

Министерство науки и высшего образования Российской Федерации  
 федеральное государственное автономное  
 образовательное учреждение высшего образования  
 «Национальный исследовательский Томский политехнический университет» (ТПУ)

Инженерная школа информационных технологий и робототехники  
 Направление подготовки 09.04.04 Программная инженерия  
 Отделение школы (НОЦ) Информационных технологий

### МАГИСТЕРСКАЯ ДИССЕРТАЦИЯ

Тема работы
<b>Monitoring Land Cover Changes Using Satellite Images</b>

УДК 004.937.72:528.2:629.78

Студент

Группа	ФИО	Подпись	Дата
8ПМ9И	Мачука Мендоса Кристиан Родриго		21.06.2021 г.

Руководитель ВКР

Должность	ФИО	Ученая степень, звание	Подпись	Дата
доцент ОИТ	Токарева О. С.	К.Т.Н.		21.06.2021 г.

### КОНСУЛЬТАНТЫ ПО РАЗДЕЛАМ:

По разделу «Финансовый менеджмент, ресурсоэффективность и ресурсосбережение»

Должность	ФИО	Ученая степень, звание	Подпись	Дата
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### ДОПУСТИТЬ К ЗАЩИТЕ:

Руководитель ООП	ФИО	Ученая степень, звание	Подпись	Дата
доцент ОИТ ИШИТР	Савельев А.О.	К.Т.Н.		

**ПЛАНИРУЕМЫЕ РЕЗУЛЬТАТЫ ОСВОЕНИЯ ООП**  
по направлению 09.04.04 «Программная инженерия»

<b>Код компетенции</b>	<b>Наименование компетенции</b>
<b>Универсальные компетенции</b>	
УК(У)-1	Способен осуществлять критический анализ проблемных ситуаций на основе системного подхода, выработать стратегию действий
УК(У)-2	Способен управлять проектом на всех этапах его жизненного цикла
УК(У)-3	Способен организовывать и руководить работой команды, выработывая командную стратегию для достижения поставленной цели
УК(У)-4	Способен применять современные коммуникативные технологии, в том числе на иностранном (-ых) языке (-ах), для академического и профессионального взаимодействия
УК(У)-5	Способен анализировать и учитывать разнообразие культур в процессе межкультурного взаимодействия
УК(У)-6	Способен определять и реализовывать приоритеты собственной деятельности и способы ее совершенствования на основе самооценки
<b>Общепрофессиональные компетенции</b>	
ОПК(У)-1	Способен самостоятельно приобретать, развивать и применять математические, естественно-научные, социально-экономические и профессиональные знания для решения нестандартных задач, в том числе в новой или незнакомой среде и в междисциплинарном контексте
ОПК(У)-2	Способен разрабатывать оригинальные алгоритмы и программные средства, в том числе с использованием современных интеллектуальных технологий, для решения профессиональных задач
ОПК(У)-3	Способен анализировать профессиональную информацию, выделять в ней главное, структурировать, оформлять и представлять в виде аналитических обзоров с обоснованными выводами и рекомендациями

ОПК(У)-4	Способен применять на практике новые научные принципы и методы исследований
ОПК(У)-5	Способен разрабатывать и модернизировать программное и аппаратное обеспечение информационных и автоматизированных систем
ОПК(У)-6	Способен самостоятельно приобретать с помощью информационных технологий и использовать в практической деятельности новые знания и умения, в том числе в новых областях знаний, непосредственно не связанных со сферой деятельности
ОПК(У)-7	Способен применять при решении профессиональных задач методы и средства получения, хранения, переработки и трансляции информации посредством современных компьютерных технологий, в том числе, в глобальных компьютерных сетях
ОПК(У)-8	Способен осуществлять эффективное управление разработкой программных средств и проектов
<b>Профессиональные компетенции</b>	
ПК(У)-1	Способен к созданию вариантов архитектуры программного средства
ПК(У)-2	Способен разрабатывать и администрировать системы управления базам данных
ПК(У)-3	Способен управлять процессами и проектами по созданию (модификации) информационных ресурсов
ПК(У)-4	Способен проектировать и организовывать учебный процесс по образовательным программам с использованием современных образовательных технологий
ПК(У)-5	Способен осуществлять руководство разработкой комплексных проектов на всех стадиях и этапах выполнения работ

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 Направление подготовки (специальность) 09.04.04 Программная инженерия  
 Отделение школы (НОЦ) Информационных технологий

УТВЕРЖДАЮ:  
 Руководитель ООП  
 \_\_\_\_\_ Савельев А.О.  
 (подпись)      (дата)      (Ф.И.О.)

**ЗАДАНИЕ**  
**на выполнение выпускной квалификационной работы**

В форме:

Магистерской диссертации

(бакалаврской работы, дипломного проекта/работы, магистерской диссертации)

Студенту:

Группа	ФИО
8ПМ9И	Мачука Мендоса Кристиан Родриго

Тема работы:

Monitoring Land Cover Changes Using Satellite Images	
Утверждена приказом директора (дата, номер)	№ 40-5/с от 09.02.2021

Срок сдачи студентом выполненной работы:	15.06.2021
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**ТЕХНИЧЕСКОЕ ЗАДАНИЕ:**

<p><b>Исходные данные к работе</b></p> <p><i>(наименование объекта исследования или проектирования; производительность или нагрузка; режим работы (непрерывный, периодический, циклический и т. д.); вид сырья или материал изделия; требования к продукту, изделию или процессу; особые требования к особенностям функционирования (эксплуатации) объекта или изделия в плане безопасности эксплуатации, влияния на окружающую среду, энергозатратам; экономический анализ и т. д.).</i></p>	<p>Объект исследования – национальный парк Мачалилья в Эквадоре. Предмет исследования – карты классификации безоблачного земного покрова.</p>
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<p><b>Перечень подлежащих исследованию, проектированию и разработке вопросов</b></p> <p><i>(аналитический обзор по литературным источникам с целью выяснения достижений мировой науки техники в рассматриваемой области; постановка задачи исследования, проектирования, конструирования; содержание процедуры исследования, проектирования, конструирования; обсуждение результатов выполненной работы; наименование дополнительных разделов, подлежащих разработке; заключение по работе).</i></p>	<ol style="list-style-type: none"> <li>1. Обзор дистанционного зондирования и искусственного интеллекта.</li> <li>2. Выбор программного обеспечения, данных и области исследования.</li> <li>3. Разработка алгоритмов.</li> <li>4. Результаты и анализ исследуемой территории.</li> <li>5. Работа над разделом по финансовому менеджменту, ресурсоэффективности и ресурсосбережению.</li> <li>6. Работа над разделом о социальной ответственности.</li> </ol>
<p><b>Перечень графического материала</b></p> <p><i>(с точным указанием обязательных чертежей)</i></p>	<ol style="list-style-type: none"> <li>1. Карта расположения исследуемой территории.</li> <li>2. Карты земного покрова.</li> <li>3. Диаграмма Ганта.</li> </ol>
<p><b>Консультанты по разделам выпускной квалификационной работы</b></p> <p><i>(с указанием разделов)</i></p>	
<p><b>Раздел</b></p>	<p><b>Консультант</b></p>
<p>Основная часть</p>	<p>Доцент ОИТ ИШИТР, к.т.н., доцент Токарева О. С.</p>
<p>Финансовый менеджмент, ресурсоэффективность и ресурсосбережение</p>	<p>Доцент ОСГН ШБИП, к.э.н., доцент Гончарова Н. А.</p>
<p>Социальная ответственность</p>	<p>Доцент ООД ШБИП, к.б.н., доцент Антоневиц О. А.</p>

<p><b>Дата выдачи задания на выполнение выпускной квалификационной работы по линейному графику</b></p>	<p>1.03.2021</p>
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**Задание выдал руководитель:**

Должность	ФИО	Ученая степень, звание	Подпись	Дата
доцент ОИТ ИШИТР	Токарева О. С.	к.т.н., доцент		1.03.2021

**Задание принял к исполнению студент:**

Группа	ФИО	Подпись	Дата
8ПМ9И	Мачука Мендоса Кристиан Родриго		1.03.2021

Министерство науки и высшего образования Российской Федерации  
 федеральное государственное автономное  
 образовательное учреждение высшего образования  
 «Национальный исследовательский Томский политехнический университет» (ТПУ)

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 Уровень образования магистратура  
 Отделение школы (НОЦ) Информационных технологий  
 Период выполнения весенний семестр 2020 /2021 учебного года

Форма представления работы:

Магистерская диссертация

(бакалаврская работа, дипломный проект/работа, магистерская диссертация)

### КАЛЕНДАРНЫЙ РЕЙТИНГ-ПЛАН выполнения выпускной квалификационной работы

Срок сдачи студентом выполненной работы:	21.06.2021
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Дата контроля	Название раздела (модуля) / вид работы (исследования)	Максимальный балл раздела (модуля)
01.06.2021	Основная часть	70
01.06.2021	Финансовый менеджмент, ресурсоэффективность и ресурсосбережение	10
01.06.2021	Социальная ответственность	10
01.06.2021	Английский язык	10

**СОСТАВИЛ:**

**Руководитель ВКР**

Должность	ФИО	Ученая степень, звание	Подпись	Дата
доцент ОИТ ИШИТР	Токарева О. С.	к.т.н.		

**СОГЛАСОВАНО:**

**Руководитель ООП**

Должность	ФИО	Ученая степень, звание	Подпись	Дата
доцент ОИТ ИШИТР	Савельев А. О.	к.т.н.		

**TASK FOR SECTION  
“FINANCIAL MANAGEMENT, RESOURCE EFFICIENCY AND RESOURCE  
SAVING”**

**Student:**

<b>Group</b>	<b>Name</b>		
8PM9I	Cristian Rodrigo Machuca Mendoza		
<b>School</b>	ИШНТФ	<b>Division</b>	OIT
<b>Educational level</b>	Graduate	<b>Course/Specialty</b>	09.04.04 Software Engineering

**Initial data for the chapter “Financial management, resource efficiency and resource saving”:**

<i>1. Resource cost of scientific and technical research (STR): material and technical, energetic, financial and human</i>	Salary of performers: 96013.42 RUB Additional salaries: 9601.34 RUB STR budget: 140050.88
<i>2. Expenditure rates and expenditure standards for resources</i>	Electricity costs (10.18 RUB per kWh): 934.52 RUB
<i>3. Current tax system, tax rates, charge rates, discounting rates and interest rates</i>	Labor tax (27.1%): 28621.60 RUB Overhead costs: 2880 RUB

**List of questions to be researched, designed and developed:**

<i>1. Assessment of commercial and innovative potential of STR</i>	Competitive analysis scorecard
<i>2. Development of charter for scientific-research project</i>	SWOT-analysis
<i>3. Scheduling of STR management process: structure and timeline, budget, risk management</i>	Calculation of working hours for project; Creation of the time schedule of the project; Calculation of scientific and technical research budget;
<i>4. Resource efficiency</i>	Integral indicator of resource efficiency for the developed project.

**A list of graphic material (with list of mandatory blueprints):**

<ol style="list-style-type: none"> <li><i>1. Competitiveness analysis</i></li> <li><i>2. SWOT- analysis</i></li> <li><i>3. Gantt chart and budget of scientific research</i></li> <li><i>4. Assessment of resource, financial and economic efficiency of STR</i></li> <li><i>5. Potential risks</i></li> </ol>	
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<b>Date of issue of the task for the section according to the schedule</b>	01.03.2021
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**Consultant:**

<b>Position</b>	<b>Full name</b>	<b>Scientific degree, rank</b>	<b>Signature</b>	<b>Date</b>
Associate professor	Goncharova N.A.	Ph. D.		

**Student:**

<b>Group</b>	<b>Name</b>	<b>Date</b>	<b>Signature</b>
8PM9I	Cristian Rodrigo Machuca Mendoza		



**TASK FOR SECTION  
“SOCIAL RESPONSIBILITY”**

**Student:**

<b>Group</b>	<b>Name</b>		
8PM9I	Cristian Rodrigo Machuca Mendoza		
<b>School</b>	ИИИИТР	<b>Division</b>	OIT
<b>Educational level</b>	Graduate	<b>Course/Specialty</b>	09.04.04 Software Engineering

**Topic of FQW:**

Monitoring Land Cover Changes Using Satellite Images	
<b>Initial data for the chapter “Social Responsibility”:</b>	
<i>1. Characteristics of the researched object (substance, material, device, algorithm, technique, working area)</i>	Artificial Intelligence algorithms for Land Cover Classification of multispectral satellite images, and analysis of changes on the landscape including cloud removal and image reconstruction.
<b>List of questions to be researched, designed and developed:</b>	
<p><b>1. Legal and organizational issues of occupational safety</b></p> <ul style="list-style-type: none"> <li>– consider special (specific to the projected work area) law norms of labor legislation.</li> <li>– indicate the features of the labor legislation in relation to the specific conditions of the project.</li> </ul>	<p>ISO 9241-3. Ergonomic requirements for office work with visual display terminals (VDTs).</p> <p>SanPiN 2.2.2 / 2.4.1340-03. Hygienic requirements for personal computers and work organization.</p>
<p><b>2. Occupational safety:</b></p> <p>2.1. Analysis of the identified harmful and dangerous factors: the source of factor, the impact on human's body.</p> <p>2.2. Suggest measures to reduce the impact of identified harmful and dangerous factors.</p>	<p>Sources and means of protection against hazardous and harmful factors existing in the workplace.</p> <p>Harmful factors: -Abnormal microclimatic parameters of the air. -Lack of natural light, insufficient illumination -Increased level and other unfavorable characteristics of noise.</p>

	-Static physical overload. -Neuropsychic overload.  Dangerous factors: -Electric current caused by the difference in electrical potentials.
<b>3. Environmental Safety:</b> <i>Influence on the atmosphere, hydrosphere, lithosphere</i>	Developing and executing the research project has indirect influence on the lithosphere when proper disposal of the equipment is not carried out.
<b>4. Emergency Safety:</b> <i>Describe the most likely emergency situation</i>	Fire
<b>Date of issue of the task for the section according to the schedule</b>	

<b>Date of issue of the task for the section according to the schedule</b>	01.03.2021
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**Consultant:**

Position	Name	Academic degree	Date	Signature
Associate Professor	Antonevich O. A.	Ph. D.		

**Student:**

Group	Name	Date	Signature
8PM9I	Cristian Rodrigo Machuca Mendoza		

## **ABSTRACT**

The present document consists of 94 pages, 30 figures, 35 tables, and 72 sources cited.

Key words: artificial intelligence, machine learning, deep learning, land cover classification, land cover maps, semantic segmentation, inpainting, satellite data.

The research problem lies in the fact that in some areas the acquisition of cloud-free satellite images is simply impossible, difficulting the assessment of the surface, therefore, precluding changes detection.

This graduation qualification work aims to detect land cover changes, through the use of Artificial Intelligence algorithms and satellite images.

The research consists of four main stages: data acquisition, removal of clouds and reconstruction of images (inpainting), production of land cover maps (semantic segmentation) and change detection.

The object of research is the Machalilla National Park in Ecuador. The subject of research is cloud-free land cover classification maps.

The document presents the results of assessing cloud-free land cover maps to determine changes on the landscape in the Machalilla National Park during the period 2016-2020.

Scientific novelty of the research is the development of an image inpainting algorithm based on partial convolutions for multispectral satellite imagery, and the introduction of an evaluation approach of inpainting based on semantic segmentation, while the practical significance lies on the results of assessing land cover changes in the Machalilla National Park in Ecuador.

## **LIST OF ABBREVIATIONS AND SYMBOLS**

AI – Artificial Intelligence

CNN – Convolutional Neural Network

DL – Deep Learning

EMR – Electromagnetic Radiation

EO – Earth Observation

FCN – Fully Convolutional Network

FN – False Negatives

FP – False Positives

GIS – Geographic Information System

INPE – National Institute for Space Research

IoU – Intersection Over Union

IT – Information Technology

KNN – K-nearest Neighbor

LC – Land Cover

LCC – Land Cover Classification

LU – Land Use

LULC – Land Cover and Land Use

MAE – Mean Absolute Error

ML – Machine Learning

MSD – Musculoskeletal Disorders

MSE – Machine Squared Error

MSI – Multi-Spectral Imaging Instrument

NASA – National Aeronautics and Space Administration

NIR – Near Infrared

NN – Neural Network

OA – Overall Accuracy

RGB – Red Green Blue

SPL – Sound Pressure Level

SWIR – Short Wave Infrared

TN – True Negatives

TP – True Positives

TOA – Top of Atmosphere

USGS – United States Geological Survey

UTM – Universal Transverse Mercator

WEEE – Waste of Electrical and Electronic Equipment

WGS – World Geodetic System

WHO – World Health Organization

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## INTRODUCTION

Population growth, urbanization, agriculture, natural disasters and environmental processes are among the main factors that drive land-cover changes. In turn, detecting, measuring, monitoring and assessing these changes could provide significant insights to better understand environmental dynamics and human activities, which could lead to improve decision making in urban planning, natural resources management, and natural disasters prevention. Land cover maps provide critical information to supervise and monitor ecosystems, natural resources and land management.

Satellite earth observation data can provide high levels of information and detail, great area of coverage and coverage of difficult access areas. However, high spatial and spectral resolution images represent a challenge and a complex task when processing them. In addition, land cover classification is highly affected by clouds, which impact the interpretation of ground objects and the assessment of the physical parameters of the land, ocean and atmosphere.

Cloud-free satellite imagery is a fundamental requirement for land-cover research; requiring a high number of data acquisitions. Some areas are consistently cloudy, and cloud-free satellite data are extremely difficult to acquire, sometimes even over a period of years.

New methods to address these challenges including classical Machine Learning (ML) algorithms have been widely used to provide land cover maps from remotely sensed data with reliable results. Nevertheless, Deep Learning (DL) algorithms have rapidly become state-of-the-art in computer vision tasks such as image classification, inpainting, coloration and object detection due to their ability to learn discriminative and representative hierarchical features achieving significant results.

### **Purpose of research**

This graduation qualification work aims to detect land cover changes, through the use of Artificial Intelligence algorithms and satellite images.

The research consists of four main stages: data acquisition, removal of clouds and reconstruction of images (inpainting), production of land cover maps (semantic segmentation) and change detection.

