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ASSESSING THE STATE OF SUSTAINABLE DEVELOPMENT GOALS IN MEXICO USING OPEN REMOTE SENSING DATA:

Indicator 15.3.1 Proportion of land that is degraded over total land area.

Frida A. Ruiz Mendoza

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Indicator 15.3.1 "Proportion of land that is degraded over total land area"

Frida A. Ruiz Mendoza

Registration number 940403716070

Supervisor:

Dr. Sarah Carter

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The Netherlands.

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Abstract

The 2030 Agenda for Sustainable Development poses different challenges for the participant countries, but it also offers new opportunities for the implementation of geospatial technologies. Due to the nature of the Sustainable Development Goals (SDG), traditional methods might be technically and financially unfeasible for the necessary coverage range and frequency of measurements. Geospatial information, and more specifically Earth Observation (EO) data, offer increasing opportunities for countries to efficiently track all facets of sustainable development over time (Paganini et. al, 2018). This project aimed to assess the state of SDG indicator 15.3.1 *"Proportion of land that is degraded over total land area"* in Mexico, using different currently available geospatial open data, by means of a raster-based analysis in a GIS software. The indicator was assessed three times, using three different input land cover (LC) datasets which were then compared in (dis)agreement maps. Results showed that depending on the LC dataset used, percentages in degradation can change up to 11% (~215,620 km^2). ESA-CCI-LC and MODIS datasets showed the least discrepancy. Whilst Uso de Suelo y Vegetación dataset showed 10% and 17% less spatial agreement with the previously mentioned datasets respectively. Furthermore, these differences also suggest that, in the case of Mexico, integrating different LC datasets for SDG monitoring as suggested in the Good Practice Guidance (GPG) might not be the best solution. Overall, this study showed that land degradation affects roughly 23-32% of the study area, depending on the input LC data. Finally, stating which dataset yields the most accurate degradation result falls out of the scope of this research. However, the importance of noticing these differences relies on the subjectivity it adds to the SDG assessment which could affect decision-making and ultimately jeopardize meeting the SDG targets; raising the importance of non-governmental actors, researchers and citizens in general to stay informed and closely follow the 2030 Agenda development.

Key words: SDG monitoring, land degradation, earth observation, geospatial data, open data, Trends.Earth.

Resumen

La agenda 2030 para el desarrollo sustentable, supone un desafío en diferentes aspectos para los países participantes. De igual manera, ofrece una gran oportunidad para la implementación de métodos no convencionales como los son las tecnologías geoespaciales. Debido a los requerimientos de cobertura, temporalidad, frecuencia y numero de mediciones necesitadas para el monitoreo de los ODS, los métodos tradicionales pueden llegar a ser técnica y económicamente irrealizables. El abordar este reto desde la información geoespacial, en especial los datos originados por percepción remota ofrecen una opción viable para monitorear diferentes facetas del desarrollo sustentable a través del tiempo. El presente proyecto tiene como objetivo el evaluar el estado actual del indicador 15.3.1 de los ODS: *"Proporción de tierras degradadas en comparación con la superficie total"* en México utilizando datos abiertos de percepción remota y técnicas SIG. Este indicador fue evaluado tres veces utilizando tres diferentes datos de uso de suelo después, mapas de desacuerdo para la comparación de los resultados fueron generados. Los análisis demostraron que dependiendo de los datos de entrada utilizados, el porcentaje de degradación pueden cambiar hasta en un 11%, siendo los conjuntos de datos globales ESA-CCI-L y MODIS, los que menores discrepancias presentaron. Al comparar el conjunto de datos de Uso de Suelo y vegetación, el porcentaje de desacuerdo fue mayor en los dos casos. Las diferencias encontradas sugieren que la integración de diferentes conjuntos de datos de uso de suelo podría no ser la mejor opción para la evaluación de este indicador en México; aun cuando es sugerido en la guía de buenas prácticas para su evaluación. Finalmente, indicar qué conjunto de datos produce el resultado de degradación más preciso queda fuera del alcance de esta investigación. Sin embargo, la importancia de notar estas diferencias recae en la subjetividad que agrega a la evaluación de los ODS. Misma que podría afectar la toma de decisiones y en última instancia, comprometer el cumplimiento de los ODS; destacando la importancia de que actores no-gubernamentales, investigadores y ciudadanos en general se mantengan informados y sigan de cerda el desarrollo de la Agenda 2030.

Palabras clave: monitoreo ODS, degradación de la tierra, percepción remota, datos abiertos, Trends.Earth

Table of Contents

List of figures

LIST OF TABLES

1. INTRODUCTION

1.1. The 2030 Agenda and the role of geospatial data

To face some of the worlds current environmental, economic and social challenges, the United Nations put forth firstly, the Millennium Development Goals (MDGs) and more recently the Sustainable Development Goals (SDGs). These two are closely related as the latter was created to "complete what the MDGs did not achieve, particularly in reaching the most vulnerable" (United Nations, 2015, p.16).

The *2030 Agenda for Sustainable Development,* mostly referred to as the 2030 agenda is comprised of 17 goals disaggregated into 169 targets (United Nations, 2015). Its main purpose is to serve as a framework for political, technological and social decision making during the next 15 years. To assess the extent of the progress in achieving those goals, 232[1] global indicators were agreed on in 2017 (United Nations, 2017).

From the MDGs implementation we have learned two key lessons. Firstly, scarcity of reliable data can frustrate a country's ability to optimize investment, create policy, make decisions and measure progress. Secondly, even though significant progress has been made in some areas, such progress has been unequal amongst countries — especially in developing countries like those in Africa and Latin America. Some of those inequities are attributed to different technological capacities and data availability (United Nations, 2015). Consequently, the UN emphasizes the need and importance of encompassing a wide range of data types within the collection, analysis and monitoring process of the SDGs, including some of the less conventional ones like earth observation and geospatial data (DigitalGlobe, 2016). The 2030 Agenda poses different challenges for the participant countries as well as new opportunities for different approaches like geospatial technologies to be implemented (UN-GGIM, 2017).

Due to the nature of the SDG indicators, their coverage range and frequency of measurements needed for their assessment, more conventional methods might be technically or financially unfeasible. Geospatial information and more specifically earth observation (EO) data offer increasing opportunities for countries to efficiently track all facets of sustainable development over time (Paganini, et al., 2018). Its implementation can significantly reduce the costs of monitoring the aspirations reflected in the SDGs, making the already challenging monitoring and reporting processes viable within the limited resources (monetary and time-wise) available to governments (Group on Earth Observations, 2017).

Some of the concrete opportunities for SDG completion that the use of EO data could offer are: measuring indicators consistently in a global scale, potentially allowing timelier statistical outputs and provide data at a more disaggregated level for improving accuracy in countries reporting by making the process spatially explicit. Furthermore, the increasing availability of free of access datasets improves access of data that might be difficult to produce by developing countries (Paganini, et al., 2018). Figure 1 shows an overview of SDG Targets and Indicators that can be supported by EO (Group on Earth Observations, 2017). According to Group on Earth Observations at least 28 indicators could be potentially measured entirely using EO while around 71 targets could benefit from this kind of data.

[1] While the official number of indicators is 244 however; 9 indicators repeat under different targets, making the actual number of individual indicators 232 (https://unstats.un.org/sdgs/indicators/indicators-list/)

Target Contribute to progress on the Target, not necessarily the Indicator									Goal	Indicator Direct measure or indirect support to the Indicator				
							1.4	1.5	1 No poverty	1.4.2				
						2.3	2.4	2.c	2 Zero hunger	2.4.1				
					3.3	3.4	3.9	3.d	3 Good health and well-being	3.9.1				
									4 Quality education					
								5.a	5 Gender equality	5.a.1				
		6.1	6.3	6.4	6.5	6.6	6.a	6.b	6 Clean water and sanitation	6.3.1	6.3.2	6.4.2	6.5.1	6.6.1
					7.2	7.3	7.a	7.b	7 Affordable and clean energy	7.1.1				
								8.4	8 Decent work and economic growth					
					9.1	9.4	9.5	9.a	9 Industry, innovation and infrastructure	9.1.1	9.4.1			
						10.6	10.7	10.a	10 Reduced inequalities					
	11.1	11.3	11.4	11.5	11.6	11.7	11.b	11.c	11 Sustainable cities and communities	11.1.1	11.2.1	11.3.1	11.6.2	11.7.1
				12.2	12.4	12.8	12.a	12.b	12 Responsible consumption and production	12.a.1				
					13.1	13.2	13.3	13.b	13 Climate action	13.1.1				
		14.1	14.2	14.3	14.4	14.6	14.7	14.a	14 Life below water	14.3.1	14.4.1	14.5.1		
	15.1	15.2	15.3	15.4	15.5	15.7	15.8	15.9	15 Life on land	15.1.1	15.2.1	15.3.1	15.4.1	15.4.2
								16.8	16 Peace, justice and strong institutions					
17.2	17.3	17.6	17.7	17.8	17.9	17.16	17.17	17.18	17 Partnerships for the goals	17.6.1	17.18.1			

Figure 1Indicators and targets in which EO data can contribute to their assessment retrieved from Group on Earth Observations.

1.2. Mexico and SDG monitoring

Mexico has been one of the developing countries actively participating in the 2030 Agenda implementation efforts. For instance, it is one of the two volunteer countries in the region to present progress on the SDGs before the High-Level Political Forum on Sustainable Development. Furthermore, the country has tried to tackle the need of making data collection, distribution and access better through launching an online open data platform. In such a platform people can filter the spatial and temporal dimension of several datasets to gain insight on the current situation of existing information (Gobierno de la Republica, 2015). Moreover, as a way of sharing the progress towards SDG achievement, the Sustainable Development Goals Information System (SIODS for its acronym in Spanish) was developed. This platform publishes the official information on the progress towards meeting the 2030 agenda (Gobierno de la Republica and INEGI, 2018). By enabling this information to the public, stakeholders from different organizations can use it as background for decision making as well as for creating informed solutions for the successful implementation of the agenda in Mexico.

Moreover, Mexico hosted the UN Fifth High Level Forum on Global Geospatial Information Management (UN-GGIM) on November 2017. Which had as main purpose to discuss the "enhancement of the geospatial technology role in implementing the SDGs", as well as discussing the strengthening of national geospatial information management capacities of participant countries — especially developing countries — towards implementing the 2030 Agenda (UN-GGIM, 2017). Which indicates the increasing interest and importance of geospatial data in the SDGs context not only in Mexico but worldwide.

Tracking the progress on the 2030 agenda requires collection, processing, analysis and dissemination of an unprecedented amount of data at different levels (sub-nationally, regionally, globally). Several national statistical systems across the globe face serious challenges in this regard since, data gaps are still one of the most important limitations towards SDG assessments (United Nations, 2016). Despite all the previously mentioned efforts, Mexico is not the exception — data availability at a national level is still a constraint to achieve indicator assessment.

Table 1 shows an overview of existing SDG progress data in Mexico compared to the number of targets and indicators that should be reached by 2030. The assessed indicators differ temporally (time-wise) and in specificity (scale) of information (i.e. some can be also seen per state when others only nationally). Some of the indicators in table 1 are global *(G)* and others national *(N)*. In general, according to the SIODS platform 66 out of 232 global indicators have been to some extent monitored and published. Some of them have not been assessed at all (i.e. SDG 12) and have no expected publishing date.

According to SIODS , reasons for uneven assessment of some goals are: *A)* The update of the indicator is subject to the publication of microdata by INEGI, *B)* It will depend on the year in which data is scheduled to be acquired by INEGI and *C)* The update will be made when the greenhouse gases emission inventory is published (there is no defined periodicity for the publication of the inventories) (Gobierno de la Republica and INEGI, 2018). In that sense, the publication of 166 indicators (more than 70%) depends on data availability and data acquisition which supposes a high effort for the institutions in charge of these tasks. Consequently, the use of national data for reporting might not be available in the most convenient periodicity for stakeholder’s decision making and compliance with UN reporting periodicity, making the potential use of global datasets increasingly important for countries like Mexico.

Table 1 *Summary of indicator monitoring progress available in SIODS platform*

SDG	**NO. TARGETS**	**NO. GLOBAL INDICATORS**	**NO. ASSESSED INDICATORS (MEXICO)**
1	7	14	5 (G) 1 (N)
2	8	13	1 (G) 4(N)
3	13	27	7(G) 11 (N)
4	10	11	7 (G) 9 (N)
5	9	14	8(G) 6(N)
6	8	11	1(G) 1(N)
7	5	6	3(G)
8	12	17	11(G) 6(N)
9	8	12	6 (G) 3 (N)
10	10	11	1(G) 2 (N)
11	10	15	1 (G) 3 (N)
12	11	13	-
13	5	8	1(G)
14	10	10	2(G)
15	12	14	3(G) 1(N)
16	12	23	2(G)
17	19	25	7(G) 5(N)

1.3. Indicator Overview

For measuring the SDGs progress, a set of indicators has been agreed on by the Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs). These indicators are categorized into three different levels depending on their characteristics (IAEG-SDGs, 2018).

The first level (Tier 1) is the ideal, as it reflects that an indicator is conceptually clear, has an internationally established methodology with available standards and regularly produced data by countries (at least 50% of countries and of the population in every region where the indicator is relevant). As of December 2018, only 93 out of 232 indicators have reached this category. Tier II reflects indicators that are conceptually clear, have an internationally established methodology and available standards, but were data is not regularly produced by countries. In this category we find 66 out of the total amount of indicators (Addams & Judd, 2018), including the one studied in this project. Lastly, Tier III indicators are those with no internationally established methodology or standards available yet.

It is important to note that tier methodologies are expected to change as data availability increases, the current published methods intend to serve as a guide for the indicators monitoring by listing several alternatives to assess them depending on data availability, processing and analysis capacities of each country (IAEG-SDGs, 2018). Ideally, all indicators should eventually achieve a Tier level 1.

Some indicators can be linked to other initiatives taken in favor of the environment. Such is the case of Indicator 15.3.1 *"Proportion of land that is degraded over total land area"*. Efforts to combat this problems in Mexico are visible through the country's early incorporation of international initiatives such as the United Nations Convention to Combat Desertification (UNCCD) in 1994, as well as the strengthening of the Soil and Water conservation law in the General Law of Ecologic Equilibrium and Nature protection (LGEEPA by its acronym in Spanish) and more recently to the Land Degradation Neutrality Target Setting Program (LDN-TSP) (UNCCD, 2018). This last initiative includes 119 countries that with the UNCCDs help, set baselines and targets to achieve land degradation neutrality (LDN) (UNCCD, 2018). Countries participating receive among other things, access to the best available data on LDN and trends. Recently (2018) these datasets became available to the general public through a Quantum GIS plugin created by The Land Degradation Monitoring Project as a partnership of Conservation International, Lund University, and the National Aeronautics and Space Administration (NASA).

Despite these efforts, several studies indicate that degraded land in Mexico represents more than 50% of the territory (SEMARNAT, 2011; CONAFOR-UACh, 2013). A more recent work suggests land degradation in Mexico is even higher, with an estimation of close to 70% degraded land in the country (Lopez Santos, 2016).

2. PROBLEM DEFINITION AND RESEARCH QUESTIONS

The secretary-general of the UN Antonio Guterres noted the following when the first SDG report was issued: "Implementation has begun, but the clock is ticking. This report shows that the rate of progress in many areas is far slower than needed to meet the targets by 2030". One of the ways to fight delays in reporting could be to use existing free of access datasets. They could offer an alternative to improve the timeliness and effort of SDG reporting for countries like Mexico in which detailed national data acquisition and availability are still insufficient or will take longer time to be produced. Additionally, the results of such assessment could offer a proxy of the indicators current state which can potentially be used by stakeholders as a guide for decision making until more detailed data becomes available.

As mentioned before, the number of datasets available for free is increasing. In the past years, initiatives like US government free data mission, and the free and open data policy of the European Union's Copernicus program (Breger, 2017) have emerged. Because of this, the prospects for access to EO data required by developing countries have improved considerably. Furthermore, more specific SDG related initiatives like EO for Sustainable Development in Service of the 2030 Agenda (EO4SDG) and the Data Hub for SDG have been launched. The first one aims to expand the potential use of EO within the 2030 Agenda (Paganini et al, 2018) whereas the latter "seeks to enable data providers, managers and users to discover, understand, and communicate patterns and interrelationships in the wealth of SDG data and statistics that are now available" (Esri, 2018). This speaks of the increasing interest in enabling EO data for SDG reporting purposes.

Results of any process are highly dependent on the input datasets (see Hibbard, et al., 2010; Benítez et al., 2004). Due to the large number of indicators and the relatively short time that countries have had to face the 2030 Agenda challenge, little has been done to assess the impact of different input datasets in the SDG assessment process. This is notably relevant for countries like Mexico, which have volunteered to report the results of some indicators (including 15.3.1) early (Gobierno de la República and INEGI, 2018). This means that despite the possible restrictions on existing data, indicators will be assessed, and results will still be used for decision making. It is therefore relevant to investigate the existing datasets and their impact on the generated results.

As such, the *availability* of different datasets, their *relevance* and *impact* on the assessment of indicator 15.3.1 is a useful area of study to ensure continuity and comparability of SDG monitoring.

The current project aims to assess the state of SDG indicator 15.3.1 *"Proportion of land that is degraded over total land area"* in Mexico using different openly available geospatial data by means of a raster-based analysis in a GIS software.

To achieve this objective, the following research questions are proposed:

1. What datasets are available that could potentially be used for the assessment of indicators 15.3.1 in Mexico?

2. What is the current state of indicator 15.3.1 in Mexico?

3. To what extent do different input datasets (default UNCCD, global, national) influence the result of indicator 15.3.1 in Mexico?

3. METHODOLOGY

For this project, land degradation will be defined according to the UNCCD (Sims, et al., 2017) as:

"The reduction or loss of the biological or economic productivity and complexity of rain fed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from a combination of pressures, including land use and management practices"

The proposed method for this project was divided in three main parts (Figure 2): One per research question. The first part consisted of dataset research, the result of which was used for the second part (indicators assessment). The method used to assess the indicator was the one proposed in the Good Practice Guidance (GPG) (Sims, et al., 2017), which divides the indicator in three sub-indicators: Land cover (LC) change, Land productivity change and Above and Below ground carbon change. Each analysis was performed three times, with three different input datasets using Trends.Earth plugin in QGIS 2.18.2. ArcMap 10.5 was used for all pre-processing. As a third and final step, a cell-based comparison between the results obtained from different input datasets was processed in ArcMap 10.5. Each of the three steps are further explained in the following sections.

