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Cali Urban Development

Using NASA Earth Observations to Assess Wetlands and Land Reclamation in Cali, Colombia

DEVELOP Technical Report

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1. Abstract

Recent research has documented the global decline of wetlands, largely attributed to increased urbanization and agriculture. This NASA DEVELOP study partnered with two local environmental entities in Cali, Colombia: The Fundación Dinamizadores Ambientales and the Departamento Administrativo de Gestión del Medio Ambiente. The team utilized Earth observations to evaluate trends in wetland extent, potential, and land cover in Cali between 2002 and 2023. A supervised classifier was generated within Google Earth Engine to create land use analyses of the region using Landsat 5 TM, Landsat 8 OLI, and Landsat 9 OLI-2 imagery. To identify locations of wetland potential within the study area, wetland probability was assessed by inputting PlanetScope, Sentinel-2 MSI, and partner-provided datasets into the Wetland Intrinsic Potential Tool in ArcGIS Pro and R. Data from Sentinel-1 C-SAR, Sentinel 2-MSI, and Suomi-NPP VIIRS were used to evaluate wetland extent using the Wetland Extent 3.0 Tool in Python. Overall, results indicated areas with high wetland potential, particularly in the southeast region where agricultural fields were previously wetlands. Outputs also suggest a vast network of riparian wetlands in Cali. This study did not investigate socioeconomic data as it relates to wetlands, which is a topic suggested for future research. This project included research into links between land use change, wetland extent, and wetland potential, and provided partner organizations with an objective foundation from which they can identify at-risk wetlands and develop community initiatives for wetland management, conservation, and education.

Key Terms

Cali, Colombia, Wetlands, Wetland Intrinsic Potential Tool, WET 3.0, LULC, SAR, DEM

2. Introduction

2.1 Background Information

Wetlands include some of Earth's most productive ecosystems. Despite comprising only 5-8% of the Earth's land, they hold between 20 and 30% of Earth's soil carbon and provide habitat for 40% of both plants and animals (Nahlik et. al., 2016). While there is no universal definition of wetlands, they typically have a high water table and are more poorly drained compared to upland areas, and can be generally defined by the presence of water-adapted vegetation, permanent or periodic inundation, and the formation of hydric soils (Cowardin, 1979). Wetlands provide several essential ecosystem services, including flood regulation, water quality improvement, and serve as important sources of cultural identity (Flórez-Ayala, 2015). Wetlands are so influential in the regulation of flooding that, according to the Washington Department of Ecology, watersheds with degraded wetlands can have an 80% increase in peak flood discharge (Leschine et al., 1997).

Despite the numerous benefits that wetlands bring, they are one of the most vulnerable ecosystems on the planet. An estimated 64–71% of global wetlands have been lost since 1900, although this figure is based primarily on wetland loss within North America, Europe, and Asia (Davidson, 2014). Within this project's study area of Santiago de Cali, Colombia, colloquially known as Cali, the conversion of wetlands for the purpose of agricultural development, primarily sugarcane crop, has occurred since 1929 and resulted in a loss of 99% of wetland area within the municipality of Cali (Ocampo-Marulanda et al., 2021). Decisions made by agricultural firms and sugarcane shareholders in the 1960s-80s encouraged the desiccation of wetlands for agricultural production and displaced the Afro-Colombian communities who held a close relationship with the wetlands from their lands (DAGMA, 2018a, p. 9; Moreno-Quintero & Selfa, 2018).

Cali is Colombia's third largest city, with a population of nearly 3 million (Macrotrends, 2024). It is located in Valle del Cauca, in the southwest region of Colombia (Figure 1). The city of Cali is highly urbanized, with extensive agriculture mostly east of the city. Regional and local governments have made efforts to recognize and protect Cali's wetlands, which contain diverse aquatic life. In its Resolution No. 4133.0.21.1350 of December 2018, Cali's municipal environmental authority declared environmental management plans for 10 urban wetlands. This resolution followed a history of environmental policies from 1993 to 2018 that recognized Cali's wetlands as areas of special ecosystem importance and set expectations to manage them sustainably and preserve their biological diversity and productivity (DAGMA, 2018b). A 2010 national water study, Estudio Nacional del Agua (ENA), stated that wetlands in Colombia have been greatly affected by sediments and toxic substances (IDEAM, 2010). By mapping Cali's wetlands, today's environmental decision-makers seek to remedy the damage to wetlands caused by decades of pollution stimulated by urban and agricultural development.

Due to many wetlands being difficult to access or too expensive to inventory via ground survey, remote sensing and mapping of wetland extent is a vital way to identify wetlands. The methods to sense wetlands are varied, and include the use of optical, radar, and LiDAR imagery. Previous studies have relied on NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), aerial image interpretation, SAR (Synthetic Aperture Radar) data, and topographical indicators derived from DEMs (Digital Elevation Models) (Guo et al., 2017). Each of these methods presents certain challenges and benefits; for example, optical data can relay information about wetland characteristics in multiple spectral bands and identify unique spectral signatures of wetlands and surrounding land cover classes but is unable to detect conditions under canopy or cloud cover (Mahdavi et al., 2018). Whereas SAR data can penetrate cloud cover and canopy and be more sensitive to "biomass and flooded vegetated structures," but is more difficult to process (Hong et al., 2015).

Previous wetland studies in Cali have used ground surveying with some GIS analysis and visual inspection of aerial imagery. For this project, the team aimed to address past limitations in wetland mapping by using the Wetland Intrinsic Potential (WIP) tool and Wetland Extent Tool (WET) 3.0, which have yielded accurate results for wetland identification, classification, and extent in other study sites (Berberian et al., 2023; Halabisky et al., 2023; Valenti, et al., 2020). In addition to these tools, which integrate SAR and optical data to help mitigate frequent regional cloud cover, the team utilized a land cover classification method that in part combines multiple Landsat datasets to achieve gap-free imagery. Incorporating these datasets alongside topographic indicators presents a promising approach to accurately map and understand the extent of wetlands in Cali, Colombia.

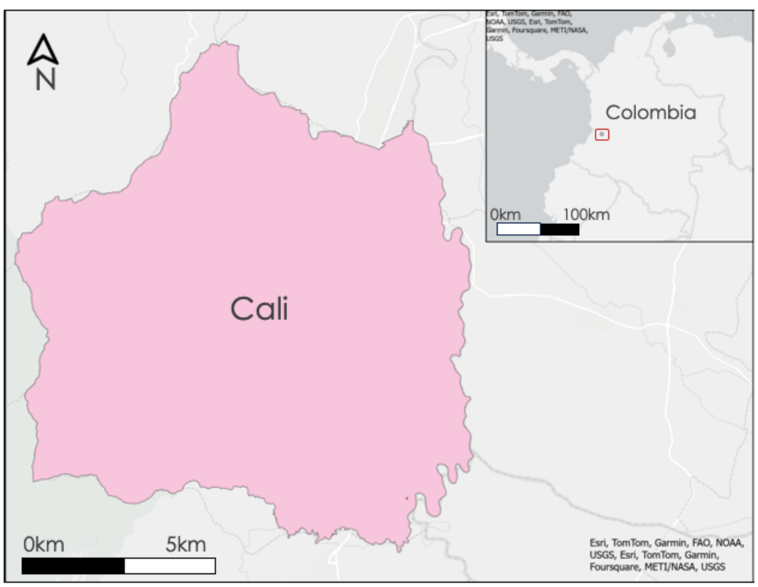


Figure 1. Study area map indicating the municipality of Santiago de Cali, Colombia, the region of interest selected to conduct wetland analysis. Inset: Location of study area within Colombia, South America.

2.2 Project Partners & Objectives

The team partnered with Fundación Dinamizadores Ambientales an environmental justice nonprofit local to Cali, and the Departamento Administrativo de Gestión del Medio Ambiente (DAGMA, The Administrative

Department of Environmental Information), a municipal government entity dedicated to environmental management. The partners' shared interests in ecological conservation, citizen participation, and community education led to a collaboration which they sought to strengthen through this project. As of now, DAGMA hosts wetland value groups in which local community members are involved in committees to co-manage the wetlands. DAGMA and Fundación Dinamizadores Ambientales plan to share this project's methods with Colombian universities and in community mapping workshops to replicate wetland analysis as needed.