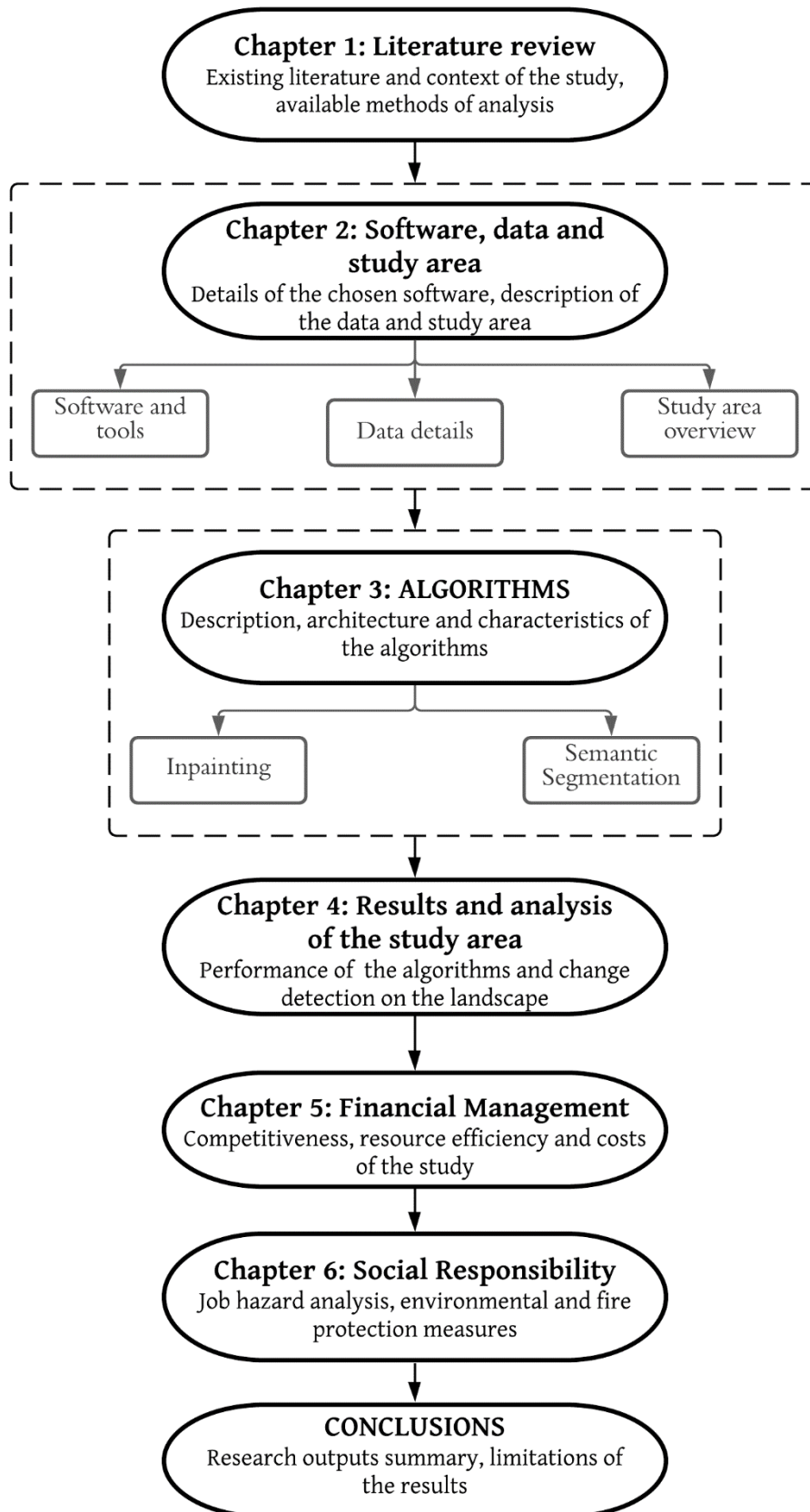
The object of research is the Machalilla National Park in Ecuador. The subject of research is cloud-free land cover classification maps.

### **Scientific novelty and practical significance**

Scientific novelty of the research is the development of an image inpainting algorithm based on partial convolutions for multispectral satellite imagery, and the introduction of an evaluation approach of inpainting based on semantic segmentation, while the practical significance lies on the results of assessing land cover changes in the Machalilla National Park in Ecuador.

Results of this research were presented at the “INTERNATIONAL CONFERENCE ON ADVANCES IN IT AND ROBOTICS” organized by School of Computer Science & Robotics, Tomsk Polytechnic University, Tomsk, Russia (24-26 March 2021).

## Organization of the document



## **1 LITERATURE REVIEW**

Remote sensed data in conjunction with machine learning and artificial intelligence (AI) algorithms have found a wide range of earth science applications. The multispectral characteristics of satellite data and the capacity of DL and ML algorithms to learn and extract valuable features from the input data can be exploited to generate cloud-free land cover maps. Thus, this chapter starts with the definition of land cover and land use, an introduction to remote sensing and the description of spectral imaging. The second and final section of the chapter refers to machine learning, and deep learning.

### **1.1 Land use and land cover (LULC)**

The topic of land cover changes is divided conveniently into two linked components: land-cover (LC) and land-use (LU) [1].

Land cover a concern mainly of the natural sciences can be defined as the biophysical material over the surface of the Earth and immediate sub-surfaces including, among others, snow, bare soil, grass, shrubs, forests, croplands, barren, waterbodies (including groundwater), and man-made structures [2]. By contrast, land use is referred as to how humans exploit the land cover; thus, the term denotes the human employment of the land. Land use includes settlement, cultivation, pasture, rangeland, and recreation areas [2]. In other words, land cover is what covers the surface, while land use is the definition of how the land is used [3].

Consequently, land cover changes are driven by land use; therefore, LULC change could be defined as the modification of the terrestrial surface features of the earth, and is based on a comparison of present and historical conditions of the landscape.

### 1.1.1 Land cover classification (LCC) maps

A land cover map is the representation of spatial information on different types of physical coverage of the Earth's surface by assigning each pixel of an image to one predefined land cover class [4,5].

There are many ways and options for creating land cover maps, such as satellite image interpretation, aerial photo interpretation, field surveys using simple angle and distance measurements, and interpretation of videography [5]. Land cover classification maps have to capture the main land cover classes needed for ecosystem accounting [6]. The standard reference adopted by [7] of land cover classes are shown in table 1.1.

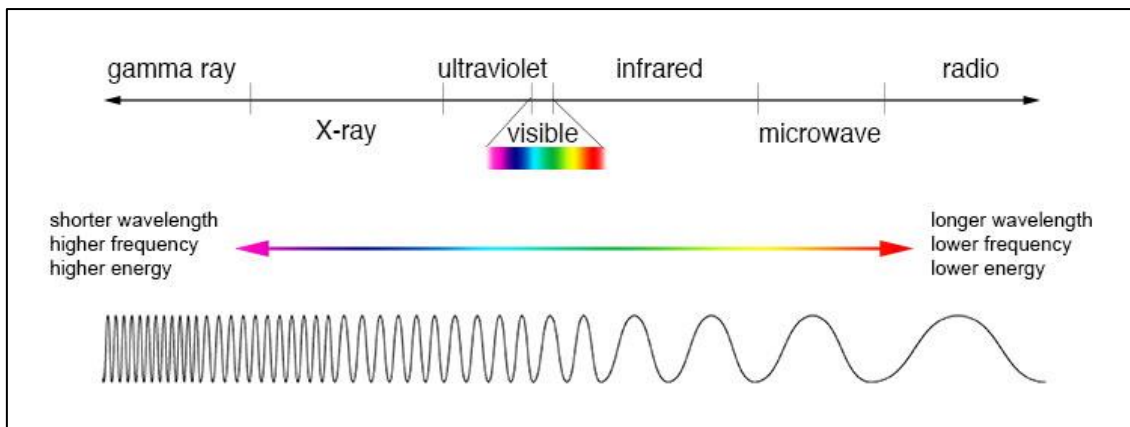
*Table 1.1 – Land cover types*

<b>Code</b>	<b>Title</b>
01	Artificial surfaces (including urban and associated area)
02	Herbaceous crops
03	Woody crops
04	Multiple or layered crops
05	Grassland
06	Tree covered areas
07	Mangroves
08	Shrub covered area
09	Shrubs and/or herbaceous vegetation aquatic or regularly flooded
10	Sparsely natural vegetated areas
11	Terrestrial barren land
12	Permanent snow and glaciers
13	Inland water bodies
14	Coastal water bodies and inter-tidal areas

According to [5], the selection of appropriate imagery plays an important role to accurately define the land cover classes, and frequently is a subjective task which is mainly limited to budgetary resources. This limitation can be overcome by using inexpensive and free sources of Earth observation (EO) data such as Copernicus Open Access Hub, USGS EarthExplorer, NASA Earthdata Search, and INPE Image Catalog, which in turn could affect the level of information that can be extracted for the map.

## 1.2 Spectral imaging

Spectral imaging, also known as imaging spectroscopy, denotes the technology that combines photography and spectroscopy techniques to obtain spatial and spectral information from an object [8]. The information is acquired by measuring the amount of reflected or emitted energy at several wavelength bands across the electromagnetic spectrum (Figure 1.1). This information can reveal what chemical or anatomic features the object may contain [9,10].



*Figure 1.1 – Comparison of wavelength, frequency and energy for the electromagnetic spectrum [11]*

As shown in Figure 2.1 spectral imaging generates a spectral data cube (hypercube). This data structure is simply a three-dimensional dataset (two spatial dimensions and one spectral dimension) that contain spectral information at every spatial coordinate [12].

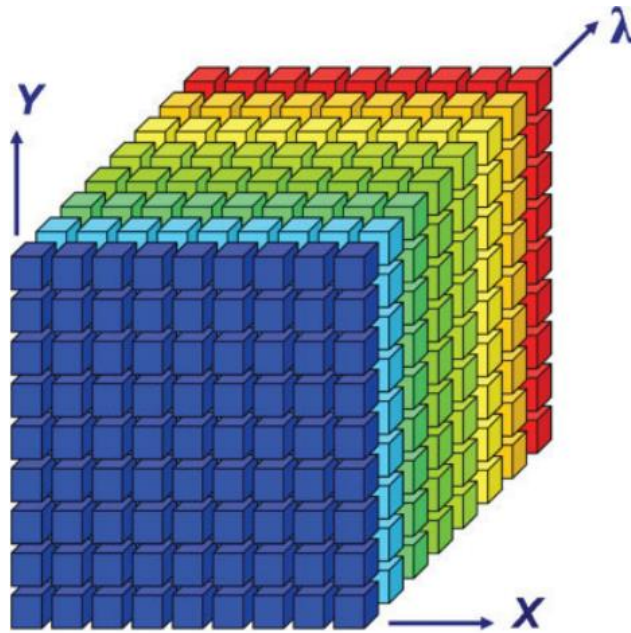


Figure 1.2 – Description of a spectral image set (data cube). Each point of the cube represents a pixel  $I(x,y)$  at each wavelength  $\lambda$  (spectrum) [12]

### 1.2.1 Remote Sensing

Remote sensing is defined as obtaining information about an object without physically being in contact with it. Information is acquired by detecting and measuring the changes that an object imposes on the surrounding field, whether it is electromagnetic, acoustic, or potential [13].

In general sense, remote sensing at present means satellite remote sensing, and exploits the properties of electromagnetic radiation (EMR), its intensity, frequency spectrum, polarization and time delay of received energy, to infer properties of a target by measuring its reflected and emitted radiation [14,15].

#### 1.2.1.1 Sensors

Satellites carry sensors, or instruments, which acquire data by measuring the energy reflected from the Earth.

Sensors can be passive or active depending on whether respond to external or internal stimuli. Passive sensors use the natural energy that is reflected or emitted from the Earth's surface, while active sensors provide their own source of energy.

Active sensors are especially useful when penetrating the atmosphere under most conditions, in turn passive sensors present limitations under the same conditions [16].

### **1.2.1.2 Resolution**

The ability of a satellite sensor to measure specific wavelengths along the electromagnetic spectrum is referred to as spectral resolution, while spatial resolution refers to size measure of the smallest feature that can be resolved by the sensor.

The time taken for a satellite to complete an orbit and revisit the same observation area is called temporal resolution.

## **1.3 Machine learning and deep learning**

Nowadays, machine learning (ML) and deep learning (DL) are rapidly becoming the dominant problem-solving techniques in many fields, achieving state-of-the-art results in a variety of remote sensing applications.

### **1.3.1 Machine Learning**

Machine Learning is the technique used to find a model from data. It is suitable for problems that involve intelligence, such as image recognition and speech recognition, where physical laws or mathematical equations fail to produce a model [17].

Machine learning algorithms are able to learn from data by choosing a function, in order to explain the relationships between features in a dataset.



The algorithm has the capacity to learn from experience  $E$  with respect to some class of tasks  $T$  and performance measure  $P$ , if its performance at tasks in  $T$ , as measured by  $P$ , improves with experience  $E$  [18–20].

Machine learning techniques can be categorized as unsupervised or supervised by what kind of experience they are allowed to have during the learning process (training method). Unsupervised learning algorithms are based on datasets containing inputs without correct outputs, in order to learn useful properties of the dataset structure. In contrast, supervised learning algorithms are based on datasets containing features, but each example is also associated with an output or target [19].

### **1.3.1.2 Machine learning classifiers**

Supervised classification is one of the most common tasks in machine learning and is defined as the process of categorizing a set of data into classes. The main goal of a classifier is to build a generalized model of the distribution of class labels in terms of predictor features. The resulting classifier is then used to assign class labels to the testing instances where the values of the predictor features are known, but the value of the class label is unknown [21].

### **1.3.1.3 K-nearest neighbor classifier**

K-nearest neighbor is a non-parametric classification method of instance-based learning or non-generalizing learning type. Therefore, its aim is not to construct a general internal model, but simply stores and “remembers” all of its instances of the training data. Classification is achieved by simple majority vote of the nearest neighbors of each point: a query point is assigned the data class that has the most representatives among the nearest neighbors of the point [22].

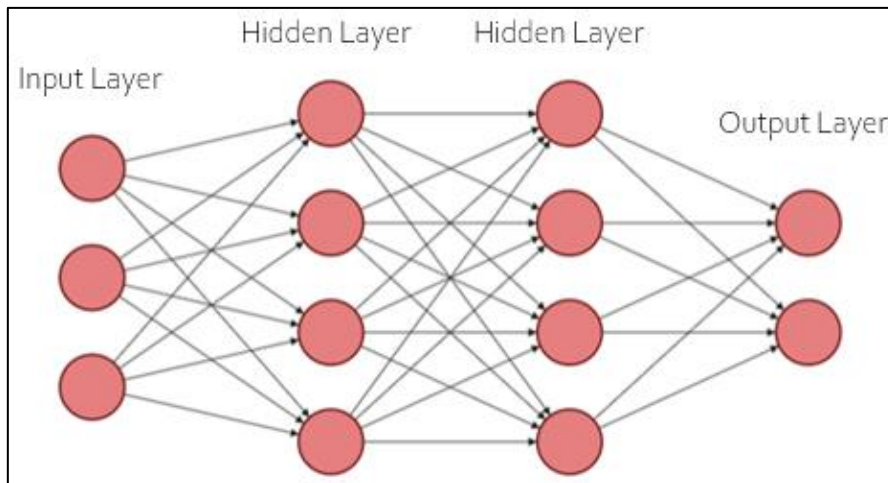
In summary, the backbone of nearest neighbor methods is to find a predetermined number of training samples closest in distance to the new point. The distance can be any metric measure, being the standard Euclidean (equation 1.1) and Manhattan (equation 1.2) distance the most common [22].

$$d_{(x,y)} = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (1.1)$$

$$d_{(x,y)} = \sum_{i=1}^n |x_i - y_i| \quad (1.2)$$

### 1.3.2 Deep Learning

Deep learning is a form of machine learning capable of learning from large amounts of unstructured data. Deep learning allows computational models to process data through multiple processing layers to learn representations of data with multiple levels of abstraction [23,24]. In Figure 1.3, each node (circle) represents an artificial neuron, and the arrows represent the connections from the output of one neuron to the input of another [25].



*Figure 1.3 – Simple four layered feedforward neural network*

A standard neural network (NN) is composed of many simple, connected processors called nodes. To each of its incoming connections, a node will assign a numeric value known as a weight. Learning or credit

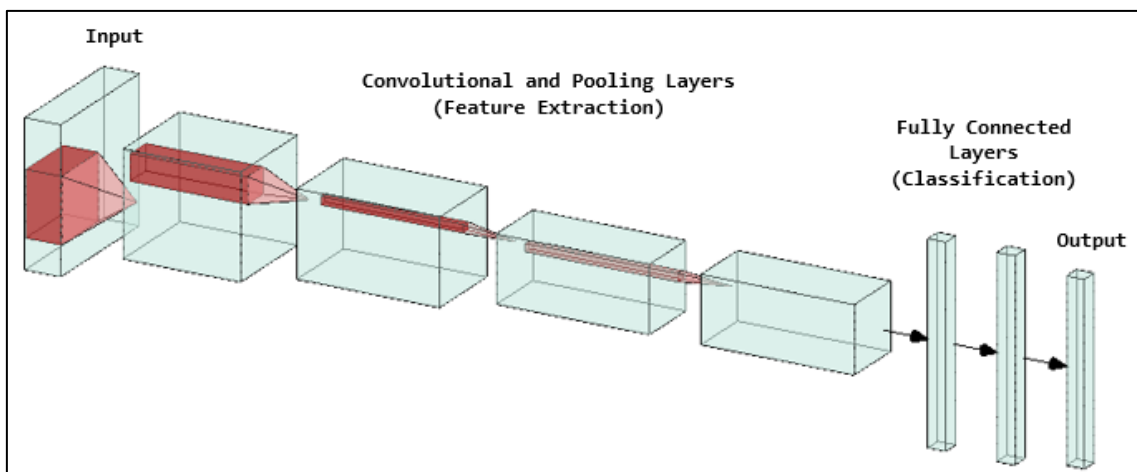
assignment is about finding weights that make the NN exhibit a desired behavior in order to calculate a target output [26,27].

### 1.3.2.1 Convolutional neural networks (CNNs)

CNNs are primarily used in the field of pattern recognition within images by allowing specific image features to be encoded into the architecture, making the network more suitable for image-focused tasks - whilst further reducing the parameters needed to build the model.

Convolutional networks use convolution in place of general matrix multiplication in at least one of their layers, which in its most general form, is an operation on two functions that produces a third function that expresses how the shape of one is modified by the other [17,19].

CNNs typically consist of three types of layers: convolutional, pooling, and fully connected layers (Figure 1.4).



*Figure 1.4 – Simple architecture of a Convolutional Neural Network*

The functionality of CNNs can be divided into four areas [28]:

1. The input layer contains the pixel values of the image.
2. The convolutional layer converts the image using the convolution operation (scalar product between their weights and the region connected to the input volume).

3. The pooling layer performs a down-sampling operation, reducing the spatial size of the convolved feature, as well as the number of parameters to learn and computational complexity.
4. Once features are extracted, the features map is flattened into a one-dimensional vector, which feeds the fully connected layer in order to perform classification.

In other words, CNNs transform the original image layer by layer using convolutional and pooling techniques to produce class scores for classification and regression tasks.

### 1.3.2.1.1 Activation functions

Activation functions are specially used to transform an input signal into an output signal which in turn is fed as input to the next layer in the stack. In an artificial neural network, the sum of products of inputs and their corresponding weights are calculated, and finally apply an activation function to it to get the output of that particular layer and supply it as the input to the next layer.

A neural network's prediction accuracy is dependent on the number of layers used and more importantly on the type of activation function used [29]. The most common activation functions are illustrated in Figure 1.5.

