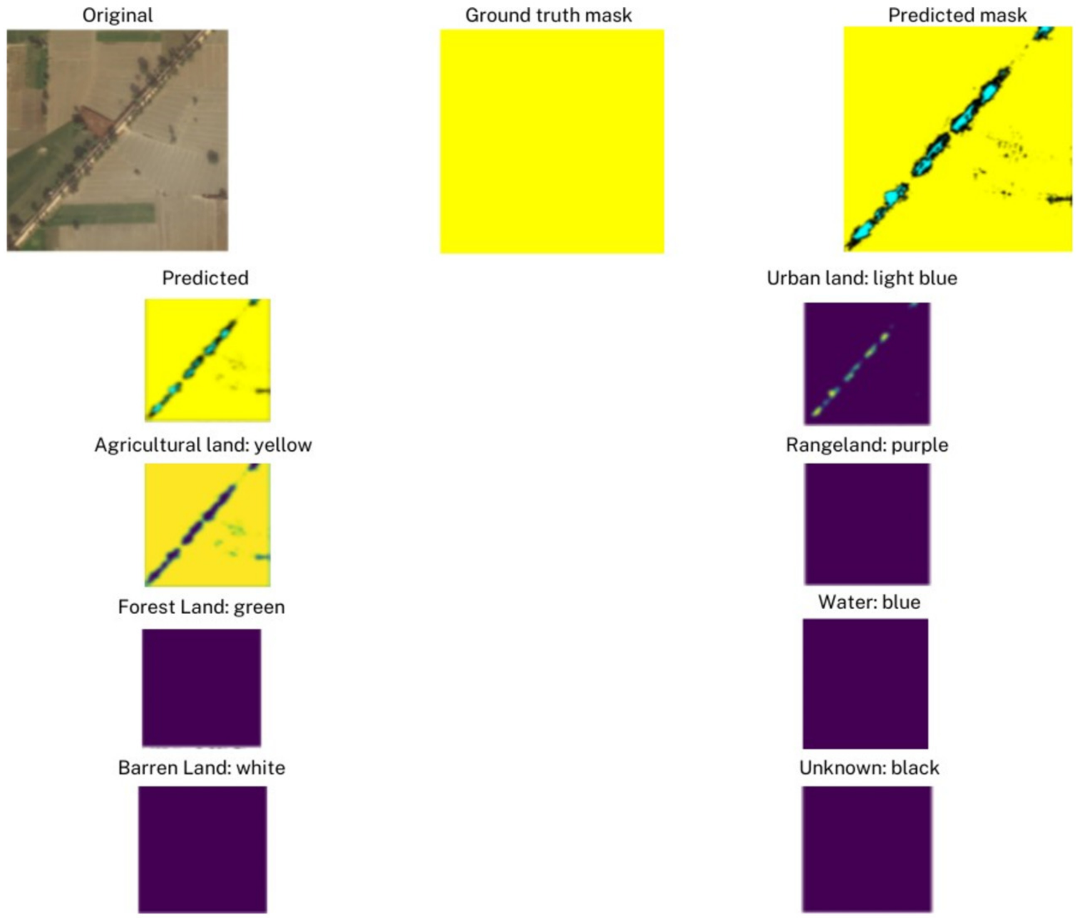

Fig.8: *Sample predictions vs. ground truth masks in validation data for UNet.*

As can be seen in Fig.8, the model does quite well in predicting urban areas in light blue, as the predicted mask follows the shape of the urban area, just like the satellite image in the original. However, the roads are also being mistaken for urban areas as well. Sometimes, it can be considered an urban area with no urban area. To overcome this, further tuning and training is required. Given the class imbalances in the dataset, it affected the overall result of the model as the agriculture class has more than 58%. That is why, in upcoming works, we need to apply more data augmentation to remedy the class imbalances. As a further improvement as well, another required preprocessing is to use grayscale instead of RGB. That being said, the results of the trained model are decent and can be applied in land segmentation using remote sensing publicly available datasets without expensive human intervention.