Based on the priorities voiced by the partners, the team developed the following objectives. To start, team members mapped land use and land cover change in Cali from 2002–2023 using Google Earth Engine, and generated time series analyses to visualize wetland loss during this period. Concurrently, the team delineated current wetland extent using the WET 3.0 tool and the potential for wetland presence using the WIP tool. End products from this project will supplement the partners' on-the-ground knowledge of threats to wetlands and inform decision-making for local wetland management and conservation.

3. Methodology

3.1 Data Acquisition

3.1.1 Wetland Intrinsic Potential Tool

The team utilized the Wetland Intrinsic Potential (WIP) tool to perform data processing for wetland probability mapping within ArcGIS Pro. The WIP tool is a public ArcGIS toolbox developed by the University of Washington Remote Sensing and Geospatial Analysis Lab and watershed mapping company Seattle Terrain Works. Its primary purpose is the identification and mapping of "cryptic wetlands," which are defined as "small, ephemeral wetlands with dense canopy cover" (Halabisky et al., 2023). This tool incorporates several DEM-derived topographical indicators, as well as NDVI, NDWI, and in situ soil data (Table 1).

Team members used the Planet Basemap Viewer to collect high-resolution PlanetScope July 2022 Basemap tiles to serve as a basemap of the study area. To incorporate elevation data, the team acquired an InSAR DEM raster at 5m spatial resolution from the partners. The partners provided other input datasets for the WIP tool, including the 2014 Cali, Colombia soils dataset accessed through the Instituto Geographico Agustin Codazzi (IGAC), wetland extent data through the Infrastructura de Datos Espaciales: Santiago de Cali (IDESC), and local hydrology dataset from Portal Hidroclimatologico Cali.

Table 1
Datasets utilized in the WIP tool.

Dataset	Spatial Resolution	Source	Purpose
PlanetScope	3 m	Planet Labs Web Tool: Basemap Viewer	Basemap of study area and Normalized Difference Vegetation Index (NDVI)
InSAR DEM	5m	DAGMA	Elevation input
Sentinel-2 MSI	10 m	Google Earth Engine	Modified Difference Water Index (MNDWI)
Infraestructura de Datos Espaciales de Santiago de Cali (IDESC)	N/A	Central District Administration of Cali, Colombia	Soils dataset
IGAC Local Wetland Extent Dataset	N/A	El Instituto Geográfico Agustín Codazzi (IGAC)	Known wetlands input

Portal Hidroclimatologico Cali	N/A	Corporación Autónoma Regional del Valle del Cauca	Local hydrology dataset

3.1.2 Wetland Extent Tool 3.0

The Wetland Extent Tool (WET) 3.0 utilizes SAR and optical data for automated wetland extent mapping using Google Earth Engine (GEE)'s Python API (Berberian et al., 2023). The team worked with WET 3.0 to process and analyze multiple datasets to map wetland extent and classify open water, inundated vegetation, and areas with no water. The GEE data catalog provided access to Copernicus European Space Agency (ESA) Sentinel-1 and Sentinel-2 imagery (Table 2). The Sentinel-1 C-band Synthetic Aperture Radar (SAR) imagery is a C band cross-polarized with VV and VH bands utilized for inundation classification. Meanwhile, the Sentinel-2 Multispectral Instrument (MSI) Dynamic World Near Real Time (NRT) Land Use/Land Cover (LULC) is a global, 10m product used as a reference in selecting training polygons for classification. The team employed Suomi-NPP VIIRS VNG Flood 1.0 data to calculate floodwater fraction for assessment of the classification tool.

Table 2

Earth observation data utilized in the WET 3.0 tool.

Earth Observation	Spatial Resolution	Dates	Source	Purpose
Sentinel-1 C-SAR	10 m	2014–2023	European Space Agency (ESA)	Classifying inundation
Sentinel-2 MSI	10 m	2017–2023	European Space Agency (ESA)	Reference to select training polygons
Suomi-NPP VIIRS	375 m	2011–2023	NASA and National Oceanic and Atmospheric Administration (NOAA)	Calculating floodwater fraction for comparison to Sentinel-1-based flood maps

3.1.3 Land Use Land Cover Classification

This study used Google Earth Engine (GEE) to work through the land use land cover (LULC) classification methodology. Within GEE, team members processed United States Geological Survey (USGS) Landsat 5 TM, Landsat 8 OLI, and Landsat 9 OLI-2 imagery. The team utilized Landsat imagery (Table 3) for LULC classification, to calculate LULC change, and develop time series analyses. To validate the classification for consistency, team members performed a visual comparison of the generated LULC maps with high-resolution Google Earth Engine (GEE) basemap imagery, looking for inconsistencies and areas where the classification does not agree visually with the GEE imagery. The team also conducted a comparison of the wetland area in hectares generated by the LULC results and WIP tool results to determine the likeness and reliability of the wetland class.

Table 3

Datasets utilized for land use land cover classification

Earth Observation	Spatial Resolution	Dates	Source	Purpose
Landsat 5 TM	30 m	2002-2012	United States Geological Survey (USGS) and NASA	Imagery for LULC classification
Landsat 8 OLI	30 m	2013-2023	United States Geological Survey (USGS) and NASA	Imagery for LULC classification

Landsat 9 OLI-2	30 m	2021-2023	United States Geological Survey (USGS) and NASA	Imagery for LULC classification

3.2 Data Processing

3.2.1 Wetland Intrinsic Potential Tool Data Processing

In order to derive topographical and optical indicators of Wetland Intrinsic Potential, the team began by clipping the input DEM and PlanetScope basemap to each of the three watersheds within the city of Cali, as the Random Forest model needs to be run at the watershed level. Figure 2 shows the three main watersheds Cali possesses pertaining to three major rivers: Cali, Lili, and Pance. After those data were processed, we derived NDVI from PlanetScope and MNDWI from Sentinel-2 imagery, and derived the Topographical Wetness Index (TWI), Depth to Water Index (DTW), and the surface metrics of curvature, slope, deviation from mean elevation (DEV), and gradient from the input DEM (Maxwell et al., 2018; Kriegler et al., 1969; Xu, 2006; Beven & Kirkby, 1979). NDVI, MNDWI, and TWI are represented by Equation 1, Equation 2, and Equation 3. Surface metrics were calculated at 3 distinct scales of 50m, 150m, and 300m to ensure that the model could account for the variation in landscape across scales.

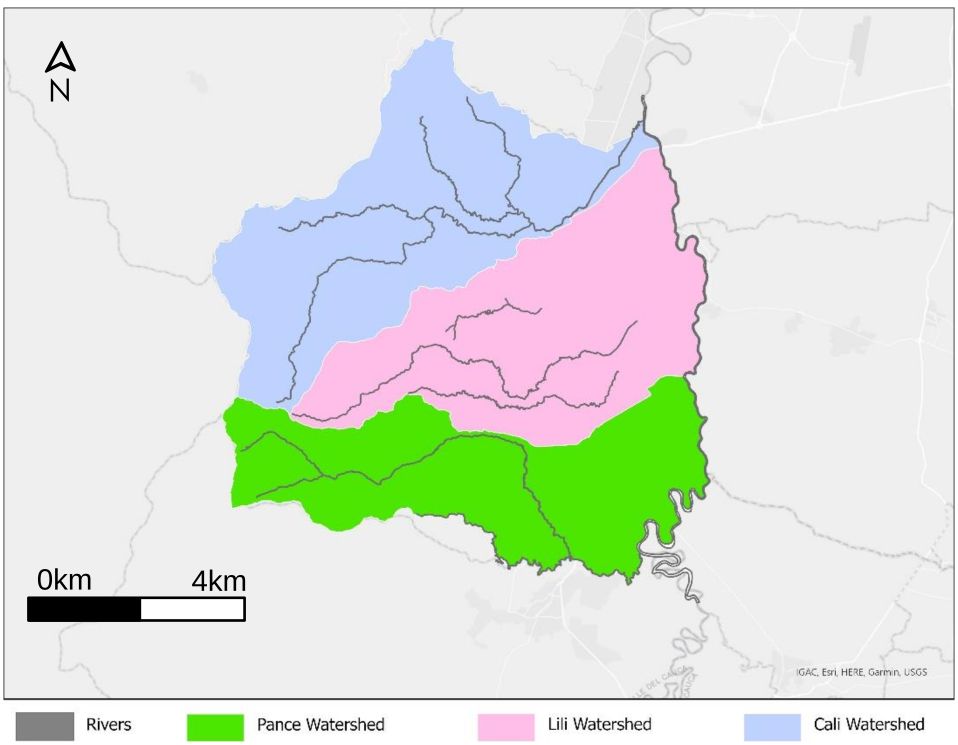


Figure 2. Map of watersheds within the study area.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Equation 1. Normalized Difference Vegetation Index.

$$MNDWI = \frac{Green - SWIR}{Green + SWIR}$$

Equation 2. Modified Normalized Difference Water Index.

$$\text{TWI} = \ln\left(\frac{\text{a}}{\tan\beta}\right)$$

Equation 3. Topographical Wetness Index.