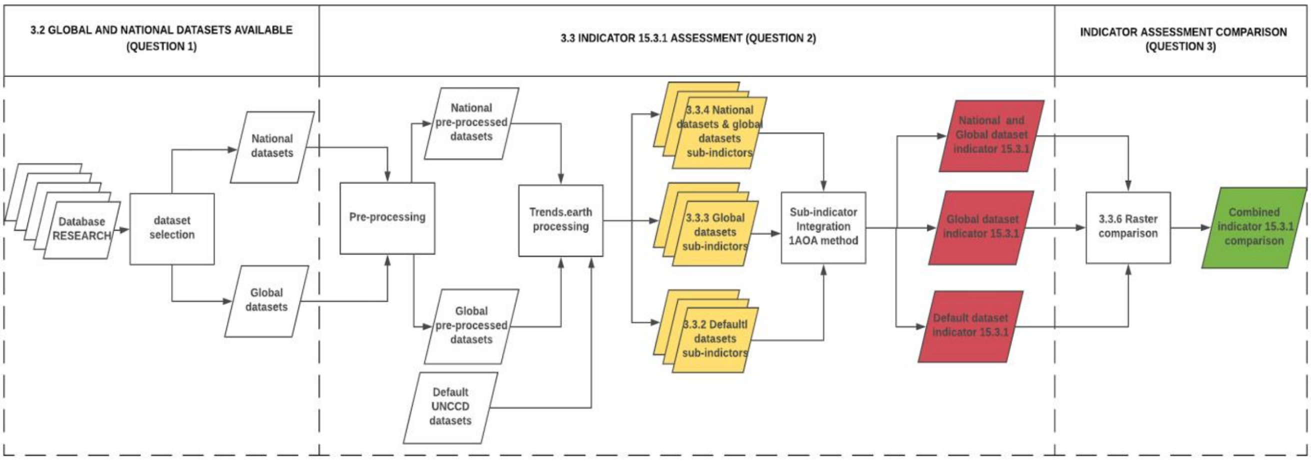


Figure 2 General overview of the method followed in this project.

3.1. Study Area

The study area for this project is the continental territory of the United States of Mexico with a total of 1,960,189 km^2 of area (see Figure 3).

Figure 3 Reference map of the United States of Mexico

3.2. Available global and national datasets

For the first step of the project, a review of different databases for dataset selection was made. The thematic detail of the datasets should be relevant in order to evaluate change in at least one of the three sub-indicators. Therefore, datasets representing LC, land productivity and organic carbon stock content were searched for in public databases.

The first criteria for selecting the data was its ease of processing. Due to the limited time available for the completion of this project, datasets were chosen that would need fewer pre-processing steps to meet the criteria (see Conservation International, 2017) needed for Trends.Earth plugin. Additionally, their spatial extent needed to cover the entire United States of Mexico, be free of access and have enough data to assess the baseline and at least one monitoring period (i.e. availability of time series data including at least two epochs) (Mattina, et al., 2018).

For the specific case of Mexico, we know from CONABIO (n.d) that changes in LC occur in a smaller scale due to the socio-economic conditions of the country. Thus, another criterion for data selection was its spatial resolution. For this project it was assumed that the higher the resolution, the better to detect change. Moreover, datasets mentioned in the GPG (Sims, et al., 2017) were also reviewed according to the previously mentioned criteria.

Lastly, for the studies to be comparable, it is ideal for the input datasets to contain information of the same years. The baseline and motoring period were chosen under the premise that at least one global, national and the default datasets have enough data to assess the sub-indicators in the same period. An overview of the found datasets and their characteristics can be seen in Table 2.

Table 2 Overview of datasets with possible use for indicators 15.3.1 assessment in Mexico

Thematic detail	Dataset	Spatial Resolution	Dataset Provider	Temporal resolution	Spatial extent
Land Cover	MCD12Q1.006 MODIS Land Cover Type Yearly Global	500 m	NASA LP DAAC at the USGS EROS Center	Yearly (2001-2017)	global
Land Cover	ESA-CCI-LC	300 m	Catholic University of Louvain Geomatics as part of the Climate Change Initiative of the European Spatial Agency (ESA)	Yearly (1992-2015)	global
Land Cover	Uso de suelo y vegetación Serie II capa unión	N/A	INEGI	1993	National
Land Cover	Uso de Suelo y Vegetación Serie III	N/A	INEGI available at CONABIO database	2002	National
Land Cover	Uso de Suelo y Vegetación Serie VI capa unión	N/A	INEGI	2014	National
Land Cover	NALCMAS	250m	North American Land Change Monitoring System (NALCMAS)	2005 and 2010	North America
Land Productivity	Land Productivity Dynamics (LPD)	1 km	Joint Research Commission	Daily (1999-2013)	Global
Land Productivity	Terra MODIS (MOD13A1, MOD13A2, MOD13Q1)	500 m, 1 km, 250 m	NASA LP DAAC at the USGS EROS Center	16-Day (February 2000-present)	Global
Land Productivity	Aqua MODIS (MYD13A1, MYD13A2 and MYD13Q1)	500 m ,1 km, 250 m	NASA LP DAAC at the USGS EROS Center	16-Day (July 2002 - Present)	Global
Land Productivity	NDVI3g (third generation GIMMS NDVI from AVHRR sensors). Latest version 3g.v1	1/12=0.833 degrees	NASA/NOAA	July 1981 - December 2015	Global

Land Productivity	NOAA CDR AVHRR NDVI, Version 4	0.05° by 0.05° grid	NOAA (National Centers for Environmental Information)	1981 to present	Global
Land Productivity	VNP13A1	500 m	NASA	2012 to present	Global
Land Productivity	NDVI 0	300 m	Copernicus Global Land Service	February 2016-present	Global
Land Productivity	NDVI version 2.2	1 km	Copernicus Global Land Service	April 1998-present	Global
Soil organic carbon	SoilGrid250m	250 m	ISRIC	Static	Global
Soil organic carbon	Inventario Nacional de Gases de Efecto Invernadero	N/A	INECC México	1990-2005	National

After comparing the datasets with the established criteria (see results in section 4.1), the selection was made. All three analysis used the same NDVI product from MODIS and SoilGrids250m datasets. However, all LC input datasets differed. For the first analysis, the default LC dataset proposed by the UNCCD was used, which can be accessed directly through Trends.Earth (Conservation International, 2018). For the second analysis, the LC product from MODIS MCD12Q1.006 was selected. For the third and last analysis, the national datasets on LC "Uso de suelo y vegetación" series III and VI were selected. Table 3 shows an overview of the selected input datasets and the sub-indicator they are used with.

Table 3 Overview of selected datasets and the sub-indicator they were used to calculate.

Selected datasets and their application for Indicator 15.3.1 assessment.

	Land Cover Change	Land Productivity	Soil Organic Carbon
Default datasets	Europeans Space Agency CCI-LC	MOD13Q1	SoilGrids 250m
Custom Global datasets	MCD12Q1.006	MOD13Q1	SoilGrids 250m
Mexican datasets	Uso de Suelo y Vegetación series III and VI	MOD13Q1	SoilGrids 250m

3.3. Indicator 15.3.1 assessment

As mentioned before, indicator 15.3.1 was assessed using the plug-in “Trends.Earth”. The tool was produced by a partnership between Conservation International, Lund University, and NASA with the support of the Global Environment Facility (GEF) and follows the methods described in the GPG for SDG Indicator 15.3.1 (Sims, et al., 2017). The GPG mentions that to assess this indicator, it is necessary to evaluate the change in: *1. Land Cover, 2. Land Productivity and 3. Above and Below ground Organic carbon.*

Section 3.3.1 of this chapter is meant to give an overview on the computational processes that take place when using the plug-in. While sections 3.3.2, 3.3.3 and 3.3.4 describe the pre-processing and parameters used for each input dataset.

The following aspects are constant in all cases:

- For the land productivity assessment, the Normalized Difference Vegetation Index (NDVI) was selected as proxy for Net Primary Productivity (NPP). The latter variable is both time consuming and costly to estimate. Remote sensing can measure land productivity across large areas using estimations of NPP. One of the most common surrogates for this variable is NDVI (Sims, et al., 2017) and is therefore used in this project.
- The temporality of the analysis is from 2002 to 2014 which represents the first monitoring period of this indicator. These dates were chosen according to data availability from all three cases so that a comparison of the results would be possible.
- The default LC Change Matrix for the first sub-indicator is used in all analysis as it is recommended in the GPG (Sims, et al., 2017).
- The study area extent was set by using the same shape file from the United States of Mexico created by INEGI (2017).

According to the GPG, the third sub-indicator should be computed by looking at the change between above- and below-ground carbon. However, due to inconsistency and incompatibility between currently available datasets it is recommended to use Soil Organic Carbon (SOC) stock as a proxy (Conservation International, 2018). Therefore, the SoilGrids250m Organic Carbon Stock dataset for the first 30 cm of the surface (Sims, et al., 2017) is used as one of the inputs for the third sub-indicator for all three cases. Even though this dataset comprises data from a diverse time frame, it is assumed to be representative of the initial year of the analysis when using this tool (Conservation International, 2018).

3.3.1. Trends.Earth Plug-In

As previously mentioned, the GPG sub-divides the indicators assessment in three steps starting by assessing the change in LC. Figure 5 shows the computation process for this sub-indicator (final dataset produced in this step in yellow). Input datasets for this step are LC rasters which then are reclassified into general IPCC LC classes (Sims, et al., 2017). Consequently, a cell-based change analysis is performed. Cells that have experienced LC changes are reclassified into stable, improving or degraded using a LC change IPCC matrix inbuilt in the tool (Figure 4) (Sims, et al, 2017; Conservation international, 2018).

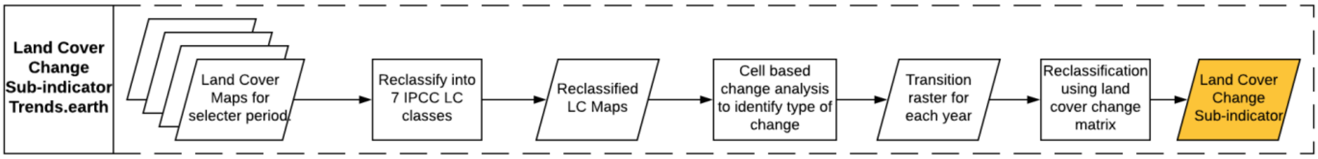
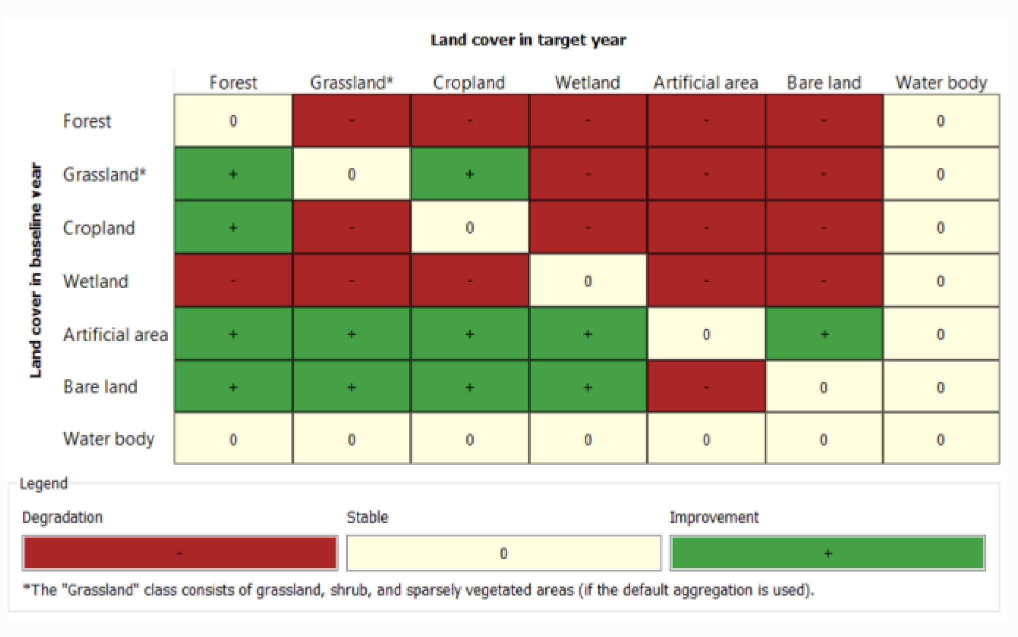


Figure 5 LC Change sub-indicator processing steps (Trends.Earth)



Land cover in target year (columns); Land cover in baseline year (rows)

	Forest	Grassland*	Cropland	Wetland	Artificial area	Bare land	Water body
Forest	0	-	-	-	-	-	0
Grassland*	+	0	+	-	-	-	0
Cropland	+	-	0	-	-	-	0
Wetland	-	-	-	0	-	-	0
Artificial area	+	+	+	+	0	+	0
Bare land	+	+	+	+	-	0	0
Water body	0	0	0	0	0	0	0

Legend

Degradation - | Stable 0 | Improvement +

*The "Grassland" class consists of grassland, shrub, and sparsely vegetated areas (if the default aggregation is used).

Figure 4 LC change matrix as used in the plug-in

The second sub-indicator evaluates the change in land productivity, which is defined as: *the biological productive capacity of the land, the source of all the food, fiber and fuel that sustains humans* (Sims, et al., 2017). Trends.Earth uses vegetation indices as proxy for this measurement and assesses them in terms of their *trend*, *performance* and *state* Figure 6 shows the overall computational process of this sub-indicator (dataset produced in this step in yellow).

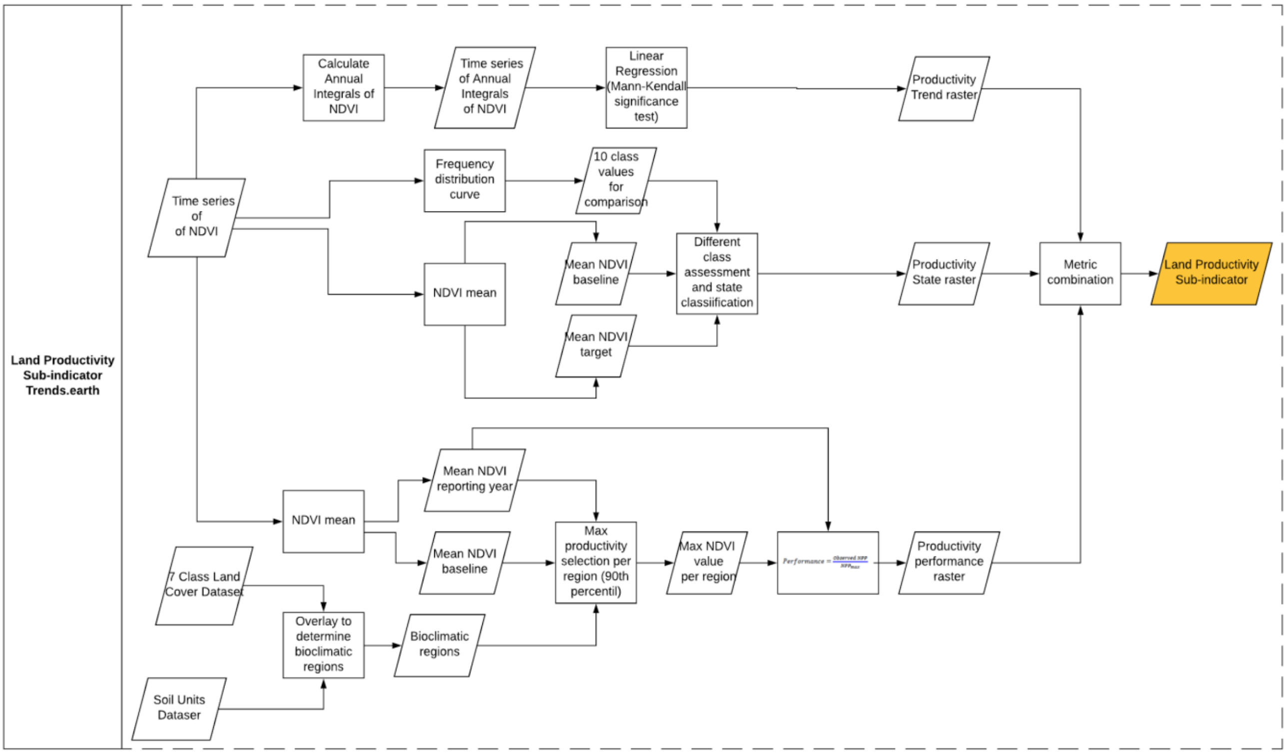


Figure 6 Land Productivity Sub-indicator processing steps

Once these three metrics are calculated, the last step is to combine them. Figure 7 shows the criteria followed for the final classification assessment of each cell, a One-Out All-Out rule (1AOA) is used for the metric integration. This means that if any of the metrics show degradation, the final state of that cell will be degraded even if the other metrics show improvement or stability.

Aggregating the productivity sub-indicators

Trajectory	State	Performance	3 Classes	5 Classes
Improvement	Improvement	Stable	Improvement	Improving
Improvement	Improvement	Degradation	Improvement	Improving
Improvement	Stable	Stable	Improvement	Improving
Improvement	Stable	Degradation	Improvement	Improving
Improvement	Degradation	Stable	Improvement	Improving
Improvement	Degradation	Degradation	Degradation	Stable
Stable	Improvement	Stable	Stable	Stable
Stable	Improvement	Degradation	Stable	Stable
Stable	Stable	Stable	Stable	Stable
Stable	Stable	Degradation	Degradation	Stable but stressed
Stable	Degradation	Stable	Degradation	Early signs of decline
Stable	Degradation	Degradation	Degradation	Declining
Degradation	Improvement	Stable	Degradation	Declining
Degradation	Improvement	Degradation	Degradation	Declining
Degradation	Stable	Stable	Degradation	Declining
Degradation	Stable	Degradation	Degradation	Declining
Degradation	Degradation	Stable	Degradation	Declining
Degradation	Degradation	Degradation	Degradation	Declining

Figure 7 Productivity metrics aggregation method (1AOA) final cell classification

The final sub-indicator calculates the change in SOC stock as proxy for above- and below-ground carbon. Trends. Earth uses a combined method employing LC and SOC stock to estimate changes in SOC in a given period. It determines the SOC reference values using SoilGrids250m carbon stocks for the first 30 cm of the soil profile, then reclassifies the LC maps to the IPCC LC classes and estimates its change in SOC stock by using LC conversion coefficients recommended by the IPCC and the UNCCD (Conservation International, 2018). Finally, the difference in SOC between baseline and monitoring period is computed. Cells that report a loss of 10% or more in SOC are then classified as potentially degraded whereas areas that experience a gain of 10% or more are classified as potentially improved. Figure 8 shows the overall computation process of this sub-indicator in Trends. Earth (dataset produced in this step in yellow).