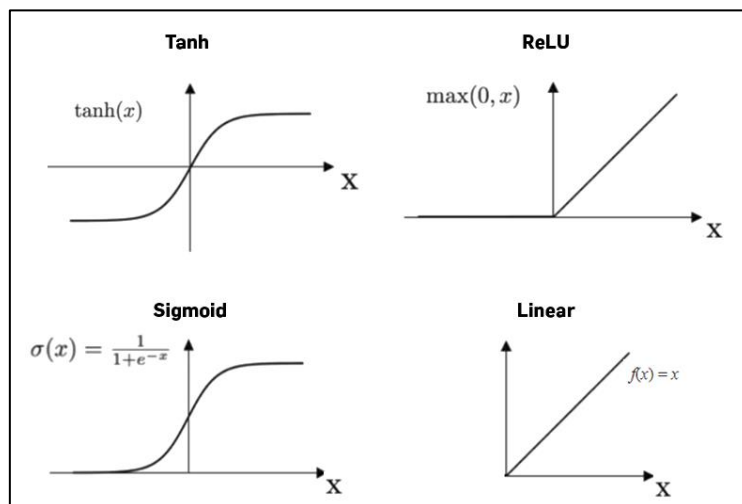
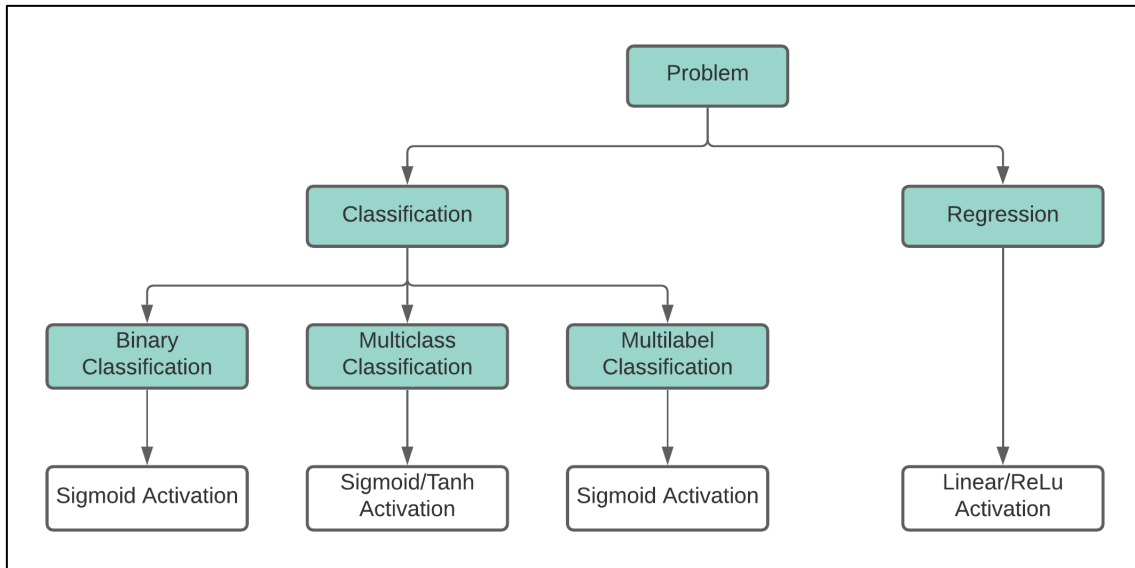


Figure 1.5 – Common activation functions used in deep learning [30]

According to [31] the Figure 1.6 summarizes how to choose the activation function.



*Figure 1.6 – How to choose the activation function for neural network models*

### 1.3.2.1.2 Loss functions

Error measurement plays an important role in the performance of algorithms, and require the choice of a loss function in order to minimize such error.

In machine and deep learning the most common loss functions include cross-entropy, mean absolute error (MAE) and mean squared error (MSE).

Cross-entropy loss, measures the performance of a classification model when its output is a probability that ranges between 0 and 1 [32].

Mean absolute error, also known as L1 loss, used principally in regression tasks, is calculated as the average value of the absolute difference between the predicted and actual values [33].

Mean squared error, or L2 loss, is computed as the average of the squared differences between the actual and predicted values [33]. It is used in regression problems, and is less robust to outliers compared to MAE loss.

### 1.3.2.1.3 Optimizers

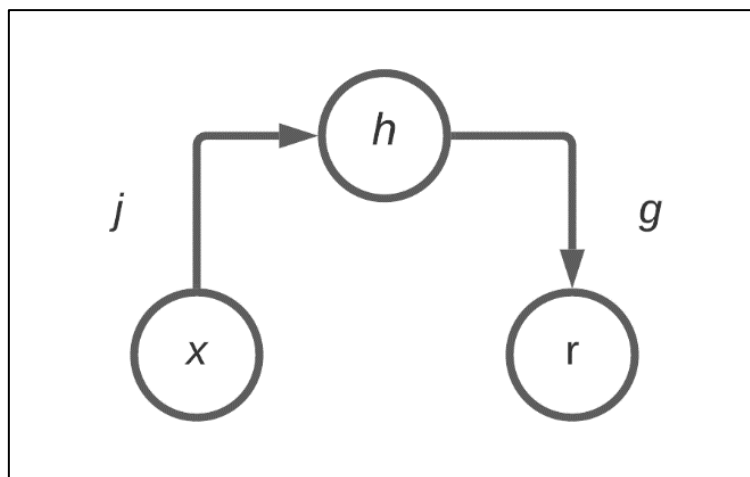
The role of an optimizer is to constantly change or update the attributes of neural networks such as weights and learning rate to reduce the loss function.

The choice of the optimizer determines the training speed and the final predictive performance of the model. To date, there is no theory that adequately explains how to make this choice [34].

The most common and basic optimizer is the Adam algorithm, which is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order momentum [35].

### 1.3.2.2 Autoencoders

An autoencoder is an unsupervised learning algorithm and a type of feedforward neural network, which attempts to copy its input to its output [36]. The network consists of two stages: an encoder function and a decoder that produces a reconstruction. The autoencoder architecture is shown in Figure 1.7.



*Figure 1.7 – General structure of an autoencoder, mapping an input  $\mathbf{x}$  to an output (reconstruction)  $\mathbf{r}$  through an internal representation  $\mathbf{h}$ . The autoencoder has two parts: the encoder  $\mathbf{j}$  (mapping  $\mathbf{x}$  to  $\mathbf{h}$ ) and the decoder  $\mathbf{g}$  (mapping  $\mathbf{h}$  to  $\mathbf{r}$ ) [19]*

Autoencoders are designed to be unable to learn to copy perfectly. Instead, the main purpose is to learn to copy approximately, and to copy only input that resembles the training data by forcing the model to learn useful aspects of the data.

Generally, autoencoders take as input an image, encoding it into a lower dimensional latent representation, then decodes the latent representation back to an image [19].

### **1.3.2.3 U-Net**

The habitual use of convolutional neural networks is on classification problems, where the output to an image is a single class label. Nevertheless, in many visual applications, the desired output is a new image based on its input.

The U-Net architecture (Figure 1.8) contains two paths: a contracting path on the left and an expansive path on the right.

The contracting path (encoder) follows the typical architecture of a convolutional network, and is used to capture the context in the image. It consists of the repeated application of convolutions and down-sampling layers.

Every step in the expansive path (decoder) consists of up-sampling layers of the feature map followed by the convolution operation layer, and a concatenation with the correspondingly cropped feature map from the contracting path [36].

To summarize, U-Net architecture is an end-to-end fully convolutional network (FCN), which in contrast with CNN's does not contain any fully connected layer, making it possible have as input and output images of any size.

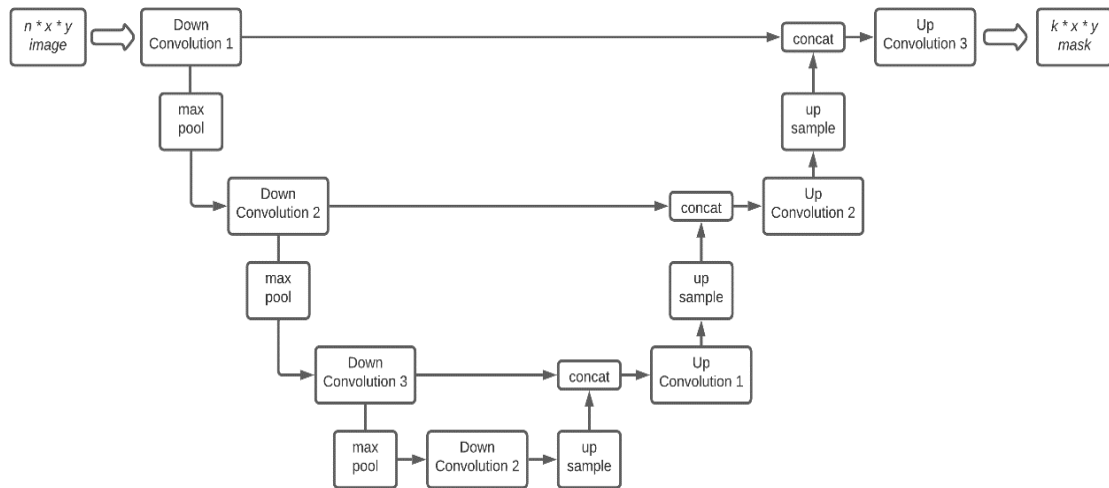


Figure 1.8 – General U-Net architecture

## 1.4 Image inpainting

Image inpainting is the process of replacing missing or corrupted regions of the image data by retrieving information from the surrounding pixels [37].

The major challenge of image inpainting resides in predicting visually realistic and semantically meaningful pixels for missing regions that can integrate smoothly with the rest of the image. Deep neural networks learn end-to-end significant semantic hidden representations, which have been used for recent image painting efforts. These networks employ convolutional filters on images, replacing the corrupted regions with a fixed value. In consequence, this approach suffers from dependence on the initial corrupted values, which often manifests itself as lack of texture in the predicted regions, difference color contrasts, or obvious blur and spurious edge responses surrounding predicted regions [38,39].

The use of partial convolutions, where the convolution is masked and renormalized to be conditioned on only valid pixels can achieve state-of-the-art inpainting results [39].



## 1.5 Semantic Segmentation

Semantic segmentation refers to the process of partitioning an image into multiple non-overlapping regions, pixels in a region are similar according to some homogeneity criteria such as color, intensity or texture, in order to locate and identify objects and boundaries in an image [40]. Segmentation methods are divided into four groups: edge-based, neighborhood-based, histogram-based and cluster-based methods [41].

Neighborhood algorithm-based methods adapted to the multispectral domain have been successfully applied to satellite image segmentation [42].

## 1.6 Evaluation metrics

Effectiveness of semantic segmentation can be determined with the use of metrics such as Intersection over Union (IoU) [43]. This metric known also as the Jaccard index, evaluates how close the prediction is to the ground truth [44].

The mean Intersection Over Union value (mIoU) is the unweighted average of IoU over all the classes [45], and the Overall Accuracy (OA) value refers to the total true predicted results compared to all predictions. To determine the IoU per class the following formula is used:

$$IoU = \frac{TP}{TP+FN+FP} \quad (1.3)$$

where: TP is the true positives,  
TN is the true negatives,  
FP is the false positives,  
FN is the false negatives.

The OA index is calculated as follows:

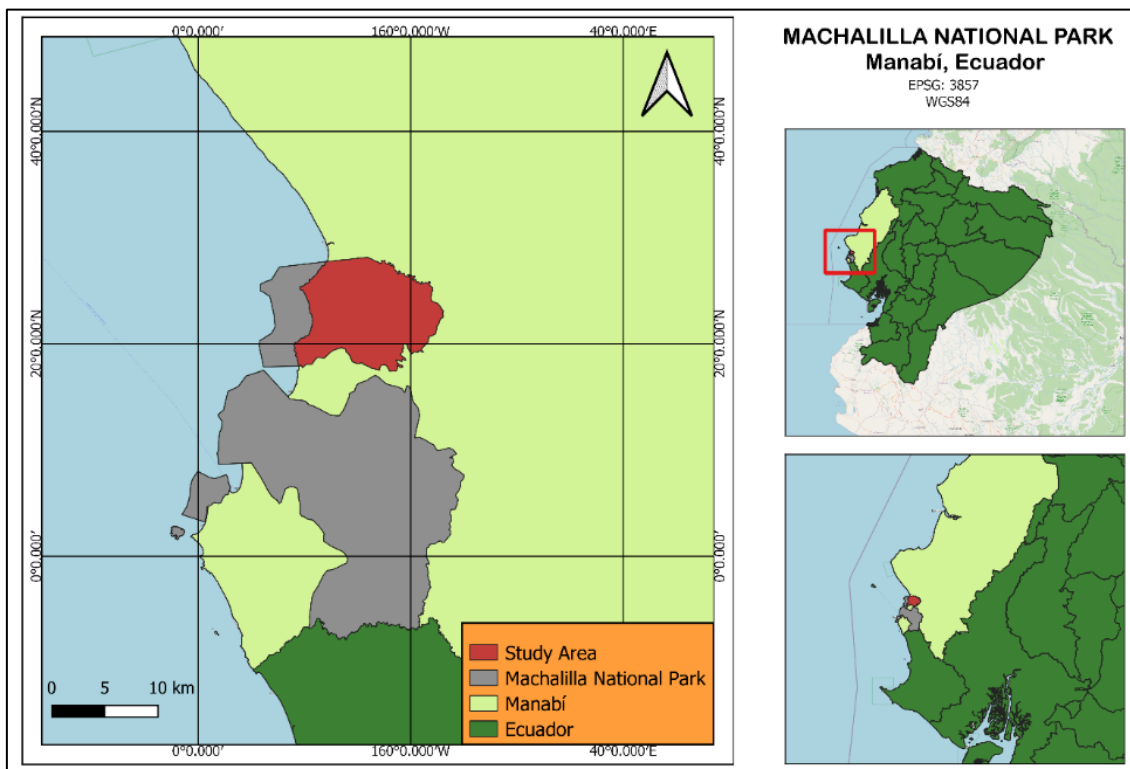
$$OA = \frac{TP+TN}{TP+TN+FN+FP} \quad (1.4)$$

## 2 STUDY AREA, DATA AND SOFTWARE

In this section characteristics of the study area and data are introduced. In addition, a brief description of the selected software, tools, packages and services used in order to achieve the desired results in this research are presented.

### 2.1 Study area

The study area is located in the Machalilla national park, in the south-west of the province of Manabí at  $1^{\circ}33'45''\text{S}$   $80^{\circ}49'48''\text{W}$  in Ecuador (Figure 2.2) and covers an area of about  $210\text{ km}^2$  with an altitudinal range between 0-840 meters.



*Figure 2.1 – Location of the study area*

It is one of the country's first protected areas and its ecosystems include tropical scrubs deserts and tropical dry forests. The topography of its coastal strip is very irregular and includes eroded cliffs, rocky beaches, valleys, bays, inlets, islands and islets (Figure 2.2) [46].



*Figure 2.2 – Satellite view of the study area (RGB composition)*

The study area has been threatened by deforestation, commercial fishing and poaching, and consequently, conservation and protection efforts are highly expected in this vulnerable terrain. Land cover maps of this area were produced in order to assess the changes on the landscape.

## **2.2 Data**

### **2.2.1 Sentinel-2 imagery**

Sentinel-2 is a European multi-spectral imaging mission. It carries a multi-spectral imaging instrument (MSI) which delivers high-resolution, wide-swath optical images. The MSI provides a set of 13 spectral bands spanning from the visible and near infrared to the shortwave infrared [47]. Characteristics of the Sentinel-2 mission are presented in Table 2.1.

*Table 2.1 – Basic facts of Satellite-2 imagery*

<b>Property</b>	<b>Description</b>
Spatial resolution	10m, 20m, and 60m depending on the wavelength
Temporal resolution	5 days with two satellites
Data availability	Since November 2015

Spectral bands and data available from the Sentinel-2 mission which can be accessed through the Copernicus Open Access Hub are described in Table 2.2.

*Table 2.2 – Bands and data which can be downloaded*

<b>Name</b>	<b>Description</b>	<b>Wavelength</b>	<b>Resolution</b>
B01	Coastal aerosol	4442,7 nm	60 m
B02	Blue	492,4 nm	10 m
B03	Green	559,8 nm	10 m
B04	Red	664,6 nm	10 m
B05	Vegetation red edge	704,1 nm	20 m
B06	Vegetation red edge	740,5 nm	20 m
B07	Vegetation red edge	782,8nm	20 m
B08	NIR	832,8 nm	10 m
B8A	Narrow NIR	864,7 nm	20 m
B09	Water vapour	945,1 nm	60 m
B10	SWIR – Cirrus	13733,5 nm	60 m
B11	SWIR	1613,7 nm	20 m
B12	SWIR	2204,4 nm	20 m
CLP	Cloud probability	N/A	160 m
CLM	Cloud masks	N/A	160 m
DataMask	Mask of data/no data pixels	N/A	N/A

The satellite images captured for this research are Level-1C, this product provides ortho-rectified Top-Of-Atmosphere (TOA) reflectance data with a sub-pixel multi-temporal registration between images (UTM/WGS84 projection). Level-1C products contain 13 UINT16 spectral bands scaled by 10000. Additionally, the products include radiometric and geometric corrections generating accurate geolocated images.

## **2.3 Software**

### **2.3.1 Copernicus open access hub**

Open earth observation data of the study area and training datasets were acquired from the Sentinel hub services, mainly because of its easy connection to python scripts, which provides optimum handling of the satellite data for further analysis. Additionally, it allows to configure the parameters of the images to download, such as: cloud coverage percentage, resolution, and data type.

The Sentinel-2 services include the possibility to download cloud masks at 60 m resolution, defective pixels masks, no data masks and valid pixels masks.

### **2.3.2 Python programming language**

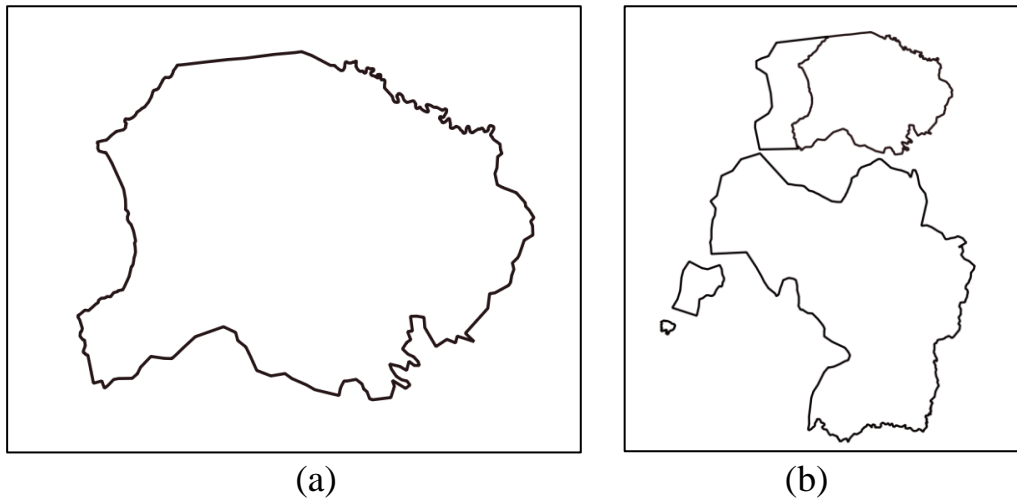
Because of its flexibility, scalability and a huge collection of libraries, the data processing and analysis were carried out using Python through the following packages and libraries:

1. Sentinel hub python package: It provides connection between Python and the sentinel hub services for downloading and managing satellite imagery.
2. Scikit-learn library: Used for developing machine learning algorithms and for the evaluation of results (Jaccard index).
3. Keras and TensorFlow libraries: Used for implementing the neural network

### **2.3.3 QGIS**

The sentinel hub services require the geographic coordinates of the area in order to access the data, therefore, a geographical shape is the best way to determine the area of interest. For the creation of shapefiles (digital geospatial vector format which stores geometric location and associated

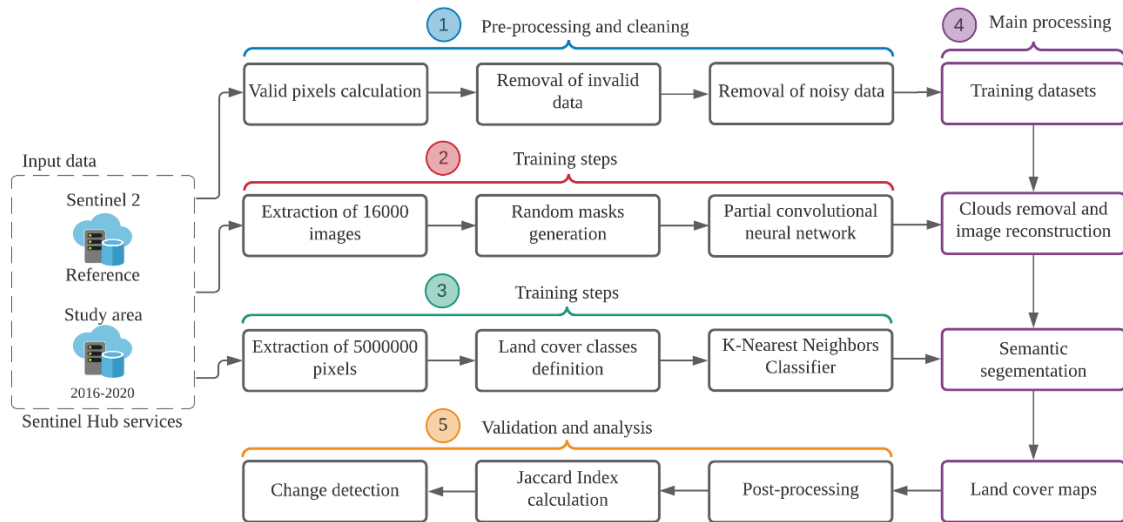
attribute information), the free and Open-Source Geographic Information System QGIS was selected. Shapefiles created in QGIS are presented in Figure 2.3.