The tool rasterized soil data the partners provided on relevant indicators, such as dampness, texture, and drainage, and was similarly clipped to the three separate watersheds within the area. To generate training data points, team members drew polygons on wetland and non-wetland regions based on partner-provided data, and randomly generated points within those polygons.

As the final step in the analysis, the team developed random forest models for each watershed using the input raster. The generated probability raster was then reviewed based on training data, and the model was re-run to reduce false outputs.

3.2.2 Wetland Extent Tool 3.0 Data Processing

To compute the number of pixels of open water, inundated vegetation, and no water using WET 3.0, the team first clipped the study area of Cali as the region of interest (ROI). Then, team members used the SUOMI NPP VIIRS product VNG Flood 1.0 to assign the variables of VV as inundated vegetation and VH as open water. The tool utilizes the VV polarization of Sentinel-1, meaning the radar signal was both sent and received vertically, and the VH polarization, meaning that the radar signal was sent vertically and received horizontally. From these two polarizations, the ratio image of VV/VH bands was calculated. The team chose to use Dynamic World's classification system to begin identifying the areas of open water, inundated vegetation, and no water, to create training polygons. Then, team members compared the unsupervised classification with Sentinel-2 MSI imagery to cross-check Dynamic World's classification system. Because of the study area's drier climate during the season chosen for analysis, some water bodies were inaccurately identified as either 'built-up area' or 'bare ground'. This prompted the team to use a separate file of Colombia's wetlands from ArcGIS Living Atlas as reference when manually classifying the data. Team members calculated the VV/VH ratio images and mean pixel values, then determined thresholds to create histograms. The team then used the computed histograms to plug into the final script of the WET 3.0 tool to generate map outputs.

3.2.3 Land Use Land Cover Classification Data Processing

To create annual near-cloud-free Landsat images of Cali, team members used the GEE-Best Available Pixel (BAP) interface, which enabled the generation of annual best-available-pixel image composites for the study area by tuning parameters and combining multiple Landsat sensors and images (Hermosilla et al., 2024). The temporal compositing period was acquired from a 165 day range from July 1 of each year of the study period on a band-by-band basis, meaning that each band was processed separately to create composite images of best pixels across each band. The team utilized the image composites to create a supervised classifier of land cover (Table A1).

Team members visually interpreted the composites and selected points manually by delineating areas corresponding with different land cover classes to create training points for the pixel-based supervised classifier. The team collected training points in GEE to classify the study areas into 5 classes: urban, agricultural, forest, wetlands, and water. Team members then cross compared the training points to the Sentinel-2 MSI dataset. The criteria and number of training points for each class are shown in Table A2. The classifier applied a Random Forest (RF) algorithm, which employs 50 machine learning decision trees and training data to classify pixels within the input satellite image data (Breiman, 2001). The RF algorithm trained the supervised classifier, and team members applied it to each annual composite image to create LULC maps for each year of the study period.

3.3 Data Analysis

3.3.1 Wetland Intrinsic Potential Tool Data Analysis

As part of the WIP Tool, the team generated several model statistics to analyze the accuracy of the model. Among these, the out-of-bag (OOB) error rate is a key performance metric. This error rate comes from the construction of the random forest, which comprises many individual decision trees. The out-of-bag data points, those not included in the training of a particular tree, are used to provide an estimate of model prediction error. Other metrics calculated include the mean accuracy decrease which measures how much model accuracy would decrease if the variable was removed.

3.3.2 Wetland Extent Tool 3.0 Data Analysis

At first when deriving data from the threshold script, WET 3.0 output values for open water, inundated vegetation, and no water proved to be ineffective to the study due to the drier months chosen for analysis. Some known wetlands had not been identified by the script as water bodies. In response, the team manually searched for a period with a significant amount of rainfall and with less cloud cover, which was limited to the year 2023 from the 1st of January through the 30th of March. Once the team corrected the variables in the script, the tool output the VV and VH ranges into a histogram. The histograms classified open water, inundated vegetation, and areas that contained no water. The tool itself generally outputs four histograms, but because of the small study site and cloud cover issues, it could only compute three histograms. In these histograms there are three ranges that are based on pixel density. Typically, the first histogram range ($0 <= VV < 0.1$) is dominated by the open water variable because of its lower pixel density which showed to be true in the scope of Cali. In the second histogram ($0.1 <= VV < 0.2$), the output was dominated by inundated vegetation, which showed the team how quickly the 'grasslands' i.e. agricultural areas become flooded during the rainy season. The final histogram output ($0.2 <= VV < 0.3$) displayed lower inundated vegetation and was mainly dominated by "no water." In short, "no water" remained the densest variable in terms of pixel density, which was reflected by its domination of the final output maps showing areas of no water and inundated vegetation.

3.3.3 Land Use Land Cover Classification Data Analysis

The team applied the supervised, trained classifier to generate a land cover map for each year of the study period to compare and analyze the changes in land use between different years. This allowed team members to calculate the area in hectares for each land cover class year to year, generate time series graphs displaying temporal changes, and analyze land use changes. To validate the classification for consistency, team members performed a visual comparison of the generated LULC maps with high-resolution Google Earth Engine basemap imagery, looking for inconsistencies and areas where the classification did not align. The team also compared the land use maps with wetland maps of Cali shared by partners, and wetland probability maps produced by the WIP tool. To assess the accuracy of the LULC classifier, the team generated a confusion matrix, user accuracy, and kappa coefficient comparing the RF classified imagery with the Sentinel 2 10m Land Use Land Cover map in ArcGIS Pro (Karra et al., 2021).

4. Results & Discussion

4.1 Analysis of Results

The team expected to see similar spatiotemporal correlation of wetlands in Cali, Colombia among the three tools utilized for this study: the WIP Tool, WET 3.0 Tool, and the Land Use Land Cover Classification. Instead, the team observed that the WIP Tool provided a much lower estimate of wetland area compared to the two other methods. The final output area from the WIP tool was 1613.3 hectares of wetland area throughout the whole of Cali, with 59% of wetland area being located within the rural areas of Cali. However, wetlands occupied a higher proportion of the urban area compared to the rural areas: a total of 5.5% vs 2.2% respectively, as shown in Figure 3. According to the final probability raster in Figure 4, areas with high wetland intrinsic potential were found primarily in riparian zones and within the agricultural zones of southeastern Cali, which were historically wetlands before being replaced by sugarcane fields. Areas with low potential were concentrated in the denser urban areas and the non-riparian mountainous regions.

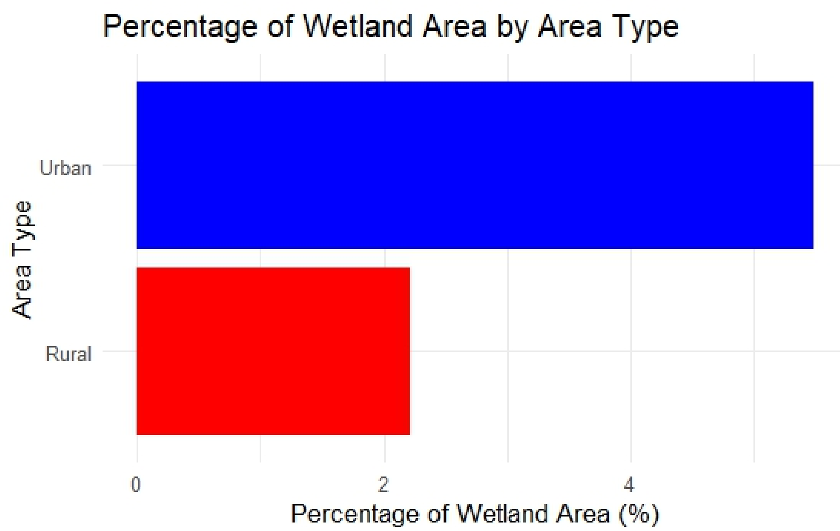


Figure 3. Graph showing the proportion of wetland that occupies the urban and rural areas.