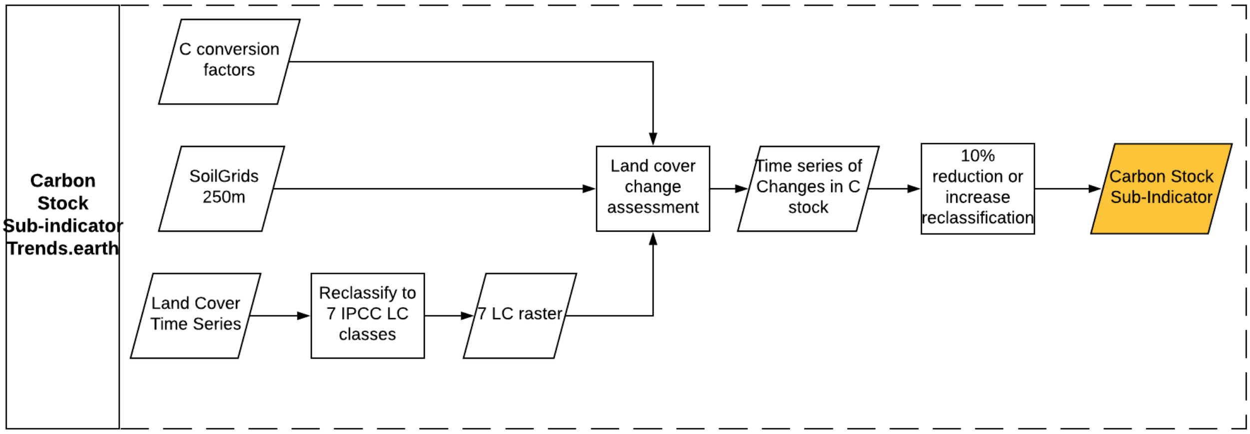
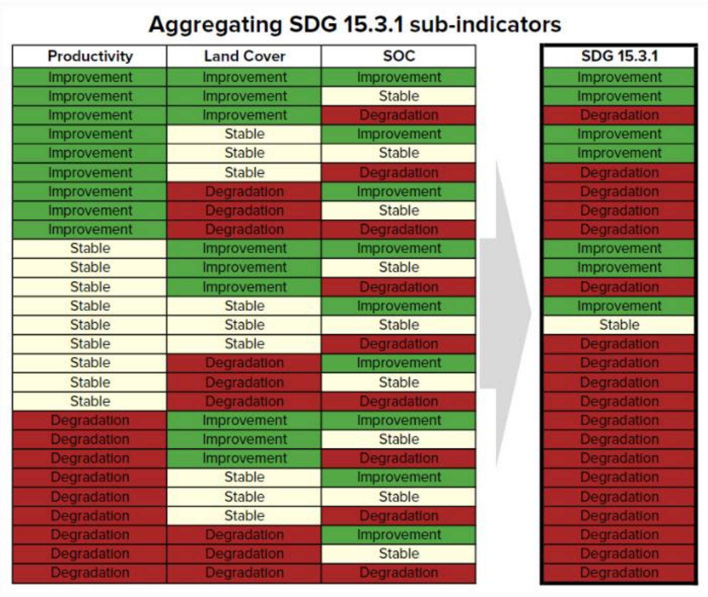


Figure 8 Carbon Stock Sub-indicator processing steps

Lastly, all three sub-indicators are integrated to get the final degradation assessment. Such integration is done by following the 1AOA rule. Figure 9 shows the assessment logic for all the possible combinations. The result of this step is a raster dataset representing one monitoring period of indicator 15.3.1. This raster is composed by four main classes showing degradation (-1), stability (0), improvement (1) or no data (3) (Figure 2 in red).



Aggregating SDG 15.3.1 sub-indicators

Productivity	Land Cover	SOC	SDG 15.3.1
Improvement	Improvement	Improvement	Improvement
Improvement	Improvement	Stable	Improvement
Improvement	Improvement	Degradation	Degradation
Improvement	Stable	Improvement	Improvement
Improvement	Stable	Stable	Improvement
Improvement	Stable	Degradation	Degradation
Improvement	Degradation	Improvement	Degradation
Improvement	Degradation	Stable	Degradation
Improvement	Degradation	Degradation	Degradation
Stable	Improvement	Improvement	Improvement
Stable	Improvement	Stable	Improvement
Stable	Improvement	Degradation	Degradation
Stable	Stable	Improvement	Improvement
Stable	Stable	Stable	Stable
Stable	Stable	Degradation	Degradation
Stable	Degradation	Improvement	Degradation
Stable	Degradation	Stable	Degradation
Stable	Degradation	Degradation	Degradation
Degradation	Improvement	Improvement	Degradation
Degradation	Improvement	Stable	Degradation
Degradation	Improvement	Degradation	Degradation
Degradation	Stable	Improvement	Degradation
Degradation	Stable	Stable	Degradation
Degradation	Stable	Degradation	Degradation
Degradation	Degradation	Improvement	Degradation
Degradation	Degradation	Stable	Degradation
Degradation	Degradation	Degradation	Degradation

Figure 9 Final assessment aggregation method (1AOA)

3.3.2. Assessment using UNCCD default LC dataset

The calculation of each sub-indicator was done individually, each for the period 2002-2014. To compute the LC change sub-indicator, the option "use the ESA CCI-LC dataset" was left as marked. LC Change classification aggregation method was unaltered as the tool already had the right legend classification from default datasets to IPCC LC classes preloaded. Table 4 shows the aggregation scheme used for this first sub-indicator.

Table 4 Legend aggregation from ESA ICC-LC to IPCC classes according to Sim, et al. (2017)

ESA CCI-LC	IPCC Land Cover Classes
Tree cover, broadleaved, evergreen, closed to open (>15%) Tree cover, broadleaved, deciduous, closed to open (>15%) Tree cover, needleleaved, evergreen, closed to open (>15%) Tree cover, needleleaved, deciduous, closed to open (>15%) Mosaic tree and shrub (>50%) / herbaceous cover (<50%)	Forest Land/ Tree covered.
Mosaic natural vegetation, tree, shrub, herbaceous cover (>50%)/ cropland (<50%) Scrubland Grassland Lichens and mosses Sparse vegetation, tree, shrub, herbaceous cover (<15%)	Grassland
Cropland, rainfed: -herbaceous cover -Tree or shrub cover Cropland irrigated or post-flooding Mosaic cropland (>50%)/natural vegetation, tree, shrub, herbaceous Cover (<50%) Mosaic herbaceous cover (>50%)/tree and shrub (<50%)	Cropland
Tree cover flooded, saline water Tree cover, flooded, fresh or brackish water Shrub or herbaceous cover flooded fresh/ saline / brackish water	Wetlands
Urban areas	Settlements
Permanent Snow and Ice Barren areas	Other land
Water bodies	Water bodies

The LC change matrix was unaltered as Trends.Earth uses the LC/land change matrix from IPCC which is recommended on the GPG (2017). A shapefile from INEGI (2017) was used to set the extent of the calculations.

Finally, the integration of all sub-indicators was made by inputting the results of the previous steps into the plug-in for the 1AOA final assessment under the option "calculate final SDG 15.3.1 spatial layer and summary table for total boundary".

3.3.3. Assessment using Global Land Cover dataset

For this analysis the option to use custom datasets and calculate each sub-indicator individually was used. The selected global dataset to calculate the LC Change sub-indicator was MCD12Q1.006. with International Geosphere-Biosphere Program (IGBP) legend for the years 2002 and 2014. This legend was reclassified for both rasters into the 7 IPCC classes during the pre-processing. Table 5 shows the legend aggregation used for these rasters to fit the 7 classes for the UNCCD report. The reclassification criteria were decided upon a comparison between LC definitions from the IPCC (2006) (Paustian, et al.,2006) , the MCD12Q1 legend (Sulla-Menashe & Friedl, 2018) and table 2.1 from the GPG (Sims, et al., 2017). Definitions that fell into the desired IPCC classes were assign on each category. Savannas (10-30%) Woody savannas (30-60%) were not mentioned in the previous documents due to the tree cover similarities with other categories mentioned in table 2.1 (Sims, et al., 2017), as a result they were classified as Grassland and Forest Land respectively.

Table 5 Legend aggregation from MODIS MCD12Q1 to IPCC classes.

MCD12Q1 (IGBP) Class Name	IPCC Land Cover Classes
Evergreen Needleleaf Forests Evergreen Broadleaf Forests Deciduous Needleleaf Forests Deciduous Broadleaf Forests Mixed Forests Woody Savannas	Forest Land/ Tree covered.
Savannas Closed Shrublands Open Shrublands Grassland Cropland/Natural Vegetation Mosaics	Grassland
Croplands	Cropland
Permanent wetlands	Wetlands
Urban and Built-up Lands	Settlements
Permanent Snow and Ice Barren	Other land
Water bodies	Water bodies

Clipping to the right extent was done within the plug-in by using the same INEGI (2017) shapefile as in the previous analysis.

For the land productivity sub-indicator, MOD13Q1 dataset was used as input. The following parameters were used in the tool for each metric:

- *Trend*: NDVI trend option.
- *Performance*: 2002-2014
- *State*: initial period from 2002 -2011 with a comparison period from 2012-2014

For the third sub-indicator, the plugin required two input datasets. Firstly, the LC reclassified rasters for which the same rasters for the first sub-indicator were used. Secondly, a custom soil organic carbon stock raster which was derived from three layers OCSTHA_M_sd1_250m (0.0-.05 cm), OCSTHA_M_sd2_250m (0.05-.15 cm) and OCSTHA_M_sd3_250m (.15-.30 cm) of the SoilGrids250m dataset was used. Even though these are the same input datasets used in the previous assessment (3.3.2), when custom LC datasets are used, the SOC stock layer needs to be calculated outside the tool. To do so, the raster calculator in Arc Map 10.5 was used to sum the three previously mentioned layers. As a result, a raster containing the organic carbon stock values of the first 30 cm of the surface was created.

Finally, the integration of all sub-indicators was made by inputting the results of the previous steps into the plug in for the 1AOA final assessment under the option "calculate final SDG 15.3.1 spatial layer and summary table for total boundary".

3.3.4. Assessment using national LC datasets

The Mexican government through INEGI has issued national specific LC vector data since 1978 (INEGI, 2017). Such datasets are derived from photographic image interpretation techniques as well as *in situ* measurements. They represent the official ciphers from the Mexican government and are therefore used for this assessment. Specifically, datasets Uso de Suelo y Vegetación series III and VI representing years 2002 and 2014 respectively. The most relevant pre-processing steps were: LC class reclassification into IPCC classes, conversion to raster and resampling of the rasters. To lose as little detail as possible, the LC vector layers were first rasterized to a 30m resolution accordingly to the satellite image resolution they were derived from. However, for both ease of processing and comparison between results, a resampling to a 250m resolution using majority resampling technique was performed.

The original classification legend was presented differently for each year, while the 2002 raster had 176 distinct classes with a description. The dataset representing 2014 had 182 classes defined with a code. The explanation of each code can be found on the Land Use and Vegetation Dictionary (INEGI, 2014). Legend aggregation scheme was decided from the comparison of LC definitions from INEGI, 2014; Sims, et al., 2017 table 2.1, the IPCC LC Class definitions and the LC definitions by INEGI (2014). Appendices A and B contain a table with all the original LC Codes and their corresponding IPCC reclassification LC classes for the year 2014 and 2002 respectively.

It was found that there are no country-specific land productivity datasets available. It was therefore decided to use the same NDVI product MODIS13Q1 as in both previous analyses. Furthermore, according to the first Mexican indicator 15.3.1 report (Gobierno de la Republica, 2018) MODIS13Q1 was the official dataset used by the government for this sub-indicator assessment.

The following parameters were used in the tool for each of the metrics:

- *Trend*: NDVI trend option
- *Performance:* 2002-2014
- *State*: initial period from 2002 -2011 with a comparison period from 2012-2014

For the third sub-indicator, a SOC stock layer created in the previous analysis (see chapter 3.3.4) and the pre-processed Uso de Suelo y Vegetación series III and VI were used.

Finally, the integration of all sub-indicators was made by inputting the results of the previous steps into the plug-in for the 1AOA final assessment under the option "calculate final SDG 15.3.1 spatial layer and summary table for total boundary".

3.4. Indicator assessment comparison

A (dis)agreement map was performed doing a cell-based comparison of the final degradation maps. Firstly, all datasets were imported from their original extension (.json) to a raster file in ArcMap. Secondly, all datasets were resampled to have an exact cell size of 250m using majority as the resampling technique. Finally, to assess (dis)agreement between the three input rasters, and to be able to trace back the original value given in each study, the following expression was used in the raster calculator:

$$(Global*1) + (Mexican*10) + (Default*100)$$

Once this operation was done, all pixels that had been given a classification of "no data" in at least one degradation map were masked. In this way, only pixels that had been classified as degraded, improving or stable were compared with each other. Once the "no data" had been masked, percentages were calculated using Excel. For this first map, only cells that agreed in all three maps were considered as agreement, although it was possible to trace cells that agreed in two maps and disagreed in one.

Following the same logic, a comparison between two maps using each final degradation map was made. This resulted in a total of 3 (dis)agreement maps. The following expressions were used in the raster calculator for each comparison:

1. *(MODIS * 1) + (Mexican *10)*
2. *(ESA-CCI-LC *100) + (Mexican *10)*
3. *(MODIS *1) + (ESA-CCI-LC *100)*

All cells that were classified as "no data" in at least one map were masked before calculating the (dis)agreement percentages in each case. Percentages and confusion matrices for each comparison was made in Excel.

4. RESULTS

In this chapter the results of the project will be described. First, the reviewed datasets and their compatibility for the study are listed (RQ1), then the results of indicator 15.3.1 and each sub-indicator for all input dataset are presented (RQ2). Finally, the results of the spatial comparison between the different land degradation maps are described (RQ3).

4.1. Availability of datasets

More than 16 different open source datasets possessed at least one of the criteria to be of potential use for indicator 15.3.1 assessment in Mexico. However, for the selection process, datasets should be characterized by all criteria mentioned in chapter 3.4. An overview of the most relevant LC datasets compared to the selection criteria is available in Table 6.

From all reviewed LC datasets, the ESA-CCI-LC had the most straightforward pre-processing steps in terms of legend aggregation to fit the 7 IPCC classes. Such legend aggregation scheme was already agreed on in the GPG (Sims, et. Al, 2017). In addition, the UNCCD set it as the default LC dataset for indicator 15.3.1 monitoring. This means, that countries that lack country-specific LC data, are encouraged to use this dataset to either complete their own data or as the only input for LC change analysis.

MODIS LC product MDC12Q1.006 offered the opportunity to expand the monitoring period to a more recent year (2017); it is free of access and covers the entire study area. Despite the resolution being coarser than ESA-CCI-LC dataset, it met the criteria in terms of temporal frame and ease of processing. Moreover, it was to the best of our knowledge the only other land cover global dataset product with the needed characteristics for this project.

From a regional level, the North American Land Change Monitoring System (NALCMAS) products posed and interesting option. This trilateral effort between Canada, the United States, and Mexico (Commission for Environmental Cooperation, 2018) offers datasets on LC and LC change for north America. The first three datasets are for the year 2005, the year 2010 and one which represents the LC change between those years at a 250m resolution. Despite their resolution being higher and thus potentially better for this study, they had to be ruled out due to the lack of time series data.

Lastly, when it comes to national datasets, INEGI offers the land cover vector dataset: Uso de Suelo y Vegetación from series I to VI. These vector datasets are based on 30m resolution satellite image interpretation from different years, accompanied by field work observation and verification efforts. Due to the high effort of *in situ* verification needed for the creation of these datasets, their temporal availability is low, being the latest map available for the year 2014 and only released in 2017. These datasets contain detailed information on the land use in Mexico classified in 12 major vegetation ecosystems and more than 100 types of vegetation (INEGI, 2017). Regardless of their accuracy, national specific datasets are more likely to be used as input for the SDGs assessment. Therefore, the series Uso de Suelo y Vegetación INEGI were considered important to include in this study. The temporal frame of these datasets was limited in comparison to the first two global datasets. However, there is still enough data to assess one monitoring period using the latest LC dataset (2014) in combination with series III (2002).

Table 6 LC datasets of potential use for indicator 15.3.1 assessment in Mexico

LC DATASET	SELECTION CRITERIA				
	SPATIAL RESOLUTION	TEMPORAL FRAME		SPATIAL EXTENT	ACCESSIBILITY
		Baseline year	Monitoring year		
MCD12Q1.006 MODIS	500 m	2001	2017	global	free
ESA-CCI-LC	300 m	1992	2015	global	free
Uso de suelo y vegetación Series II	Based on 30m LTM images	1993	-	National	free
Uso de suelo y vegetación Series III	Based on 30m LTM images	2002	-	National	free
Uso de suelo y vegetación Series VI	Based on 30m LTM images	-	2014	National	free
NALCMAS	250m	2005	-	North America	free
NALCMAS	250m		2010	North America	free

As mentioned before, NDVI vegetation index was chosen as proxy for land productivity. Therefore, research of datasets to calculate the second sub-indicator was limited to NDVI products. The variety of NDVI products was higher than that of the LC ones. With information on this variable ranging from the 1980's until the current year, with a global extent and different resolutions (see Table 7).