*Figure 2.3 – From left to right: (a) study area, (b) Machalilla National Park*

### 3 ALGORITHMS DEVELOPMENT

The research is based on open satellite imagery (Sentinel-2), inpainting method (partial convolutional neural network with U-Net-like architecture) and semantic segmentation method (K-nearest neighbors) to generate cloud free land cover maps of the study area. The detailed procedure is depicted in Figure 3.1.



*Figure 3.1 – Framework for land cover mapping using inpainting and semantic segmentation methods*

In the following section the training data, architecture and parameters of the inpainting algorithm are described. The dataset used for semantic segmentation of satellite images, and the implementation of the classification algorithm are introduced.

#### 3.1 Inpainting algorithm

##### 3.1.1 Training data

In total, 22000 random Sentinel satellite images from 2016 to 2021 were downloaded. In addition, their associated valid pixels and cloud probability masks were acquired. Images from dry forests, deserts, beaches, urban areas, and the ocean were taken into account in order to build a dataset of heterogenous scenes.

Before downloading the images, a set of parameters must be configured, despite having set the maximum cloud coverage percentage parameter to 5%, a cloudy scene filter was developed. Since the Copernicus Access Hub provides a cloud probability mask, it was possible to calculate the probability that each pixel is a cloud. If the number of pixels that are more likely to be clouds was greater than 2%, the image was discarded.

With the aim of removing no-valid scenes the valid pixels in the images were counted, selecting the images with minimum 99% of valid pixels. After applying the filters, about the 76% of the images met the requirements.

The image size chosen was 256 by 256 pixels, mostly because smaller images could cause that clouds cover most of the scene, making more difficult the reconstruction of the images in the study area, while bigger images require a greater amount of computational power for training the network.

Finally, the dataset was composed of  $256 \times 256 \times 13$  images at 10m spatial resolution, it contains 13000 train examples and 3630 validation examples (Figure 3.2).

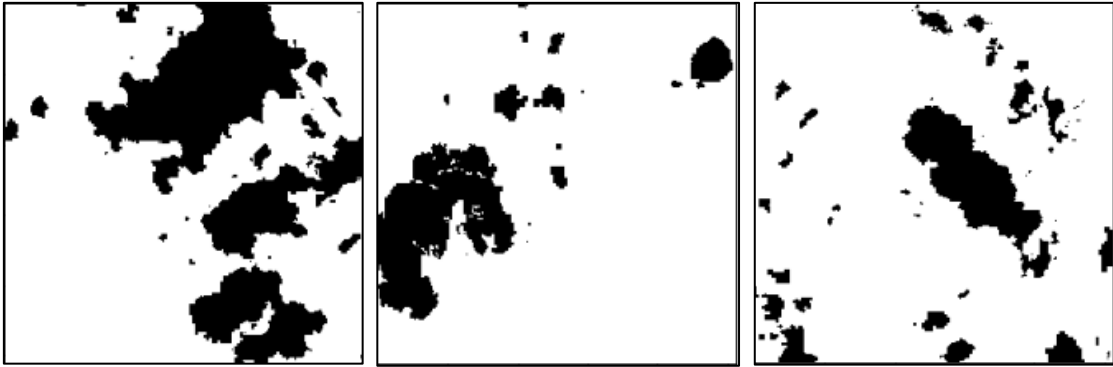


*Figure 3.2 – Satellite images from the training dataset (RGB composition)*

Each one of the examples (training and validation) has an associated random binary mask of random streaks and holes. The binary masks were created using the cloud probability masks, as illustrated in Figure 3.3, the

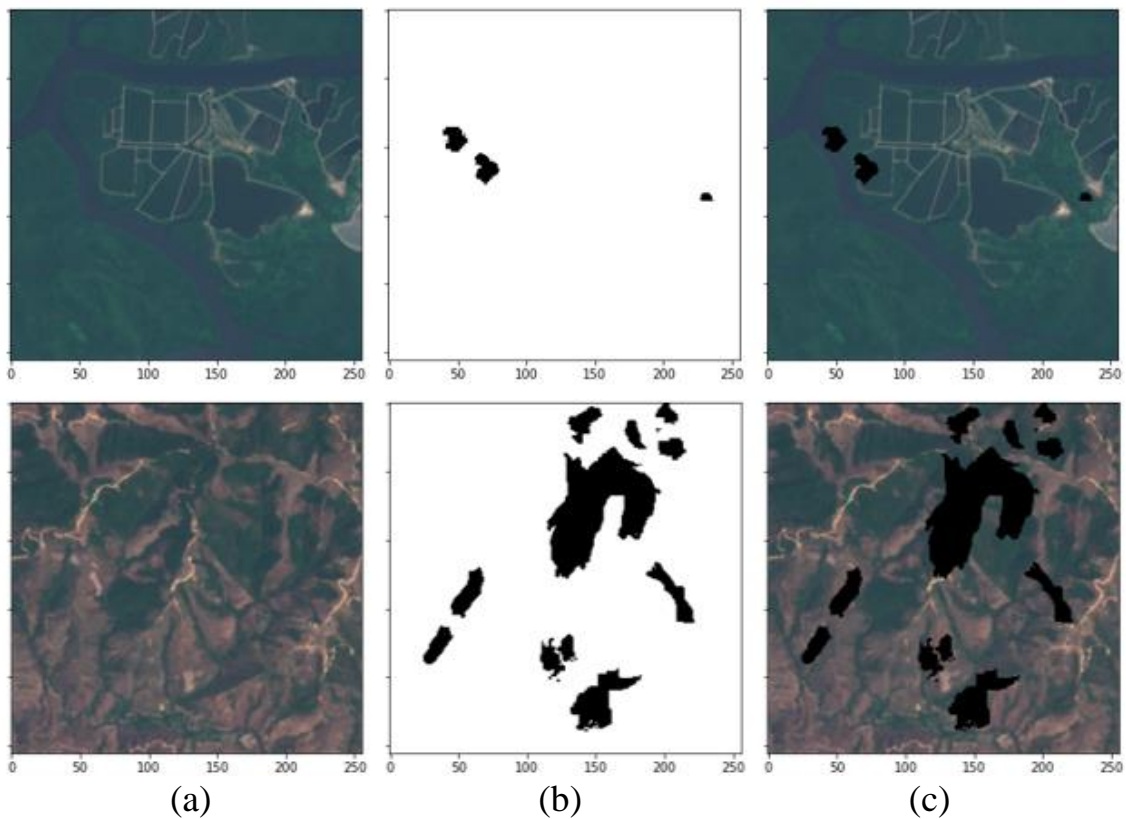


area in black is the region to be predicted, while the area in white is the region of valid pixels used to predict the corrupted pixels.



*Figure 3.3 – Binary masks from the training dataset*

The inpainting algorithm takes as inputs the satellite image and its associated mask as shown in Figure 3.4, the masked image is used as a reference of the area to predict, however, it is not taken into account during the training process.



*Figure 3.4 – From left to right: (a) satellite image (RGB composition), (b) random binary mask, (c) masked image*

### 3.1.2 Network architecture

The proposed network follows a UNet-like architecture, where the convolutional layers are replaced with partial convolutional layers. Since it is an autoencoder, the architecture has two stages: encoder and decoder. In the decoding stage the inputs are up-sampled using nearest neighbor interpolation. The resulting feature map and mask from the previous up-sampling process are concatenated with the resulting feature map and mask from its linked corresponding partial convolutional layer output from the encoder stage, producing a new input feature map and mask for the next partial convolutional layer.

Unlike [39] who use loss functions for per-pixel reconstruction accuracy and composition (how smoothly the predicted pixels transition into their surrounding context), the mean absolute error was used as loss function due to the main purpose of the inpainting process is to generate reliable reconstructed images for semantic segmentation; therefore, smooth transitions are beneficial for RGB visualization but not required for land cover maps generation. In Table 3.1 the architecture of the proposed network is presented.

*Table 3.1 – Structure and details of network architecture*

Module	Input	Output	Filter	Stride Factor	BatchNorm	Activation
Input layer	256*256*13	256*256*13	7x7	-	-	-
PConv1	256*256*13	256*256*64	5x5	1	-	ReLU
PConv2	256*256*64	128*128*128	5x5	2	-	ReLU
PConv3	128*128*128	64*64*256	3x3	2	-	ReLU
PConv4	64*64*256	32*32*512	3x3	2	-	ReLU
PConv5	32*32*512	16*16*512	3x3	2	-	ReLU
PConv6	16*16*512	8*8*512	3x3	2	-	ReLU
PConv7	8*8*512	4*4*512	3x3	2	-	ReLU
PConv8	4*4*512	2*2*512	3x3	2	-	ReLU
Up_sample1	2*2*512	4*4*512	-	-	-	-
Concatenate1 (PConv7, Up_sample1)	4*4*512 + 4*4*512	4*4*1024	- - -	- - -	- - -	- - -
PConv9	4*4*1024	4*4*512	3x3	1	Y(0.00005)	LeakyReLU(0.2)

Up_sample2	4*4*512	8*8*512	-	-	-	-
Concatenate2 (PConv6, Up_sample2)	8*8*512 + 8*8*512	8*8*1024	-	-	-	-
PConv10	8*8*1024	8*8*512	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Up_sample3	8*8*512	16*16*512	-	-	-	-
Concatenate3 (PConv5, Up_sample3)	16*16*512 + 16*16*512	16*16*1024	-	-	-	-
PConv11	16*16*1024	16*16*512	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Up_sample4	16*16*512	32*32*512	-	-	-	-
Concatenate4 (PConv4, Up_sample4)	32*32*512 + 32*32*512	32*32*1024	-	-	-	-
PConv12	32*32*1024	32*32*512	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Up_sample5	32*32*512	64*64*512	-	-	-	-
Concatenate5 (PConv3, Up_sample5)	64*64*256 + 64*64*512	64*64*768	-	-	-	-
PConv13	64*64*768	64*64*256	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Up_sample6	64*64*256	128*128*256	-	-	-	-
Concatenate6 (PConv2, Up_sample6)	128*128*128 + 128*128*256	128*128*384	-	-	-	-
PConv14	128*128*384	128*128*128	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Up_sample7	128*128*128	256*256*128	-	-	-	-
Concatenate7 (PConv1, Up_sample7)	256*256*64 + 256*256*128	256*256*192	-	-	-	-
PConv15	256*256*192	256*256*64	3x3	1	Y(0.00005)	LeakyReLU(0.2)
Concatenate7 (PConv15, Input)	256*256*64 + 256*256*13	256*256*77	-	-	-	-
PConv16	256*256*77	256*256*64	3x3	-	-	-
Convolutional	256*256*64	256*256*13	-	-	-	Sigmoid

  -Encoder Layers

  -Decoder Layers

### 3.1.2.1 Partial convolutional layers

Partial convolution layers (PConv) refer to the partial convolution operation and mask update function jointly. Let  $\mathbf{W}$  and  $b$  be the weights and bias for the convolution filter.  $\mathbf{X}$  represent the pixel values for the current convolution and  $\mathbf{M}$  represents the corresponding binary mask. The partial convolution operation defined in [27], is computed as follows:

$$x' = \begin{cases} \mathbf{W}^T (\mathbf{X} \odot \mathbf{M}) \frac{\text{sum}(\mathbf{1})}{\text{sum}(\mathbf{M})} + b, & \text{if } \text{sum}(\mathbf{M}) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3.1)$$

where  $\odot$  indicates element-wise multiplication, and  $\mathbf{1}$  (all-ones matrix) has the same shape as  $\mathbf{M}$ . According to equation (3.1), results depend only on the valid input pixels. As the number of unmasked inputs varies, the scaling factor  $\text{sum}(\mathbf{1})/\text{sum}(\mathbf{M})$  adjusts them.

Masks are updated after each partial convolutional layer, which eventually after successive applications of the partial convolutional operation will be an all-ones matrix. The equation is expressed as:

$$m' = \begin{cases} 1, & \text{if } \text{sum}(\mathbf{M}) > 0 \\ 0, & \text{otherwise} \end{cases} \quad (3.2)$$

### 3.1.3 Implementation and training

The satellite images were converted into a NumPy array of size  $16630*256*256*13$ , then a data generator was responsible for the creation of random batches of original images and binary masks.

Since partial convolutional layers have no official implementation in TensorFlow and PyTorch, the module developed by [48] was used and custom layers were implemented. The weights were initialized randomly, and Adam was used for optimization, which according to [35], is computationally efficient, has little memory requirement, invariant to diagonal rescaling of gradients, and is well suited for problems that are large in terms of data/parameters.

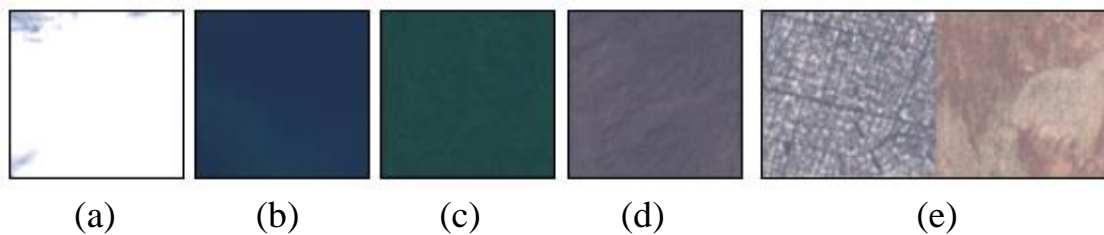
Batch normalization was applied to the decoder stage in order to achieve faster convergence and avoid mean and standard deviation issues.

The training was carried out on a single NVIDIA GTX 980 GPU (8GB) with a batch size of 3.

## 3.2 Semantic segmentation algorithm

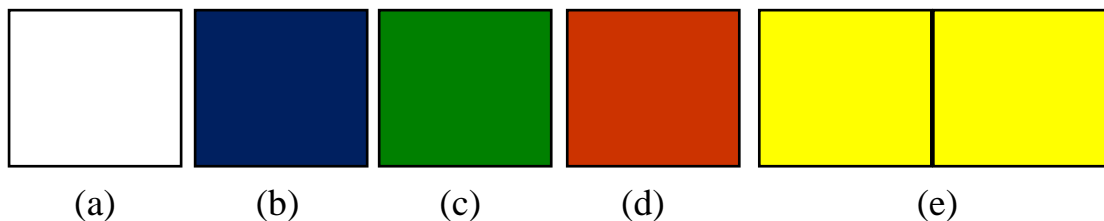
### 3.2.1 Training data

A balanced dataset for pixel-based classification was created. The dataset consists of 5 million observations (rows) and 14 variables (columns): 13-pixel spectral attributes and “label”. In turn, the “label” variable includes five land cover classes. In Figure 3.5, satellite images (RGB composition) belonging to the 5 different land cover classes are illustrated.



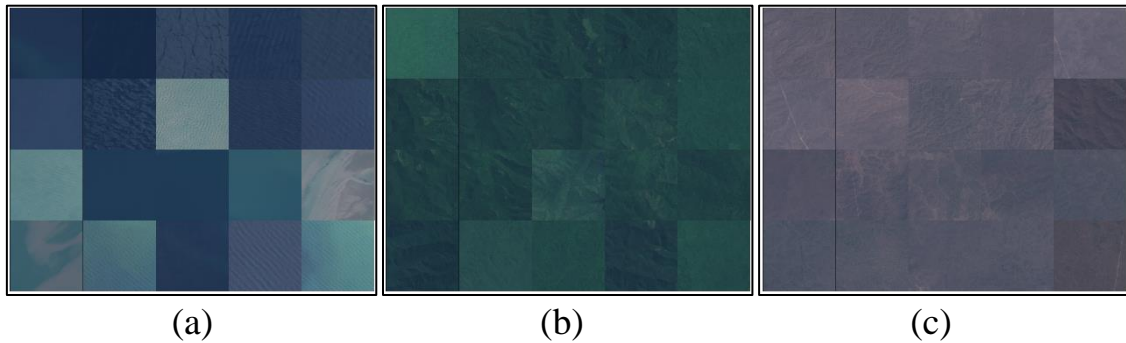
*Figure 3.5 – From left to right: (a) clouds, (b) water bodies, (c) vegetation, (d) dry vegetation, (e) buildings and bare soils*

The land cover classes were defined taking into account the biophysical characteristics of the study area, the color code used in our land cover maps are illustrated in Figure 3.6.



*Figure 3.6 – From left to right: (a) clouds, (b) water bodies, (c) vegetation, (d) dry vegetation, (e) buildings and bare soils*

Pixels were retrieved from images of size 250\*200\*13; therefore, 20 images per class were required. As can be seen in Figure 3.7 images of different spectral reflectance were acquired in order to build a robust and accurate machine learning classification algorithm.



*Figure 3.7 – From left to right: (a) water images mosaic, (b) vegetation images mosaic, (c) dry vegetation mosaic*

Filters described earlier were modified and applied to the images, in order to select images with 100 % valid pixels and 0% cloud coverage.

### **3.2.2 Implementation and training**

The dataset was splitted into a training and test dataset at a 70:30 ratio, and converted into a NumPy array. Since the column “labels” (land cover classes) is categorical, it was encoded as a one-hot array.

Since the K-nearest neighbor algorithm is one of the simplest classifiers, it was not necessary to tune its parameters. The algorithm was implemented using the Scikit-learn Python library, the Minkowski (generalization of the Euclidean and Manhattan distance) metric was selected as distance function.

## 4 RESULTS

In this section, the performance of the partial convolutional neural network and the K-nearest neighbor classifier developed in this study are presented. Moreover, the results of the inpainting and semantic segmentation methods on satellite images of the study area, and the detection of changes on the landscape by analyzing the created land cover maps are introduced.

### 4.1 Algorithms performance

Evaluating multispectral image inpainting results quantitatively is a complex task due to the multiple possible solutions and high spectral class imbalance.

