Multitemporal monitoring of Impervious Surface Areas (ISA) changes in an Arctic setting, using ML, Remote Sensing data and GEE

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Abstract

Urban expansion in Arctic environments presents unique challenges and opportunities for sustainable development, environmental management, and adaptation to the impacts of climate change. The special characteristics of these regions, including extreme climatic conditions and limited infrastructure, require customized approaches for monitoring and planning urban growth. The aim of the present study is the multi-temporal mapping of urban changes, through Impervious Surface Areas (ISA), in an Arctic setting characterized by high structural density, over the past decade. This endeavor is implemented by the application of Machine Learning classification methods in conjunction with Sentinel satellite imagery, while the execution of this methodology is carried out in Google Earth Engine (GEE) cloud platform. The results of this study map with high accuracy ISA changes in Tromso area from 1993 to 2023. These findings hold the promise of enhancing our comprehension of the dynamics behind urban expansion, the primary factors associated with urban sprawl and their interaction with the challenges posed by climate change in Arctic environments.

Keywords: *EO-PERSIST, ISA, Google Earth Engine, Remote Sensing, Arctic*

1. INTRODUCTION

Impervious Surface Areas (ISA) refer to artificial land surface elements that prevent water infiltration into soil, including structures like buildings, paved roads, driveways, sidewalks, parking lots, and rooftops (Weng, 2007; Popa et al., 2023). The ISA holds a primary source of valuable insights into environmental, ecological, and hydrological facets within the domain of urban planning. Over the past five decades, there has been a rapid global expansion of ISA, amounting to approximately 0.62 million square kilometers from 1972 to 2019 (Huang et al., 2021). This trend is closely related to the United Nations' report (2018) on urbanization trends revealing that 55% of the world's population, surpassing half, resided in urban areas in 2017 and this proportion is expected to increase to 68% by 2050. Simultaneously, human activities, including energy exploitation and urban development, have significantly contributed to ISA proliferation in the Arctic region (Lifshits et al., 2021; Nguyen et al., 2021; Usman et al., 2022). These tendencies reveal the direct correlation of ISAs with the anthropogenic influence and constitute the focal point for further studies that comprehensively explore the interplay of these two factors.

Given the importance of ISA, there is a need for systematic monitoring and mapping of those areas. A considerable body of ISA mapping research has delved into the use of Earth Observation (EO). EO offers significant advantages in monitoring ISA as it offers time and cost-efficient systematic images where they can be used to map globally the ISA expansion. Landsat archive has been a cornerstone EO mission in ISA mapping, given its status as the most extensive and consistent medium resolution EO data source (Chaudhuri et al., 2017; Schug et al., 2018; Cao et al., 2020; Xu et al., 2022). Apart

Landsat, various studies have leveraged Sentinel imagery, encompassing both the optical instrument Sentinel-2 (Feng and Fan, 2021; Kumar et al., 2020) and Synthetic Aperture Radar (SAR) images from Sentinel-1 (Shrestha et al., 2021; Wu et al., 2023). Additionally, several studies have extracted ISA from diverse SAR images, including ALOS/PALSAR images (Attarchi, 2020), TerraSAR-X images (Zhang et al., 2016), and ENVISAT Advanced Synthetic Aperture Radar (Zhang et al., 2014). A significant portion of the research has been dedicated to identifying and mapping ISAs through high-resolution images, such as IKONOS (Lu and Weng, 2008; Olufayo Adetoro, 2022), WorldView (Olufayo Adetoro, 2022), SPOT-5 (Xu, 2013), and GF-2 (Wang et al., 2022). Notably, only a limited number of studies have explored the application of hyperspectral imagery in ISA extraction, employing data like Hyperion (Tang and Xu, 2017; Liu and Gu, 2017), GF-5 (Liu et al., 2020), or EnMAP imagery (Feng and Wang, 2018). With the abundance of the existing EO datasets, challenges have risen in processing. Those challenges are being addressed using cloud-based platforms like Google Earth Engine (GEE) offering a cost-effective and computationally efficient means to process large-scale EO data. Although the use of such cloud platforms is rapidly increasing, their use in ISA mapping is still rather limited, as evidenced from the amount of published literature.

Various image processing techniques have been employed in ISA mapping utilizing EO datasets, broadly categorized into index methods, classification methods, and spectral mixture analysis (SMA) (Feng et al., 2019; Pandey et al., 2019). Index methods, which involve creating an index based on spectral distinctions between impervious surfaces and other land features, have garnered attention for their computational straightforwardness. Zha et al. (2003) devised the Normalized Difference Built-up Index (NDBI) through the utilization of near-infrared and shortwave-infrared bands. In a similar vein, Xu (2008) introduced the Index-based Built-up Index (IBI), amalgamating NDBI, Soil Adjusted Vegetation Index (SAVI), and the modified Normalized Difference Water Index (mNDWI). Xu (2010) also formulated the Normalized Difference Impervious Surface Index (NDISI) based on mNDWI, near-infrared, and shortwave-infrared bands. The Combinational Built-up Index (CBI) was innovated by integrating NDWI, SAVI, and PC1, the first principal component (Sun et al., 2016), while the Normalized Difference Impervious Index (NDII) was established by combining visible and thermal bands (Wang et al., 2015). Fang et al. (2019) introduced the Ratio-based Impervious Surface Index (RISI), a novel index for extracting Impervious Surface Areas (ISAs) from Landsat imagery, incorporating the coastal band (B1) and the Normalized Difference Vegetation Index (NDVI). Tian et al. (2018) developed the Perpendicular Impervious Surface Index (PISI) using the Blue and near-infrared bands of Landsat 8 data for mapping ISAs.