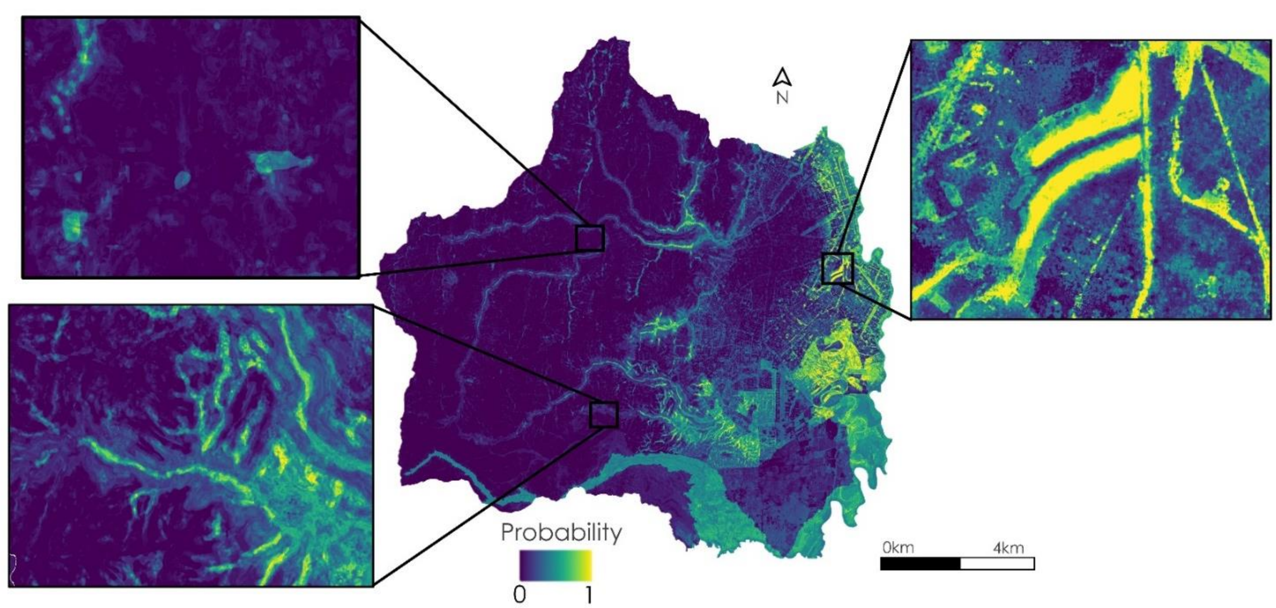
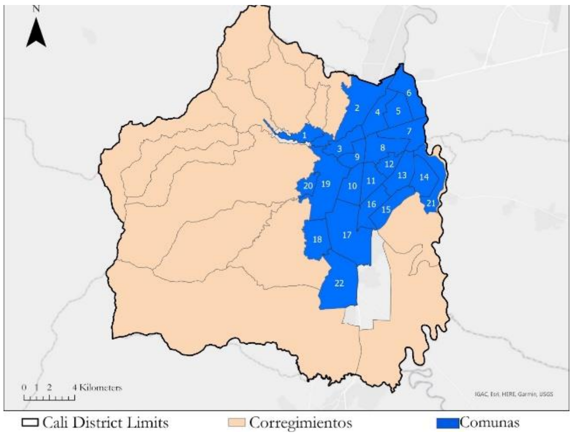


Figure 4. Probability map showing wetland intrinsic potential for all of Cali. Darker colors indicate low to 0 probability, while lighter colors indicate higher probability for wetlands. El Pondaje and Charco Azul wetlands are displayed in the right inset with values approaching 100% probability.

When observed at the comuna level, which are the urban districts within Cali, comuna 21 and 6 contained the highest proportion of wetland area out of the comuna's total area, with both being composed of more than

20% potential wetland. Most of the wetland areas within these comunas were located within the riparian zone, as both the comunas border the Cauca River, which defines the easternmost border of Cali (Figure 5). Comuna 13 and 14 also contained a relatively high proportion of wetland area but were composed of non-riparian wetlands; comuna 13 specifically was dominated by the wetlands of Charco Azul and El Pondaje, the largest urban wetlands within Cali. Figure 6 lists what percent of each comuna is composed of wetland.



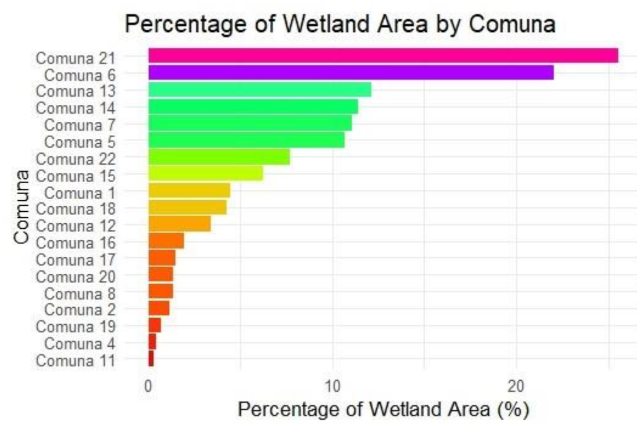


Figure 5 (left). Map of the urban districts (*comunas*) and rural districts (*corregimientos*) of the city. *Figure 6 (right)*. Graph depicting what percentage of each comuna is composed of wetland.

The WIP Tool consistently accurately classified the training points input, as evidenced by the low OOB error rate for the Pance and Lili watersheds (<5%). However, when observing wetlands not within the training set, the WIP Tool failed to classify certain wetlands, for example, riparian zones along the southernmost watershed of Cali were often misclassified as upland. Furthermore, riparian wetlands were often erroneously expanded into surrounding upland areas, such as residential zones. This is likely because those areas have great potential to become wetlands but have become built areas.

The variables that contributed most to the model's accuracy were the DTW, NDVI, MNDWI and elevation, as shown in Figure C1. These variables ranked high consistently across the watersheds. However, NDVI had a particularly high impact on model accuracy within the Lili Watershed, which is the most densely urbanized watershed. This can be attributed to the contrast in NDVI values, where vegetated wetlands exhibit markedly higher NDVI compared to the surrounding urban landscape, thus making these wetlands more distinguishable. MNDWI has a similar effect, as open bodies of water in the urban and rural environments are often a direct indicator of wetland presence. Elevation and DTW all describe how water accumulates and moves through the landscape, which are very relevant to wetland formation. The surface metric variables, surface gradient(grad), slope(prof), curvature(plan), and deviation from mean elevation, were less relevant in the model, indicating that these variables held similar values throughout the study area and did not contribute as heavily to model accuracy (Figure C1).

The team created annual LULC maps of the study region, Cali. Team members distinguished between five separate land use land cover classes: Water, Wetland, Forest, Agriculture, and Urban. In the most recently assessed year, 2023, the classification found that 16.05% of Cali was covered by wetlands, 21.01% of the area was identified as water, 37.18% was forest, 15.05% was agriculture, and 10.71% was encompassed by the urban zone. Figure 7 shows the generated LULC map of 2023, specifically calling out the Charco Azul and El Pondaje urban wetlands. Figure 8 displays the fluctuation of Wetland, Agriculture, and Urban areas in hectares throughout the study period.