The mean absolute error (MAE) was calculated to determine the accuracy of predictions. In addition, the Dice coefficient and Jaccard index were computed, achieving the results presented in Table 4.1. Nevertheless, qualitative analysis is recommended.

*Table 4.1 – Performance of the Partial Convolutional Neural Network*

<b>Dataset</b>	<b>N of epochs</b>	<b>Dice Coef.</b>	<b>Jaccard Index</b>	<b>MAE</b>
Training	25	0.6656	0.4988	0.0289
Validation	25	0.6692	0.5029	0.0288

The K-nearest neighbor classifier presented an accuracy of 100% on training and test sets. As shown in Figure 5.1, each class was evaluated on 300000 observations (pixels).

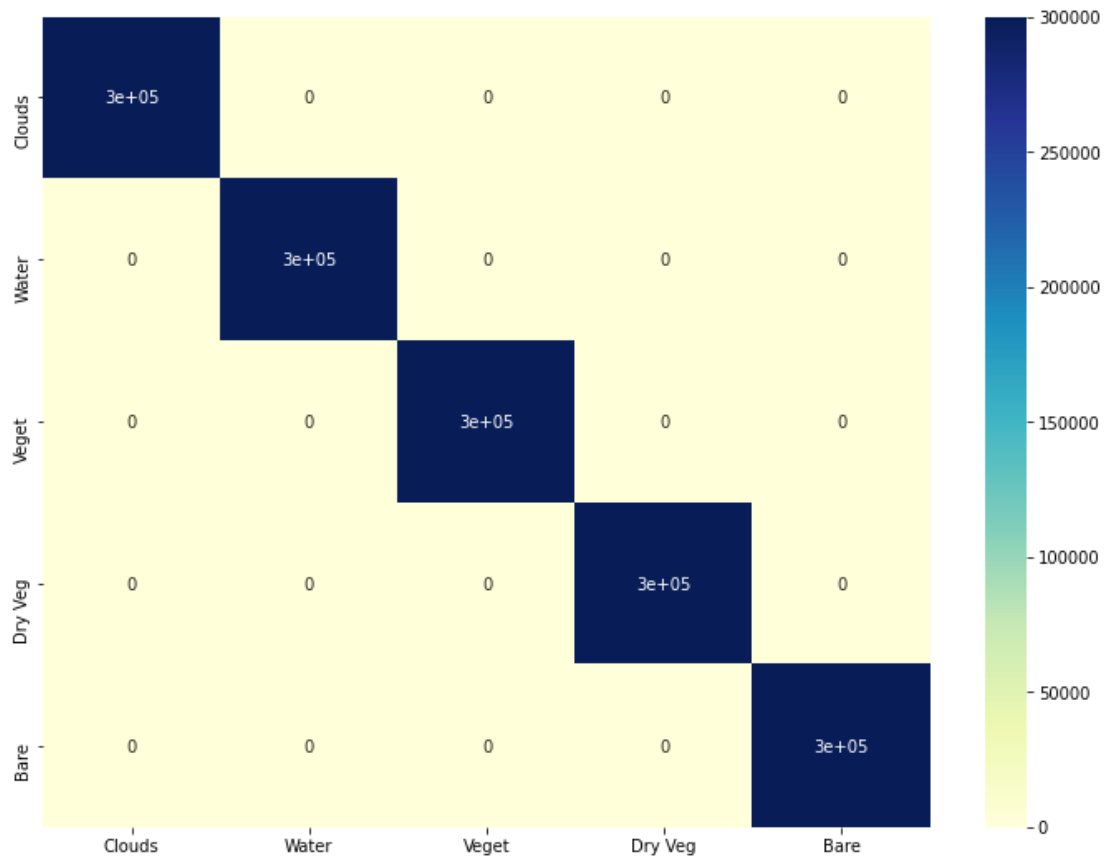


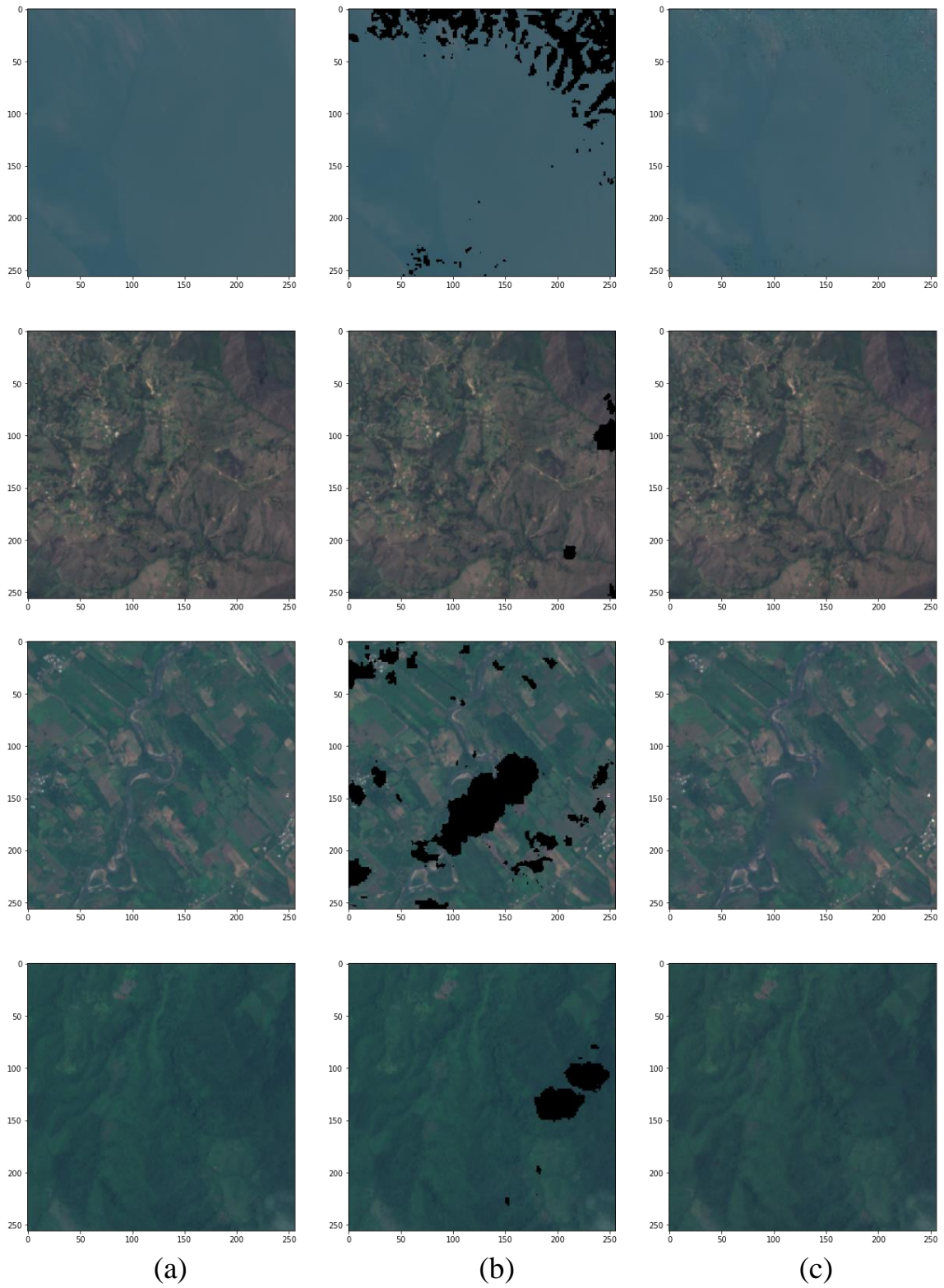
Figure 4.1 – Confusion matrix on the test dataset

## 4.2. Inpainting results

The qualitative inpainting results (RGB composition) are shown in Figure 4.2. As can be seen, the reconstructed corrupted regions integrate smoothly to the surrounding context, being in some cases (small holes) imperceptible to see the difference between the ground truth and inpainted image.

The model struggles when reconstruction of large holes is required, mostly because 13 spectral bands per pixel need to be predicted. Therefore, despite the fact that visually the RGB composition can be reliable, different compositions can be analyzed.





*Figure 4.2 – From left to right: (a) ground truth, (b) masked image, (c) inpainting result*

The color infrared band composition emphasizes healthy and unhealthy vegetation reflecting chlorophyll. Dense vegetation is red while urban areas are white as illustrated in Figure 4.3.

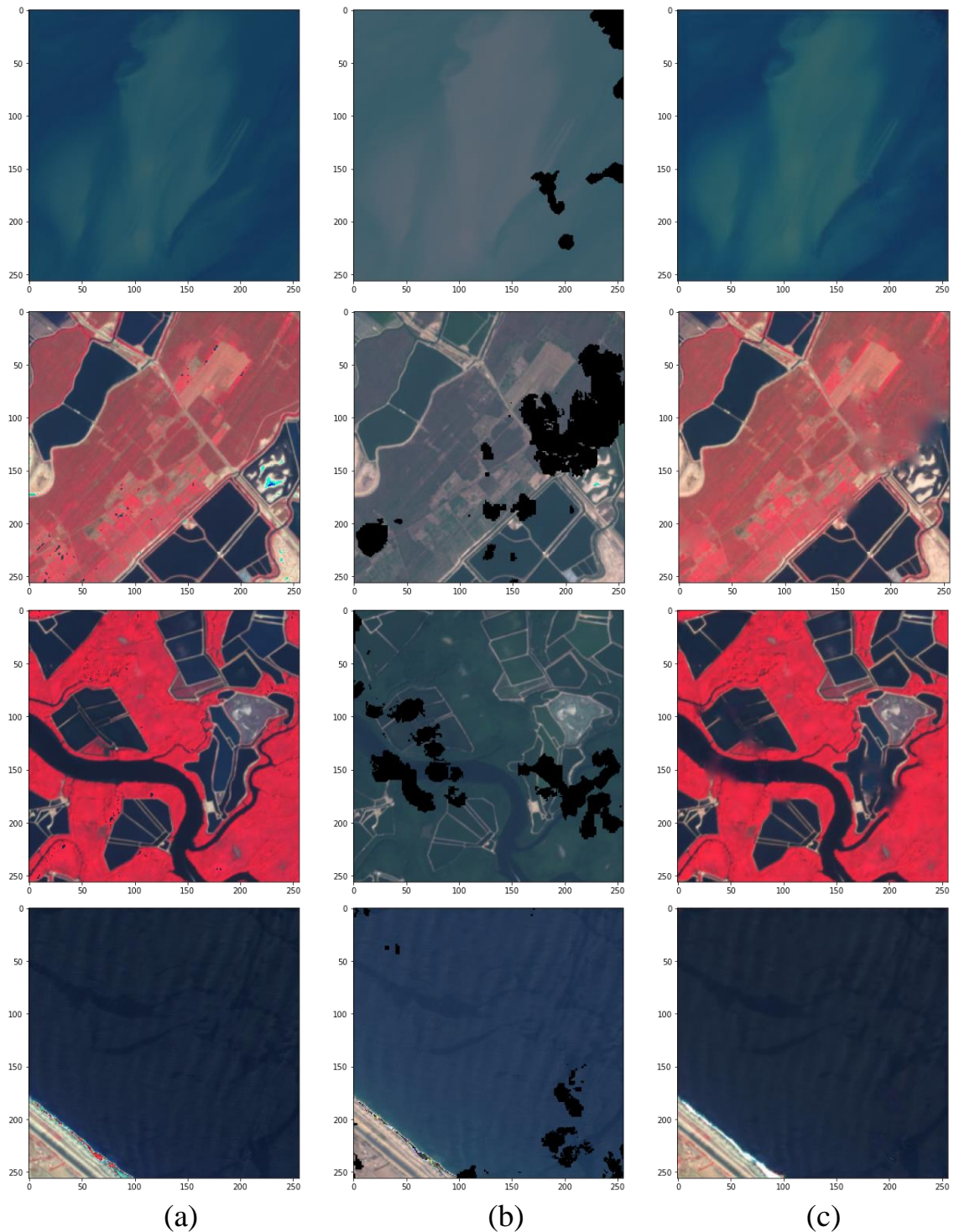


Figure 4.3 – From left to right: (a) ground truth, (b) masked image (RGB), (c) inpainting result

The short-wave infrared band combination shows vegetation in various shades of green. In Figure 4.4, darker shades of green indicate denser vegetation, while brown indicates bare soil and buildings.

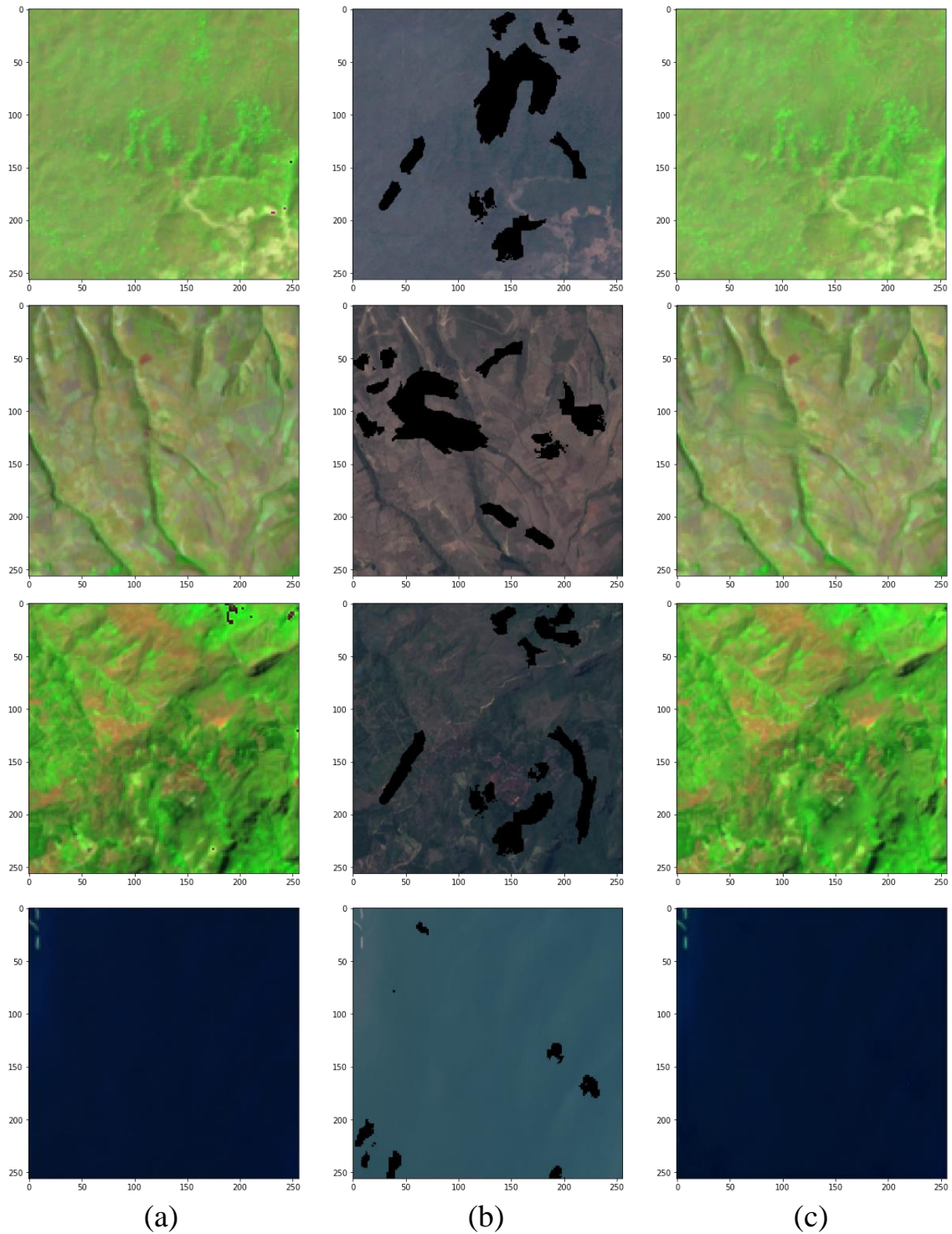


Figure 4.4 – From left to right: (a) ground truth, (b) masked image (RGB), (c) inpainting result

### 4.3 Segmentation results

As mentioned earlier, the segmented images contain 5 different land cover classes. Moreover, the class No Data was added to handle missing, defective and invalid pixels.

Unfortunately, since there is no ground truth to compare the segmentation results, it is not possible to measure the segmentation quality. However, being the classification accuracy high, the results are reliable and accurate as seen in Figure 4.5.