Regarding classification methods, pixel division into impervious and non-impervious categories based on spectral signatures is a common approach (Fang et al., 2019). Support Vector Machine (SVM) stands out as one of the frequently employed methods for ISA extraction, with studies affirming its effectiveness (Feng et al., 2021). Shi et al. (2017) utilized SVM to map ISAs from 1987 to 2016 using Landsat time series, yielding accurate results. Other studies also demonstrated the efficiency of SVM classifier in ISA mapping (Cheng et al., 2011; Elatawneh et al., 2012; Petropoulos et al., 2012a; Petropoulos et al., 2012b; Okujeni et al., 2013; Whyte et al., 2018; Cass et al., 2019; Mugiraneza et al., 2020; Fragou et al., 2020;). Additionally, Random Forest (RF) is recognized as a suitable method (Shrestha, 2021; Liu et al., 2020), and Kumar et al. (2020) compared SVM, RF, and Neural Network (NN) classification techniques, identifying NNs as the most accurate method for extracting built-up ISAs using high-resolution satellite data. Huang et al. (2018) demonstrated the effective use of deep learning methods for ISA extraction, leveraging high-resolution WorldView and Pleiades images. Notably, various studies have applied deep learning methods to map ISAs using moderate-resolution images such as Landsat (Dawson et al., 2019; Parekh et al., 2021; Xu et al., 2022). The Object-Based

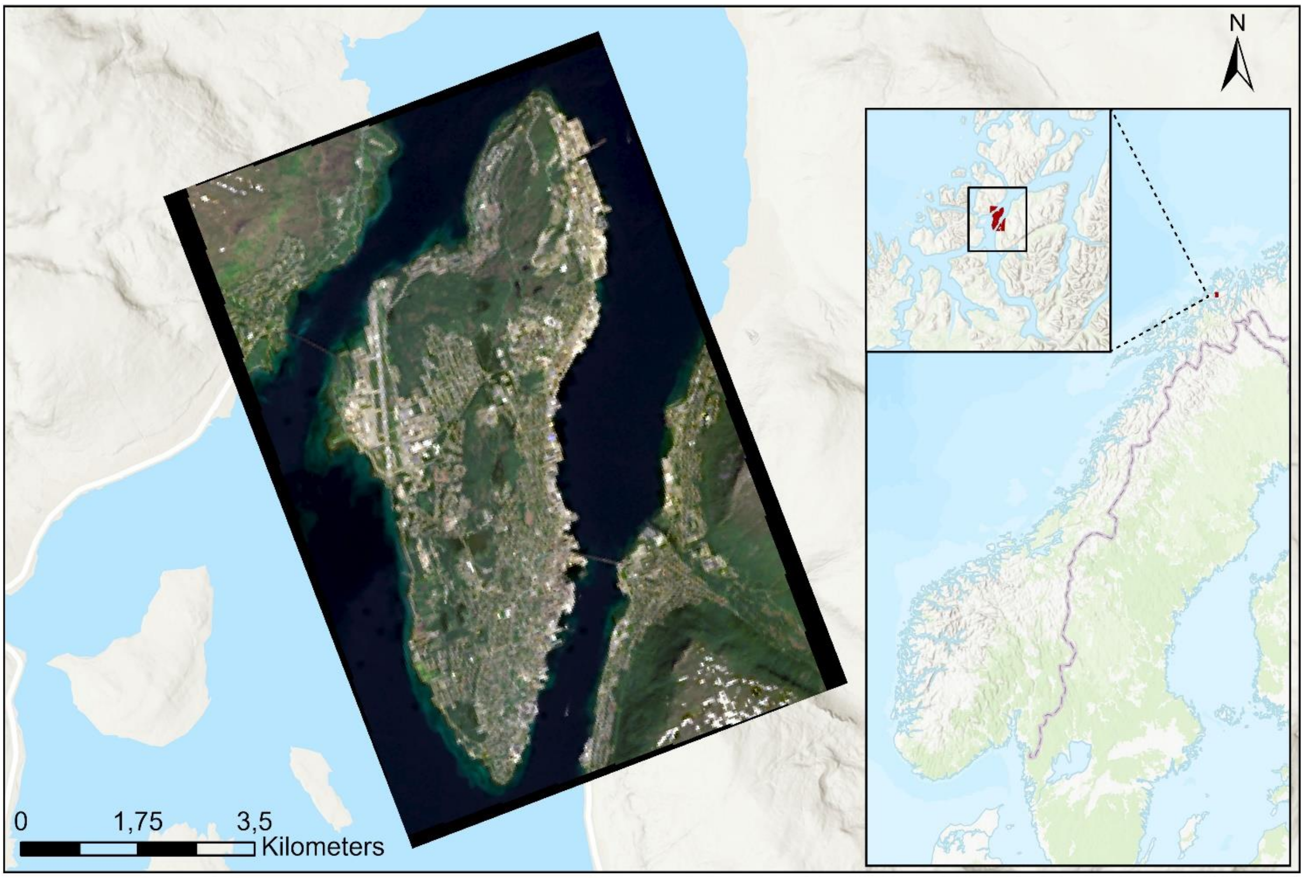
Image Analysis (OBIA) approach has also found extensive application in ISA extraction, particularly with high-resolution images (Hu and Weng, 2011; Petropoulos et al., 2012c; Sebari and He, 2013; Zhang et al., 2013).

The present study aims at mapping ISA in the Tromso region and to analyze the changes in these surfaces over the past three decades. Additionally, it seeks to explore the potential correlation of these changes with variations in the local population since 1990.

2. DATA AND METHODOLOGY

2.1. STUDY AREA

Situated north of the Arctic Circle, the island-city of Tromso is the most populated city in northern Norway (De Melo Cartaxo et al., 2021). With a thriving population of 77.544 (Statistics Norway, 2022), this affluent Arctic capital is linked to the mainland by the Tromso Bridge and Tromsoysund Tunnel, while also being connected to Kvaloya Island via the Sandnessund Bridge. Tromso, belonging to Troms County, holds historical significance as a vital economic force in Norway, dating back centuries. Before obtaining city status in 1794, it served as the gateway to the Arctic, functioning as a crucial meeting and starting point for renowned Arctic explorations. The Norwegian Sea, enveloping the city and stretching beyond its limits, constitutes a marginal sea within the Arctic Ocean, teeming with abundant resources. Presently, the Norwegian Sea maintains its importance as a key avenue for transport and communication. Through its natural resources, it continues to foster profitable industries, contributing to a thriving local economy.



Esri, HERE, Garmin, FAO, NOAA, USGS; Esri, USGS

Figure 2.1. Study area map (Landsat 9 image, 20/06/2023)

Tromso's subarctic climate is marked by substantial snowfall and chilly winds throughout its extended winters, which endure for approximately six months. Polar nights, extending from late November to mid-January, contribute to prolonged darkness. Additionally, precipitation in the form of rain is not uncommon, frequently resulting in the formation of icy and slippery road surfaces, thereby posing hazardous driving conditions. Tromso's subarctic climate is marked by substantial snowfall and cold winds throughout its extended winters, which endure for approximately six months. Polar nights, extending from late November to mid-January, contribute to prolonged darkness. Additionally, precipitation in the form of rain is not uncommon, frequently resulting in the formation of icy and slippery road surfaces, thereby posing hazardous driving conditions.