Table 7 NDVI datasets of potential use for indicator 15.3.1 assessment in Mexico

Land Productivity	SELECTION CRITERIA				
	SPATIAL RESOLUTION	TEMPORAL FRAME Baseline year	TEMPORAL FRAME Monitoring year	SPATIAL EXTENT	ACCESSIBILITY
Land Productivity Dynamics (LPD)	1 km	1999	2013	Global	free
Terra MODIS (MOD13A1, MOD13A2, MOD13Q1)	500 m, 1 km, 250 m	2000	present	Global	free
Aqua MODIS (MYD13A1, MYD13A2 and MYD13Q1)	500 m ,1 km, 250 m	2002	present	Global	free
NDVI3g (third generation GIMMS NDVI from AVHRR sensors). Latest version 3g.v1	1/12=0.833 degrees	1981	2015	Global	free
NOAA CDR AVHRR NDVI, Version 4	0.05° by 0.05° grid	1981	present	Global	free
VNP13A1	500 m	2012	present	Global	free
NDVI 0	300 m	2016	present	Global	free
NDVI version 2.2	1 km	1998	present	Global	free

The UNCCD recommends as default dataset for this sub-indicator the Land Productivity Dynamics ESA dataset (Ivits & Cherlet, 2013). This dataset provides five classes of persistent land productivity trajectories: Declining, Moderate decline, Stressed, Stable and Increasing. However, as it represents productivity dynamics until 2013, it fails to match the temporal frame chosen for this project and was therefore not considered as an input dataset. The MODIS NDVI products, specifically MOD13Q1 and MYD13Q1 offered the highest resolution (250m) from all reviewed datasets. Both datasets chose the best available pixel value from all the acquisitions (from a 16-day period) using a low cloud, low view angle and highest NDVI value as selection criteria. The dataset derived from the AQUA satellite (MYD13Q1) has as start date July 2002; whereas the one derived from TERRA satellite starts on February 2000. Furthermore, the latter is inbuilt in the plug-in Trends.Earth which along with its temporal frame, makes it the logical choice of input for this project. To the best of our knowledge, there are no national datasets that can give information on NPP or country-specific EO products of vegetation indices. This can be confirmed by the first Land Degradation report submitted by Mexico to the UNCCD PRAIS portal last October 17, 2018. Which states the use of MODIS NDVI product MOD13Q1 for the years 2002-2014 as input for the sub-indicator's assessment.

The most challenging datasets to find, were those with characteristics to assess change in Organic Carbon stock (third-sub indicator). The only global product that complied with all selection criteria for this project (see Table 8), was SoilGrids 250m provided by ISRIC. It offers global rasters for SOC stock content in tons per ha for six different depths. For this study the first three layers (0-5 cm, 5-15 cm and 15-30 cm) were selected. Furthermore, the Mexican government has a history of tracking Green House Gas (GHG) emissions since the late 1990's. However, this dataset was not spatially explicit and required several pre-processing steps to translate the variables available into Organic Carbon stock and was therefore left out of this study, further discussion on these datasets can be found in chapter five.

Land Productivity DATASET	SELECTION CRITERIA				
	SPATIAL RESOLUTION	TEMPORAL FRAME Baseline year	TEMPORAL FRAME Monitoring year	SPATIAL EXTENT	ACCESSIBILITY
Soil organic carbon	250 m	Static		Global	free

Table 8 SOC stock datasets of potential use for indicator 15.3.1 assessment in Mexico

If more exhaustive research is done, some other datasets might be deemed as relevant. However only the ones mentioned in this document were selected for the purpose of this research.

4.2. Assessing indicator 15.3.1

The following sections describe the findings of each analysis. First, the general indicators assessment percentages are showed, then an overview of the results per sub-indicator are mentioned for each reviewed case. LC datasets are perhaps the most influential input dataset of the degradation assessment. Not only because it was the only input dataset that differed in all studies but also due to its part in the assessment of two out of three sub-indicators. For this reason, the LC changes (transitions) are also explained, to explore the impact of the LC dataset selection in the degradation assessment.

4.2.1. Assessment using UNCCD Land Cover dataset

The analysis showed that the proportion of degraded land in Mexico for the period 2002-2014 using ESA-CCI-LC datasets is 23.17%. Mostly visible in the middle and northern part of the territory across the states of Coahuila, Chihuahua, Nuevo Leon, Durango, Zacatecas and San Luis Potosi. Around 18.56% of the territory was assigned as potentially improving and the majority with a 58.04% was classified as stable. Finally, 0.23% of the territory had not enough data in either of the sub-indicators to be assigned a class. Figure 10 shows the spatial distribution of land degradation assessment in Mexico for the years 2002-2014.

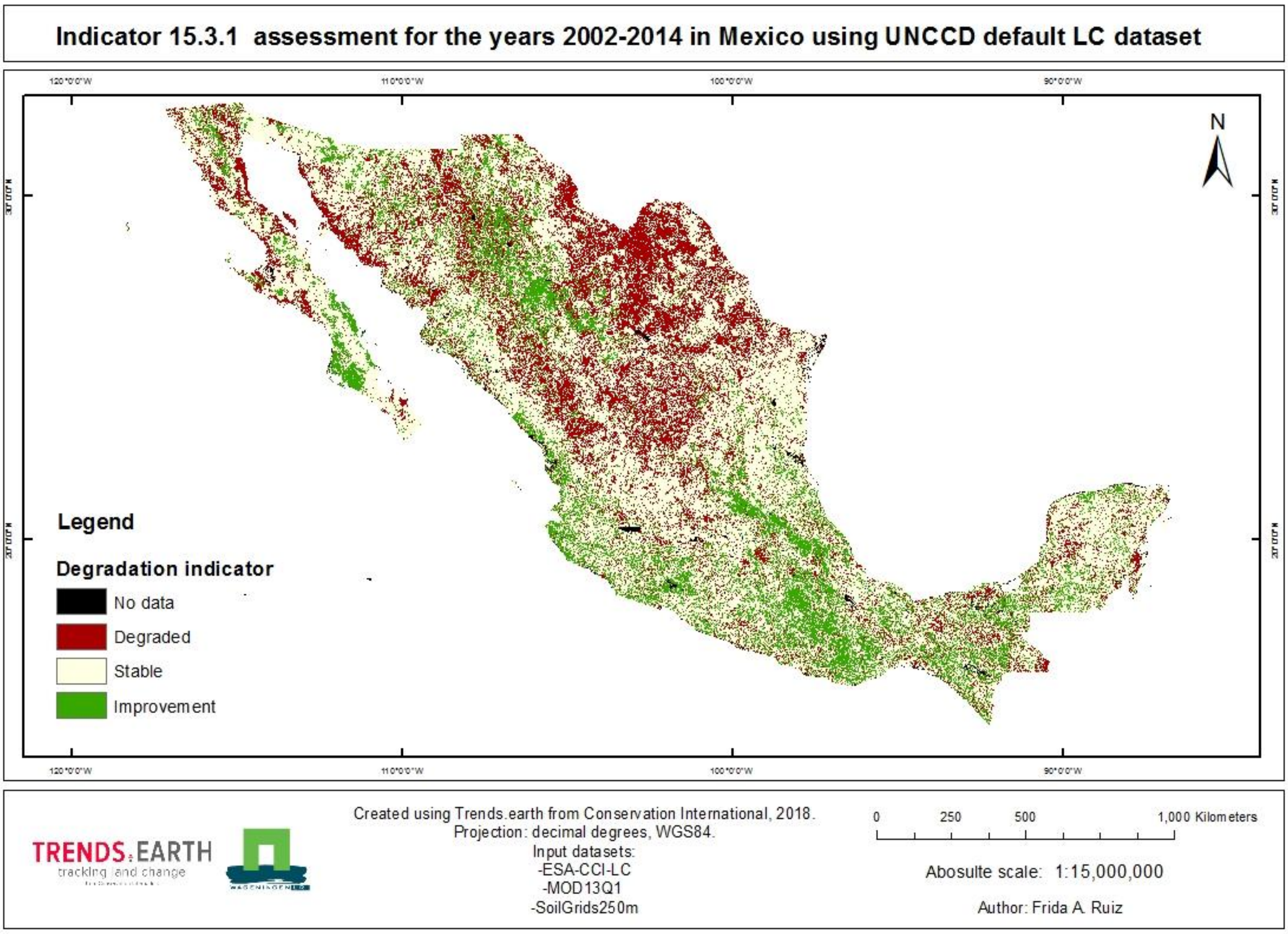


Figure 10 Indicator 15.3.1 in Mexico using ESA-CCI-LC as input dataset

Table 9 shows a summary of the percentage of degraded land according to each sub-indicator. LC change and SOC stock change were the percentages that differed the least among each category. The highest differences rely on the Land Productivity Degradation assessment, where both the degraded and improving land percentages increased notably.

Table 9 Percentage of total degraded land per sub-indicator

Percentage of total degraded land area per sub-indicator using ESA CCI-LC dataset

	Land Cover Change Degradation	Change in Land Productivity Degradation	SOC stock change Degradation
Land area improved:	**0,59%**	**18,41%**	**0,06%**
Land area stable:	**98,46%**	**58,91%**	**99,44%**
Land area degraded:	**0,95%**	**22,48%**	**0,40%**
Land area with no data:	**0,00%**	**0,19%**	**0,10%**

The most dominant LC class in Mexico according to ESA-CCI-LC dataset in both the monitoring and the target year is Grasslands, followed by Tree-covered areas, Croplands and Other lands. Categories like Wetlands, Artificial areas and Water bodies represent less than 1% of the overall extent per class. Table 10 shows the change per LC class and as percentage of the total for this LC dataset. The biggest changes per class occurred in Artificial areas with a growth of 39% from year 2002 to 2014. This is a big change in the class, but it still represents a change of only 0.20% of total study area. Furthermore, there was a loss of Tree-covered areas that represents -0.25% of total territory.

Table 10 LC Change by cover class and as percentage of the total using ESA-CCI-LC dataset.

	Baseline year % of the total area	Target year % of the total area	Change in area per LC class (%)	Change in area (% of the total)
Tree-covered areas	36.82%	36.56%	-0.69%	-0.25%
Grasslands	45.32%	45.20%	-0.26%	-0.12%
Croplands	14.61%	14.74%	0.91%	0.13%
Wetlands	0.56%	0.55%	-1.06%	-0.01%
Artificial areas	0.51%	0.71%	39.45%	0.20%
Other lands	1.42%	1.42%	-0.31%	0.00%
Water bodies	0.76%	0.81%	5.97%	0.05%
Total:				

The LC transition confusion matrix of this analysis shows the change fluxes between LC classes in percentages. Tree-covered areas changed the most to Grasslands and Croplands. Consequently, Grasslands changed the most to Artificial areas. Furthermore, we can see the classification of all LC fluxes in Table 11, which shows the land area in percentage by LC transition using ESA-CCI-LC dataset (fluxes considered as degradation in red, potential improvement in green and stable in beige).

Table 11 Land Area in % by LC transition using ESA-CCI-LC dataset, unlikely transitions in bold.

Land cover type in baseline year (2002) \ Land cover type in target year (2014)	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	36.10	0.54	0.15	**0.00**	0.01	0.00	0.01	*36.82*
Grasslands	0.39	44.64	0.14	**0.00**	0.10	0.01	0.03	*45.32*
Croplands	0.05	0.01	14.45	**0.00**	0.09	0.00	0.00	*14.61*
Wetlands	**0.01**	0.00	0.00	0.54	0.00	0.00	0.00	*0.56*
Artificial areas	**0.00**	0.00	0.00	0.00	0.51	0.00	0.00	*0.51*
Other lands	0.00	0.00	0.00	0.00	0.00	1.41	0.01	*1.42*
Water bodies	0.00	0.00	0.00	0.01	0.00	0.00	0.75	*0.76*
Total:	*36.56*	*45.20*	*14.74*	*0.55*	*0.71*	*1.42*	*0.81*	***100***

4.2.2. Assessment using Modis LC dataset

When assessment was made with MODIS MCD12Q1.006 LC dataset, the degraded area consisted of 23.59% of the national territory, 20.28% was classified as potentially improving and the majority, as in the previous analysis, was classified as stable with 55.67%. Figure 11 shows the spatial distribution of these categories, with a clear concentration of degraded cells from Aguascalientes in the center of the Mexican republic towards the north, passing by Zacatecas, Durango, Coahuila, Chihuahua and showing some patches in northern and southern Baja California.

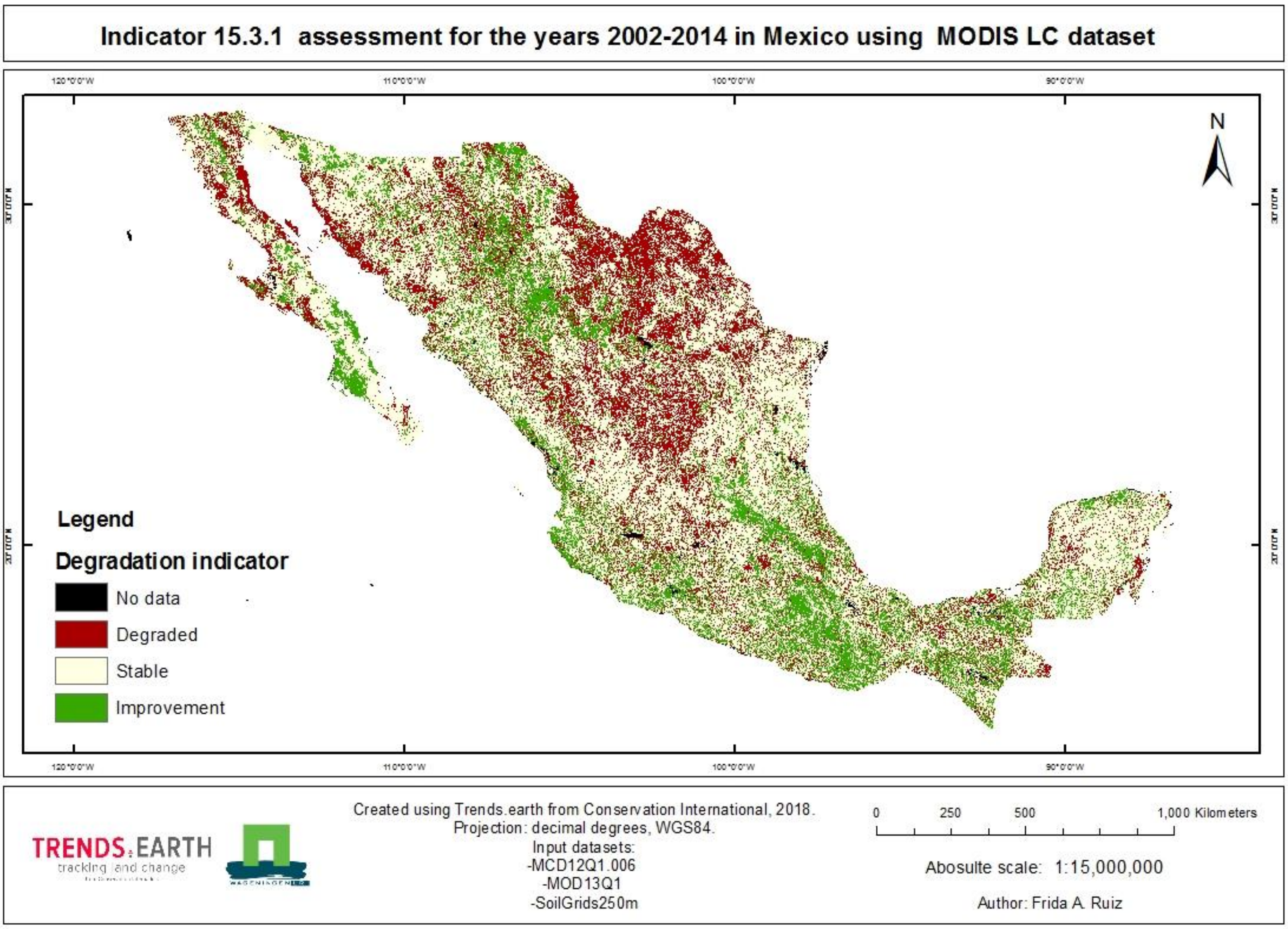


Figure 11 Indicator 15.3.1 assessment in Mexico using MODIS MCD12Q1.006 as LC input dataset

Table 12 shows a summary of percentage degraded land according to each sub-indicator. As in the last indicator, most of the cells were classified as stable in all indicators.

Table 12 Percentage of total degraded land per sub-indicator

Percentage of total degraded land area per sub-indicator using MODIS LC dataset			
	Land Cover Change Degradation	Change in Land Productivity Degradation	SOC stock content Degradation
Land area improved:	**4.03%**	**18.38%**	**2.13%**
Land area stable:	**92.81%**	**60.42%**	**96.84%**
Land area degraded:	**3.13%**	**20.80%**	**.68%**
Land area with no data:	**0.02%**	**0.40%**	**0.35%**

The most dominant LC class in Mexico according MODIS MCD12Q1.006 dataset in both the monitoring and the target year is like in the previous analysis Grasslands. Followed by Tree-covered areas, and with a much lower percentage than in the previous LC dataset Croplands and Other lands. Categories like Wetlands, Artificial areas and Water bodies represent, according to this LC dataset less than 0.50% of the overall extent per class. Table 13 shows the change per LC class and as percentage of the total. The biggest changes per class occurred in classes Other lands with a decrease of 26.18% and Wetlands with an increase of 15.74%. However, both these changes represent less than 1% change in the total area.

Table 13 LC Change by cover class and as percentage of the total using MODIS MCD12Q1.006 dataset

	Baseline year % of the total	**Target year % of the total**	**Change in area per LC class (%)**	**Change in area as % of the total**
Tree-covered areas	23.46%	24.39%	3.96%	0.93%
Grasslands	64.27%	64.96%	1.07%	0.69%
Croplands	7.38%	6.54%	-11.46%	-0.85%
Wetlands	0.42%	0.49%	15.74%	0.07%
Artificial areas	0.45%	0.48%	6.62%	0.03%
Other lands	3.54%	2.62%	-26.18%	-0.93%
Water bodies	0.47%	0.53%	12.54%	0.06%

The LC transition matrix of this analysis shows the change fluxes between land cover classes in percentages. Tree-covered areas changed the most to Grasslands and croplands. Consequently, Grasslands changed the most to Artificial areas. Furthermore, we can see the classification of all LC fluxes in Table 14, which shows the land area in percentage by LC transition using MODIS MC12Q1.006 dataset (fluxes considered as degradation in red, potential improvement in green and stable in beige).