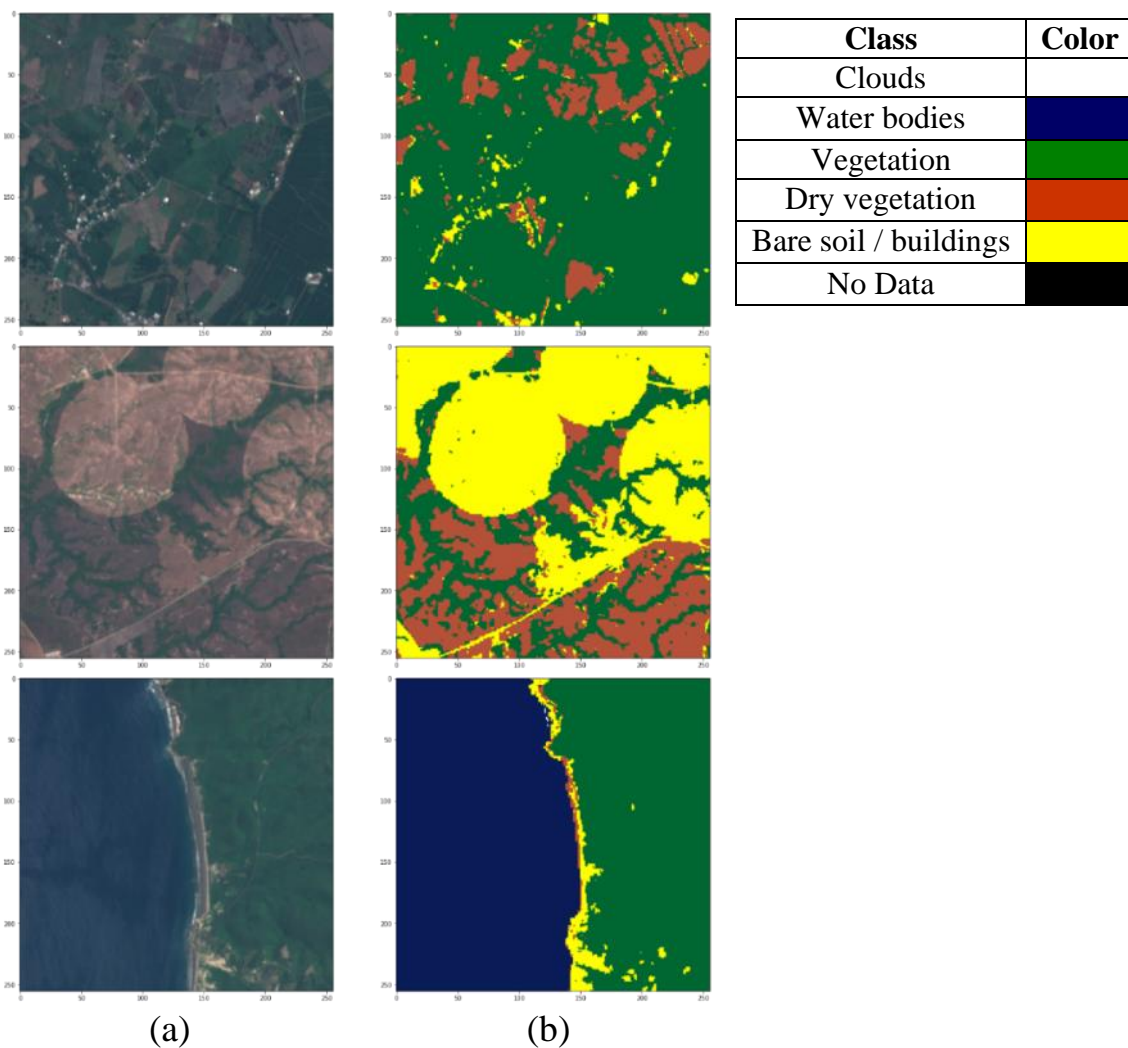


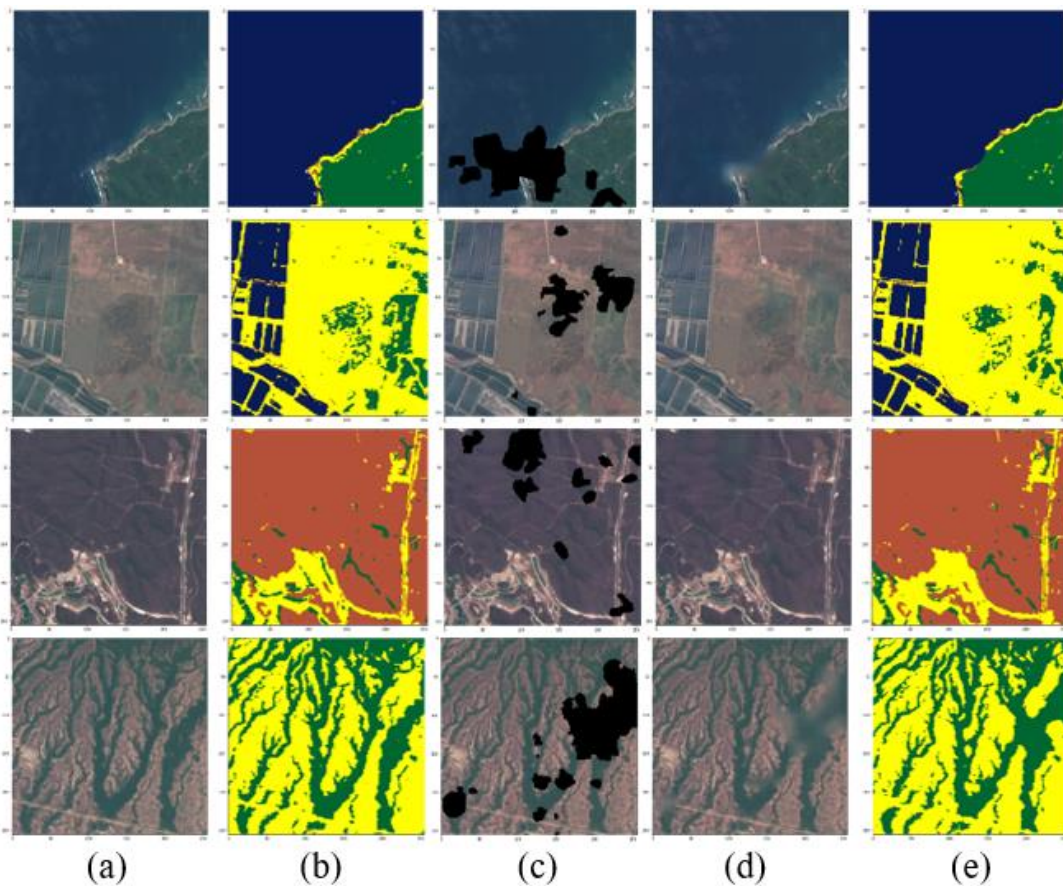
Figure 4.5 – From left to right: (a) input image, (b) segmentation result

#### 4.4 Evaluation of inpainting trough segmentation

Due to the difficulties to evaluate inpainting results on multispectral images mentioned earlier, an approach based on the comparison of the segmented ground truth image and the segmented inpainted image is proposed.

The different classes do not cover equal areas of the image; therefore, the overall accuracy (OA) score was chosen over the mean IoU score.

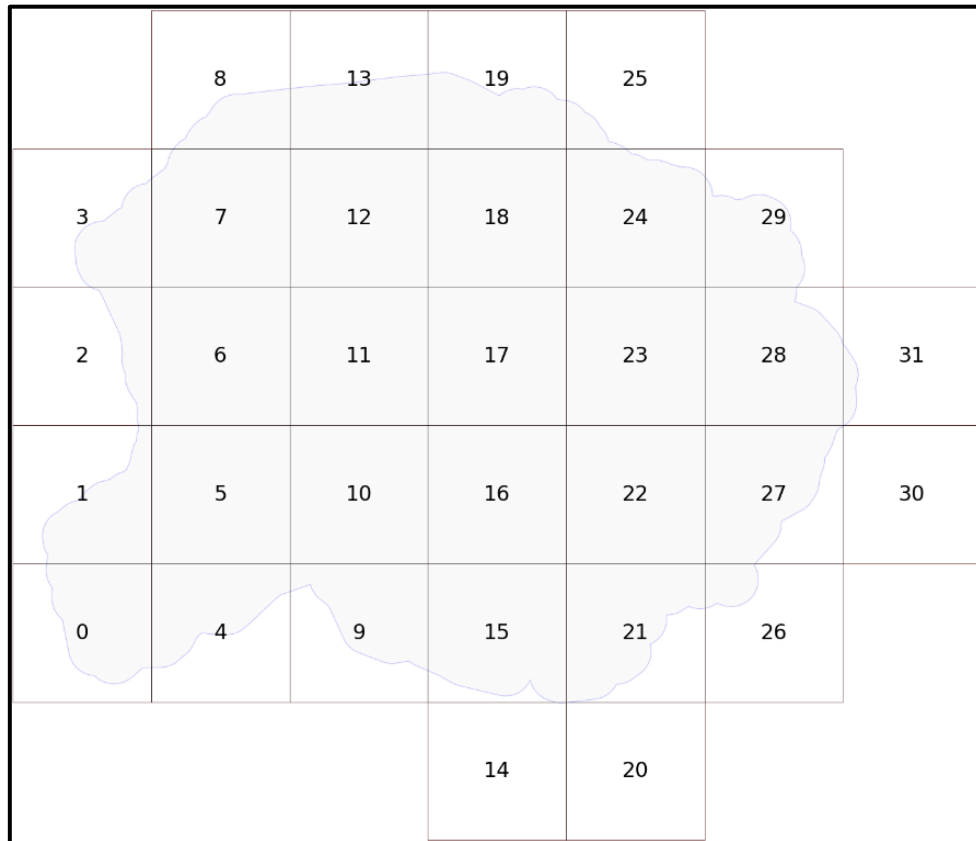
An OA of 0,9344 was achieved. The score was computed on 3630 images, random masks were assigned to the images with replacement. A random batch of images used to compute the OA are presented in Figure 4.6.



*Figure 4.6 – From left to right: (a) ground truth, (b) segmented ground truth, (c) random mask assigned to the ground truth, (d) inpainting result, (e) segmented inpainted image*

#### 4.5 Land cover maps of the study area: 2016 and 2020

The shapefile of the study area was imported into Python, in order to split it into 32 manageable smaller tiles of 2560 by 2560 meters (6.55 km<sup>2</sup>) as illustrated in Figure 4.7.



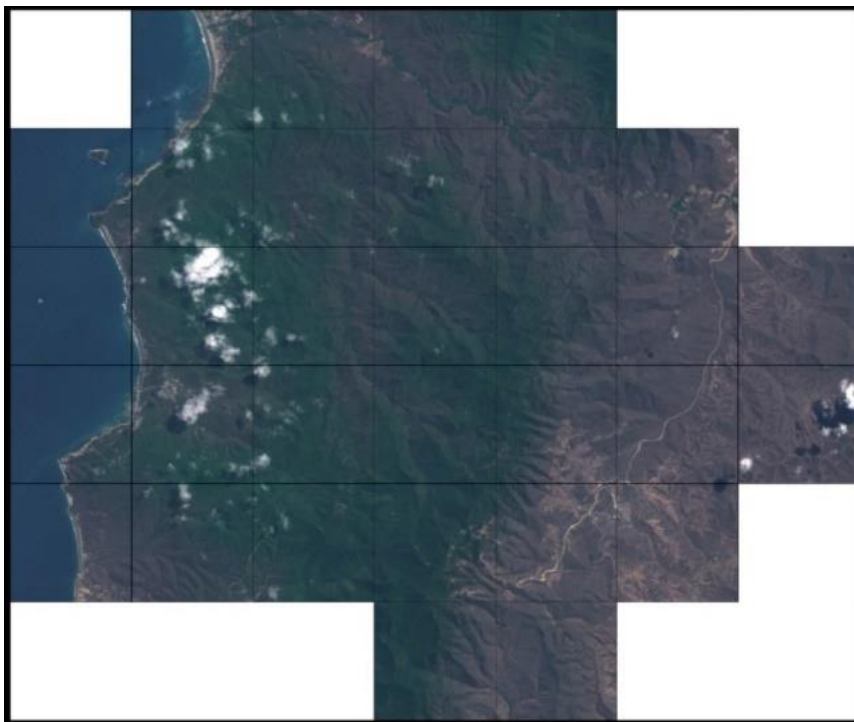
*Figure 4.7 – Study area splitted into smaller tiles*

Geographic coordinates of each patch were obtained, with the aim of downloading the satellite images of the area.

Satellite images from 2016 and 2020 were acquired, they have 10 m spatial resolution, which implies the images size is 256 by 256 pixels with 13 spectral bands, this because the inpainting algorithm requires a 256\*256\*13 image shape as input. In Figure 4.8 the mosaics of the study area from 2016 and 2020 are presented, the least cloudy scenes were chosen.



(a)

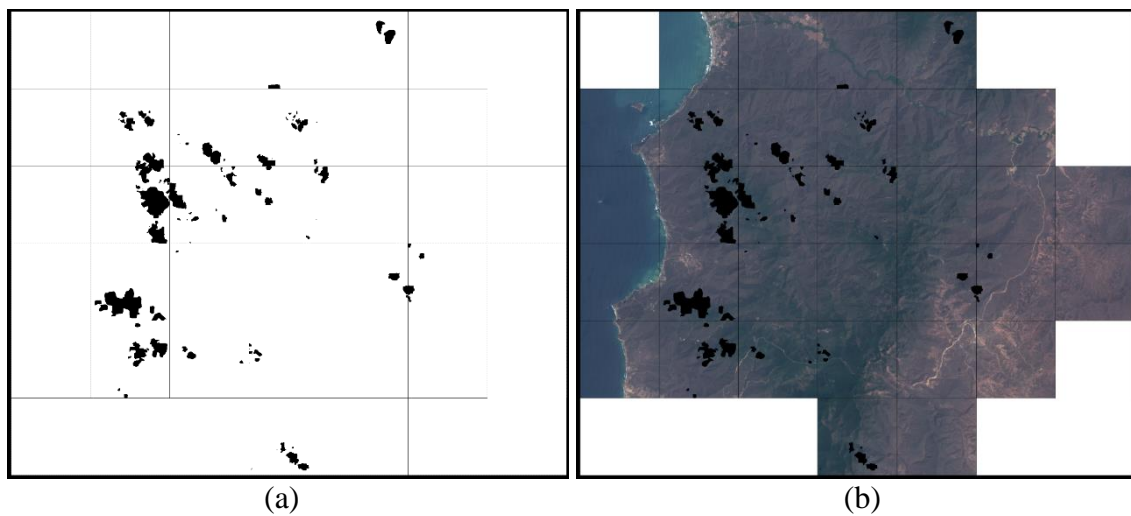


(b)

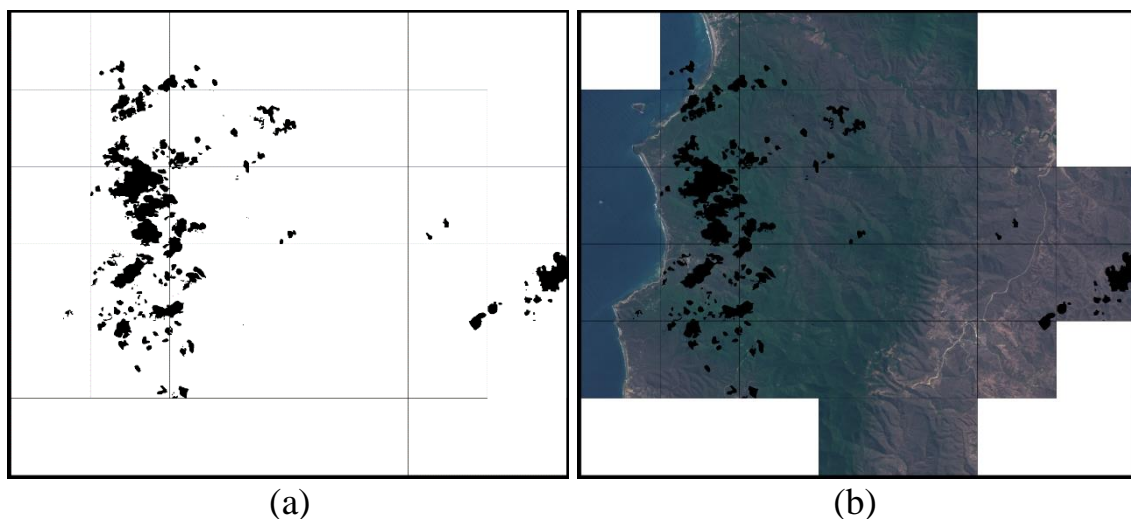
*Figure 4.8 – From top to bottom: (a) study area (RGB composition) from November 21<sup>st</sup>, 2016, (b) study area (RGB composition) from July 23<sup>rd</sup>, 2020*

The image segmentation method was applied to the selected images for detecting clouds and mask them. For this purpose, the clouds class is represented in black, while the rest of them are represented in white (Figure 4.9 and 4.10). The generated binary mask and the cloudy scene were used to feed the inpainting model.

The process described was used for both study area scenes, from 2016 and 2020.



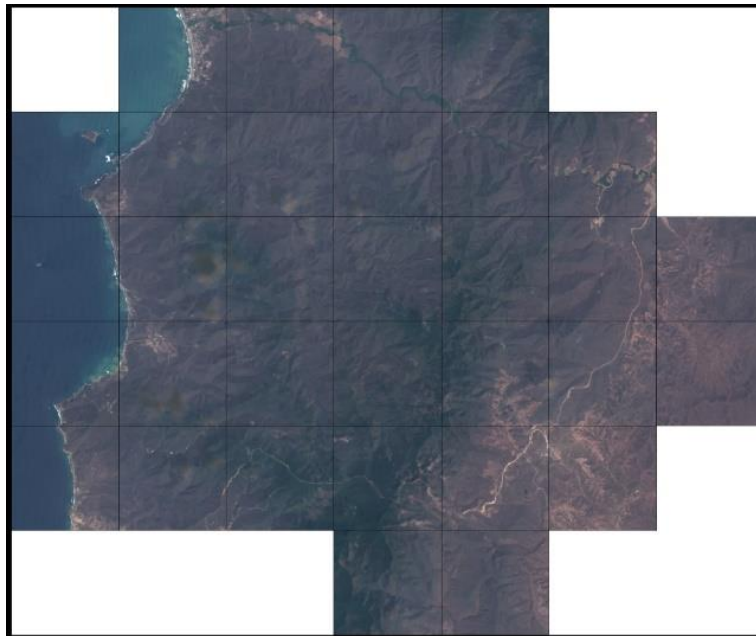
*Figure 4.9 – From left to right: (a) binary cloud mask, (b) satellite images masked from 2016*



*Figure 4.10 – From left to right: (a) binary cloud mask, (b) satellite images masked from 2020*



Inpainting results of the study area are shown in Figure 4.11. With the aim of getting reliable results, the clouds should be totally covered by the binary mask, due to even a small number of cloud pixels could lead to inaccurate image reconstruction.



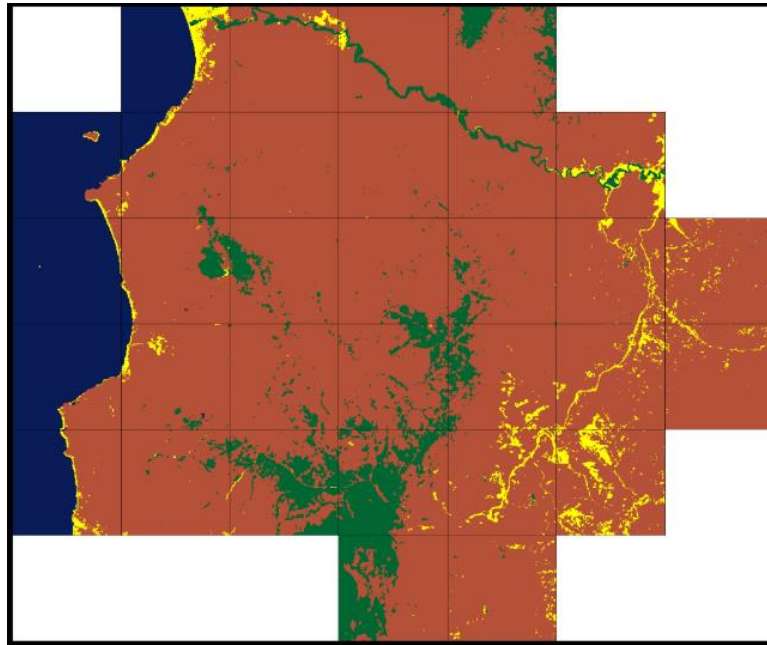
(a)



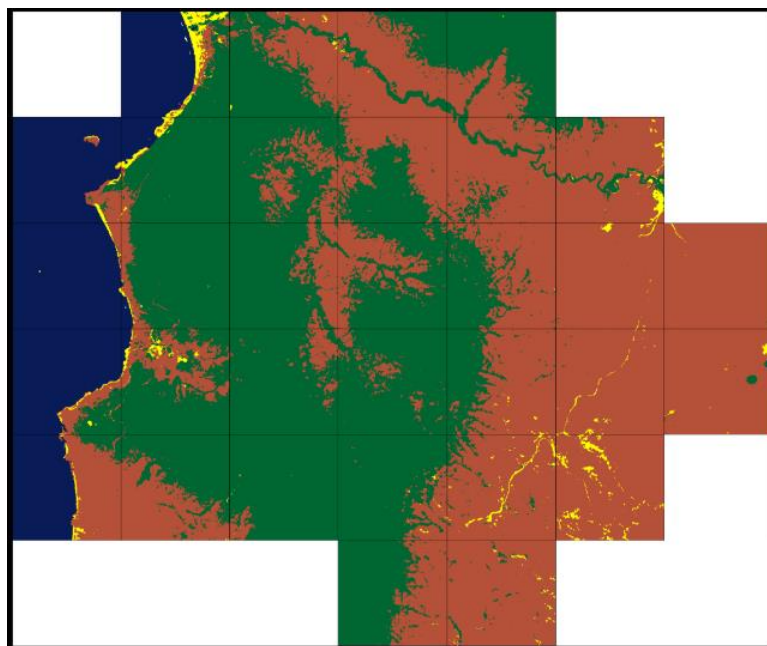
(b)

*Figure 4.11 – From top to bottom: (a) cloud removal and reconstruction of the study area – 2016, (b) cloud removal and reconstruction of the study area – 2020*

Semantic segmentation (land cover classification) process was applied to the inpainting results. In Figure 4.12 the mosaics of segmented images are presented.