2.2. DATASET DESCRIPTION

The present research utilizes Landsat imagery to conduct multitemporal monitoring of ISA in Tromso. Landsat, characterized by its moderate spatial resolution, offers extensive coverage of data over large areas. Specifically, Landsat 5 Thematic Mapper (TM) and Landsat 9 Operated Land Imager (OLI), Collection 2 Surface reflectance products were employed in this study. All the selected for this study images (Table 2.1), were acquired on anniversary dates, during summer months, to minimize the presence of significant cloud cover and ensure that the identified changes are not caused by any natural or other factor.

Table 2.1. Landsat images acquired in the study

Date	Satellite	Dataset
23/08/1993	Landsat 5	*LANDSAT/LT05/C02/T1_L2/LT05_199011_19930829*
13/08/2007	Landsat 5	*LANDSAT/LT05/C02/T1_L2/LT05_198011_20070813*
30/06/2023	Landsat 9	*LANDSAT/LC09/C02/T1_L2/LC09_198011_20230630*

Three specific dates were chosen, starting from 1993 and ending in 2023. The original intention was to acquire the third image precisely at the midpoint of this period, specifically during the summer of 2008. However, due to the lack of Landsat data with a cloud coverage percentage conducive to image processing, an image from the corresponding months of 2007 was chosen instead.

Furthermore, to be created a correlation pattern between changes in ISAs and alterations in social factors, demographic data for the broader Tromso region were utilized, sourced from the Statistical Service of Norway. Specifically, population data from 1990 to 2022 were obtained.

2.3. METHODOLOGY DESCRIPTION

The SVM method is used in this study to detect changes in ISA from 1993 to 2023. The entire following process has been implemented in Google Earth Engine (GEE) cloud platform, as shown in Figure 2.2.

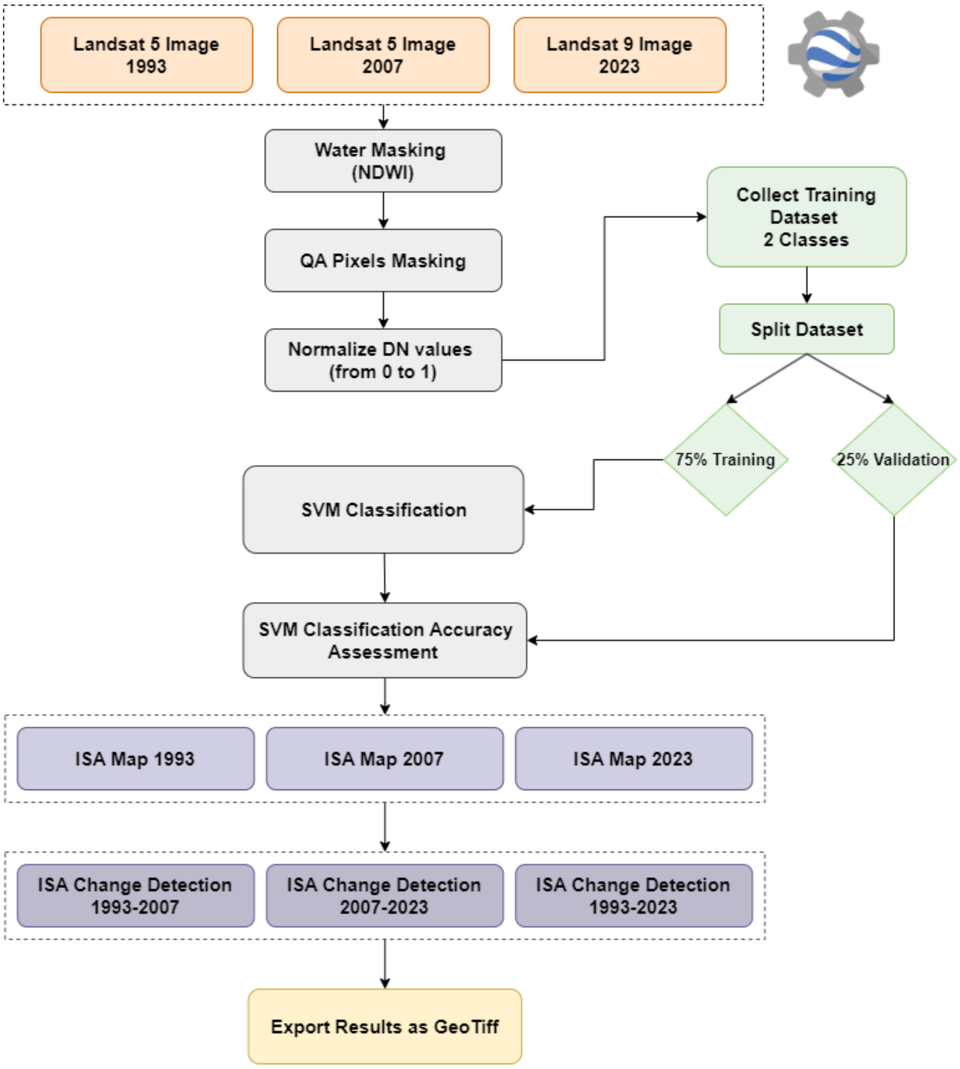


Figure 2.2. Methodology flowchart

2.3.1. DATA PRE-PROCESSING

Landsat images were selected directly from GEE platform, according to their cloud cover percentage (less than 30%). Due to the geographical characteristics of the study area, acquiring images with cloud cover below 10% posed a considerable challenge. As the images obtained were already geometrically and atmospherically corrected, no additional processing was required. The first step was to bound the study area, using a polygon and apply the Normalized Difference Water Index (NDWI) to mask out all water bodies. The subsequent step involved QA pixel masking to eliminate clouds, cloud shadows, and unused pixels from the images. The final step of the pre-processing procedure entailed applying a scale factor of 0.0000275 and the offset of -0.2 standardizing all values on a conceptual scale ranging from 0 to 1.

2.3.2. CLASSIFICATION AND CHANGE DETECTION

Along the lines of other studies like Huang et al. (2021) and Liu et al. (2023), it is also implemented herein binary classification which included the classes of Impervious and Non-Impervious, as the primary goal was to exclusively extract ISA. Before applying SVM classifier to the three images, the first step was the generation of train – validation datasets. Three different datasets were created, each corresponding to a specific date, by stratified sampling, mainly based on the false – color composite (NIR, RED, GREEN bands) which better points out the ISA (Li et al., 2013) and SWIR bands. The dataset's points number follows the rule of 10N to100N, where N is the number of bands used for the analysis. For both Landsat 5 images (6 bands) and Landsat 9 images (7 bands), almost 350 points were carefully selected, per class. Subsequently, the datasets were split into training and validation samples. 75% of the total points were allocated for training the classifier, with the remaining 25% used for validation. The SVM machine learning classifier was trained and performed for all dates by default parameters.