Table 14 Land Area in % by LC transition using MODIS MCD12Q1.006 dataset, unlikely transitions in bold and underlined

Land cover type in target year (2014)

Land cover type in baseline year (2002)	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	22.17	1.25	0.02	**<u>0.02</u>**	0.00	0.00	0.00	*23.46*
Grasslands	2.17	61.09	0.75	**<u>0.06</u>**	0.02	0.15	0.02	*64.27*
Croplands	0.03	1.56	5.78	**<u>0.01</u>**	0.01	0.00	0.00	*7.38*
Wetlands	**<u>0.01</u>**	0.01	0.00	0.38	0.00	0.00	0.02	*0.42*
Artificial areas	**<u>0.00</u>**	0.00	0.00	0.00	0.45	0.00	0.00	*0.45*
Other lands	0.00	1.05	0.00	0.01	0.00	2.47	0.02	*3.54*
Water bodies	0.00	0.00	0.00	0.00	0.00	0.00	0.47	*0.47*
Total:	*24.39*	*64.96*	*6.54*	*0.49*	*0.48*	*2.62*	*0.53*	***100***

4.2.3. National Land Cover dataset

For the National LC datasets Uso de suelo y vegetacion series II and VI, once again the highest percentage (42.42%). of cells were classified as stable, followed by the area classified as degraded representing 32.84% and 24.05% of potential improvement. Figure 12 shows the spatial distribution of indicator 15.3.1 using this land cover datasets.

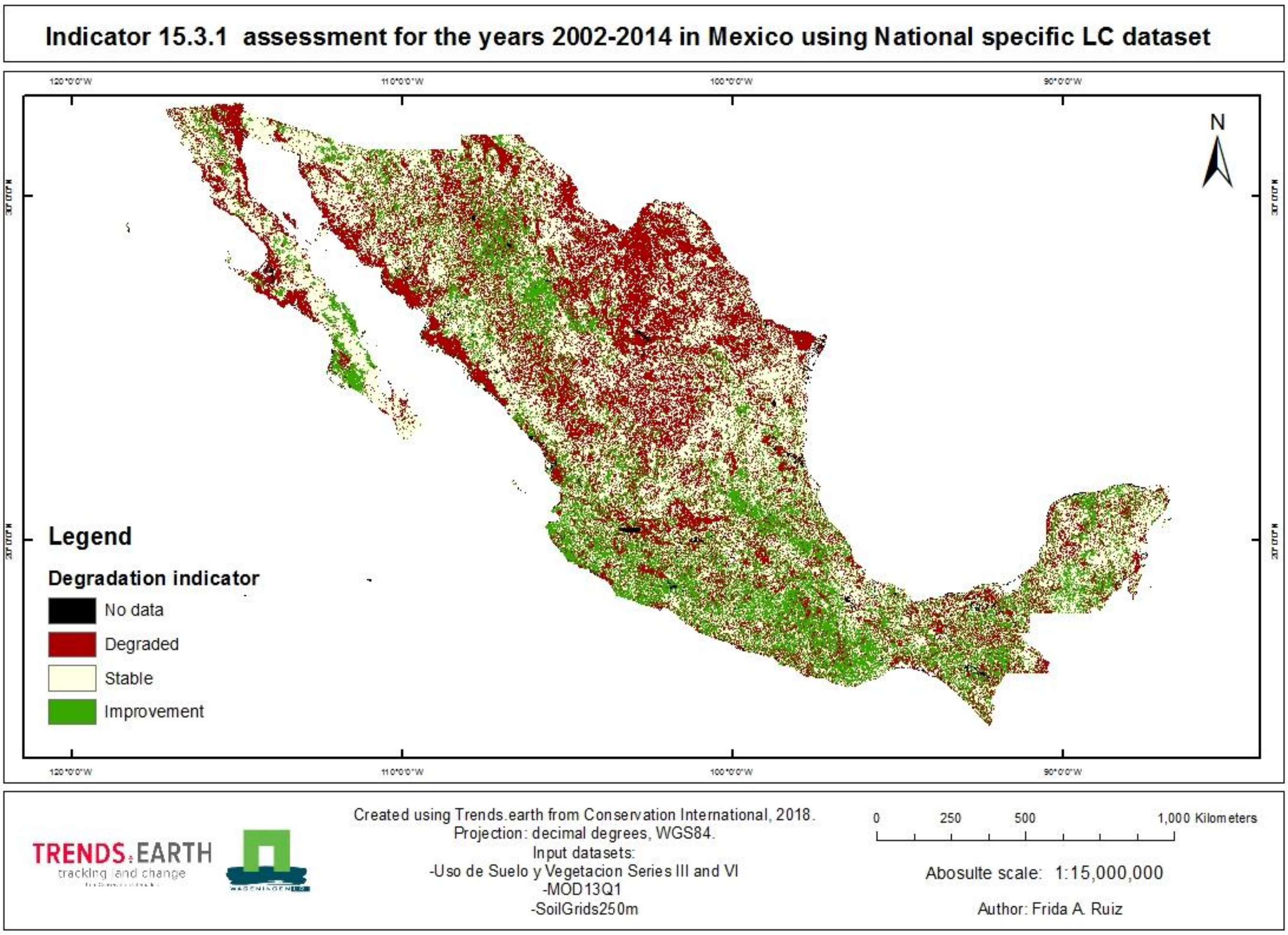


Figure 12 Indicator 15.3.1 assessment using National specific LC as input dataset

Table 15 shows a summary of the percentage of degraded land according to each sub-indicator. As in the last indicator, most of the cells were classified as stable in all indicators.

Table 15 Percentage of total degraded land per sub-indicator

Percentage of total degraded land area per sub-indicator using National specific LC dataset			
	Land Cover Change Degradation	Change in Land Productivity Degradation	SOC stock content Degradation
Land area improved:	**17.89%**	**18.38%**	**3.86%**
Land area stable:	**73.45%**	**58.79%**	**89.10%**
Land area degraded:	**8.56%**	**22.43%**	**6.52%**
Land area with no data:	**0.10%**	**0.4%**	**0.52%**

The LC transition matrix (Table 16) shows that, in comparison with the previous studies, all changes in each LC class are more dramatic with a higher percentage in change per class. Wetlands were according to this dataset the LC class that experienced more change with an increase of more than twice its extent from baseline to monitoring year followed by an increase in Artificial areas, Other lands and Grasslands. In general, Tree covered areas and Grasslands represent the biggest changes over the total area with an increase of almost 9% and a decrease of 12.88% respectively. Croplands and Wetlands experienced an increase of 1.51% and 1.26% over the total land area respectively and the rest of the LC types had a change of less than 0.60%.

Table 16 LC Change by cover class using National Specific dataset.

	Baseline year % of the total	**Target year % of the total**	**Change in area per LC class (%)**	**Change in area as % of the total**
Tree-covered areas	24.77%	33.75%	36.26%	8.98%
Grasslands	61.13%	48.25%	-21.08%	-12.88%
Croplands	10.56%	12.07%	14.30%	1.51%
Wetlands	1.12%	2.39%	112.28%	1.26%
Artificial areas	0.63%	1.09%	72.53%	0.46%
Other lands	1.20%	1.81%	49.97%	0.60%
Water bodies	0.58%	0.65%	12.46%	0.07%

Table 17 shows the LC change fluxes between baseline and monitoring period. Unlikely transitions (Sims, et al. Table 2.2, 2017) are presented in bold. For this LC dataset the number of unlikely transitions is highest from all three. For instance, there is a 1.30% change from Grasslands to Wetlands, which would imply some sort of inundation.

Table 17 Land Area in % by LC transition using National specific LC dataset, unlikely transitions in bold and underlined.

Land cover type in baseline year (2002) \ Land cover type in target year (2014)	Tree-covered areas	Grasslands	Croplands	Wetlands	Artificial areas	Other lands	Water bodies	*Total:*
Tree-covered areas	22.21	1.40	0.60	**0.07**	0.03	0.42	0.03	*24.77*
Grasslands	10.03	43.00	6.13	**1.30**	0.43	0.13	0.10	*61.13*
Croplands	1.43	3.68	5.19	**0.09**	0.09	0.03	0.05	*10.56*
Wetlands	**0.04**	0.03	0.06	0.87	0.00	0.08	0.05	*1.12*
Artificial areas	**0.01**	0.05	0.04	0.00	0.52	0.00	0.00	*0.63*
Other lands	0.00	0.03	0.01	0.02	0.00	1.13	0.00	*1.20*
Water bodies	0.03	0.06	0.03	0.03	0.00	0.01	0.42	*0.58*
Total:	*33.75*	*48.25*	*12.07*	*2.39*	*1.09*	*1.81*	*0.65*	***100***

Overall, all studies showed stability having the highest percentage followed by degradation and then potential improvement. Table 18 shows a summary of indicator 15.3.1 percentages per degradation class for each LC input dataset. Percentages were closer for both GLC datasets in all classes, specially the class degraded. These results already give an indication that the LC dataset that produced the most different results was the country-specific one, with an overall difference of 10% in degradation when compared to the other two datasets.

Table 18 Summary of Indicator 15.3.1 per LC input dataset used

	Degraded	Improving	Stable
ESA-CCI-LC	**23.17%**	**18.56%**	**58.04%**
MODIS LC	**23.59%**	**20.28%**	**55.67%**
NATIONAL LC	**32.84%**	**24.05%**	**42.42%**

4.3. Indicator assessment comparison

The spatial agreement of the three previously presented analysis showed that 68.22% of the cells were given the same classification regardless of the LC input dataset. A total of 31.78% of cells shows discrepancies. From these discrepancies, only 1.64% of the cells were classified differently in all three maps whereas the rest (30.14%) was classified differently in one out of three maps. Figure 13 shows the spatial distribution of the pixels that were classified differently in all three cases, most of them are very scattered along the south-west of the territory. However, it is possible to see some clusters in Baja California Sur and along the states of Chihuahua, Durango, Coahuila and Zacatecas. Figure 14 shows the spatial distribution of the agreement (in green) and disagreement in one or more maps (in red). This map also shows some hollow spaces in the territory, which represent pixels classified as "no data" in at least one of the three maps. It was decided to leave those pixels out of the comparison and they were not considered in the total amount of pixels from which the percentages were calculated.

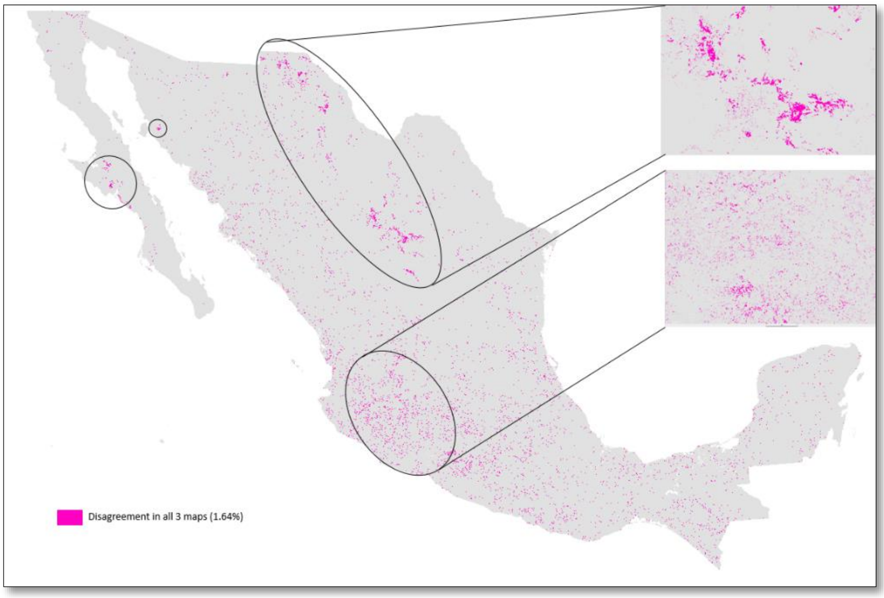


Figure 13 Spatial distribution of the pixels that were classified differently in all three cases

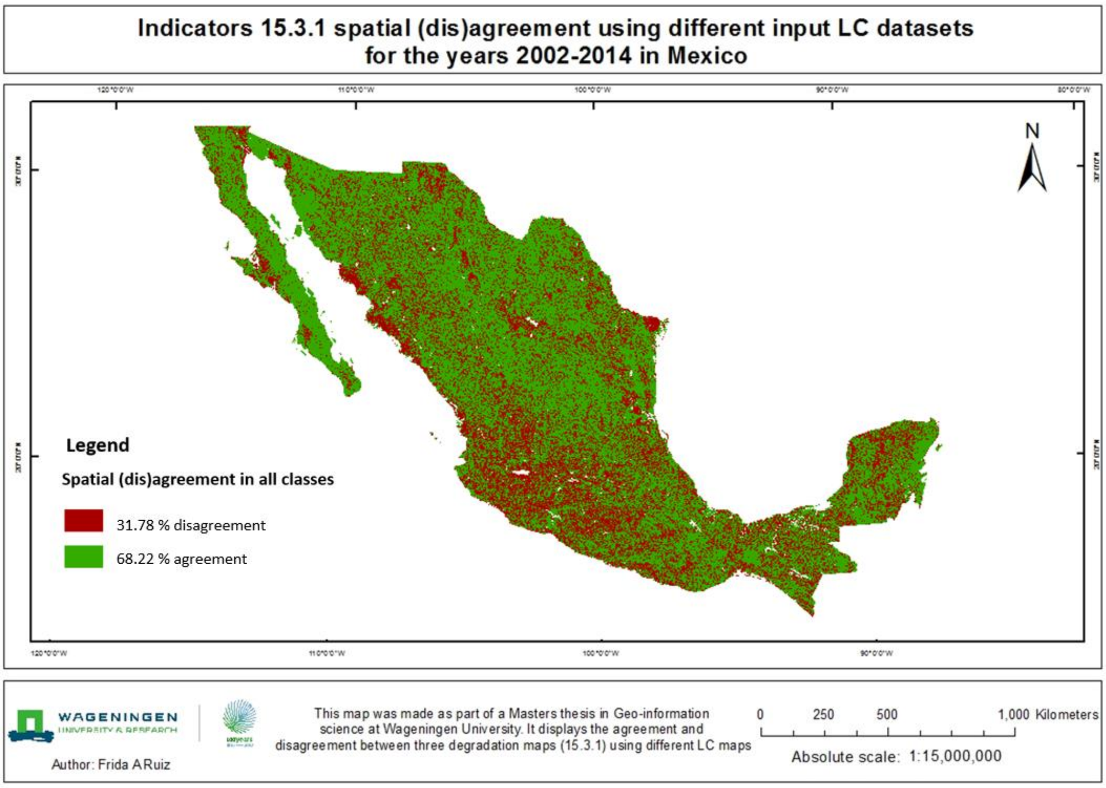


Figure 14 Spatial distribution of the agreement (in green) and disagreement in one or more maps (in red).

The highest agreement was on cells showing stability with a total of 38.01%, followed by degraded cells with 17.88% and 12.34% of the cells showed improvement on the same pixel in all three cases. Figure 15 show the spatial distribution of agreeing pixels in red (degraded), stable (beige) and improving (green).

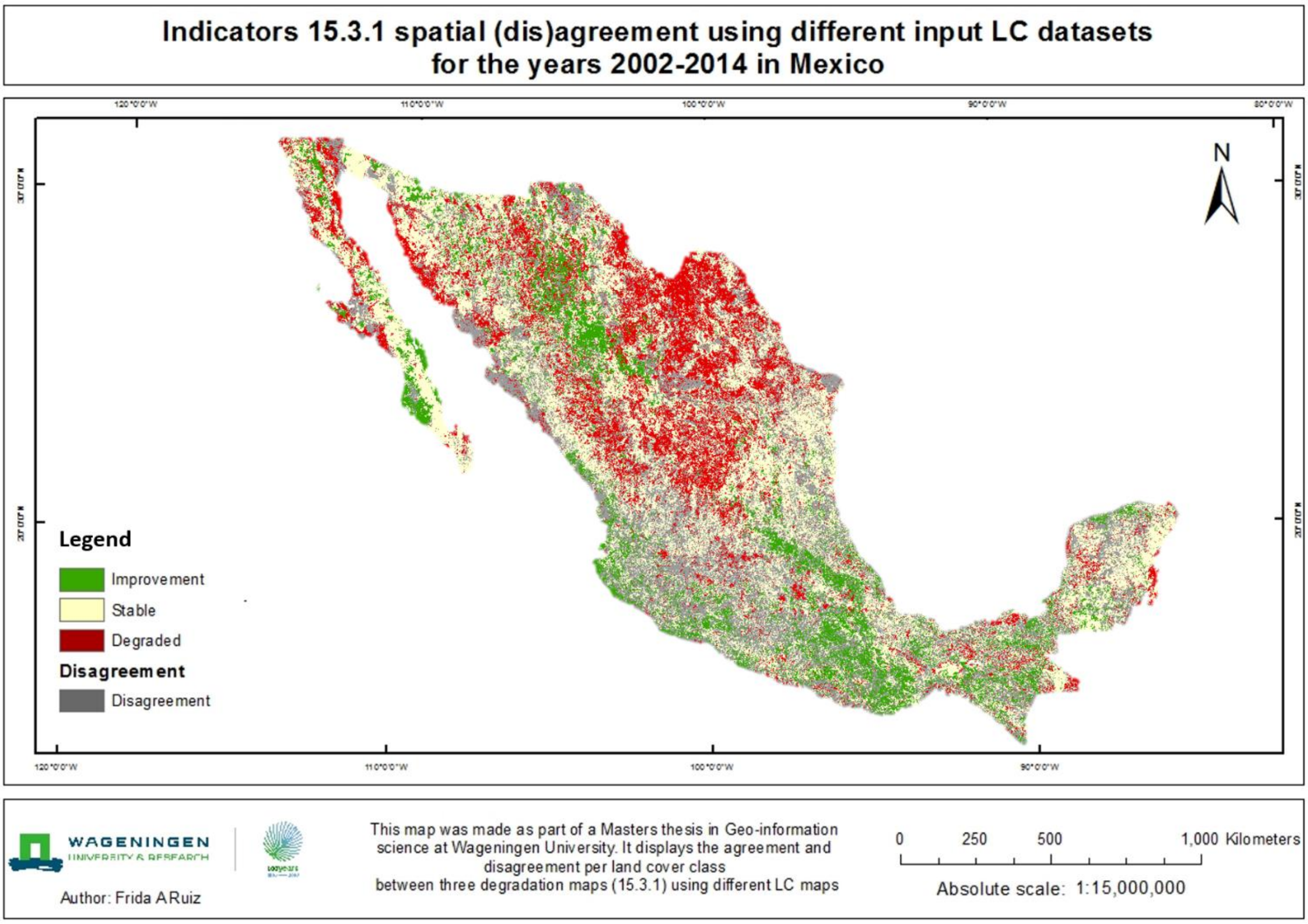


Figure 15 Indicator 15.3.1 spatial (dis)agreement per degradation class using three different LC datasets

Comparisons between only two datasets were also made. The two maps that showed highest disagreement were MODIS MCD12Q1.006 and country-specific LC with a 27.10% of cells classified differently. Table 19 shows the confusion matrix from this classification. The biggest misclassification (11.44%) occurred when pixels were classified as stable in MODIS analysis and classified as degraded in the country-specific LC analysis, followed by 7.85% pixels classified as stable in MODIS but as improving in country-specific LC. Overall, we can see that total percentages of degradation and stability differ in at least 10% while percentages of improvement remain close in both maps with a difference of less than 5%. Figure 16 shows the spatial distribution of the overall (dis)agreement and per degradation class.