(a)








(b)






*Figure 4.12 – From top to bottom: (a) land cover map of the study area – 2016, (b) land cover map of the study area – 2020*

Since the number of pixels by class and their spatial resolution are known, the area of coverage per class can be determined by multiplying both values as shown in Tables 4.2 and 4.3.

*Table 4.2 – Areas by land cover class from 2016*

Number	Class	Color	N Pixels	Area (km <sup>2</sup> )
0	Clouds		73	0.007
1	Water bodies (dark and bright)		262604	26.260
2	Vegetation		148279	14.828
3	Dry vegetation		1627590	162.759
4	Bare soil / buildings		58606	5.861
5	No Data		0	0
<b>Total</b>			2097152	209.715

*Table 4.3 – Areas by land cover class from 2020*

Number	Class	Color	N Pixels	Area (km <sup>2</sup> )
0	Clouds		78	0.008
1	Water bodies (dark and bright)		260240	26.024
2	Vegetation		837459	83.746
3	Dry vegetation		976137	97.614
4	Bare soil / buildings		23147	2.315
5	No Data		97	0.010
<b>Total</b>			2097152	209.715

#### 4.6 Change detection

The land cover change detection was calculated by measuring the difference of surface area by class (Table 4.4). The classes No Data and Clouds were not taken into account due to they represent the 0.008% of the area which is negligible. In addition, the classes dry vegetation and vegetation were merged into a single class.

According to Table 4.5 the class bare soils/buildings has the greatest change, reducing its area in 60.5% during the last 4 years, which implies growth of vegetation areas.




*Table 4.4 – Land cover change based on the number of pixels*

Class	Color	2016 (km <sup>2</sup> )	2020 (km <sup>2</sup> )	Differ. (km <sup>2</sup> )	Differ. (%)
Water bodies		26.260	26.024	0.236	0.899
Vegetation		177.587	181.360	3.773	2.125
Bare soils		5.861	2.315	3.546	60.501
<b>Total</b>		209.708	209.699	0.009	0.004

A different approach for detecting changes on the landscape is using the Jaccard index, which measures the similarity of the study area from 2016 and 2020 considering the spatial context (overlap area).

As seen in Table 4.5 the bare soils class is the only class which shows significant changes. In turn, due to this area is relatively small, the overall Jaccard index is not significantly affected. Despite the fact the bare soils class presents changes, it is not possible to determine whether this area grows or declines, therefore visual inspection of land cover maps is required.

*Table 4.5 – Land cover change based on the Jaccard index*

Class	Color	Jaccard Index (2016 vs. 2020)
Water bodies		0.982430
Vegetation		0.973609
Bare soils		0.252036
<b>mIoU</b>		0.736025
<b>OA</b>		0.952647

## **5 FINANCIAL MANAGEMENT, RESOURCE EFFICIENCY AND RESOURCE SAVING**

The commercial value of the intended research outcome can be assessed in order to identify the potential of their commercial exploitation. Therefore, the purpose of this chapter is to develop a general economic idea of the research, organize and plan the project, identify possible competitors, carry out a comparative analysis, and determine the resources and budget necessary for the completion of the project.

### **5.1 Competitive analysis**

Identifying current and potential competitors, and understanding their strengths and weaknesses in comparison to the research project allow us to recognize opportunities and find ways to penetrate the market.

Currently, the most in demand land cover changes detection tools are based on classical methods ( $P_{i1}$ ) and less frequently on intelligent algorithms ( $P_{i2}$ ). However, such tools can be highly affected by corrupted data. It is possible to build more robust systems through the use of artificial intelligence algorithms, improving the reliability considerably ( $P_f$ ). In Table 4.1 an evaluation scorecard of the research and two competitors is presented, where the competitiveness is determined by the following formula:

$$C = \sum W_i * P_i \quad (5.1)$$

where C – competitive index of the project and competitors;

$W_i$  – criterion weight;

$P_i$  – score (1-5) of the  $i^{\text{th}}$  evaluation criteria.

According to calculations (Table 5.1), the technical solution proposed meets the requirements better than the competitors in terms of technical and economic criteria. Further investment for this project can be considered reasonable.

Table 5.1 – Competitive Scorecard of the project and competitors

Evaluation Criteria	Criterion Weight	Score			Competitiveness		
		P <sub>f</sub>	P <sub>i1</sub>	P <sub>i2</sub>	C <sub>f</sub>	C <sub>i1</sub>	C <sub>i2</sub>
1	2	3	4	5	6	7	8
<b>Technical criteria for resource efficiency assessment</b>							
1. Increased productivity user labor	0,1	3	3	2	0,3	0,3	0,2
2. Reliability	0,1	4	4	4	0,4	0,4	0,4
3. Ease of use	0,05	3	3	3	0,15	0,15	0,15
4. Demand for memory resources	0,2	3	2	3	0,6	0,4	0,6
5. Ease of operation	0,05	4	4	3	0,2	0,2	0,15
<b>Economic criteria for performance evaluation</b>							
1. Competitiveness of the product	0,2	3	3	3	0,6	0,6	0,6
2. Level of market penetration	0,1	1	4	4	0,1	0,4	0,4
3. Price	0,05	4	2	1	0,2	0,1	0,05
4. Estimated service life	0,15	3	2	2	0,45	0,3	0,3
<b>TOTAL</b>	<b>1</b>	<b>28</b>	<b>26</b>	<b>25</b>	<b>3</b>	<b>2,85</b>	<b>2,85</b>

## 5.2 SWOT analysis

The primary goal of the SWOT analysis (Table 5.2) is to identify the project's strengths, weaknesses, opportunities, and threats. It helps to develop a full awareness of all the factors involved during the development and execution of the project minimizing risks, and taking advantage of opportunities.

Table 5.2 – SWOT matrix

	<p><b>Strengths:</b>  S1. Widely applicable.  S2. Real time analysis.  S3. Highly Reliable.  S4. Demand</p>	<p><b>Weaknesses:</b>  W1. Large amount of data needed.  W2. High Computational cost.</p>
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		W3. Complex integration into a single system. W4. Dependence on a single provider of data.
<b>Opportunities:</b> O1. Easy identification and assessment of resources. O2. Use in analysis and modelling applications. O3. Application for simple and complex analysis. O4. Ability to translate data into easy interpretation maps.	The results of the experiment can be easily interpreted and used in further research in various fields of science.	The structure and complexity of the project requires additional knowledge for determining a new area of study.
<b>Threats:</b> T1. The existence of classic techniques for satellite image segmentation. T2. The dependence on free satellite imagery providers. T3. High computational requirements.	The developed algorithm can reduce noise, therefore, in case of corrupted data or missing data, the system will perform the tasks reliably.	New sources of data cannot be incorporated to the developed system, because it implies the modification of the entire structure of the system.

The results presented in the SWOT matrix were obtained through the compilation of the interactive matrixes of the project, which are presented in Tables 5.3-5.6.

*Table 5.3 – Interactive matrix: Opportunities vs Strengths*

Strengths					
Opportunities		S1	S2	S3	S4
	O1	+	+	+	+
	O2	0	-	+	-
	O3	+	-	+	-
	O4	+	+	+	+

Table 5.4 – Interactive matrix: Opportunities vs Weakness

<b>Weaknesses</b>					
<b>Opportunities</b>		W1	W2	W3	W4
	O1	+	+	0	-
	O2	+	+	0	-
	O3	+	+	+	+
	O4	0	+	0	-

Table 5.5 – Interactive matrix: Threats vs Strengths

<b>Strengths</b>					
<b>Threats</b>		S1	S2	S3	S4
	T1	-	0	+	+
	T2	-	+	+	+
	T3	-	+	+	+

Table 5.6 – Interactive matrix: Threats vs Weakness

<b>Weaknesses</b>					
<b>Threats</b>		S1	S2	S3	S4
	T1	-	+	0	-
	T2	+	+	+	+
	T3	+	+	+	-

### 5.3 Project Initiation

In this section the initial purpose, content and resources of the project are determined. Internal and external stakeholders, organizational structure and limitations which influence the result of the research are defined.

#### 5.3.1 Objectives and results of the project

Stakeholders of the project are introduced in Table 5.7. They are individuals or organizations that have an interest in the research outcomes.

Table 5.7 – Project stakeholders

<b>Project Stakeholders</b>	<b>Stakeholder expectations</b>
Urban planning departments	Reliable land cover maps, easy to interpret and constantly updated.



Natural Resources research Institutes	Highly precise information of the use, distribution and temporal dynamics of natural resources.
Natural disaster response and recovery Departments	Rapid detection, assessment and evaluation of areas affected by natural disasters.

Table 5.8 provides information on the hierarchy of project goals and criteria for achieving them.

*Table 5.8 – Purpose and results of the project*

<b>Purpose of project</b>	Detect land cover changes through the use of Artificial Intelligence algorithms and satellite images.
<b>Expected results of the project</b>	1. Study of land cover classification algorithms performance. 2. Creation of a multispectral imagery dataset. 3. Creation of an automated workflow for downloading, denoising and segmenting satellite images.
<b>Acceptance criteria of the project results</b>	1. Accuracy of prediction greater than 90% 2. Jaccard index greater than 80% for inpainting.
<b>Acceptance requirements for the project results</b>	1. The research should be finalized by June 1, 2021. 2. Meet the criteria for results acceptance.

### 5.3.2 Organizational structure of the project

Members of the working group, roles and functions are defined and described in Table 5.9.

*Table 5.9 – Working group*

<b>№</b>	<b>Participant</b>	<b>Role</b>	<b>Functions</b>	<b>Labor time (hours)</b>
<b>1</b>	Olga Tokareva, Ph. D., Associate Professor, TPU	Scientific Supervisor	Responsible for the implementation of the project and coordination of activities, in order to meet the requirements for graduation research.	296

2	Cristian Rodrigo Machuca Mendoza	Executor	Responsible to carry out the research; Literature review, development of algorithms, evaluation and analysis of t results, and finally writing the dissertation.	648
<b>TOTAL</b>				944

### 5.3.3 Project limitations and assumptions

Limitations and assumptions can be defined as circumstances that can obstruct the completion of the project and reduce the project team members freedom.

*Table 5.10 – Project limitations and assumptions*

<b>Factors</b>	<b>Limitations / Assumptions</b>
1. Project budget	140050.88 rubles
1.1. Source of financing	-
2. Project timeline	01.02.2021 – 01.06.2021
2.1. Date of project management plan approval	15.02.2021
2.2. Project completion date	01.06.2021

## 5.4 Scientific research project planning

### 5.4.1 Project schedule

In order to develop the project schedule, it was required to assign tasks to project members as presented in Table 5.11.

*Table 5.11 – Stages, tasks and distribution of performers*

<b>Main Stages</b>	<b>Nº</b>	<b>Work Content</b>	<b>Performed by</b>
Terms of reference development	1	Formulation and approval of terms of reference	Supervisor Executor
Choice of research direction	2	Selection and study of materials on the topic	Executor
	3	Selection of research direction	Executor
	4	Research activity calendar	Supervisor Executor
Research and analysis	5	Design of experimental algorithms	Supervisor Executor

	6	Development of the system	Supervisor Executor
	7	System evaluation	Executor
Evaluation of results	8	Indices calculation	Executor
	9	Analysis and interpretation of indices	Executor
	10	Evaluation of effectiveness of the results	Supervisor Executor
Documentation and registration of final qualifying work	11	Draw up an explanatory note	Executor
	12	Preparation of the dissertation defense	Supervisor Executor

Once the stages and performers of the research are defined, it is necessary the creation of the timeline of the research, therefore, calculating the working days and calendar days is essential. For this purpose, the following formula is used:

$$T_{Ci} = T_{Pi} * K_{cal} \quad (5.2)$$

where  $T_{Ci}$  – duration of the job in calendar days;

$T_{Pi}$  – duration of the job in working days;

$K_{cal}$  – calendar factor.

The calendar factor is determined by the following formula:

$$k_{cal} = \frac{T_{cal}}{T_{cal} - T_{weekend} - T_{hol}} = \frac{365}{365 - 98 - 17} = 1,46 \quad (5.3)$$

where  $T_{cal}$  – number of days of the year;

$T_{weekend}$  – number of weekend days of the year;

$T_{hol}$  – number of holidays of the year.



*Table 5.12 – Project timeline in working and calendar days*



№	Labor intensity			Participants	$T_{Pi}$	$T_{Ci}$
	$t_{min}$	$t_{max}$	$t_{expi}$			
1	2	5	4	Supervisor, Executor	4	6
2	3	7	5	Executor	5	7
3	4	8	5	Executor	5	7

4	1	4	3	Supervisor, Executor	3	4
5	2	6	5	Supervisor, Executor	5	7
6	16	25	20	Supervisor, Executor	20	29
7	8	13	10	Executor	10	15
8	7	11	8	Executor	8	12
9	6	11	8	Executor	8	12
10	2	7	3	Supervisor, Executor	3	4
11	7	11	8	Executor	8	12
12	1	3	2	Supervisor, Executor	2	3
<b>Total</b>	<b>Supervisor</b>				<b>81</b>	<b>118</b>
	<b>Executor</b>				<b>37</b>	<b>53</b>

Table 5.13 – Calendar plan-graph

№	Participants	T <sub>ci</sub>	Duration of the project												
			February			March			April			May			
			1	2	3	1	2	3	1	2	3	1	2	3	
1	Supervisor, Executor	6	■ ▨												
2	Executor	7		▨											
3	Executor	7			▨										
4	Supervisor, Executor	4			■ ▨										
5	Supervisor, Executor	7			■ ▨										
6	Supervisor, Executor	29				■ ▨	■ ▨	■ ▨							
7	Executor	15							▨	▨					
8	Executor	12								▨	▨				
9	Executor	12										▨	▨		
10	Supervisor, Executor	4												■ ▨	

11	Executor	12												
12	Supervisor, Executor	3												

 -Supervisor      -Executor

## 5.5 Scientific research budget

The costs associated to the development and implementation of this project are considered in this section. To determine the total cost of the research the following items are taken into account:

- material costs;
- costs of additional and special equipment;
- basic salary;
- additional salary;
- labor tax;
- overhead cost.

### 5.5.1 Calculation of material cost

The cost of purchasing materials, components and semi-finished products required to carry out the research are shown in Table 5.14.

*Table 5.14 – Costs of materials*

Name	Description	Quantity	Unit Price	Amount (rubles)
Paper	Pack of 500 sheets. A4	1	300	300
Toner	Printer toner cartridge	1	1700	1700
<b>TOTAL</b>				2000

### 5.5.2 Calculation of costs for additional and special equipment

No additional or special equipment were purchased.

### 5.5.3 Calculation of basic and additional salary

This section includes the salaries of the participants involved in the development of the project. The base salary is calculated based on the labor intensity and is determined by the following formula:

$$S_{base} = S_{day} * T_w \quad (5.4)$$

where  $S_{day}$  – average daily salary in rubles;

$T_w$  – duration of the work of the performers in working days.

The average daily salary is calculated using the following formula:

$$S_{day} = \frac{S_{month}}{F_V} * M \quad (5.5)$$

where  $S_{month}$  – monthly salary in rubles;

$F_V$  – valid annual working time of scientific and technical staff (247 days);

$M$  – number of months of work without vacation during the year: at 24 working day of vacation,  $M=11.2$  (5-day week).

Table 5.15 – Valid annual working time

Working Time Indicators		Supervisor	Student
Days of the year		365	365
Non-working days	Weekends	98	98
	Holidays	17	17
Worktime loss	Vacation	24	24
	Sickness absence	0	0
Valid annual fund of working time		226	226

Worker's monthly salary:

$$S_{month} = S_{base} * (k_{premium} + k_{bonus}) \quad (5.6)$$

where  $S_{base}$  – base salary in rubles;

$k_{pr}$  – premium coefficient;

$k_{bonus}$  – bonus coefficient;

$k_{reg}$  – regional coefficient equals 1.3 (Tomsk).

Table 5.16 – Calculation of basic salary

Participants	Salary (rubles)	$k_{reg}$	$S_{month}$	$S_{day}$	$T_w$ , Workdays	$W_{base}$
Supervisor	22480	1,3	29224	1325,14	37	49030,18
Executor	12792	1	12792	580,04	81	46983,24
<b>Total</b>						96013,42

Additional salary is calculated on the basis of 10-15% of the base worker's salary, and is given by the following formula:

$$W_{add} = W_{base} * K_{extra} \quad (5.7)$$

where  $W_{base}$  – base salary in rubles;

$k_{extra}$  – additional salary coefficient (10%).

Table 5.17 – Calculation of additional salary

Participants	Base salary	Additional salary
Supervisor	49030,18	4903,02
Executor	46983,24	4698,32
<b>TOTAL</b>		9601,34

#### 5.5.4 Labor tax

Tax on extra-budgetary funds is mandatory and is determined based on the following formula:

$$S_{contribution} = k_b * W_{base} + W_{add} \quad (5.8)$$

where  $k_b$  – deduction coefficient for extra-budgetary funds.

The Federal law of July 24, 2009, No. 212-FL, establishes a contribution of 30%. For institutions conducting educational and scientific activities the contribution is reduced to 27,1%.

Table 5.18 – Calculation of labor tax

Participants	Base salary	Additional salary	Base + additional salary	Labor tax
Supervisor	49030,18	4903,02	53933,2	14615,90
Executor	46983,24	4698,32	51681,56	14005,70
<b>Total</b>				28621,60

### 5.5.5 Overhead costs

Due to the work was performed using a computer workstation, it is necessary to calculate the electric energy consumption as follows:

$$E = P * T \quad (5.9)$$

where P – power requirement of the equipment in kW;

T – time of use of the equipment in hours.

In accordance to the datasheet provided by the equipment manufacturer the power requirement is 0,255 kW and considering that the entire project was carried out using it, then:

$$E = 0,255 * 360 = 91,8 \text{ kWh} \quad (5.10)$$

Electricity costs are calculated as follows:

$$Ec = T_{elec} * E = 10,18 * 91,8 = 934,52 \text{ rubles} \quad (5.11)$$

where  $T_{elec}$  – industrial electricity tariff (10,18 rubles per kWh).

Internet service costs 720 rubles a month, and was used during four months, summing a total cost of 2880 rubles.

### 5.5.6 Scientific project budget

The budget calculation involves the costs previously determined, and it is presented in Table 5.19.

*Table 5.19 – Budget for the scientific and technical research*

<b>Expenditure items</b>	<b>Cost</b>
Material costs	2000
Basic salary	96013,42
Additional salary	9601,34
Labor tax	28621,60
Overhead	3814,52
<b>Total cost</b>	<b>140050,88</b>



## 5.6 Project risk register

Potential undefined events that may arise in the project and their consequences that could lead to undesirable effects are presented in Table 5.20.