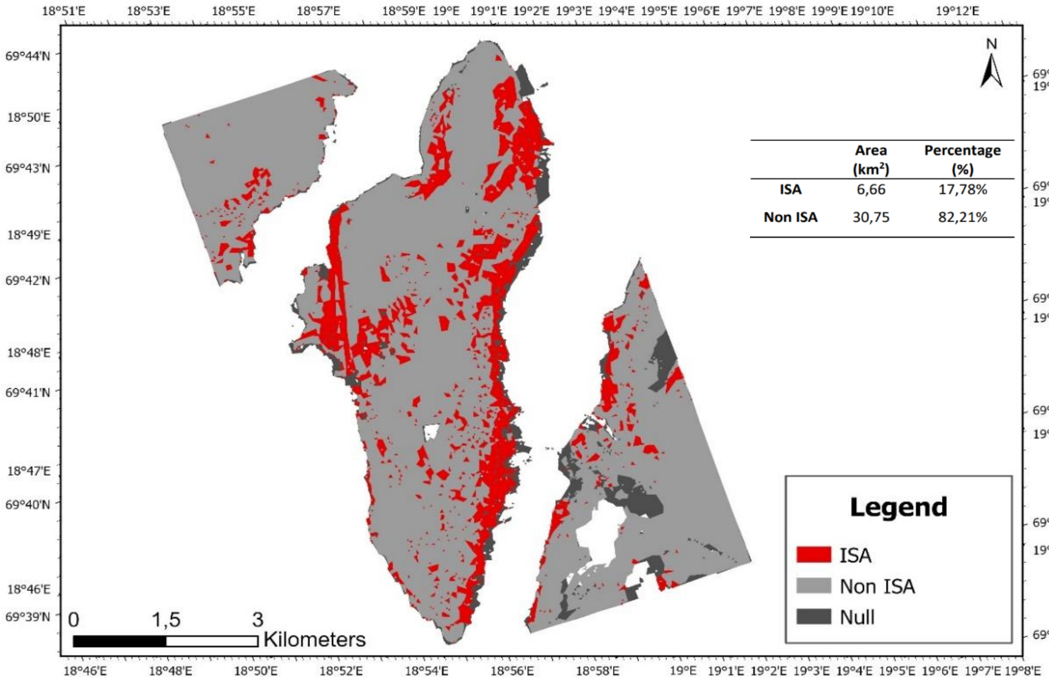
The final phase of the entire process involved implementing Change Detection (CD) in GEE platform and calculating the areas undergoing change. Post classification comparison has been employed as the most effective change detection method as the data were individually classified and normalized. This approach diminishes disparities between the dates, rendering it a robust method (Sun et al., 2009; Vivekananda et al., 2021). The ISA alterations were mapped chronologically, into pairs (i) from 1993 to 2007, (ii) from 2007 to 2023 and (iii) from 1993 to 2023. For all these dates, only changes from Non-ISA to ISA were calculated, the changed area was quantified in km^2, based on the pixel size, and was turned into percentage of change, relative to the total size of the study area. The layers were visualized using the ArcGIS Pro software, and the outcomes are presented in Section 3.

2.3.3. VALIDATION APROACH

The evaluation of ISA was conducted through a comprehensive analysis of various statistical indices (Congalton, 1991), including Cohen's Kappa (Kc), overall accuracy (OA), user's accuracy (UA) and producer's accuracy (PA). Kappa serves as a measure of agreement between the reference data and the classification, relative to the probability of agreement between the reference data and a random classifier. Overall accuracy quantifies the likelihood of a pixel being accurately classified by the thematic map. The user's accuracy identifies pixels that, though not genuinely belonging to a reference class, are incorrectly assigned to other ground truth classes while producer's accuracy carefully examines the pixels omitted from their reference class. Kappa (Kc) is a dimensionless metric ranging from 0 to 1, while the remaining statistical metrics are expressed as percentages (%). The values of OA, PA, UA as well as kappa coefficient were also automatically calculated in GEE platform, by using the validation samples that were created.

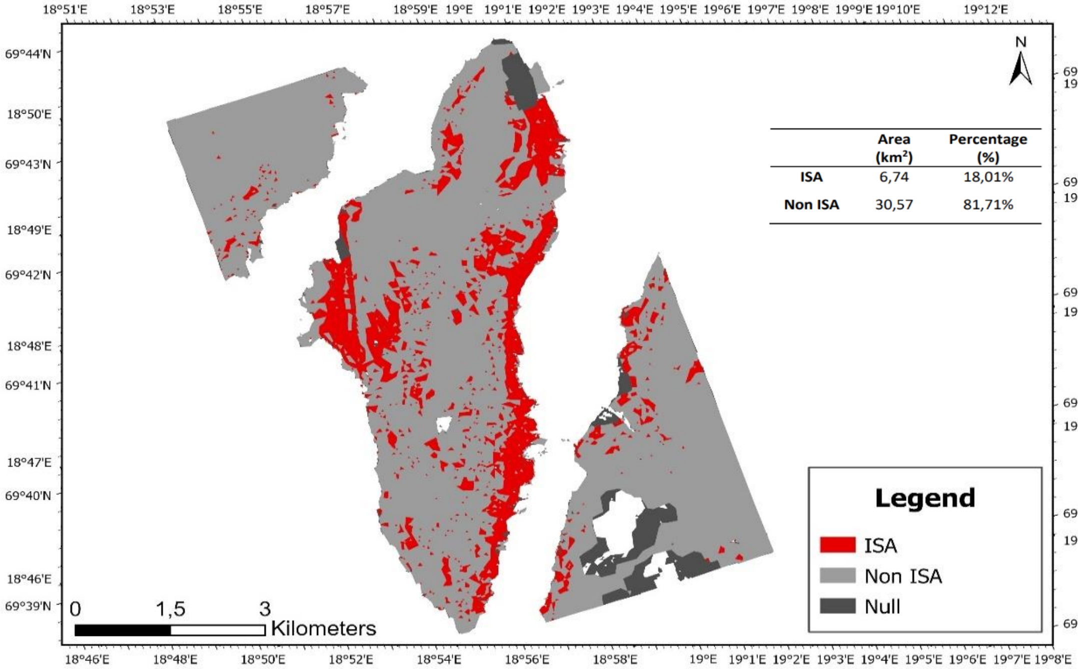
3. RESULTS

The results of the SVM classifier are shown in Figures 3.1, 3.2, 3.3, while the comprehensive summary of the statistical results concerning the accuracy assessment of the classification is included in Table 3.1. It should be noted that the term "null" pertains to pixels that have been excluded from the QA masking. The outcomes of the multi-temporal classification reveal a continuous expansion of ISAs over the investigated chronological span. To elaborate, a marginal variation in ISA is discerned from 1993 to 2007, registering at approximately 0.22%. In contrast, a highly accelerated change is observed during the temporal interval spanning 2007 to 2023, reaching 4%.