Table 19 Indicator 15.3.1 confusion matrix in percentages (MODIS vs. Country-specific LC dataset)

Country-specific LC

MODIS LC		Degraded	Stable	Improvement	
	Degraded	19.91%	2.62%	0.99%	*23.51%*
	Stable	11.44%	39.42%	7.85%	*58.70%*
	Improvement	2.63%	1.58%	13.58%	*17.78%*
		33.97%	*43.61%*	*22.41%*	**100**

Indicator 15.3.1 (dis)agreement map using MODIS MCD12Q1 and Uso de suelo y vegetación as LC input datasets (2002-2014) in Mexico.

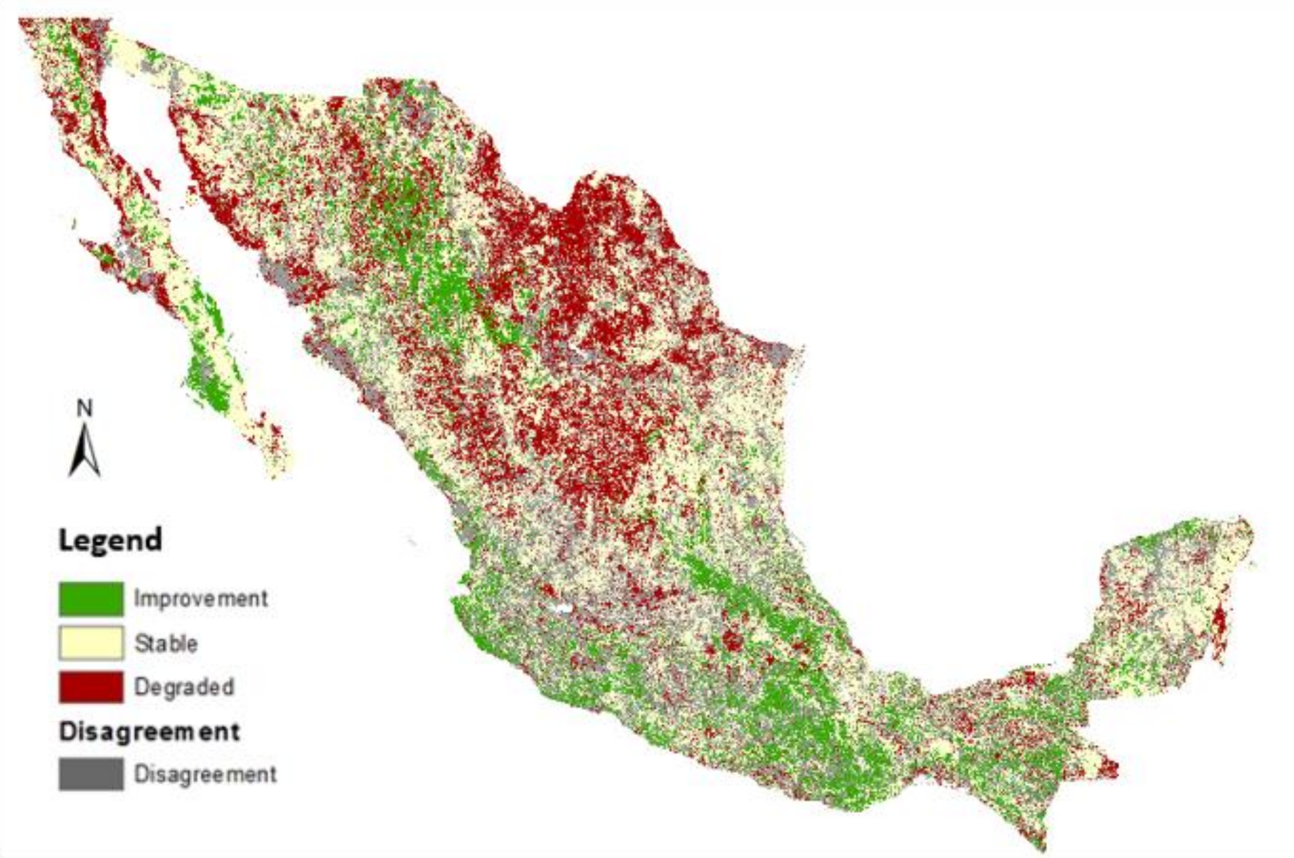


Figure 16 Indicator 15.3.1 spatial (dis)agreement between MODIS and National specific data

Disagreement percentages between ESA-CCI-LC and country-specific LC, were the second highest of the three comparisons, with a total of 23.95 % of the cells classified differently and 76.05% classified equally in both cases. Table 20 shows the confusion matrix between these two degradation maps. Overall, the category of stable has the highest difference in both maps with around 17% different in total amount of pixels classified in both maps. Most of that difference occurs when the analysis using ESA-CCI-LC classifies pixels as stable (10.55% and 8.96%) - but in the national LC those are classified as degraded and improving respectively.

Table 20 Indicator 15.3.1 confusion matrix in percentages (ESA-CCI-LC vs. country-specific LC dataset)

Country-specific LC \ UNCCD LC	Degraded	Stable	Improvement	
Degraded	21.15%	10.55%	2.27%	*33.97%*
Stable	1.11%	41.82%	0.69%	*43.62%*
Improvement	0.37%	8.96%	13.08%	*22.41%*
	22.64%	*61.32%*	*16.04%*	**100**

Figures 17 shows the spatial distribution of (dis)agreeing cells per degradation class.

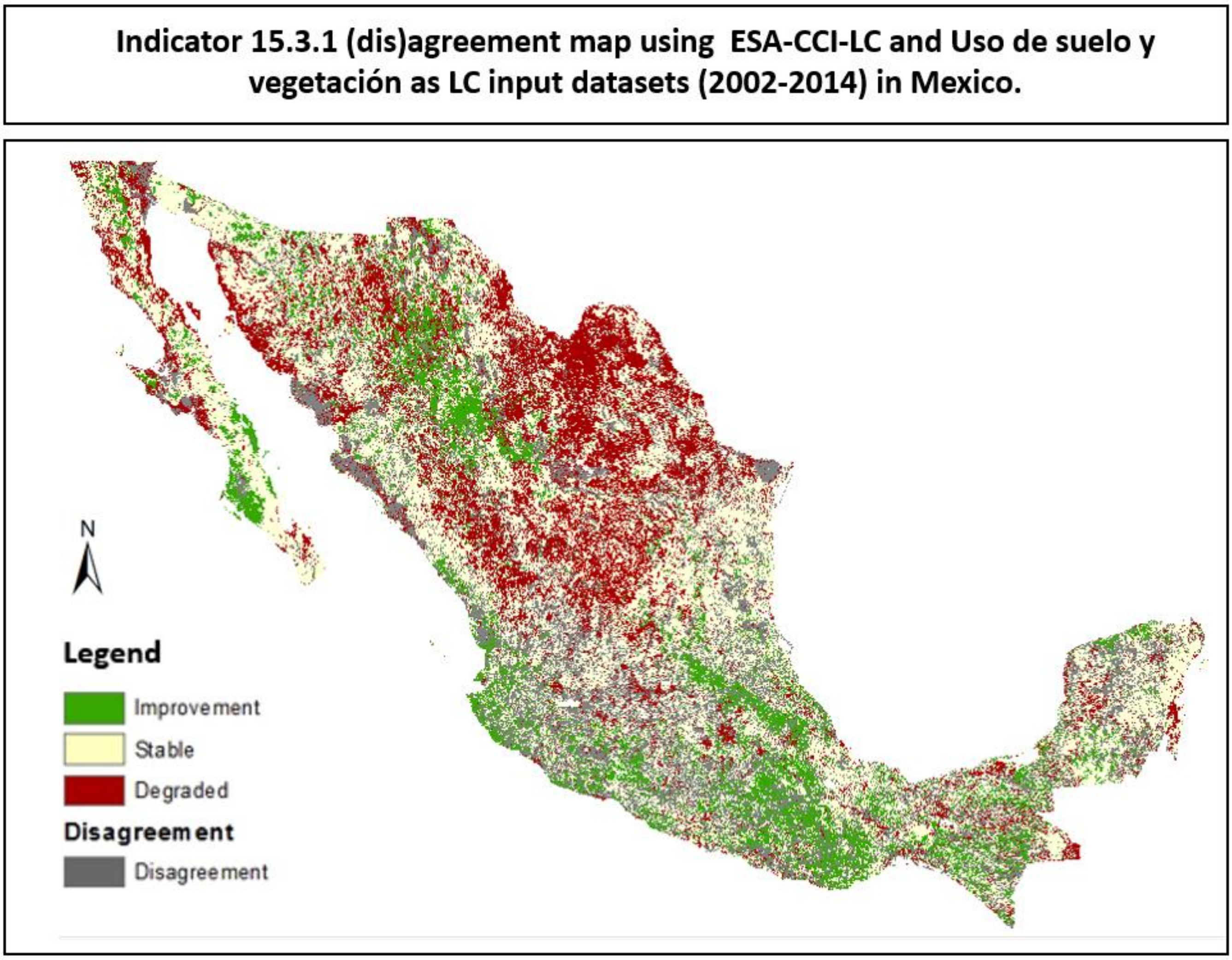


Figure 17 Indicator 15.3.1 spatial (dis)agreement between ESA-CCI-LC and country-specific LC data

Finally, the comparison between both global datasets ESA-CCI-LC and MODIS MCD12Q1.006 showed the lowest disagreement of all cases with only 14.15% of the cells classified differently and 85.8% classified the same. Table 21 shows the confusion matrix between these two maps. Overall, the highest difference occurs in the stable category with 2.63% difference in overall classification. However, all categories differ in less than 3% each, which is considerably less that in the previous comparisons (both global datasets against the country-specific LC dataset).

Table 21 Indicator 15.3.1 confusion matrix in percentages (ESA-CCI-LC vs. MODIS MOD13Q1)

MODIS LC \ UNCCD LC	Degraded	Stable	Improving	
Degraded	18.19%	4.66%	0.67%	*23.52%*
Stable	4.16%	53.41%	1.12%	*58.69%*
Improving	0.29%	3.24%	14.25%	*17.78%*
	22.64%	*61.32%*	*16.04%*	**100**

Figure 18 shows the spatial distribution of this comparison per degradation class, where it can be seen that whilst both previous maps (16 and 17) are fairly similar in terms of disagreement (gray) distribution, it is hard to even spot those places as they are inside bigger agreeing polygons (zoom into disagreement figure 18) and mostly scattered throughout the territory.

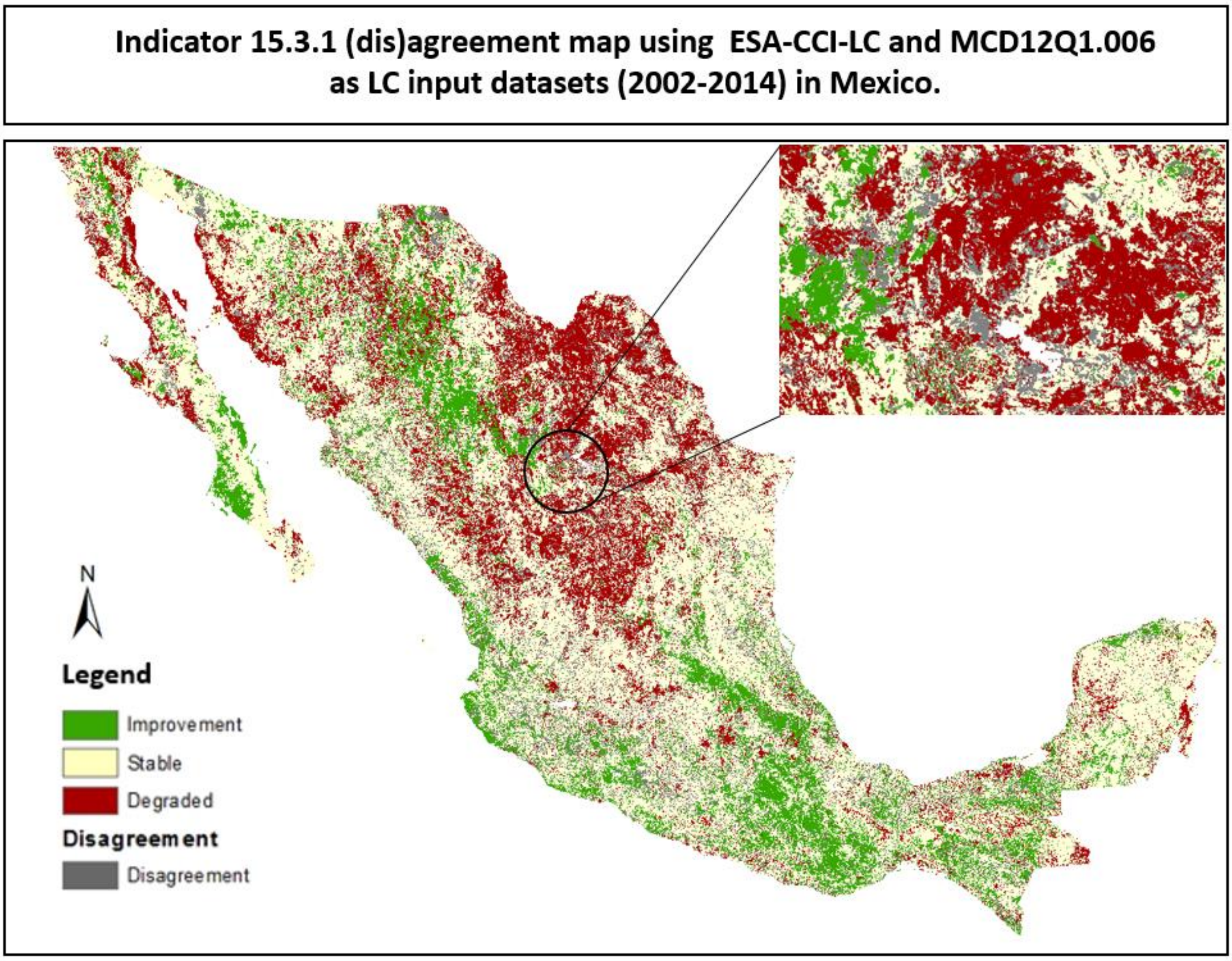


Figure 18 Indicator 15.3.1 spatial (dis)agreement between ESA-CCI-LC and MOD13Q1 LC datasets

Table 22 shows the summary of total and per class (dis)agreement for all three comparisons in percentages. Overall, when comparing two maps at the time, the highest discrepancies appeared when comparing the country-specific dataset to either of the two global datasets. However, all comparisons showed more than 70% agreement.

Table 22 Percentage (%) of total and per class (dis)agreement for all comparisons made.

COMPARISON	Agreement per class			Total agreement	Total disagreement
	Degraded	Stable	Improvement		
ESA-CCI-LC & Country-specific LC	21.15%	41.82%	13.08%	76.05%	23.95%
MODIS & Country-specific LC	19.91%	39.42%	13.58%	72.90%	27.10%
MODIS & ESA-CCI-LC	18.19%	53.41%	14.25%	**85.85%**	**14.15%**

Figure 19 presents all three maps in a binary combination of agreement (green) and disagreement (red), from highest to lowest agreement: MCD12Q1.006 vs. ESA-CCI-LC (1), ESA-CCI-LC vs. Country-specific LC (2) and MOD13Q1 vs Country-specific LC (3).