Table 5.20 – Risk register

№	Risk	Potential effects	Prob. (1-5)	Effect (1-5)	Level of impact	Mitigation strategy	Conditions of occurrence
1	Data type mismatch	Impossible to carry out the research	2	5	High	Check the data source documentation	Improper set up of input parameters
2	Inability to access services of the data provider	Unable to meet the project goals	2	5	High	Analysis of possible secondary data sources	Change of terms and conditions by the data provider
3	Noisy or corrupted data	Distortion of results	3	3	Med	Implementation of filters	Malfunction of data acquisition devices
4	Poor performance of the equipment.	Unable to complete the project on time	3	2	Low	Use of techniques and methods to create optimal workflows	Inappropriate data handling

## 5.7 Definition of resource, financial, budgetary, social and economic efficiency of the research

The project efficiency is based on the calculation of the integral indicator of resource efficiency. It is related to the definition of two weighted average values: financial efficiency and resource efficiency, and is computed as follows:

$$I_m = \sum a_i * b_i^a; \quad (5.12)$$

where  $I_m$  – integral indicator of resource efficiency of the project parameters;

$a_i$  – weighting coefficient of the i-th parameter;

$b_i^a, b_i^b$  – score of the i-th parameter for project and analogs,  
established by an expert.

Table 5.21 – Comparative assessment of project and analogues parameters

Criteria	Weighted coefficient	Current project	Analog 1	Analog 2
1. Promotes the growth of production user labor efficiency	0,10	5	5	5
2. Convenient in operation (meets the requirements of consumers)	0,15	4	5	5
3. Interference immunity	0,15	3	3	4
4. Energy saving	0,20	4	3	3
5. Reliability	0,25	4	4	5
6. Material consumption	0,15	4	4	3
<b>Total</b>	<b>1</b>			

$$Project = 5 * 0,1 + 4 * 0,15 + 3 * 0,15 + 4 * 0,2 + 4 * 0,25 + 4 * 0,15 = 3,95$$

$$Analog 1 = 5 * 0,1 + 5 * 0,15 + 3 * 0,15 + 3 * 0,2 + 4 * 0,25 + 4 * 0,15 = 3,9$$

$$Analog 2 = 5 * 0,1 + 5 * 0,15 + 4 * 0,15 + 3 * 0,2 + 5 * 0,25 + 3 * 0,15 = 4,15$$

The integral financial indicator of the project is defined by:

$$I_f^p = \frac{F_{pi}}{F_{max}}; \quad (5.13)$$

where  $F_{pi}$  – cost of the project and analogues;

$F_{max}$  – maximum cost of execution of the scientific (including analogues).

$$I_f^p = \frac{F_p}{F_{max}} = \frac{140051}{188970} = 0,74 \quad (5.14)$$

$$I_f^{a1} = \frac{F_{a1}}{F_{max}} = \frac{166320}{188970} = 0,88 \quad (5.15)$$

$$I_f^{a2} = \frac{F_{a2}}{F_{max}} = \frac{188970}{188970} = 1 \quad (5.16)$$

The integral index of efficiency of the project parameters ( $I_{fin}^p$ ) and analogues ( $I_{fin}^a$ ) is determined by the following formulas:

$$I_{fin}^p = \frac{I_m^p}{I_f^p} = \frac{3,95}{0,74} = 5,33 \quad (5.17)$$

$$I_{fin}^{a1} = \frac{I_m^{a1}}{I_f^{a1}} = \frac{3,9}{0,88} = 4,43 \quad (5.18)$$

$$I_{fin}^{a2} = \frac{I_m^{a2}}{I_f^{a2}} = \frac{4,15}{1} = 4,15 \quad (5.19)$$

Comparison of the integral index of efficiency between the current project and its analogues will allow to determine the resource efficiency of the project. The comparative effectiveness index is given by the following formula:

$$C_{eff} = \frac{I_{fin}^p}{I_{fin}^a} \quad (5.20)$$

According to Table 5.22 the project meets the requirements in resource efficiency and resource-saving.

*Table 5.22 – Comparative efficiency of the project*

<b>Indicators</b>	<b>Current project</b>		<b>Analog 1</b>	<b>Analog 2</b>
Integral financial index	0,74		0,88	1
Integral resource efficiency index	3,95		3,9	4,15
Integral performance index for parameters	5,33		4,43	4,15
Comparative performance of the parameters	$C_{eff}^{a1}$	$C_{eff}^{a2}$	$C_{eff1}^p$	$C_{eff2}^p$
	1,20	1,28	0,83	0,78

## 5.8 Conclusion on financial management analysis

In line with the findings after performing the financial evaluation, we can conclude that the project is economically viable. The total budget needed to cover the costs of developing and implementing the project is 140050,88 RUB. The time required for completion of the project is 118 calendar days.

## **6 SOCIAL RESPONSIBILITY**

The correct implementation of strategies and regulations to prevent illness and injuries at work is essential, simply because it ensures the work environment, eases the process of complying with current regulations to avoid possible sanctions, improves worker satisfaction, motivation and productivity.

This graduate research project consists of analyzing changes on the landscape in Ecuador through the use of satellite data and Artificial Intelligence algorithms. Therefore, the interaction between the researcher and a computer workstation is essential.

People working at a computer workstation may be unaware of factors that can increase their risk of development of injury and situations that may result in health concerns related to physical and psychophysical hazards. Therefore, the following section provides an analysis of dangerous and harmful production factors, and protection measures against them. Environmental and emergency safety analysis, in order to create an optimal working environment are included.

### **6.1 Occupational Safety**

The identification and assessment of the dangerous and harmful production factors that may arise during the development and operation of the project lead to ensure industrial safety.

A production factor is considered harmful if exists the probability to be harmed or experience an adverse health effect if exposed to it.

Dangerous and harmful production factors of the working environment by the nature of their impact on the body of a working person are divided into: physical, chemical and biological. By the source of origin, the production factors are divided into: psychophysiological; organizational and managerial, personality-behavioral and socio-economic.

Dangerous and harmful factors identified according to GOST 12.0.003-2015 Occupational safety standards system are shown in Table 6.1. *Table 6.1 – Identification of dangerous and harmful factors at a computer workstation*

<b>DANGEROUS AND HARMFUL FACTORS IDENTIFIED</b>		<b>REGULATIONS</b>
<b>EFFECTS</b>	<b>PRODUCTION FACTORS</b>	
Physical	<ul style="list-style-type: none"> <li>-Abnormal microclimatic parameters of the air.</li> <li>-Lack of natural light, insufficient illumination.</li> <li>-Increased level and other unfavorable characteristics of noise.</li> <li>-Electric current caused by the difference in electrical potentials.</li> </ul>	<p>GOST 12.1.005-88 General sanitary requirements for working zone air.</p> <p>SanPiN 2.2.1/2.1.1.1278-03 Hygienic requirements for natural, artificial and mixed lighting of residential and public buildings.</p> <p>GOST 12.1.003-2014 Occupational safety standards system. Noise.</p> <p>GOST 12.1.030-81 Electric safety. Protective conductive earth, neutralling.</p>
Psychophysical	<ul style="list-style-type: none"> <li>-Static Physical Overload.</li> <li>-Neuropsychic Overload.</li> </ul>	<p>GOST 9241-4-2009. Ergonomic requirements for office work with visual display terminals (VDT).</p>

### **6.1.1 Dangerous and harmful production factors**

#### **6.1.1.1 Abnormal microclimatic parameters of the air**

Computer workstations, lighting and electronic devices generate heat constantly, causing variations in the microclimate in the work environment. Increased evidence shows that indoor environmental conditions substantially influence health and productivity. High air temperatures can aggravate

medical conditions and illnesses such as high blood pressure or heart disease, in addition, it causes rapid overheating of the body and accelerates fatigue. In addition, relative humidity less than 30% can lead to skin and throat irritation, producing high static [49,50].

According to the General sanitary requirements for working zone air (GOST 12.1.005-88) a computer workstation worker belongs to Category-I work, which implies light physical work. Parameters such as: air temperature, humidity and air speed determine the thermal comfort. Optimal air parameters for a Category-I work are shown in Table 6.2 [51].

*Table 6.2 – Optimal temperature conditions for a Category I workplace*

<b>Season</b>	<b>Air Temperature</b>	<b>Humidity</b>	<b>Air Speed</b>
Summer	23-26 °C	~50%	<0.15m/s
Winter	20-23.5 °C	~50%	<0.15m/s

In general, computer rooms must be equipped with cooling equipment (HVAC – Heat Ventilation Air Condition), which can reduce the risk of static electricity, and prevent the development of hot spots during both summer and winter [52].

### **6.1.1.2 Lack of natural light, insufficient illumination**

Right illuminance level and uniformity improve occupants’ visual perception and decrease the signs of fatigue, including eye pain and headache [53].

Visual discomfort and physiological strain such as anxiety, fatigue, lethargy, headaches, eyestrain, migraine, nausea, back pain, neck pain, shoulder pain, poor concentration or lack of mental alertness, and daytime sleepiness among video display terminal (VDT) workers are primarily connected with inadequate lighting in the working place and in most cases decrease work performance and efficiency [54].

Lighting levels ranging from 300 to 500 lux are appropriate for most computer desk work. Generally, the maximum lighting level should not exceed 750 lux. Excessive lighting levels have a "masking" effect and make it difficult for the operator to see the display on the screen [55].

### **6.1.1.3 Increased level and other unfavorable characteristics of noise**

Air-condition and equipment cooling fans necessary for the proper operation of IT equipment run continuously and create excessive noise that influence comfort, poses risk to hearing and impairs communication and concentration [56].

Noise can cause permanent hearing loss at chronic exposures equal to an average sound pressure level (SPL) of 85 dBA or higher for an eight-hour period. the World Health Organization (WHO) recommend maintaining environmental noises below 70 dBA over 24-hours (75 dBA over 8-hours) to prevent noise-induced hearing loss. The background noise in computer rooms can range from 70 to 80 dBA, pushing noise exposure to almost dangerous levels when timed over 8 hours [57].

Installing acoustic ceiling clouds or baffles and adding acoustic foam to the computer room in floor and walls can absorb sound waves and decrease undesirable sounds. They not only reduce noise levels but also control sound reverberation.

Routine maintenance, monitoring and control of computer equipment ensures 100% efficient operation. In turn, it leads to heat reduction, thereby reducing fan usage and noise.

#### **6.1.1.4 Electric current caused by the difference in electrical potentials**

The major hazards associated with electricity are electrical shock and fire. Electrical shock occurs when the body becomes part of the electric circuit, either when an individual comes in contact with both wires of an electrical circuit, one wire of an energized circuit and the ground, or a metallic part that has become energized by contact with an electrical conductor [58].

*Table 6.3 – General relationship between the degree of injury and amount of current hand-to-foot path of one second’s duration of shock.*

<b>Current</b>	<b>Reaction</b>
1 Milliampere	Perception level
5 Milliamperes	Slight shock felt; not painful but disturbing
6-30 Milliamperes	Painful shock; “let-go” range
50-150 Milliamperes	Extreme pain, respiratory arrest, severe muscular contraction
1000-4300 Milliamperes	Ventricular fibrillation
10000+ Milliamperes	Cardiac arrest, severe burns and probable death

Electrically powered equipment, such as power supplies, routers, switches, servers, computers and projectors are essential elements of a computer room. These devices can pose a significant hazard to computer workstation users, particularly when mishandled or not maintained. Large capacitors found in power supplies and other systems are capable of storing lethal amounts of electrical energy. In addition, poor wiring, defective electric wires, extension cords and heavy covering of wires pose a serious danger [59].

Circuit protection devices and electrical grounding systems must be installed in order to eliminate over-voltage and electric shock risks. Fuses



and circuit breakers prevent over-heating of wires and components that might otherwise create hazards. In addition, inspecting the wiring of equipment before each use, reporting and not using damaged or frayed electrical cords minimize electrical hazards.

### 6.1.1.5 Static Physical Overload

Individuals who use computers and do monotonous repetitive manipulations with or without objects over long periods of time may experience discomfort or pain as a result of poor posture, improper adjustment or use of workstation components or other factors which may lead to musculoskeletal disorders (MSD). In most cases, there are relatively simple and inexpensive corrective measures which can be employed to reduce the likelihood of discomfort or injury [60].

Musculoskeletal conditions are typically characterized by pain (often persistent) and limitations in mobility, dexterity and overall level of functioning, reducing people’s ability to work. Low back pain is the main contributor to the overall burden of musculoskeletal conditions which are also the highest contributor to the global need for rehabilitation [61].

Regardless of the working position, sitting for long periods of time is unhealthy. Table 6.4 gives the summary sheet of different recommendations of work-rest schedules [62].

*Table 6.4 – Break’s schedule when working with computers*

<b>Continuous Work</b>	<b>Rest</b>
210 minutes	30 minutes
60 minutes	10 minutes
30 minutes	5 minutes
15 minutes	1 minute

### **6.1.1.6 Neuropsychic Overload**

There is growing evidence of the global impact of mental illness. Mental health problems are among the most important contributors to the burden of disease and disability worldwide. Five of the ten leading causes of disability worldwide are mental health problems. The impact of mental health problems in the workplace has serious consequences not only for the individual but also for the productivity of the enterprise. Employee performance, rates of illness, absenteeism, accidents and staff turnover are all affected by employees' mental health status.

Boring work, monotony, tight deadlines, heavy workload, poor relationships with colleagues, poor work organization, and lack of support are some of the factors that commonly cause work-related mental stress [63].

### **6.2 Environmental Safety**

This section refers the environmental impact caused by the development of the project and its deployment in the production environment.

Although the development of software during the research process is not harmful for the environment, the equipment necessary to carry it out use and contain at least some materials that can be considered toxic to the environment.

Perhaps the most damaging impact of computers is upon disposal. E-waste contains a number of hazardous components, which when dismantled and processed inappropriately, can threaten healthy lives through the contamination of water, soil and air.

Chromium can be found in circuit boards, metal plates, switches and relays. In soils strongly attaches to soil particles and as a result it will move towards groundwater. In water chromium will absorb on sediment and become immobile. Only a small part of the chromium that ends up in water

will eventually dissolve. Chromium is mainly toxic to organisms. It can alter genetic materials and cause cancer [64].

Lead makes up about 6% of the total weight of a computer and is used in monitors, screens, batteries and printed circuit boards. About 40% of the lead found in landfills comes from electronics [65].

According to WHO reports, it is estimated that about 1.43 million cases of death happened due to lead poisoning every year along with 6 million new cases of children with intellectual disabilities [66]. Lead contamination in the soil results in the manifestation of morphological, biological and physiological changes in plants [67].

Semiconductors and chip resistors contain cadmium which is one of the most toxic pollutants emitted in the biosphere, as evidenced by its adverse influence on microbial activities and interactions [68].

Mercury is used in batteries, fluorescent lamps and printed circuit boards in addition to a variety of electrical equipment and can cause brain damage [65].

The main document that stipulates general principles of waste management in Russia is the federal law, 'On waste of production and consumption' (Federal law 49-FZ). Legislative and regulatory support, accounting and supervision of waste management of home appliances and electronics in Russia is going on in accordance with the general law on waste management, as Russia has no separate legislation on waste of electrical and electronic equipment (WEEE) management [69]. WEEE Recyclers Association was established on the platform of the Chamber of Commerce and Industry of the Russian Federation (CCI of Russia) and CCI of Moscow, and with the support of the UNIDO (United Nations Industrial Development Organization) Centre for International Industrial Cooperation in the Russian Federation [71]. On September, 1<sup>st</sup>, 2011, the Ministry of Natural Recourses

created the order number 721, which directs, that all entities should maintain a record of WEEE generated and transferred to the disposal organizations.

### **6.3 Emergency Safety**

Among the emergencies that may arise in a computers room, fire has the highest probability of occurrence. In this section an emergency plan in case of fire, and its probable causes are discussed and described.

The most common sources of fires in computer rooms are the electrical system or the hardware. Breakdowns in insulation and the resultant short circuiting can lead to intense heat that can melt materials or cause a fire which can spread rapidly and be very costly.

#### **6.3.1 Mitigation measures**

For computer rooms, there are recommended measures (technical and organizational) to prevent the spread of fire and ensure sufficient fire alerts and effective fire extinguishing.

Construction measures: The IT equipment room shall be separated from other occupancies in the IT equipment area by fire-resistant rated construction (not less than 1 hour). Every opening in the fire-resistant rated construction shall be protected to limit the spread of fire and to restrict the movement of smoke from one side of the fire-resistant rated construction to the other.

Installation of automatic fire detection and fire alarm systems: Automatic detection equipment shall be installed to provide early fire warning. The equipment used shall be a listed smoke-detection- type system. The alarms and trouble signals of automatic detection or extinguishing systems shall be arranged to annunciate in a constantly occupied location.

Installation of automatic fire protection systems: Where there is a critical need to protect data in process, reduce equipment damage and

facilitate return to service, consideration should be given to the use of a gaseous clean agent inside units or total flooding systems in sprinklered or non-sprinklered IT equipment areas. Electronic and heating, ventilation, and air conditioning equipment should be automatically shut down in the event of any suppression system discharge.

Additional organizational and other measures: Designated IT equipment area personnel shall be continually and thoroughly trained in the functioning of the alarm system, desired response to alarm conditions, location of all emergency equipment and tools, and use of all available extinguishing equipment.

Listed portable fire extinguishers of the carbon dioxide type or a halogenated agent type shall be provided for the protection of electronic equipment [70,71].

### **6.3.2 Procedure in case of fire**

Once a fire has been detected by an automatic detector or by a person activating a manual call point, the fire detection system will generate the preprogrammed control and alarm signals. A fast and efficient evacuation procedure is essential. This not only saves lives, but once the evacuation of the building has been completed, the fire services can concentrate on minimizing the damage to property [72].

Alerting people: In case of fire and if the situation cannot be contained or creates risks beyond the capabilities of the personnel in attendance then a general alarm (evacuation) can be activated.

Alerting the fire department: Alarm transmission to the intervention forces for the internal – and external alarm or organization like the local or remote fire brigade is accomplished by means of monitored dedicated lines, telephone lines, dialup connection, radio connection, network connection or a combination of these transmission methods.

## CONCLUSION

Partial convolutional neural network with automatic mask updating provides the ability to explore spatial-spectral deep features for achieving highly reliable and accurate inpainting results. In this research, a new approach for cloud removal and reconstruction of multispectral satellite images was introduced, which in conjunction with semantic segmentation method, allows to detect changes on the landscape accurately.

A cloud free dataset with 16000 high resolution satellite images was created, and a dataset with 5000000 (5 classes) multi-spectral pixels for pixel-based classification.

In general, it was demonstrated that the proposed framework can be successfully applied to areas where the acquisition of cloud free images is not possible.

The model can handle images with clouds of any shape, size and location. However, the model struggles with images that contain roads, rivers or thin long objects divided into two or more sections by clouds, and, like most methods, is limited when the image is mostly covered by clouds.

According to the results obtained the study area has no significant changes on the landscape. In addition, the vegetation coverage has suffered a slight growth during the last 4 years.

The proposed framework within the methodology has a universal approach, guaranteeing the replication of this methodology in different study areas and works with similar characteristics.

## **List of participation in conferences and publications**

### **Related to the research**

1. INTERNATIONAL CONFERENCE ON ADVANCES IN IT AND ROBOTICS, organized by School of Computer Science & Robotics, Tomsk Polytechnic University, Tomsk, Russia (24-26 March 2021).

### **In other fields**

1. INTERNATIONAL SYMPOSIUM ON AUTOMATION, INFORMATION AND COMPUTING, held in Beijing, China (02-04 December 2020)
2. Machuca C.R., Gallardo C., Toasa R.M. Twitter Sentiment Analysis on Coronavirus: Machine Learning Approach // Journal of Physics: Conference Series. 2021. Vol. 1828, № 1.

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