	Area (km²)	Percentage (%)
ISA	6,66	17,78%
Non ISA	30,75	82,21%

Figure 3.1. Classification results of the Tromso Area using the SVM classifier, 1993. (Pixels removed from QA masking are represented as "Null")



	Area (km²)	Percentage (%)
ISA	6,74	18,01%
Non ISA	30,57	81,71%

Figure 3.2.. Classification results of the Tromso Area using the SVM classifier, 2007. (Pixels removed from QA masking are represented as "Null")

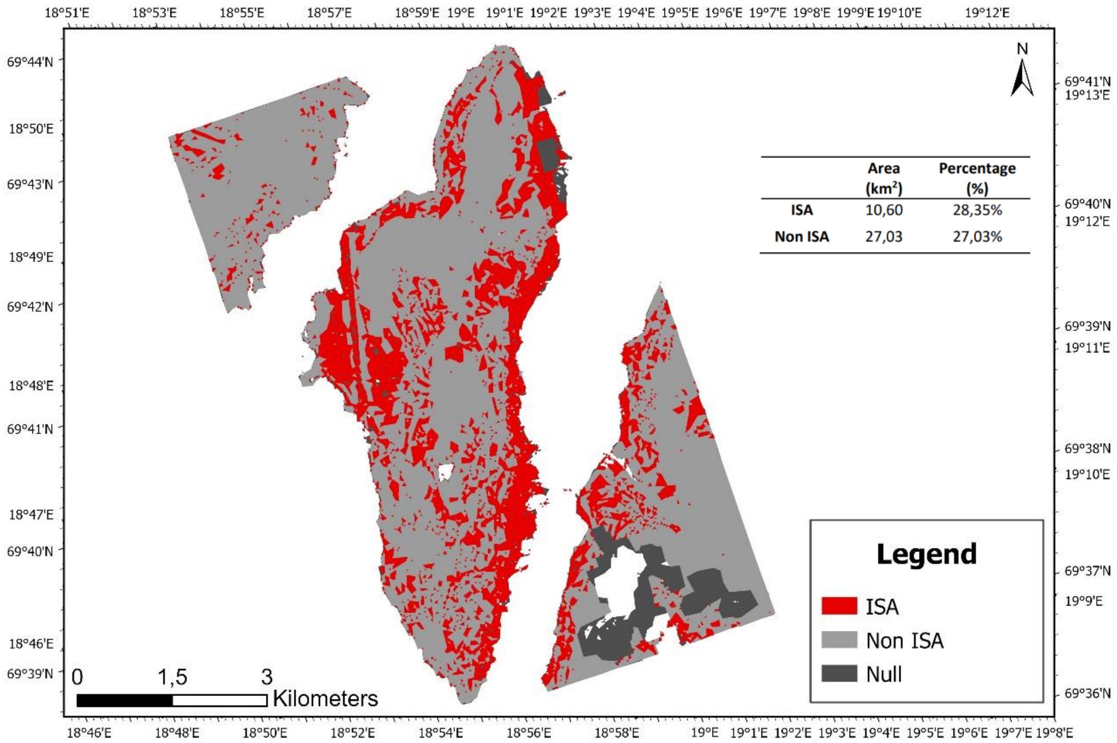


Figure 3.3.. Classification results of the Tromso Area using the SVM classifier, 2023. (Pixels removed from QA masking are represented as "Null")

In 1993, ISAs covered an area of 6,66 km^2 or 17,79% of the total area, spanning nearly the entire territory of Tromso Island. The primary settlement of Tromso in the east, as well as the airport in the western part of the island, are easily discernible. In 2007, ISA occupied an area of 6.74 km^2, constituting 18.01% of the total area. The urban fabric of Tromso appears more contiguous, with an observable increase in ISA around the airport area. Pixels that have been removed in the northern part of the island can be assumed to have been ISA, both from the 1993 classification results and from surrounding pixels. Finally, in 2023, a substantial expansion of ISA is observed, covering 10.6 km^2, accounting for approximately 30% of the total area. In this scene, ISA is also identified in the eastern part of the study area, delineating the growth of the Tromsdalen settlement. This quantitative alteration of ISA is presented in Figure 3.7.

The accuracy assessment for all classifications was conducted using the confusion (error) matrix, which is presented in Table 3.1. It is obvious that the methodology used in the present study leads to highly accurate results, according to the following metrics. The OA reached 93,18%, 95,13% and 90,19% for 1993, 2007 and 2023 respectively, while kappa coefficient was 0,864, 0,903 and 0,802. As for the rest of the accuracy metrics, PA took values from 91,2% to 95,71%, percentages that strongly indicate a high probability that the classification of each class aligns closely with reality. UA values ranged from 88,63% to 95,74% providing the accurate and subjective selection of training samples.

Table 3.1. Confusion matrix results

	1993		**2007**		**2023**	
	PA(%)	**UA(%)**	**PA(%)**	**UA(%)**	**PA(%)**	**UA(%)**
ISA	95,29	91,01	95,55	94,50	93,97	88,63
Non ISA	91,20	95,40	94,73	95,74	95,71	92,30
OA	93,18		95,13%		90,19%	

kappa	0,864	0,903	0,801

Based on the classification, results presented above, a CD analysis was performed in order to map the ISA changes. The change detection analysis was processed in three series (a) 1993 to 2023; (b) 1993 to 2007; (c) 2007 to 2023 and were selected only changes from non-Impervious to Impervious class. In Figures 3.4, 3.5 and 3.6, are demonstrated the results of this analysis based on SVM classification.