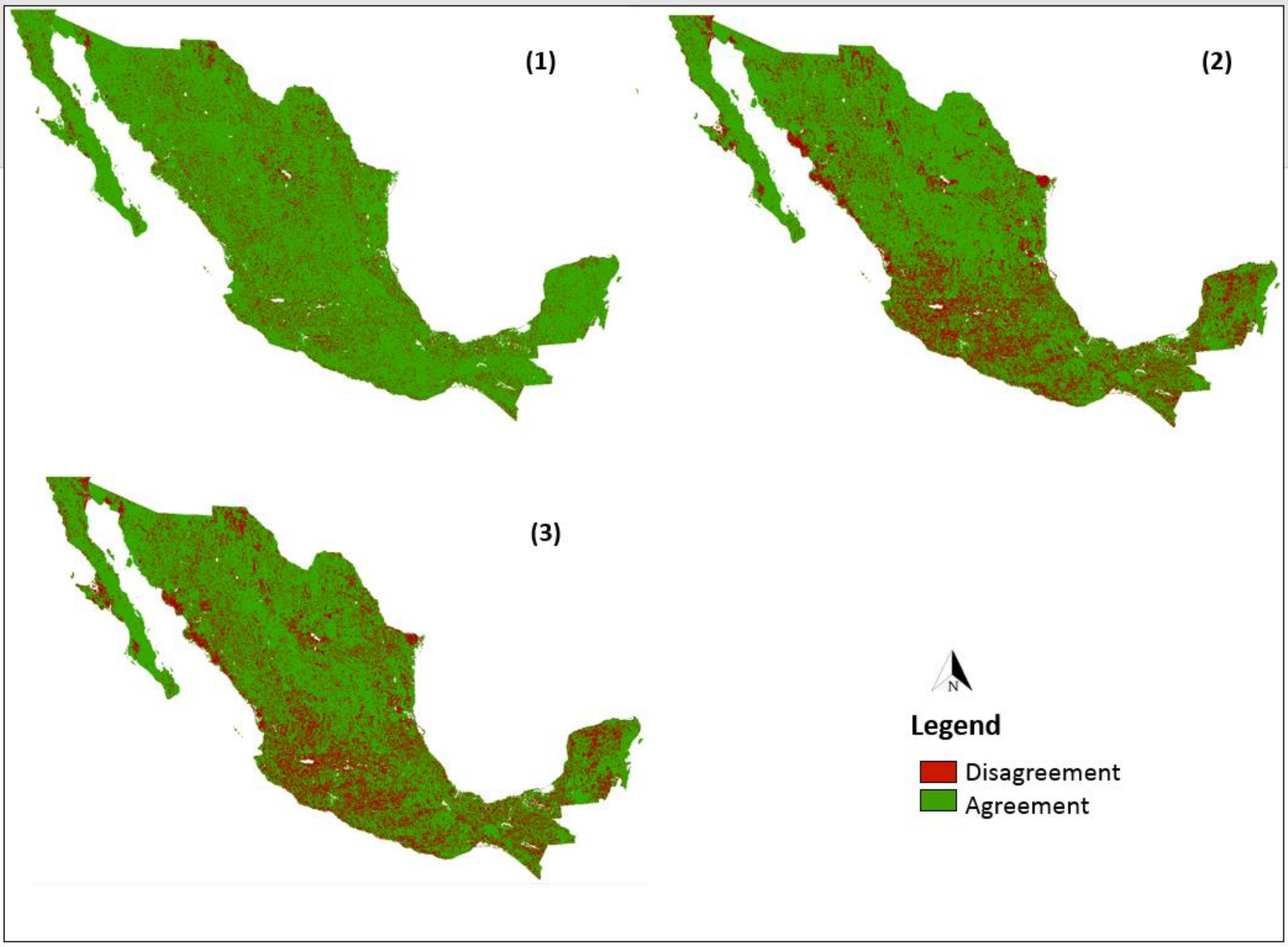


Figure 19Indicator 15.3.1 (dis)agreement maps (1) MODIS and UNCCD default, (2) Country-specific and UNCCD default and (3) Country-specific and MODIS

5. DISCUSSION

5.1. Dataset availability for Indicator 15.3.1 in Mexico

The results of this study showed that availability of datasets (for indicator 15.3.1 assessment) in Mexico differ greatly per sub-indicator. While options for NDVI and LC are varied, the production of frequent SOC stock data both internationally and nationally is still challenging. This is also noted by Sims, et al (2017) and Conservation International (2018). This becomes important because, due to lack of data availability, the third sub-indicator becomes highly dependent on LC input dataset. As a result, degradation percentages of LC change and SOC stock change sub-indicators are very closely related (like shown in tables 9, 12 and 15).

One of the concerns on SDG reporting is that countries could use lack of data coverage to avoid delivering results on their progress (Adams & Judd, 2018). Results of this project show that with existing data it is possible to deliver a report that monitors year 2014 in Mexico. However, continuity of reporting could be jeopardized by lack of frequency in potentially usable input datasets. For instance, the government of Mexico uploaded the first SDG 15.3.1 report last August (2018). Datasets used for that assessment (Country-specific LC, MODIS NDVI product and Baseline of LDN in Mexico, 2007) allow only monitoring of the indicator until year 2014, whereas GLC products offer the possibility of monitoring a more recent period (2017). On the one hand, national datasets are more likely to be used by countries for SDG assessment (Sims, et al, 2017) as they are produced under a country-specific context and could therefore be more appropriate (see Kussul, et. al., 2017). On the other hand, at least in the case of Mexico, country-specific dataset production can take longer than that of a global dataset (i.e. country-specific LC maps are available every 2 to 3 years, stopping in 2014, while some global maps offer an up to date yearly product). Thus, making reporting time frames slower and dependent on a country’s capacity to produce their own data increasing the already difficult reporting task.

Even though only three LC datasets complied with the characteristics to be selected for this project (see chapter 3.2), other LC datasets could offer interesting opportunities for future monitoring in Mexico if they were updated. Examples of this are NALCAMS LC products (CONABIO, n.d.) and the Chinese project GlobeLand30 (2010) which offers rasters for the years 2000 and 2010. Both datasets offer a higher spatial resolution (30 m) than the global datasets used for this project (300 m and 500 m) and are free of access under registration and therefore of interest if their temporal availability improved. In addition, Copernicus project Global LC maps (C-GLOPS) aims to offer a yearly global LC map at 100 m spatial resolution (IIASA, 2018) which could be used to assess several indicators from SDG 15, including the one in this study. It could also offer consistency amongst countries due to its spatial and temporal resolution. Unfortunately, its current availability reaches only one reference year (2015) over Africa.

Finally, another potentially interesting dataset for Mexico is the 30 m raster derived from the work of Cartus, et al. (2014). This forest aboveground carbon stock map of Mexico was generated from empirical modeling on forest inventory, optical and radar data from the years 2004 and 2007 and was planned to be free of access. Nevertheless, to the best of our knowledge this raster is not yet free of access. The combination of this dataset and ISRIC SoildGrids250m (used in this project), could offer an option to assess the third sub-indicator, as it was originally intended in the GPG (Sims, et al. 2017), which states that changes in both above- and below-ground carbon stock should be considered in the evaluation. In the present study, SOC stock is used as a proxy for this measurement.

5.1.1. Open data for SDG monitoring

Over the recent years open data has become more important. Driven by the data revolution, which was recognized by the UN as key factor to achieve global goals such as the 2030 Agenda (Gurin, et al, 2015), different authors have stressed the necessity of open data to fulfill SDG monitoring (see Gurin, et al., 2015; Lu, et al. 2015; MacFeely, 2019). In fact, without freely available datasets, the completion of this research would have been complicated, or even impossible, and while it is true that participant countries have considerably more resources destined for monitoring purposes, to achieve the 2030 Agenda it is necessary to use all available resources. In that sense, open data has the potential to be a universal resource towards measuring and achieving the SDGs; sharing data and methods for using it across countries can accelerate progress and help making the SDGs completion possible (Gurin, et al, 2015).

On September 26, 2018, the conference "National Reporting for the SDGs: Using open data interoperability to maximize impact" was held in Argentina. Representatives from national statistical offices (NSOs) were invited to give their perspectives on SDG reporting challenges and opportunities. One of the outcomes was that NSOs reported an increasing need for resources and capacity building to keep up on SDG reporting, stressing the fact that NSOs are expected to handle and create increasingly complicated datasets. Moreover, the necessity of more domestic and international resources as well as coordination and cooperation between different governmental and non-governmental organizations, private actors and international agencies for data production was stressed (IODC18, 2018). In the case of Mexico, the government's commitment to enabling open data can be seen through initiatives like SIODS portal and more recently in the strengthening of their Spatial Data Infrastructure (SDI): Sistema Nacional de Información Estadística y Geográfica (SNIEG), which aims to "build collaborative networks of knowledge and development, in response to the need in all areas, to access, integrate and use spatial data from various sources" (Guerrero Elemen, 2016, p.2). Even with the SNIEG implementation, country-specific datasets used in this research had to be accessed through different databases from different institutions, which speaks of the challenge and work that building an SDI represents. Further confirmed by Vela Salinas, et al, (2018) whose work mentions that one of the biggest challenges to overcome is the pace in which data from all other governmental sources is being incorporated to the platform; which is related to the sensibilization of all governmental offices to adopt open data strategies within their organizations.

According to the World Bank Group (2015), one of the key benefits of open data for sustainable development is that it increases the transparency, accountability and citizen participation processes. Gurin, et al, (2015) mentioned that by releasing open data all parties involved in SDG monitoring can show their commitment and hold themselves accountable for the results, which in turn potentially increases citizens engagement on the completion of the 2030 Agenda. This is reinforced by the Center for Open Data Enterprise (CODE)(2018), when they state that implementation of open data facilitates the sharing of information within governments and provides public insight into a country's progress in a way that allows a variety of stakeholders to contribute data, expertise, and resources. This research and the results obtained from it are an example of how access to open data enabled creating information for decision-making outside the governmental context, opening the discussion on different topics related to indicator 15.3.1 and SDG monitoring in general. It is hoped that this project sets a reference for future research on SDG monitoring independent of governmental bodies. Thus, encouraging different stakeholders in Mexico to contribute and get involved in ensuring the 2030 Agenda completion.

Overall, it is logical to adopt open data as an important tool for the 2030 Agenda completion, as it directly relates to one of the core principles under which the Agenda was created: "to ensure that no one is left behind". In other words, open data gives the potential of citizens, private and non-governmental organizations to engage in monitoring and solving (at least to some extent) the SDGs targets; it is after all a global challenge where everyone has the right to know how progress is being made.

5.2. The state of land degradation in Mexico

The degradation assessment showed that despite of which LC dataset was used, the percentage of degraded land for the evaluated period is surprisingly lower than calculated in other degradation studies in Mexico (between 50% and 70%) (see SEMARNAT, 2011; CONAFOR-UACh, 2013). An explanation for this could be the difference in study years as well as degradation definitions and methods used for the assessment. While degradation in the SDG context is assessed in terms of LC, NDVI and SOC stock change, the other three studies assess degradation by looking at the physical and chemical changes as well as the wind and water driven changes. These differences make the results of the studies incomparable, raising the importance of countries validating their monitoring process as soon as possible; which is both costly and time consuming (Sims, et al, 2017). Moreover, the first official SDG 15.3.1 Mexican report (Gobierno de la Republica, 2018) found 47,09% degradation in Mexico. This percentage is almost twice as high as the one obtained in this project using GLC (22.3% and 22.12%), but naturally closer to the percentage obtained when using the same input LC data (32.84%). One possible reason why these results are not identical to the figures reported by the Mexican government is the use of a different input dataset for the third sub-indicator. For this project, SOC stock from SoilGrids250m was used. This dataset is the result of different data sources from different years (Conservation International, 2018), when using it for the third sub-indicator, it is assumed to represent the conditions of SOC stock content in the baseline period. However, it is likely that a more specific dataset like the one used by the Mexican government can change the results on degradation as it removes the use of LC data for the third sub-indicator evaluation; making it independent and thus different to the results from the first sub-indicator. Moreover, the use of the plug-in for the assessment (not used by the Mexican government) could also affect the results. In addition, the LC aggregation method used to translate the datasets original legend to the 7 IPCC LC classes could differ; as there was, to the best of our knowledge no way of accessing the aggregation schemes the government used for this first monitoring. Naturally, different legend aggregations could result in different total percentages over class, affecting the LC change assessment and eventually the final degradation assessment.

Furthermore, the degradation assessment also showed that results from both global LC datasets (MODIS and ESA-CCI-LC) are almost identical (see table 18). However, the country-specific LC dataset showed an 11% increase in estimation of degraded land. Due to the short time that has passed since the countries took on the challenge of the 2030 Agenda, there is no further research that studied the impact of different LC for SDG assessment. However, studies in other disciplines have shown that selection of LC datasets influence the outcomes of the models they are applied to (Mora, et al., 2014), which is strengthened in this study, where depending on the LC dataset used, classification of degradation, improvement or stability varies by 11%, 5.5% and 15.6% respectively (see table 18). A possible explanation for this could be the differences (inconsistencies) in original LC classification of each input dataset, as well as the aggregation method used to translate the datasets original legend to the 7 IPCC LC classes. Differences in GLC have been studied before (see Fritz et al., 2011; Fritz & Lee, 2005; Giri, et al., 2005). However, comparison between national-specific LC maps and global LC has not been researched. Tsendbazar, N. et al., (2016), made a comparative assessment of the thematic accuracy of GLC (Globcover, LC-CCI and MODIS) maps for different applications. Amongst their findings they identified that regardless of the application, all maps had high confusion errors for Shrubs, Grass and Cropland LC classes.

Findings of our project further confirm high differences in the overall percentages for these classes (both in baseline and monitoring year). Likewise, Tree covered areas and Other land LC classes showed high differences in percentages in all three LC datasets used. According to Tsendbazar, et al, (2016) p.131 one of the reasons these classes can be easily misclassified is “their low spectral separability and mixed vegetation components”. In addition to this, the method followed for translating the original LC classes into the 7 IPCC LC classes in this study could be a factor that enhances these differences.

The harmonization process was especially difficult for the country-specific LC dataset due to its original legend complexity (more than 100 classes). This becomes evident when looking at the percentages of each LC class in the baseline and target per input dataset (see tables 10 ,13 and 16) which clearly affect the percentage of change per LC class — especially if such changes are classified as degradation in the land cover change matrix (see table 17). As an example, results show that national-specific LC datasets, overall percentages for each year are close to MODIS LC data in the baseline year, but very different in the monitoring period, making changes in LC classes more abrupt and thus increasing the percentage of final degradation. Conversely, overall percentages of GLC in the baseline year have a higher difference between them than when compared to the country-specific LC but have a smaller overall change per class in the monitoring period, making changes in LC less abrupt and thus decreasing degradation classification. A possible solution would be that experts in different disciplines could help in the harmonization process of the LC legend. Furthermore, the work of Kussul, et. al (2017) suggests that using international standards for production of country-specific LC products could facilitate both their comparison and integration with GLC for LDN assessment. This is reinforced by Lu, et al. (2015) when they mention that standardization and verification of data is one of the main priorities to be established globally for the 2030 Agenda. The lack of these aspects increases the likelihood of collecting wrong or useless information, thus compromising global comparability of SDG progress.

5.3. Degradation spatial (dis)agreement in Mexico

When looking at the resulting maps, spatial distribution of degradation classes can look similar (see figures 10, 11 and 12). To know exactly how similar, the last research question of this study aimed to spatially compare the outputs previously discussed. The spatial comparison of the three degradation maps (see Figure 14), showed an overall higher agreement (68.2%) than disagreement (31.7%). However, in only 1.64% out of that disagreement percentage all three maps disagreed. The rest resulted from the disagreement of only one map. This can be further seen in the results obtained when comparing two maps at a time, were the overall agreement percentages increased and the discrepancies decreased (see table 22). Not surprisingly, (dis)agreement percentages between both global datasets ESA-CCI-LC and MODIS were the lowest (14.15%). While discrepancies between country-specific LC and both Global LC were similarly high (23.9% for ESA-CCI-LC and 27.1% for MODIS). Confusion matrices for each case (see tables 19, 20 and 21,) show that the highest misclassification occurred in stability class, followed by degradation and finally potential improvement. Possible explanations for this are, as mentioned before, the LC classification legend harmonization which can affect the results of the first and third sub-indicator and thus the final degradation assessment. Furthermore, the agreement percentages per class, could have been affected by the way the plug-in works. For example, even though the extent was set using the same shape-file in all three cases, the total extent of the final maps was not the same for all three studies. According to Conservation International (2017), the reason for this is that to increase computation speed of the analysis, the plug-in creates a bounding box to run the initial three sub-indicators analysis which could explain differences in final total area when integrating sub-indicators (final step). Currently, it is not possible to modify this within the plug-in, a possible solution could be to integrate sub-indicators outside the plug-in. Nonetheless, this could make the overall method more complex. Finally, as part of this bounding box process within the plug-in, the number of pixels with "no data" differs per degradation map, making the overall compared percentages different for each case. It is noticeable that some of this "no data" cells are around or in water bodies. Thus, a way of potentially decreasing the amount of "no data" cells could be to mask them from the beginning of the assessment. This will however, make the changes in waterbodies difficult to track. Other reasons that could have influenced the overall degradation assessment could be linked to the NDVI datasets and methods used for that sub-indicator (i.e. the chosen vegetation index or non-existent climate correction). Furthermore, the plug-in currently uses ESA-CCI-LC datasets to estimate ecological units in the productivity performance metric (second sub-indicator), regardless of the LC dataset used for the other sub-indicators. This means that LC datasets used in the assessment process are currently different and therefore introduce inconsistency in the methodology. Due to the limited amount of time and scope of this project it was decided to leave these topics out of the discussion, but further research is necessary to assess the extent of their impact on the degradation results.

The overall monitoring purpose is to serve as a basis for informed decision-making. Therefore, it is important to note the possible impacts of these comparisons for relevant stakeholders even though discrepancies found are scattered along the study area. When comparing the country-specific LC to both GLC, there is a clear disagreement concentration in the southern part of Mexico; the Yucatan peninsula, Jalisco, Aguascalientes and some parts of Sinaloa and Nayarit (see figure 19). This suggests, at least to some extent, that such states are more susceptible to changes in LC datasets, which increases the challenges for stakeholders to choose the right course of actions against land degradation, as well as the need for validation. Even when stating which degradation map is more accurate falls outside of the scope of this project, obtained results can be an indication of priority areas in terms of investment, validation processes and further studies. Helping relevant stakeholders focalize efforts in areas that are potentially more affected.

Lopez Santos (2016) made a review on the challenges Mexico faces towards achieving LDN. One of the authors findings was that Mexico biggest challenge - like for most developing countries - is establishing public policies that reconcile both environmental and economic growth as goals to achieve gradual LDN. The author also noted that information available for decision-making is not always frequently generated or easy to access and interpret. This is reinforced on the National Report for the Voluntary Review of Mexico within the High-Level Political Forum on Sustainable Development Framework (Gobierno de la Republica & PNUD, 2016). In the report, the Mexican government recognizes that at first sight, national goals can be adapted to fit the 2030 Agenda goals. However, it is necessary to carry out a more exhaustive analysis that includes the review of indicators, as well as the data used for their assessment with the objective to know the results effectiveness and relevance for public policies related to SDGs. Thus, reinforcing the importance of projects like this report, which results can directly help stakeholders. For instance, if stakeholders had to decide on which course would policy making take with the maps created in this project, special attention (i.e. stronger measures) should be taken in areas with disagreement; as they could be less sure that the degradation classification was given correctly on those spots.