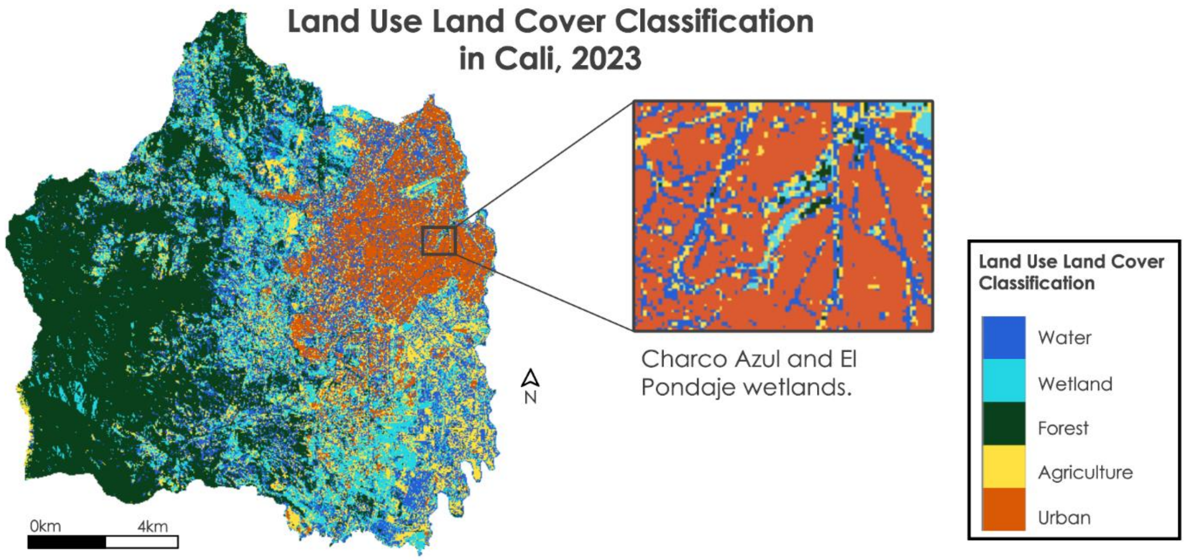


Figure 7. LULC classification map of Cali, Colombia in 2023 using Landsat 5 TM, Landsat 8 OLI, and Landsat 9 OLI-2 imagery. Inset: The Charco Azul and El Pondaje urban wetlands.

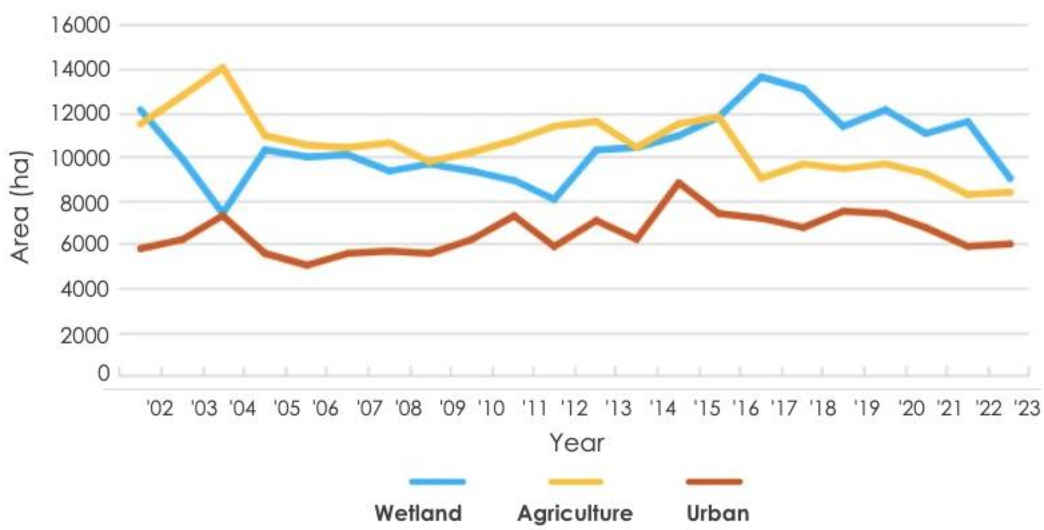


Figure 8. Time series graph of LULC type area by year over the full study period. It displays the fluctuation of Wetland, Agriculture, and Urban areas in hectares between 2002-2023.

The team computed a confusion matrix in ArcGIS Pro between the generated LULC classification and the Karra et. al., 2021 Sentinel-2 10m Land Use Land Cover, as a truthing dataset, to evaluate the accuracy of the RF classifier. The outputs suggested that urban and forest land cover classes were predicted most accurately, at 95.4% and 88.3% accuracy, respectively (Table C2). Wetlands were predicted with only 3.4% accuracy, and the comparatively low accuracy of the other classes resulted in a Kappa coefficient of 0.20, indicating only slight agreement between the RF classification and the Sentinel-2 classification. It is important to note that the Sentinel-2 LULC map defined wetlands differently from the RF classifier. Due to the difference in the two classifications of wetlands, the team's generated RF LULC wetland class scored poorly in the agreement comparison. In this case, both the test and reference data have classification errors.

In several of the maps generated, the LULC classification algorithm classified certain non-urban forest areas as urban land classes. This result suggests misclassifications due to clouds moving across the study area during a few years of the study period, such as 2017. Because the study region contains persistent cloud cover throughout the year, the team's use of the GEE-BAP interface to select cloud-free Landsat imagery was not able to generate completely-cloud-free images. This is also in part because the Landsat revisit is low relative to data collected daily. Pixels containing consistent cloud cover had their values infilled by the interface, which enabled the generation of gap-free image composites by applying linear interpolation to the temporal spectral values (Hermosilla et al., 2024). These infilled pixels may have had different characteristics which could have been misidentified by the classifier as other land cover types. Therefore, the LULC classification algorithm sporadically misclassified bubbles of clouds that appear as urban or water classes that seemed to float in and out of the maps over several years, particularly in the forest areas. In general, the wetland class was overidentified by the classification, averaging a surprising 18.70% of the study area across all years of the study period. To put this figure into perspective, a lower average of 11.66% of Cali was identified as urban cover. This overidentification may relate to the spectral characteristics of wetlands, which are similar to both vegetated areas and areas of open water. The overclassification also potentially identifies wetlands along hydrographic features in non-urban areas such as bodies of water, rivers, and streams. Consequently, wetlands were often misclassified as both forest and water classes, inflating the wetland class area.

The team used the Wetland Extent Tool to classify possible temporary wetlands and generate three histograms that use pixel density to illustrate the difference between the temporary wetlands (inundated vegetation), permanent wetlands (open water), and other factors (no water). Since clouds cover much of the study area during Cali's rainy season beginning in March and ending around November, affecting the ability of WET 3.0 to accurately classify imagery, the team focused on the period immediately before this season, from January until the end of March of 2023. In Figure 9, we can see that the pixel density ranges from 0 to 0.1 are dominated by open water, signifying that their lowest variable is the permanent wetlands within the rainy season in Cali.

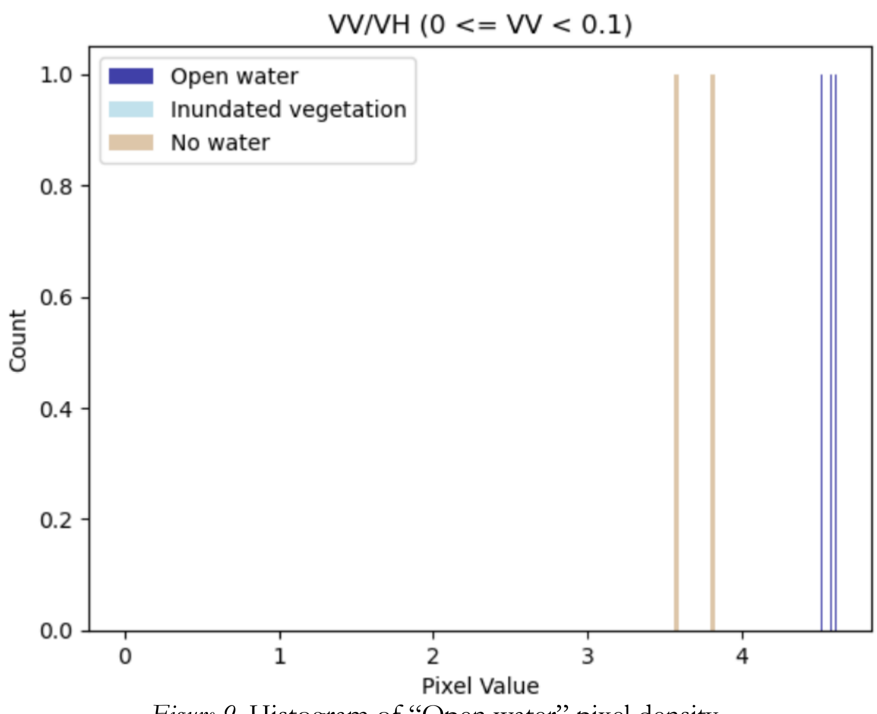


Figure 9. Histogram of "Open water" pixel density.

In the second histogram, Figure 10, there were more values that corresponded to the pixel density range 0.1-0.2 and a broader x-axis in contrast to the other two histograms, which signifies that inundated vegetation was most abundant in this study period compared with the other wetland types. Because some of the vegetation pixels represent areas with agricultural uses built on past wetlands, this vegetation will continue to hold rainfall, creating temporary wetlands.