6.6 Benefits of land segmentation in climate change mitigation:

By allowing for more specialized and efficient land use management, conservation, and restoration measures, land segmentation can help in the fight against climate change. Land segmentation, which divides land into distinct units based on different factors like land cover, soil type, topography, or ecosystem services enable a more nuanced understanding of the land and its resources and make it easier to identify regions that are most susceptible to the effects of climate change or that require protection or restoration. For instance, to echo the example we gave in section 3.3.1, we suggest using and segmentation at the application layer level. To determine the factors that will be used to segment the land, we suggest factors such as land use, vegetation cover, elevation, soil, and precipitation. Next, we can use the thermal emissive bands 20–25 and 27–36 on MODIS, with wavelengths ranging from 3.7 to 14.2 microns, which detect photons coming from the atmosphere and the surface, to calculate land surface temperature. After segmenting the land, an AI algorithm can assess historical data on land surface temperatures and identify trends that point to global warming. This could entail employing time series analytic methods to find patterns and trends in temperature data, such as autoregressive models or neural networks.

In the second example in section 3.3.2, we suggest using land segmentation combined with LoRaWAN to optimize water use and reduce water waste. There are several factors that we can base our segmentation on, like plant type, since different plants have different water requirements, segmenting land based on plant type can help to optimize water use. So plants that require less water can be irrigated less frequently than plants that require more water. Soil moisture and air temperature are other possible factors so irrigation is applied only when and where it is needed.

In the third example in section 3.3.3, in addition to the crowd classifier, we suggest coastal areas be segmented based either on their land use, such as urban areas, agricultural land, or natural areas, so we can better understand where human activity contributes to the most to coastal erosion, or to be partitioned via land segmentation based on coastline characteristics including cliffs, beaches, and dunes. Given their location, sediment properties, and exposure to wave action, these sites may be particularly susceptible to erosion. Another possible factor could be events such as wave erosion, tidal currents, or storm surges to identify areas more vulnerable to erosion due to their location and exposure to these processes.

7. CONCLUSION

In this paper, we discussed the over looming repercussions of climate change as one of the most critical threats to our planet. We gave an overview of how the idea of climate change fully formed to require immediate international cooperation activities. We proposed land segmentation using deep learning as an artificial intelligence method to achieve better environmental monitoring rather than using sensors. To start, we introduced state-of-the-art projects implemented worldwide that take advantage of sensor data advancements to monitor, model, and mitigate the effects of climate change around the globe. We gave an overview of artificial intelligence and remote sensing and how they progressed, thanks to the recent technological advancements. We then suggested combining Artificial Intelligence and Remote Sensing to achieve land segmentation based on a UNet architecture applied to the DeepGlobe dataset to segment seven classes of land types. The results were satisfactory and proved helpful as an alternative to the solutions implemented in the projects mentioned beforehand to monitor land cover, boost precision agriculture, and avoid coastal erosion to have a better understanding of the climate.

References

[1] S. El Maachi, R. Saadane, M. Wahbi, A. Chehri and A. Badaoui, "Vision of IoT, 5G and 6G Data Processing: Applications in Climate Change Mitigation," *2022 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, Penang, Malaysia, pp. 1-6, 2022.

[2] M. Mancini *et al.*, "An Open Source and Low-Cost Internet of Things-enabled Service for Irrigation Management," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, pp. 1714-1719, 2019.

[3] C. D. Butler, "Climate Change, Health and Existential Risks to Civilization: A Comprehensive Review (1989-2013)," *International Journal of Environmental Research and Public Health*, vol. 15, no. 10:2266, Oct. 2018.

[4] Enayat A. Moallemi *et al.*, "Achieving the Sustainable Development Goals Requires Transdisciplinary Innovation at the Local Scale," *One Earth 3*, vol. 3, no. 2, pp. 300-313, Sep. 2020.

[5] X. Zheng *et al.*, "Consideration of Culture Is Vital If We Are to Achieve the Sustainable Development Goals," *One Earth*, vol. 4, no. 2, pp. 307-319, Feb. 2021.