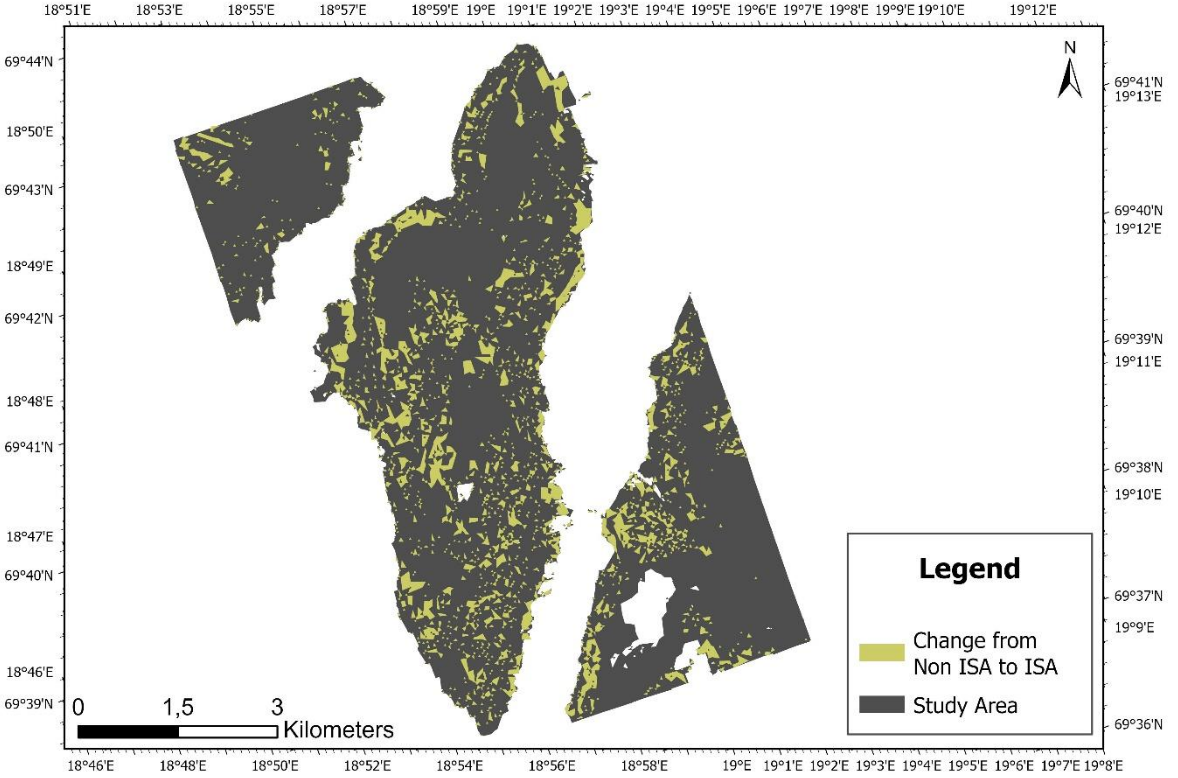


Figure 3.4. Change detection results for 1993-2023 period

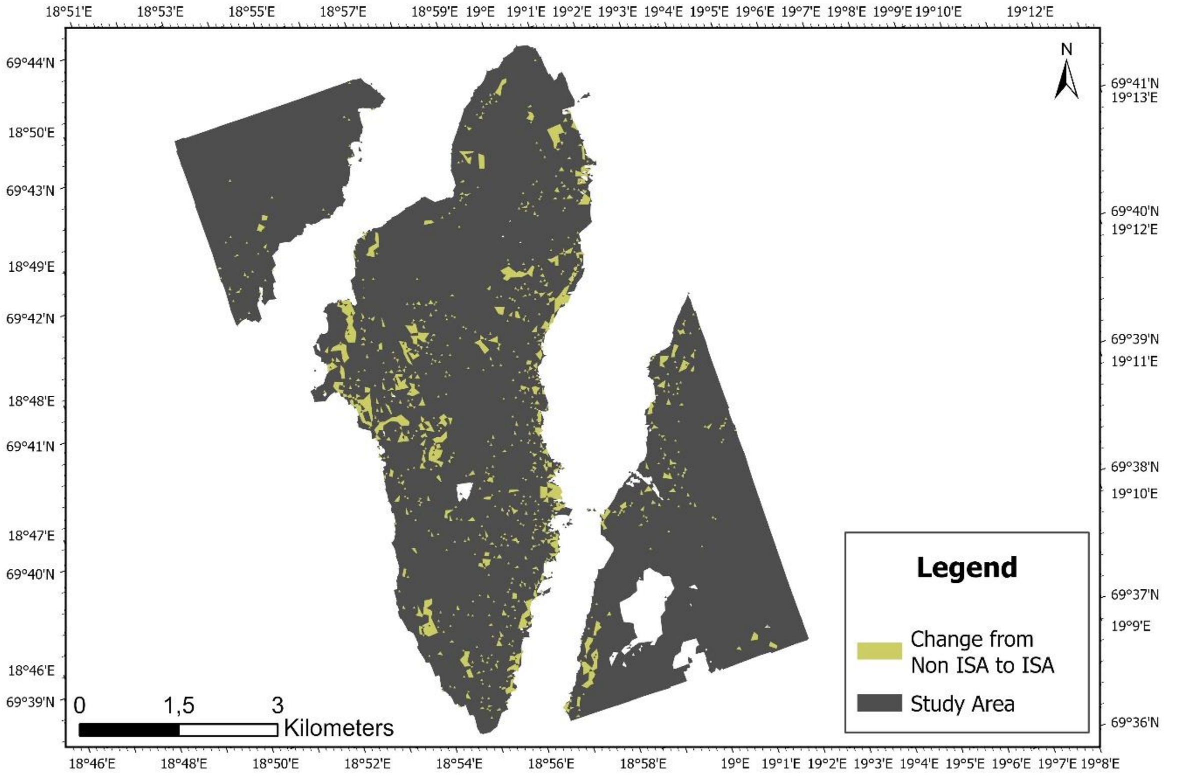


Figure 3.5. Change detection results, for 1993-2007 period

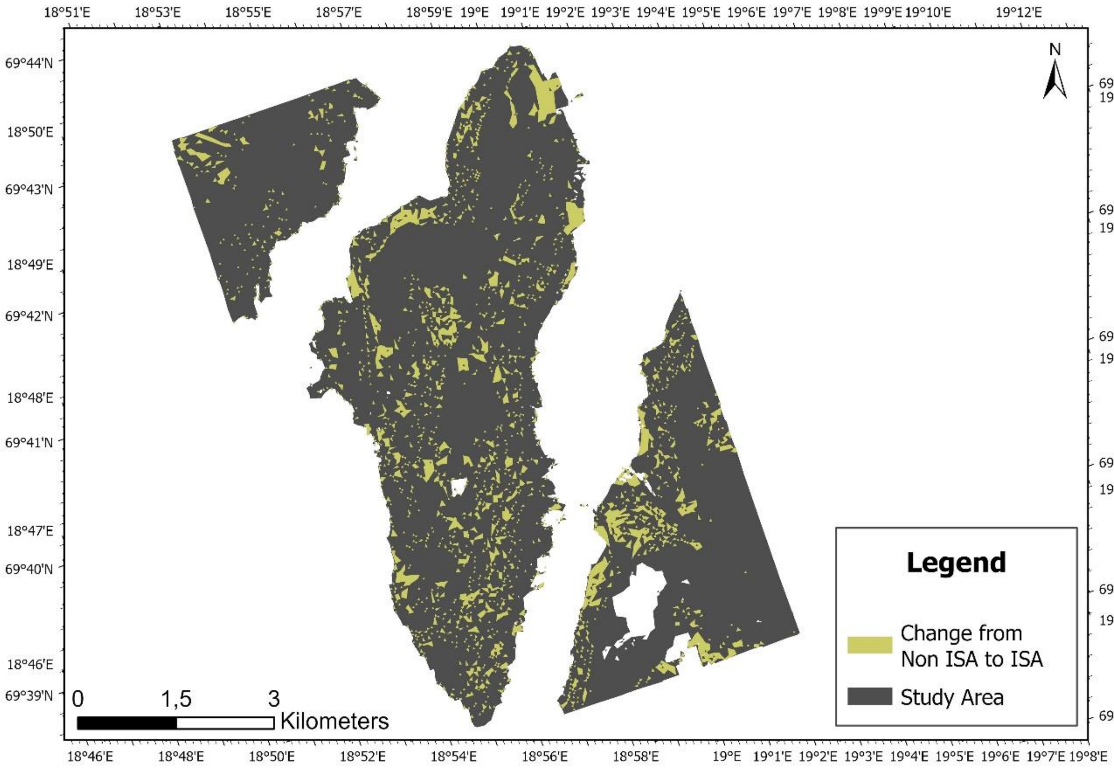


Figure 3.6. Change detection results, for 2007-2023 period

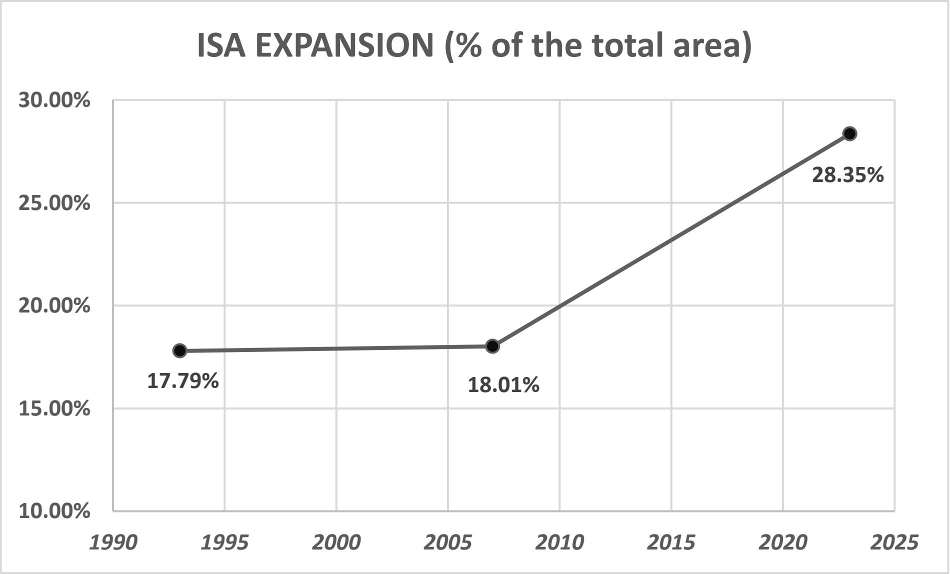


Figure 3.7. ISA expansion graph, based on SVM classification results.

As expected, the highest ISA growth is recorded in 1993-2023 period. ISA growth is detected across the whole study area, with a characteristic spread in the eastern part and in the island area of Tromso. From these changes, some limited are observed in 1993-2007 period, which are concentrated in the western and southwestern part of the island, as mentioned also in classification results. The majority of the detected changes are noticed in the 2007-2023 period, where the expansion of ISA throughout the whole island and also the eastern part of the study area, is highly marked.

4. DISCUSSION

This study implemented SVM classifier with medium spatial resolution imagery from Landsat and 9 to map ISA and detected changes from 1993 to 2023 in Tromso area, Norway. This method, in contrast to the traditional classification and change detection methods, provides a semi supervised tool for extracting ISA from Landsat data series, detecting alterations in the imperviousness of the surface, and calculating the changed areas simply by selecting the appropriate images and providing the training samples. SVM classifier is one of the most efficient and commonly used for land cover mapping, as shown by many studies (Cheng et al., 2011; Wei and Blaschke, 2018; Shao et al., 2023). Regarding the efficacy of the classifier, the superior overall accuracy achieved