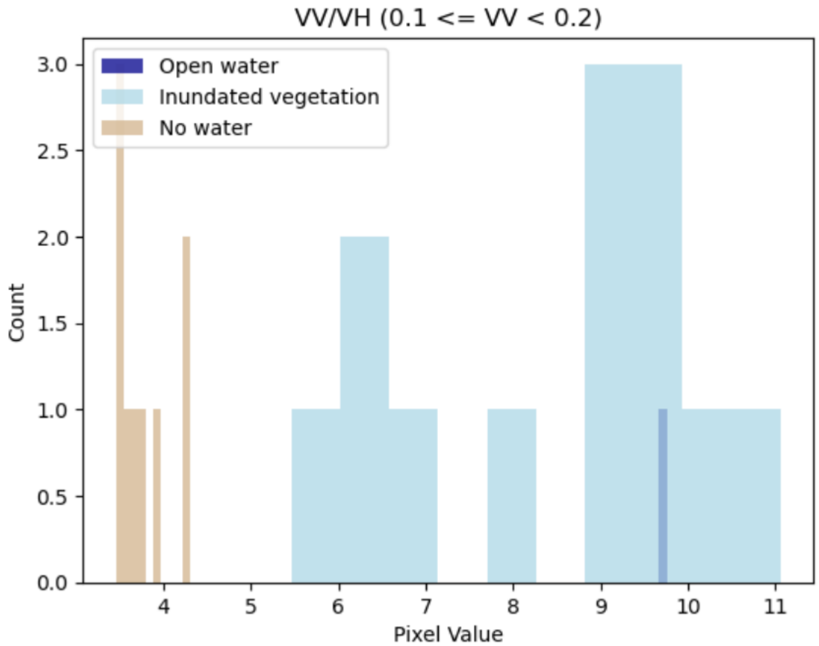


Figure 10. Histogram of "Inundated vegetation" pixel density.

For the last histogram, Figure 11, the higher pixel count with pixel density range 0.2-0.3 will be classified as no water which means the higher pixel count generated by the Wetland Extent Tool script will classify the "denser" pixels as no water. This would account for grasslands, urbanization, and bare land.

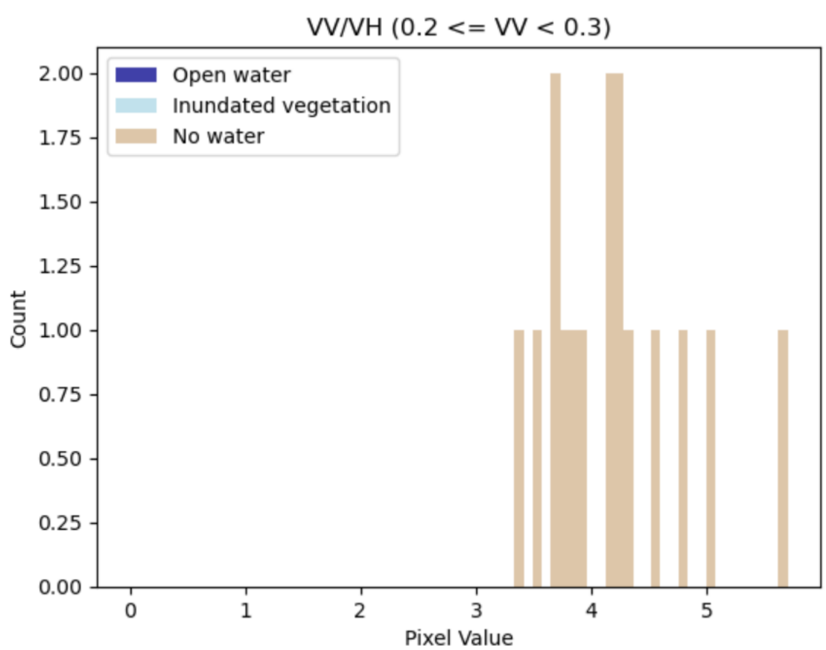


Figure 11. Histogram of "No water" pixel density.

Once the team adjusted the code to produce an output for the small area of Cali, it created a map that analyzed the pixel density ranges of the composed histograms. The period used for the map output was January 2023, which was chosen because it had the least amount of clouds compared to the rainfall months (March through November). In Figure 12, the tan color is where the tool presumes the drier parts of Cali. Cross referenced with Figure 5, the tan area on the far right of the map is where Cali's urbanized zone resides, while the far left is the mountainous area. The light blue is where the tool suggests there is a probability of temporary wetlands. The darker blue represents open water, some of which may be permanent wetlands, scattered across the study area but primarily occurring in the mountain area. The low amount of permanent wetlands could be attributed to the drier season taking place in January. Figure B1 depicts the map outputs the tool created and neatly separates them based on dates and land cover type. Since the tool overestimated the vegetation because of the shaded region within the mountain area of Cali there is inaccuracy in the inundated vegetation and no water land classification. With the future addition of an accuracy assessment within the WET 3.0 script, it will detect inaccuracies resulting from the overestimation. Through the assessed values the script created a statistical assessment with various ranges that shows the various ranges in Table C3.

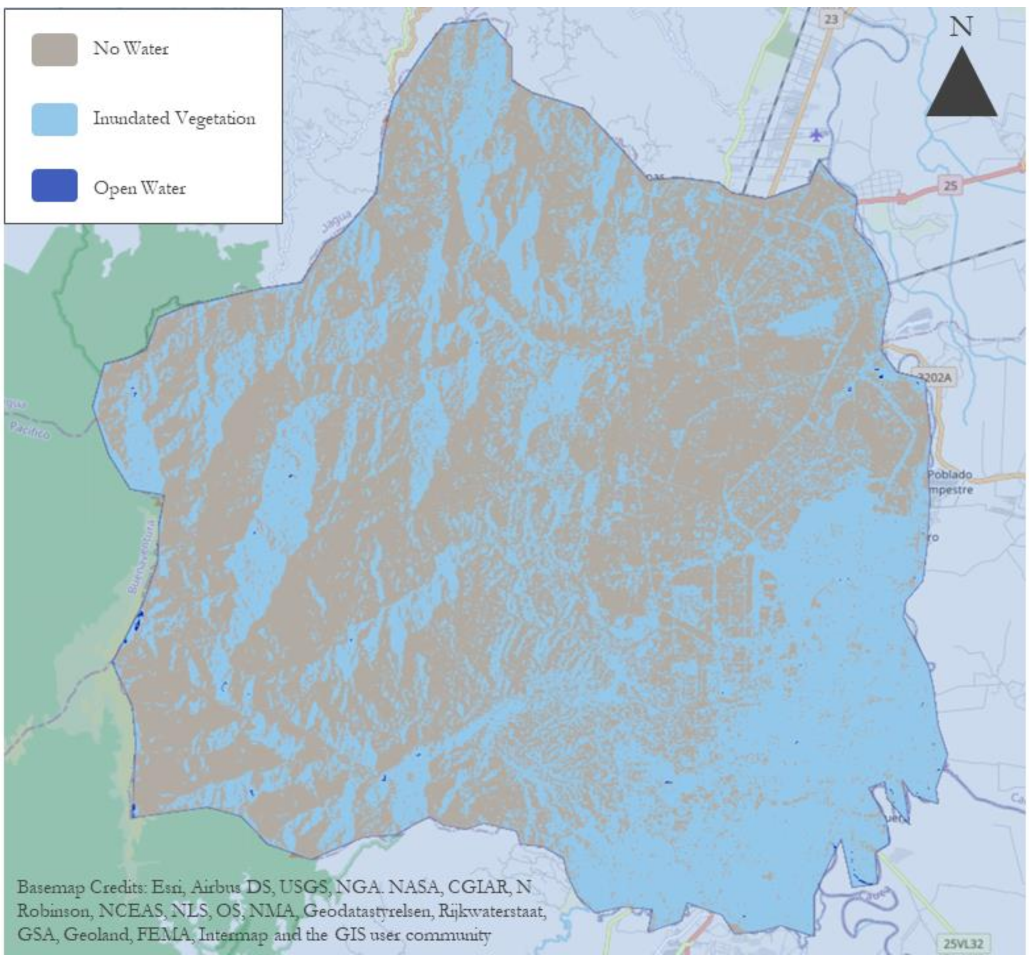


Figure 12. Map of Cali displaying predicted occurrences of open water, inundated vegetation, and no water areas as of January 23, 2023.