[6] S. Fang *et al.*, "An Integrated System for Regional Environmental Monitoring and Management Based on Internet of Things," in *IEEE Transactions on Industrial Informatics*, vol. 10, no. 2, pp. 1596-1605, May 2014.

[7] Food and Agriculture Organization of United Nations (FAO), "FAO. 2016. AQUASTAT Main Database." [Online] Available: `http://www.fao.org/nr/water/aquastat/data/query/index.html`, accessed on 2019 March 28th.

[8] H. V. Meijl *et al.*, "Comparing impacts of climate change and mitigation on global agriculture by 2050," *Environmental Research Letters*, vol. 13, no. 6:064021, 2018.

[9] R. Girau *et al.*, "Coastal Monitoring System Based on Social Internet of Things Platform," in *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1260-1272, Feb. 2020.

[10] IPCC. (2018) Intergovernmental Panel On Climate Change, "Special Report: Global Warming of 1.5C," [Online]. Available: `https://www.ipcc.ch/sr15/`

[11] UNEP. (2019) United Nations Environment Programme, "Coordinating Unit for the Mediterranean Action Plan - Secretariat to the Barcelona Convention and its Protocols," [Online]. Available: `http://web.unep.org/unepmap/`

[12] M. Mancini *et al.*, "An Open Source and Low-Cost Internet of Things-enabled Service for Irrigation Management," *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, Bari, Italy, pp. 1714-1719, 2019.

[13] C. Kulatunga, L. Shalloo, W. Donnelly, E. Robson and S. Ivanov, "Opportunistic Wireless Networking for Smart Dairy Farming," in *IT Professional*, vol. 19, no. 2, pp. 16-23, March-April 2017.

[14] D. K. Fisher and P. J. Gould, "Open-Source Hardware Is a Low-Cost Alternative for Scientific In- Instrumentation and Research," *Modern Instrumentation*, vol. 1, n. 2, pp. 8-20, April 2012.

[15] https://www.flaticon.com/

[16] S. Seferbekov, V. Iglovikov, A. Buslaev and A. Shvets, "Feature Pyramid Network for Multi-class Land Segmentation," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, Salt Lake City, UT, USA, pp. 272-2723, 2018.

[17] K. Pichai, B. Park, A. Bao and Y. Yin, "Automated Segmentation and Classification of Aerial Forest Imagery," *Analytics*, vol. 1, no.2, pp. 135-143, 2022.

[18] V. Pollatos, L. Kouvaras and E. Charou, "Land Cover Semantic Segmentation Using ResUNet," *arXiv preprint*, 2020. [Online]. Available:https://doi.org/10.48550/arXiv.2010.06285

[19] J. H. Kim *et al.*, "Objects Segmentation From High-Resolution Aerial Images Using U-Net With Pyramid Pooling Layers," in*IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 1, pp. 115–119, Jan. 2019.

[20] B. C. Reed, J. F.Brown, D. VanderZee, T. R. Loveland, J. W. Merchant and D. O. Ohlen, "Measuring phenological variability from satellite imagery," *Journal of Vegetation Science*, vol. 5, no. 5, pp. 703–714, 1994.

[21] Y. Sawada, T. Koike, E. Ikoma and M. Kitsuregawa, "Monitoring and Predicting Agricultural Droughts for a Water-Limited Subcontinental Region by Integrating a Land Surface Model and Microwave Remote Sensing," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 58, no. 1, pp. 14-33, Jan. 2020.

[22] Global Soil Data Task Group, "Global Gridded Surfaces of Selected Soil Characteristics (IGBPDIS)," 2000. [Online]. Available:http://www.daac.ornl.gov/

[23] https://climate-adapt.eea.europa.eu/en/metadata/adaptation-options/use-of-remote-sensing-in-climate-change-adaptation

[24] D. Fernandez, F. Palazzo, A. Lipponen and S. Iris, "TIGER: Earth observation to improve African water resources management," *2009 IEEE International Geoscience and Remote Sensing Symposium*, Cape Town, South Africa, pp. I-248-I-251, 2009.