can be attributed to its capacity for optimally delineating hyperplanes between classes when compared to alternative pixel-based techniques (Petropoulos et al., 2012). Unlike certain methods that may not easily identify such hyperplanes, SVM has the ability to generalize the optimal separating hyperplane to unseen samples with minimal errors among various separating hyperplanes. This capability allows SVM to yield the most effective class separation in the final classification phase (e.g., Huang et al., 2002). It is also suitable for ISA monitoring, as SVM was originally designed as a binary linear classifier (Shi and Yang, 2015). This is also confirmed in the present study, where the performance of the classifier is high. SVM yielded highly satisfactory results for the implemented study area, as indicated by the statistical metrics that were calculated. The findings presented in this study are like those observed in other research endeavors that used the SVM technique with multispectral images in remote sensing applications (Wang et al., 2018; Liu et al., 2023; Zheng et al., 2023).

Various factors may be identified as potential sources of error in the technical execution of our case study, influencing the performance of the technique. On the one hand in all images, a notable removal of pixels has occurred due to the presence of clouds and cloud shadows. These removed pixels could potentially differentiate the quantitative results of the classification. On the other hand, several studies have demonstrated that there is a strong confusion in the spectral characteristics between impervious surfaces and bare soil (Su et al., 2022; Deng et al., 2020). Therefore, it is possible that pixels may have been incorrectly classified as ISA when representing bare ground.