4.2 Feasibility for Partner Use

The Wetland Intrinsic Potential tool was demonstrated in this study for helping partners to utilize the tool in the future. Due to its nature of accepting a variety of input data for a given study area, the WIP tool is flexible to be run with data at several spatial scales that the partners have on hand, including drone imagery and LiDAR. However, the tool was originally designed with large watersheds in mind, so it is optimized for study areas larger than the municipality of Cali and would perhaps be useful for regional wetland studies. On a similar note, the tool struggles with detecting wetlands in urban areas that may have distinct characteristics due to their artificial or managed nature as compared to wetlands in rural areas. Additionally, NDVI had an inordinate impact on the model, signaling that forested areas may be misclassified as wetlands. One might exclude using the tool in highly urbanized areas. However, the tool also over classified wetlands in non-urban areas, especially in areas with topographic relief. Therefore, it would not be feasible to utilize this tool for applications where it is necessary to clearly delineate wetlands in urban areas.

The Wetland Extent Tool has great potential for use in wetland studies, however, it may not be as feasible for partner use because the interface is not user-friendly for those with limited coding experience. The tool yielded two major limitations, the first being that it did not accommodate dates before 2016 for analysis using Dynamic World. Therefore, it would not be feasible to use this tool to map wetland extent for dates preceding that range. Second, the team found that the WET tool struggled to identify wetlands in the study area because of Cali's persistent cloudy conditions, which resulted in underestimation of both permanent and temporary wetlands. Due to this cloud cover, the tool could not run in Cali's wet season and the code had to be adjusted. The map output shows a higher possibility of temporary wetlands; however, it does not account for all existing wetlands. This is due to the misclassification error of the mountain region in the northwest area of Cali overclassified as inundated vegetation.

The methods used for land use and land cover classification in Google Earth Engine are overall feasible for partners to apply, but with a few caveats. First, team members visually extracted the training points to train the land cover land use classification, leading to potential inaccuracies due to human error and bias. For best accuracy, this workflow needs at least a week dedicated to assigning training points and re-training after the first results outputs, as well as cross-checking for accuracy with existing land cover maps. Second, Cali is an exceptionally cloudy area, which results in an inability to procure completely cloud-free images. The team found that land cover misclassifications take place in areas where clouds cover the images, which may result in this method being less viable for organizations that want to analyze conditions in Cali. Third, the BAP interface utilizes gap-infill data to create Landsat cloud-free composite images using linear interpolation. While infilling data gaps helped the team create gap-free image composites, it can lead to inaccuracies in the infilled pixel values, particularly in regions with abrupt land use transitions. There must be sufficient cloud free data to make the use of the tool viable for producing realistic composites. If there is insufficient cloud free data, then the resulting temporal composites will be sub-optimal from a usability standpoint. Another approach to cloud mitigation is to extend the compositing period. Results indicate it is feasible to generate LULC maps of the region that identify wetland classes, but the limitations advise stronger input imagery, and more time dedicated to re-training the model for higher accuracy.

In summary, the team found that all three methods have potential for use in partner assessments of wetlands and land reclamation but recommends that future studies incorporate adjustments to the methodologies and datasets used to improve these tools' reliability and the accuracy of the results generated. There are also other potential wetland classification methods that could be tried as well, such as unsupervised classification of multi-variate data stacks over a broader area than Cali that could include other data than what was tried in this project.

4.3 Future Recommendations

Currently, a second term of this project is slated for Summer 2024 to study urban heat islands in relation to land use and wetlands, and to incorporate demographic data. The project partners have hypothesized that wetlands may face more external pressures such as pollution in areas with socioeconomically disadvantaged communities. Current team members recommend that the next term's team solicit specific, highly relevant socioeconomic indicators from the partners which are relevant to urban heat islands and wetland area.

The team suggests that the partners' continuing wetland research expand analyses to incorporate a larger study region, based on the finding that the tools used would be better suited for studying more extensive areas. More specifically, the LULC classifier has potential to generate better results for a larger study area to accommodate imagery resolution, and the WIP tool was originally designed for a wide swath of natural area. Wetlands as shown on the LULC map are occurring in areas that are upland in foothills between the urban areas on the flats and the forests in the west. This kind of apparent classification error can be addressed by using topographic data to constrain where wetlands can possibly occur.
A continuation of this project would also benefit from enhancing the land classification to incorporate greater detail, both in terms of including a greater variety of classes and subclasses as well as including additional satellite data to create stronger classifications. To validate the Random Forest algorithm-derived classifications of the LULC and WIP methods, future studies can incorporate in-situ land classification data of the region. Implementing the use of unsupervised classification may improve the LULC classifier, given that the selected classification scheme is very general. Additional work is needed to quantitatively validate the land cover and flood maps. Furthermore, further analyses could examine historical wetland and land use maps to evaluate longer-term trends of wetlands before and after urbanization and increased agricultural land uses. To increase the effectiveness of the WET tool, a larger study area, greater cloud masking abilities, and finer resolution imagery would be necessary to properly classify permanent wetlands and distinguish vegetation from urbanization pixels. Utilizing supervised classification would enable the tool to create its own accuracy assessment which would solidify the map output results.

5. Conclusions

The city of Cali, Colombia is a dynamic region experiencing urban and agricultural expansion, posing a risk to natural ecosystems such as wetlands. This study used Earth observations and remote sensing techniques to work through three workflows to generate wetland probability and land use land cover classification of the study area. The team created wetland probability rasters using the WIP tool to assess the potential for wetlands, identifying 1613 hectares of potential wetlands in the region. This number is over five times partner estimations. False positives were frequent in urban areas with high NDVI. Furthermore, the probability raster signaled that much of Cali is a potential wetland, particularly in the southeastern region. The team also generated LULC classification maps to evaluate changes in land areas throughout the study period, finding that the classification method used greatly overestimated the wetland class at an average of 10,521 hectares over the entire study period. The results of this study saw a general overestimation of wetland classes and occasional misclassification by the LULC classifier due to the cloudiness of the Landsat imagery and classification methodology, suggesting that the use of the GEE-BAP interface is unsuitable for creating cloud-free image composites of a cloudy study area for land classification. Both the WIP and LULC methods for identification of wetlands suggest an extensive network of riparian wetlands in Cali not previously included in shared partner inventories. The team performed a statistical comparison of WIP results to LULC results which showed a difference of 8,908 hectares between the average LULC wetland class area and the WIP tool's identification of potential wetland area, as outlined prior. The misclassification and overclassification of wetlands by the LULC classifier demonstrate the potential of the WIP tool as an indicator of wetlands over LULC classification in this study. The WET 3.0 output maps indicated that in January, there are lower amounts of permanently flooded wetlands but higher likelihood of temporarily flooded wetlands. Based on an analysis of the wetland extent histograms, which showed a high count of pixels classified as temporary wetlands during Cali's heavy rainfall season, the team found that temporary wetlands provide crucial capacity to manage floods in Cali, indicating a pressing urgency to protect these areas from conversion and other harmful interference.

Future research should expand analyses to incorporate a larger study region. The team found that the tools used would be better suited for studying broader areas than an area the size of Cali. More specifically, the LULC classifier showed potential to generate better wetland classification results for a larger study area to accommodate needs for more imagery training areas. Also, the WIP tool was originally designed for a wide swath of natural area, as opposed to a smaller more urbanized area.

The project partners received a map package of the WIP, WET, and LULC geoTIFF results, results from statistical comparisons, time series, and written materials (in both scientific and creative science communication formats) upon completion of this project. In summary, this study supplemented research into links between land use change, wetland extent, and wetland potential, and provided local environmental organizations in Cali with an objective foundation from which they can identify at-risk wetlands and develop community initiatives for wetland management, conservation, and education in both urban and rural areas.