Furthermore, the effects of degradation in developing countries and their correlation with poverty has been widely studied (see Barbier, 2000; Munk, H. 2004). This is especially relevant in the SDG context as there is a connection between targets, causing synergies and potential trade-offs (Lu., et al, 2015). Morales (2005) studied the correlation between poverty and land degradation in some Latin American countries. Concluding that there is a correlation between poverty and land degradation, as in most cases the poorest people whose only income comes from the land live in already degraded areas, causing a loop of poverty and degradation. In that sense, having relevant information to act against land degradation is also related to other social dimensions like poverty, which in turn is related to different objectives and indicators of the 2030 Agenda (i.e. targets under Goal 1: end poverty in all its forms everywhere). Moreover, the UNCCD, highlights three main aspects of other SDGs that are related to degradation: food security, safe use and access to water and migration (Lopez Santos, 2016).

As further research related to this report, studying the correlation between degradation and poverty (per state) in Mexico would be interesting. The different dis(agreement) maps generated, could be used as input for such an analysis. Furthermore, the integration of statistics on population density could help giving an estimation of the percentage of people that are most vulnerable.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

Reporting on SDGs progress requires frequent, up to date, and easy to access data. Even though indicator 15.3.1 is a Tier II indicator, this study shows that data availability with the right characteristics for its assessment in Mexico is still insufficient to ensure continuous reporting. In general, the biggest limitation of most regional and national datasets is their frequency. As such, a continuous and comparable monitoring process becomes an even more challenging task. The available country-specific data enables a monitoring temporality from 2002-2014, while GLC (ESA-CCI-LC and MODIS) datasets offer the possibility to monitore a more recent period (2016 and 2018 respectively). The Mexican government has taken several actions to promote the use open data across governmental organizations and for SDG monitoring. Likewise, several global initiatives particularly on LC monitoring were found. However, most of them are still in the making and thus require further research on the implications and best practices of their integration with country-specific datasets.

According to this study, land degradation in Mexico – regardless of the input LC data– is lower (23.17%, 23.59% and 32.84%) than results from previous studies (more than 70%). This could be attributed to the definitions of degradation, studies temporality and methods used. This makes SDGs degradation results incomparable to previous research, increasing the importance of validation processes to be implemented by the government. Moreover, the first Mexican official 15.3.1 document reports degradation of 47.09%, which is close to the results obtained using the same LC dataset in this project (32.84%). Although differences in this study are mostly linked to LC map discrepancies and methods used to harmonize original legends to IPCC LC classes, further research needs to be done to explore the extent of the other two sub-indicators – and the input datasets –impact on the final degradation assessment as well as the accuracy of the used plug-in.

Depending on the LC input dataset used, the state of indicator 15.3.1 in Mexico can differ up to 11%. The spatial comparison of the maps showed that both GLC datasets had the highest agreement (85.85%) when assigning any of the degradation classes (degraded, improvement and stable). However, when comparing country-specific LC to both GLC, agreement percentages decreased (76.05%- ESA-CCI-LC and 72.90%- MODIS). Overall, all comparisons showed higher agreement than disagreement, nevertheless maps showed disagreeing cells clustered in certain parts of the study area, suggesting – at least to some extent – that such areas are more susceptible to changes in LC datasets, which increases the challenges for stakeholders to choose the right course of actions against land degradation. Results of this study can potentially serve as basis for stakeholders to set priority areas and focalize efforts in terms of investment, validation processes, potentially vulnerable population and further research.

Finally, stating which dataset yields the most accurate degradation result falls out of the scope of this research. However, the fact that results differ suggests that stakeholders can (un)knowingly steer the output of the indicator in different directions. The importance of noticing these differences relies on the subjectivity it adds to the SDG assessment which could affect decision-making and ultimately jeopardize meeting the SDG targets; raising the importance of non-governmental actors, researchers and citizens in general to stay informed and closely follow the 2030 Agenda development.

6.2. Recommendations

Recommendations for different stakeholders involved in SDGs assessment are listed in the following sections.

6.2.1. Further research

- Validation of each sub-indicator for the first monitoring period as suggested in the GPG (Sims, et al.,2017) could help to know where the IAOA method is over or underestimating degradation.

- Knowing the accuracy of the method used in Trends.Earth would indicate where efforts need to be placed to reduce the uncertainties.

- A more detailed review of the LC classes from the Mexican Uso de Suelo y Vegetacion datasets. This review could be with input from experts on the topic who were involved in the map production. Paying special attention to those LC classes that are national specific and therefore difficult to categorize in broader classes.

- Quantification of the spatial (dis)agreement per state could help understand which states are more sensitive to changes in LC datasets. Likewise, the possible correlation of degradation with states in Mexico with high poverty levels, as well as the integration of statistics on population density could help giving an estimation of the percentage of people that are most vulnerable. The different dis(agreement) maps generate, could be used as input for such an analysis.

- Seeking the possibility of undertaking a spatial comparison between the degradation map produced by the Mexican government (Gobierno de la Republica, 2018) and the results obtained in this project to identify any differences, and potential areas for improvement in this project and for degradation monitoring in general.

6.2.2. Data Users

- We encourage stakeholders to use these results as an indication of potential degradation misclassification in their own maps (if they have not carried any validation process) or the maps created in this project (if they are comparable to future research).

- Focusing efforts on areas in which discrepancies are highest to build action plans that prioritize susceptible areas and potentially address degradation in a more efficient way.

- Include in countries policy a clear strategy for the indicators validation process. By for example, coordinating with INEGI, CONABIO, SEMARNAT and CONAFOR in their surveying and gathering of data activities to evaluate the possibility of including the collection of information that would help validate indicator 15.3.1. Without validation, there is no way of ensuring the accuracy of the monitoring results and consequently ensuring that actions to achieve LDN are correctly aimed.

6.2.3. Data producers and providers

- The implementation of existing global legend standards like those mentioned in the GPG (Sims, et al., 2017) in the data production process could be of help for both, people in charge of SDG monitoring, as well as people who use and interpret the results for policy making. Furthermore, it could increase the possibilities to integrate National LC datasets with GLC, potentially decreasing the pressure on the government to produce national LC and encouraging the use of already made products.

- Trends.Earth was a very helpful tool for the assessment. Using the same custom LC dataset in all sub-indicators could be a way of making the process more constant. Therefore, an option for changing the input LC to a custom one to calculate land productivity metrics is of interest.

- Timely updating the SIODS platform to ensure stakeholders access to the most recent official SDG information in Mexico.

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APPENDIX A

LC Codes and their corresponding IPCC class. Each IPCC class represented by a number Tree-covered (1), Grassland (2), Cropland (3), Wetland (4), Urban Settlements (5), Other land (6), Waterbodies (7)

Country-specific CVU code (2014)	**IPCC**
BA	1
BB	1
BC	1
BG	1
BI	1
BJ	1
BM	1
BP	1
BPQ	1
BQ	1
BQP	1
BS	1
MK	1
MKE	1
SAP	1
SAQ	1
SBC	1
SBK	1
SBP	1
SBQ	1
SBQP	1
SBS	1

SG	1
SMC	1
SMP	1
SMQ	1
SMS	1
VS	1
VSa/BA	1
VSA/BA	1
VSa/BB	1
VSA/BB	1
VSa/BG	1
VSA/BG	1
VSa/BJ	1
VSA/BJ	1
VSa/BM	1
VSA/BM	1
VSa/BP	1
VSA/BP	1
VSa/BPQ	1
VSA/BPQ	1
VSa/BQ	1
VSA/BQ	1
VSa/BQP	1
VSA/BQP	1
VSa/BS	1
VSA/BS	1

VSA/MK	1
VSa/SAP	1
VSA/SAP	1
VSa/SAQ	1
VSA/SAQ	1
VSa/SBC	1
VSA/SBC	1
VSa/SBK	1
VSA/SBK	1
VSa/SBP	1
VSA/SBP	1
VSa/SBQ	1
VSA/SBQ	1
VSa/SBQP	1
VSA/SBQP	1
VSa/SBS	1
VSA/SBS	1
VSA/SG	1
VSa/SMC	1
VSA/SMC	1
VSa/SMP	1
VSa/SMQ	1
VSA/SMQ	1
VSa/SMS	1
VSA/SMS	1
VSh/BJ	1

VSh/BM	1
VSh/BP	1
VSh/BPQ	1
VSh/BQ	1
VSh/BQP	1
VSh/SAP	1
VSh/SAQ	1
VSh/SBC	1
VSh/SBK	1
VSh/SBQ	1
VSh/SMC	1
VSh/SMQ	1
VSh/SMS	1
MC	2
MDM	2
MDR	2
MET	2
MKX	2
ML	2
MRC	2
MSC	2
MSCC	2
MSM	2
MSN	2
MST	2
PH	2

PI	2
PN	2
PY	2
TA	2
TAP	2
TAS	2
TP	2
TS	2
TSP	2
VG	2
VSa/MC	2
VSa/MDM	2
VSa/MDR	2
VSa/MET	2
VSa/MJ	2
VSa/MK	2
VSa/MKE	2
VSa/MKX	2
VSa/ML	2
VSa/MRC	2
VSa/MSC	2
VSa/MSCC	2
VSa/MSM	2
VSa/MSN	2
VSa/MST	2
VSa/PH	2

VSa/PN	2
VSa/PY	2
VSa/VG	2
VSh/MC	2
VSh/MDM	2
VSh/MDR	2
VSh/MET	2
VSh/MRC	2
VSh/MSCC	2
VSh/MSN	2
VSh/MST	2
VSh/PN	2
VSh/VH	2
VSI	2
VW	2
VY	2
HA	3
HAP	3
HAS	3
HP	3
HS	3
HSP	3
PC	3
RA	3
RAP	3
RAS	3

RP	3
RS	3
RSP	3
VPI	3
PT	4
VH	4
VHH	4
VM	4
VSA/PT	4
VSa/VH	4
VSa/VHH	4
VSa/VM	4
VSA/VM	4
VSh/VM	4
VT	4
AH	5
ACUI	6
ADV	6
DV	6
VA	6
VD	6
VPN	6
VSa/VD	6
VSa/VPN	6
VSA/VPN	6
VSa/VU	6

VSh/VPN	6
VU	6
H_2O	7
P/E	NODATA

APPENDIX B

LC Codes and their corresponding IPCC class. Each IPCC class represented by a number Tree-covered (1), Grassland (2), Cropland (3), Wetland (4), Urban Settlements (5), Other land (6), Waterbodies (7)

Country-specific LC (2002)	**IPCC**
BOSQUE DE AYARÍN	1
BOSQUE DE CEDRO	1
BOSQUE DE ENCINO	1
BOSQUE DE ENCINO-PINO	1
BOSQUE DE GALERÍA	1
BOSQUE DE MEZQUITE	1
BOSQUE DE OYAMEL	1
BOSQUE DE PINO	1
BOSQUE DE PINO-ENCINO	1
BOSQUE DE TÁSCATE	1
BOSQUE INDUCIDO	1
BOSQUE MESÓFILO DE MONTAÑA	1
SABANA	1
SELVA ALTA PERENNIFOLIA	1
SELVA ALTA SUBPERENNIFOLIA	1
SELVA BAJA CADUCIFOLIA	1
SELVA BAJA ESPINOSA CADUCIFOLIA	1
SELVA BAJA ESPINOSA SUBPERENNIFOLIA	1
SELVA BAJA PERENNIFOLIA	1
SELVA BAJA SUBCADUCIFOLIA	1
SELVA DE GALERÍA	1
SELVA MEDIANA CADUCIFOLIA	1
SELVA MEDIANA PERENNIFOLIA	1
SELVA MEDIANA SUBCADUCIFOLIA	1
SELVA MEDIANA SUBPERENNIFOLIA	1
SIN VEGETACIÓN APARENTE	1
VEGETACIÓN DE GALERÍA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE AYARÍN	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE ENCINO	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE ENCINO-PINO	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE GALERÍA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE MEZQUITE	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE OYAMEL	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE PINO	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE PINO-ENCINO	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE DE TÁSCATE	1
VEGETACIÓN SECUNDARIA ARBÓREA DE BOSQUE MESÓFILO DE MONTAÑA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE MANGLAR	1

VEGETACIÓN SECUNDARIA ARBÓREA DE PALMAR NATURAL	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA ALTA PERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA ALTA SUBPERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA CADUCIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA ESPINOSA CADUCIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA ESPINOSA SUBPERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA PERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA SUBCADUCIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA BAJA SUBPERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA DE GALERÍA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA MEDIANA CADUCIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA MEDIANA SUBCADUCIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE SELVA MEDIANA SUBPERENNIFOLIA	1
VEGETACIÓN SECUNDARIA ARBÓREA DE VEGETACIÓN DE PETÉN	1
AGRICULTURA DE HUMEDAD ANUAL	2
AGRICULTURA DE HUMEDAD ANUAL Y PERMANENTE	2
AGRICULTURA DE HUMEDAD ANUAL Y SEMIPERMANENTE	2
AGRICULTURA DE HUMEDAD PLANTACION AGRICOLA PERMANENTE	2
AGRICULTURA DE HUMEDAD SEMIPERMANENTE	2
AGRICULTURA DE HUMEDAD SEMIPERMANENTE Y PERMANENTE	2
AGRICULTURA DE RIEGO ANUAL	2
AGRICULTURA DE RIEGO ANUAL Y PERMANENTE	2
AGRICULTURA DE RIEGO ANUAL Y SEMIPERMANENTE	2
AGRICULTURA DE RIEGO PLANTACION AGRICOLA PERMANENTE	2
AGRICULTURA DE RIEGO SEMIPERMANENTE	2
AGRICULTURA DE RIEGO SEMIPERMANENTE Y PERMANENTE	2
AGRICULTURA DE TEMPORAL ANUAL	2
AGRICULTURA DE TEMPORAL ANUAL Y PERMANENTE	2
AGRICULTURA DE TEMPORAL ANUAL Y SEMIPERMANENTE	2
AGRICULTURA DE TEMPORAL PLANTACION AGRICOLA PERMANENTE	2
AGRICULTURA DE TEMPORAL SEMIPERMANENTE	2
AGRICULTURA DE TEMPORAL SEMIPERMANENTE Y PERMANENTE	2
CHAPARRAL	2
MATORRAL CRASICAULE	2
MATORRAL DE CONIFERAS	2
MATORRAL DESÉRTICO MICRÓFILO	2
MATORRAL DESÉRTICO ROSETÓFILO	2
MATORRAL ESPINOSO TAMAULIPECO	2
MATORRAL ROSETÓFILO COSTERO	2
MATORRAL SARCO-CRASICAULE	2
MATORRAL SARCO-CRASICAULE DE NEBLINA	2
MATORRAL SARCOCAULE	2
MATORRAL SUBMONTANO	2

MATORRAL SUBTROPICAL	2
MEZQUITAL DESÉRTICO	2
MEZQUITAL TROPICAL	2
PALMAR NATURAL	2
PASTIZAL NATURAL	2
PRADERA DE ALTA MONTAÑA	2
SABANOIDE	2
VEGETACIÓN DE PETÉN	2
VEGETACIÓN GIPSÓFILA	2
VEGETACIÓN HALÓFILA XERÓFILA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE AYARÍN	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE ENCINO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE ENCINO-PINO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE GALERÍA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE MEZQUITE	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE OYAMEL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE PINO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE PINO-ENCINO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE DE TÁSCATE	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE BOSQUE MESÓFILO DE MONTAÑA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE CHAPARRAL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MANGLAR	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL CRASICAULE	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL DE CONIFERAS	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL DESÉRTICO MICRÓFILO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL DESÉRTICO ROSETÓFILO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL ESPINOSO TAMAULIPECO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL ROSETÓFILO COSTERO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL SARCO-CRASICAULE	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL SARCO-CRASICAULE DE NEBLINA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL SARCOCAULE	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL SUBMONTANO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MATORRAL SUBTROPICAL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MEZQUITAL DESÉRTICO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE MEZQUITAL TROPICAL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE PALMAR NATURAL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE PASTIZAL GIPSÓFILO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE PASTIZAL HALÓFILO	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE PASTIZAL NATURAL	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA ALTA PERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA ALTA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA CADUCIFOLIA	2

VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA ESPINOSA CADUCIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA ESPINOSA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA PERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA SUBCADUCIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA BAJA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA MEDIANA CADUCIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA MEDIANA PERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA MEDIANA SUBCADUCIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE SELVA MEDIANA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE VEGETACIÓN DE DESIERTOS ARENOSOS	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE VEGETACIÓN HALÓFILA HIDRÓFILA	2
VEGETACIÓN SECUNDARIA ARBUSTIVA DE VEGETACIÓN HALÓFILA XERÓFILA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE DE ENCINO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE DE ENCINO-PINO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE DE PINO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE DE PINO-ENCINO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE DE TÁSCATE	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE BOSQUE MESÓFILO DE MONTAÑA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL CRASICAULE	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL DESÉRTICO MICRÓFILO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL ESPINOSO TAMAULIPECO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL ROSETÓFILO COSTERO	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL SARCO-CRASICAULE	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE MATORRAL SARCO-CRASICAULE DE NEBLINA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE PASTIZAL NATURAL	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA ALTA PERENNIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA ALTA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA BAJA CADUCIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA BAJA ESPINOSA CADUCIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA BAJA ESPINOSA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA MEDIANA CADUCIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA MEDIANA SUBCADUCIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE SELVA MEDIANA SUBPERENNIFOLIA	2
VEGETACIÓN SECUNDARIA HERBÁCEA DE VEGETACIÓN HALÓFILA XERÓFILA	2
BOSQUE CULTIVADO PLANTACION FORESTAL PERMANENTE	3
PALMAR INDUCIDO	3
PASTIZAL CULTIVADO PERMANENTE	3
PASTIZAL GIPSÓFILO	3
PASTIZAL HALÓFILO	3
PASTIZAL INDUCIDO	3
MANGLAR	4
POPAL	4
TULAR	4

VEGETACIÓN HALÓFILA HIDRÓFILA	4
VEGETACIÓN SECUNDARIA HERBÁCEA DE MANGLAR	4
ASENTAMIENTOS HUMANOS	5
ZONA URBANA	5
ACUÍCOLA	6
DESPROVISTO DE VEGETACIÓN	6
VEGETACIÓN DE DESIERTOS ARENOSOS	6
VEGETACIÓN DE DUNAS COSTERAS	6
CUERPO DE AGUA	7