At this point it is pertinent to refer to the correlation between ISAs and the demographic composition of the region. As can be derived from the data presented in Figure 4.1 the population dynamics of Tromso manifest a continuous upward trajectory from 1990 through 2020, a trajectory that extends through the year 2022. This substantiates the pivotal role played by ISAs in urban ecosystems, as the escalating extent of these surfaces (Figure 3.7) correlates with the concurrent demographic expansion within the purview of the study area.

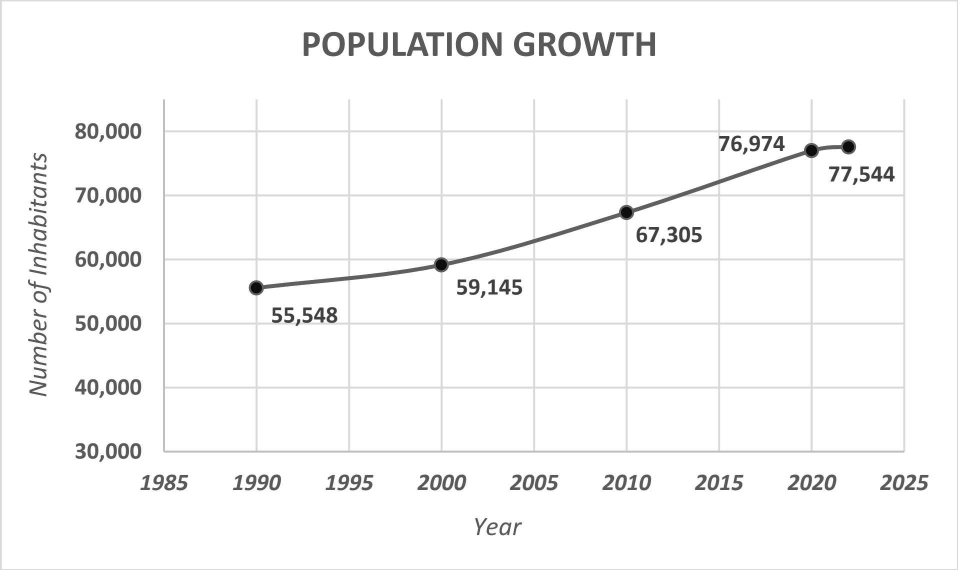


Figure 4.1. Population growth graph, from 1990 to 2022 (data obtained from Statistics Norway https://www.ssb.no/en)

This congruence underscores the complex interplay between anthropogenic infrastructure development, symbolized by the proliferation of ISAs, and the demographic dynamics shaping the urban landscape over the specified temporal span. This conclusion aligns with findings from related studies exploring the relationship between urban expansion and demographic trends (Melchiorri et al., 2018).

It is well known that the built-up area of cities cannot be accurately measured based on administrative boundaries. The analysis of remote sensing images makes it possible to delineate the total land area, the green areas (pervious surface) and the built-up areas (impervious surface). However, more sophisticated measurements are required when it comes to measuring urban built-up density, which includes the entire building area (DiNapoli and Jull 2020). Furthermore, urban expansion is not linear, as it takes very different forms in each city. It can take place through the redevelopment of built-up areas at much higher densities, by filling in the remaining 'gaps' in already built-up areas or through the urban development of areas that were previously not used for urban purposes. New urban development can be adjacent to already built-up areas, or it can “leapfrog" outside built-up areas and create new urban space. In turn, it can reduce, maintain or increase open space in and around the city (Angel et al., 2005). Depending on the city, demographic expansion is linked to the urban landscape, but not exclusively to the consolidation of built-up areas, as a larger middle class tends to move to the urban fringe, triggering the formation of metropolitan regions or larger urban regions (Mahtta et al., 2022).

Another point worth mentioning is the performance of the Google Earth Engine (GEE) platform in the present study. Through GEE, a semi-automated methodology for the processing and analysis of Landsat images, coupled with their classification utilizing the machine learning SVM algorithm, was developed. The entire procedure was carried out in a cloud environment ensuring fast execution, with only the resultant outcomes being downloaded for subsequent visualization within the ArcGIS Pro software. The unique capabilities of GEE and other similar cloud-based platforms pave the way for new opportunities in ISA mapping in large geographical scales.

5. CONCLUSIONS

The Landsat images proved to be satisfactory for the specific application, as they are freely available and already pre-processed. Despite their medium resolution, they achieved high accuracy rates, justifying the widespread use of the SVM classifier in land cover mapping applications, specifically for ISA. The classification results can be considered successful, with very high accuracy rates of 93.18%, 95.13%, and 90.19% for each date, respectively. The kappa coefficient values are also highly satisfactory, ranging above 0.8 for all dates, confirming the agreement between classification results and ground truth values.

The outcomes of the classifications reveal a notable escalation in ISA, notably conspicuous within the 2007-2023 period, trend consistently corroborated by the findings of the change detection analyses. It is noteworthy that an initial correlation was made between these results, showing an increase in ISAs with the population evolution of the study area over time, observing a trend of consistency between the two variables.

Regarding the limitations of the study, they are confined to the absence of cloud-free images, resulting in the loss of portions of the study area due to cloud masking. Additionally, the confusion of pixel values between ISAs and bare soils poses challenges, as indicated in the literature.

The implementation of the whole methodology in GEE cloud platform represents a significant advancement in innovation. GEE is a robust platform for managing large-scale geospatial datasets, enabling seamless integration and analysis of Landsat imagery over extensive temporal and spatial scales. By harnessing GEE's cloud-based infrastructure, the computational load associated with processing Landsat time series data for ISA mapping is significantly reduced, fostering efficient analysis and prompt results. The combination of Landsat's multispectral data with the robust capabilities of the SVM classifier within the GEE framework enhances the accuracy and automation of ISA extraction while also facilitates change detection analyses by providing an extensive archive of Landsat images and proper algorithms for its calculation. This holistic approach, combining GEE, Landsat data and SVM classifier, proves pivotal in generating reliable and up-to-date information crucial for urban planning, environmental monitoring, and the study of climate change impacts.

In conclusion, the results of this study constitute a significant contribution to urban planning applications adapted to the socio-human factor. Also, the employed methodology has also the potential to be used operationally for real time monitoring of ISA while can be adaptive for application in diverse study areas, requiring adjustments only in the input parameters for the classification process. It can also be applicable to all dataset types available in GEE platform constituting a useful tool of analyzing urban environments. It can play a significant role in decision making in domes such as urban planning, policy making or natural hazards management.

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