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7. Glossary

API – Application Programming Interface

BAP – Best Available Pixel, an interface utilized in Google Earth Engine to create near-cloud-free composite images from Landsat data

Confusion matrix – A matrix table used to assess the performance of a machine-learning classification model by comparing predicted class labels with actual class labels

DEM – Digital Elevation Model

Earth Observations – Satellites and sensors that collect information about the Earth's physical, chemical, and biological systems over space and time

GEE – Google Earth Engine

Kappa coefficient – A statistic measuring how closely a classification produced by a machine learning classifier matches the ground truth data provided

LiDAR – Light Detection and Ranging, a remote sensing method that uses light to measure ranges to the Earth

Linear interpolation – A method using linear polynomials to predict data points, e.g. values of cells in a raster, using known values. Used to infill data gaps in the GEE-BAP interface

LULC – Land use land cover descriptor used in classifying surface cover types with remotely sensed data

MNDWI – Modified Normalized Difference Water Index, visualizes the spatial distribution and extent of water bodies

NDVI – Normalized Difference Vegetation Index, calculated from red and near-infrared bands to quantify vegetation density

VV / VH – This regards a simple ratio of two SAR polarizations. VV is a vertical send and receive polarization used to identify water, while VH is the vertical send and horizontal received polarization used to identify inundated vegetation

WET 3.0 – Wetland Extent Tool 3.0, an open-source tool available within Google Earth Engine to classify wetlands and map wetland extent

WIP – Wetland Intrinsic Potential tool, used with a variety of local datasets as inputs to determine the probability that an identified area is a wetland

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9. Appendices

Appendix A: Data processing details.

Table A1

Parameters used for the Best Available Pixel tool.

Choose AOI	Selected .tif of study area which we had uploaded as an asset.
Start and End Years	2002, 2023
Checkbox: Download images	Checked
Drive folder	bapOutputs
Acquisition day of year	07-01
Day range	165
Max cloud cover in scene	60%
Landsat-7 ETM+ SLC-off penalty	1
Min and max opacity	0, 0.3
Distance to clouds and cloud shadows (m)	1500
Checkbox: Advanced parameters	Checked
Checkbox: Apply de-spiking algorithm	Checked
Spikes tolerance	0.65
N bands to check spikes condition	3
Checkbox: Infill data gaps	Checked
Spectral index	None

Table A2

Land use land cover classes and training points.

Class	Value	Number of Training Points
Water	0	309
Wetland	1	120
Forest	2	50
Agricultural	3	201
Urban	4	50

Appendix B: Data analysis details.

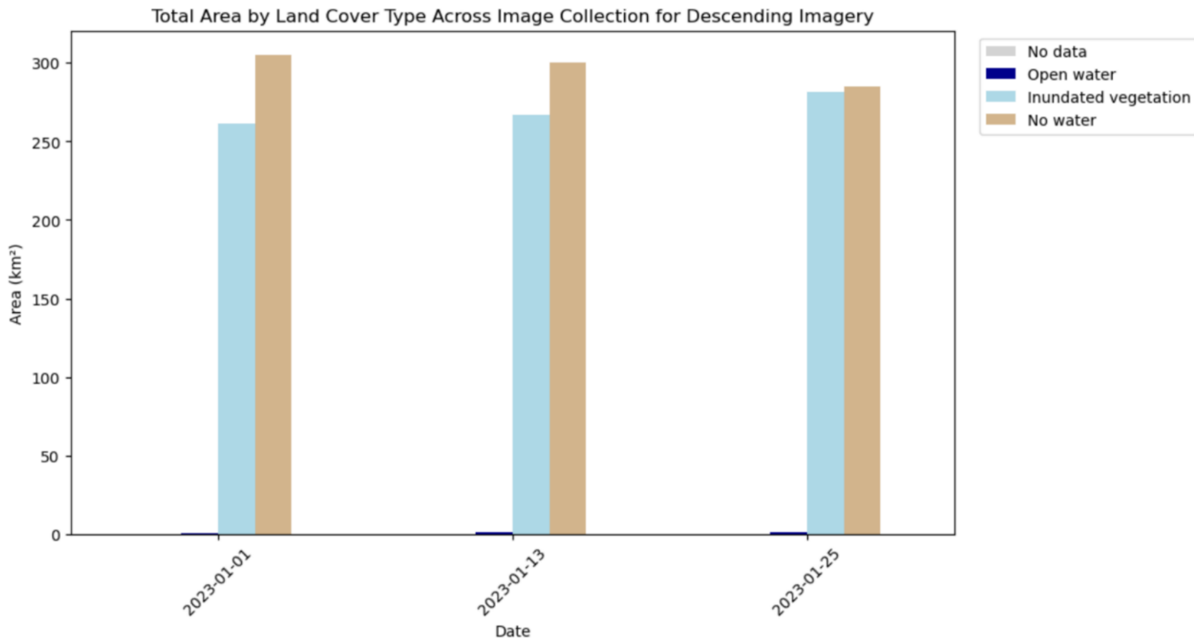

Figure B1. Shows the 'Land Cover Types' image collection and the ratios of the variables. *Since the time was shortened to January 2023 it does not account for Cali's rainy season.

Appendix C: Statistical & accuracy assessments.

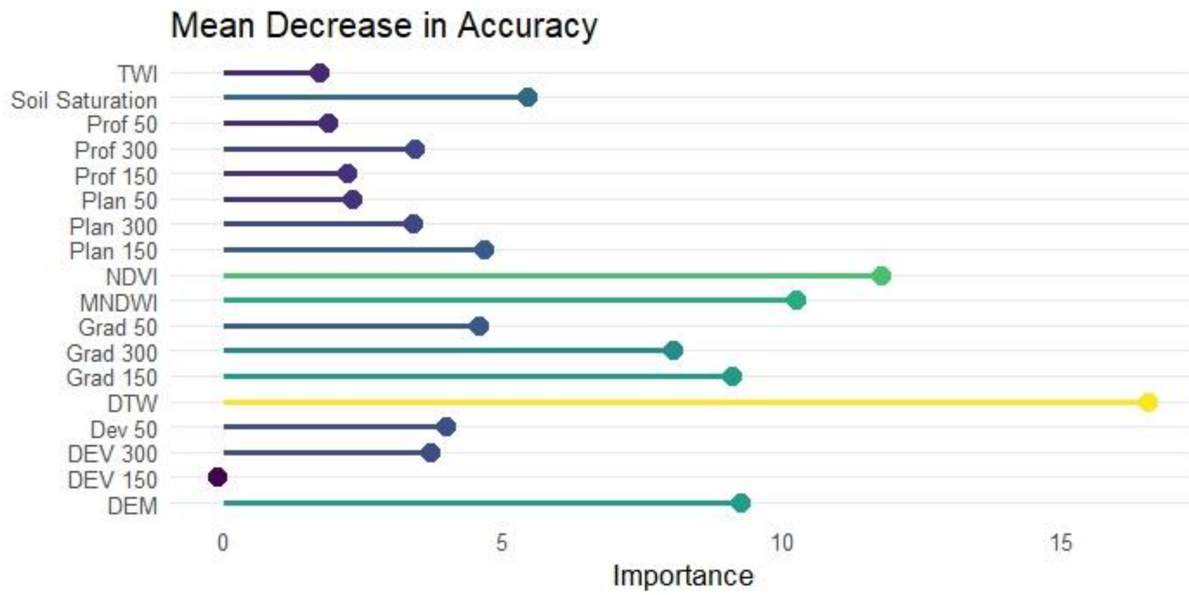

Figure C1. Graph showing by what percentage the random forest model's accuracy would decrease if each variable was removed.

Table C2

Confusion matrix showing results of LULC accuracy assessment run in ArcGIS Pro. The accuracy was highest for Forest and Urban classes, but the relatively low accuracy of the other classes resulted in a kappa coefficient of around 20%.

Class	**Water**	**Wetland**	**Forest**	**Agriculture**	**Urban**	**Total**	**U_Accuracy**	**Kappa**
Water	7	2	53	45	62	169	0.04142	0
Wetland	1	4	61	22	30	118	0.033898	0
Forest	1	0	68	4	4	77	0.883117	0
Agriculture	1	4	21	24	38	88	0.272727	0
Urban	0	0	2	1	62	65	0.953846	0
Total	10	10	205	96	196	517	0	0
P_Accuracy	0.7	0.4	0.331707	0.25	0.316327	0	0.319149	0
Kappa	0	0	0	0	0	0	0	0.19988

Table C3

Statistics assessment integrated within the WET 3.0 script. The table shows the various ranges analyzed based on the data collected from the satellite imagery collection. In short, the assessment analyzed the amount of pixel density and converted it into descriptive statistics.

	Open Water	Inundated Vegetation	No Water
Count	3.0	3.0	3.0
Mean	0.841146	270.147136	296.810234
Std	0.077421	10.463984	10.528388
Min	0.7537708	261.730562	285.034379
25%	0.811224	264.289130	292.558229
50%	0.868740	266.847697	300.698162
75%	0.884865	274.355422	302.698162
Max	0.900989	281.863147	305.314245