[25] de Sherbinin, Alex Balk, Deborah Yager, Karina Jaiteh, Malanding Pozzi, Francesca Chandra, Giri Wannebo, Antoinette. (2023). A CIESIN Thematic Guide to Social Science Applications of Remote Sensing.

[26] J. H. Kim *et al.*, "Objects Segmentation From High-Resolution Aerial Images Using U-Net With Pyramid Pooling Layers," in *IEEE Geoscience and Remote Sensing Letters*, vol. 16, no. 1, pp. 115-119, Jan. 2019.

[27] O. Ronneberger, P. Fischer and T. Brox, "Unet: Convolutional networks for biomedical image segmentation," in *International Conference on Medical Image Computing and Computer-assisted Intervention*, pp. 234–241. Springer, 2015.

[28] https://www.kaggle.com/datasets/balraj98/deepglobe-land-cover-classification-dataset

[29] A. Tzepkenlis, K. Marthoglou and N. Grammalidis, "Efficient Deep Semantic Segmentation for Land Cover Classification Using Sentinel Imagery," *Remote Sensing*, vol. 15, no.8:2027, 2023.

[30] S. Puttinaovarat, P. Horkaew and K. Khaimook, "Conjuring ANN for inundation areas identification based on relevant thematic layers," *ECTI Transactions on Computer and Information Technology (ECTI-CIT)*, vol. 8, no. 1, pp. 56-66, 2014.

[31] W. Boonpook *et al.*, "Deep Learning Semantic Segmentation for Land Use and Land Cover Types Using Landsat 8 Imagery," *Internation Journal of Geo-Information (ISPRS)*, vol. 12, no.1:14, 2023.

Soukaina El Maachi a Ph.D. candidate at the Hassania School of Engineering - EHTP. She has a B.Sc. in Mathematics and an M.Sc. degree in Telecommunications and Information Systems. Her academic journey has led her to explore synergies between artificial intelligence, and climate resilience strategies. Her research pursuits underscore her commitment to addressing environmental challenges through Machine Learning adaptation policy. Her current focus on leveraging machine learning to enhance water management practices reflects the urgency of climate change adaptation and underscores her dedication to contributing to impactful research at the nexus of innovation and environmental resilience policies.

Rachid Saadane affiliated with the Hassania School of Public Works, holds a prominent position as Deputy Director in charge of Research, Cooperation, and Partnership within the Department of Electrical and Telecommunication Engineering. With an extensive academic background, including a Doctor of Philosophy in CSEE from the Department of Electrical and Telecommunication Engineering from the University of Sciences of Rabat jointly with Eurecom Institute in 2007. His expertise spans Wireless Communication Systems, Reflective Intelligent Surface, Dynamic Spectrum Detection, and Radio Cognitive. He is the Head of LaGes Laboratory at Hassania School of Engineering.

Mohamed Wahbi is a professor emeritus, associate member of the SIRC/LAGES at Hassania School of Public Works - EHTP Casablanca/Morocco. His research interests include security systems, analog ad digital communications techniques, smart city and smart agriculture applications.

Abdellah Chehri received his M.A.Sc. Degrees in Signal and Digital Communication from the University Sophia-Antipolis in Nice, France. In Sept. 2004, he joined the Department of Electrical and Computer Engineering of Laval University, Quebec, Canada, where he was a member of the Radiocommunications and Signal Processing Laboratory (LRTS). He received his PhD in Electrical Engineering in June 2009 under the supervision of Pr Paul Fortier and Dr Pierre Martin Tardif. From 2007 to 2009, he worked as a project member at the Bell-Aliant Research Laboratory, in Quebec, Canada. During this period, he also served as a lecturer in the Information Technologies Graduate Program of UQAT.

Abdelmounaim Badaoui is a professor of Applied Informatics at Ecole supérieur de Technologies - EST Sale/Morocco. His research interests include wireless and wireline communication systems.