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REMOTE SENSING APPROACHES FOR LAND USE/LAND COVER CHANGE IN COASTAL AREAS AND OCEANIC ISLANDS: AN OPEN SCIENCE-BASED SYSTEMATIC REVIEW

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ABSTRACT: In the current climate change context, detecting and monitoring relevant land use/land cover (LULC) changes in insular and coastal areas is critical as soon as they occur. This research consists of a systematic literature review of 167 open-access articles from January 2010 to June 2022, based on several parameters, namely year of publication, journals, geographic location of the study area, time range of the studies, data source, data type, sensors, remote sensing-based approach, data processing algorithms, accuracy assessment approach, and spatial resolution, using the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) declaration as a guideline. The results revealed that the years 2020 and 2021 showed the highest number of studies published, namely 33 for each year (20%). The continent with the most case studies was Asia (48%), with China being the most productive country in this field (23%). The most analyzed time range was superior to 20 years (37% of the studies). Satellite imagery was the most applied data source (77%), followed by relevant historical data (*e.g.*, land cover maps). The multispectral data was used in 77% of the studies, and the Landsat Mission represents three of five of the most used sensors. Normalized Difference Vegetation Index was the most applied remote sensing-based approach (10%), and the Maximum Likelihood Classifier Algorithm was the most widely used data processing algorithm (10%). The Overall Accuracy is the most applied accuracy assessment approach used in 85 papers (51%). Many articles used a 30-meter spatial resolution (69%), and higher resolutions completed the top 5 approaches. This study contributes to perceiving the main current approaches for monitoring LULC changes in insular and coastal environments to identify research gaps for future developments.

Keywords: Land cover; land use; change detection; remote sensing; oceanic islands; coastal areas; climate change; natural hazards.

RESUMO: *No contexto atual das alterações climáticas, é fundamental detectar e monitorar alterações relevantes de uso/cobertura do solo em áreas insulares e costeiras logo que ocorram. A presente investigação consiste numa revisão sistemática da literatura de 167 artigos de acesso aberto publicados de Janeiro de 2010 a Junho de 2022, com base em diversos parâmetros, nomeadamente ano de publicação, revistas, localização geográfica da área de estudo, intervalo temporal analisado nos artigos, fonte de dados, tipo de dados, sensores, métodos baseados em sensoriamento remoto, algoritmos de processamento de dados, métodos de acurácia e resolução espacial, usando a declaração Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) como diretriz. Os resultados revelaram que os anos de 2020 e 2021 apresentaram o maior número de estudos publicados, ou seja, 33 para cada ano (20%). O continente com mais estudos de caso foi a Ásia (48%), sendo a China o país mais produtivo neste domínio (23%). O intervalo temporal mais analisado foi superior a 20 anos (37% dos estudos). Imagens de satélite foram a fonte de dados mais aplicada (77%), seguidas por dados históricos relevantes (por exemplo, mapas de cobertura da terra). Os dados multiespectrais foram utilizados em 77% dos estudos, sendo que a Missão Landsat representa três dos cinco sensores mais utilizados. O Índice de Vegetação por Diferença Normalizada foi o método baseado em sensoriamento remoto mais aplicado (10%) e o Algoritmo Classificador de Máxima Verossimilhança foi o algoritmo de processamento de dados mais amplamente utilizado (10%). O Overall Accuracy é o método de acurácia mais aplicado, usado em 85 artigos (51%). Muitos trabalhos usaram uma resolução espacial de 30 metros (69%) e resoluções espaciais maiores completaram as cinco mais utilizadas. Este estudo contribui para perceber as principais abordagens atuais para monitorar alterações no uso/cobertura do solo em ambientes insulares e costeiros para identificar lacunas de pesquisa para desenvolvimentos futuros.*

Palavras-chave: *Cobertura do solo; uso do solo; detecção de mudança; sensoriamento remoto; ilhas oceânicas; áreas costeiras; alterações climáticas; riscos naturais.*

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1. INTRODUCTION

Insular ecosystems are natural laboratories where evolution processes can be isolated and studied to be linked and extended to the more complex patterns exhibited by more extensive mainland systems. In analogy, islands may also provide insights into effective management approaches (Calado *et al.*, 2015). However, island environments are also more vulnerable to anthropogenic pressure and natural hazards. The 2018 IPCC report (https://www.ipcc.ch/sr15/, accessed on 13 August 2022) on Climate Change suggested an increase in extreme hydrogeological events and greater peak temperatures that expose these systems to a higher risk of natural disasters such as wildfires and flash floods (Allen *et al.*, 2019).

Small islands are land areas with less than 10,000 km^2 and a population under 500,000 inhabitants, and they are essentially coastal entities (Saffache and Angelelli 2010). Oceanic islands face several obstacles to full development (remoteness, insularity, terrain, climate, economic dependence, and narrow range of the goods they produce) and also severe environmental issues (climate variability and changes, proliferation of invasive, exotic species, natural catastrophes, and overexploitation of natural resources) (Rietbergen *et al.*, 2007).

The main threat to sustainability in small islands is LULC change, driven mainly by urban development (García-Romero *et al.*, 2016), the spread of invasive alien species (Gil *et al.*, 2014), natural hazards (Lira *et al.*, 2013), and an intensification of agricultural activity and livestock grazing (Gil, Fonseca, and Benedicto-Royuela 2018).

In the current climate change context and also taking into account the high susceptibility of most of these territories to natural hazards (*e.g.*, landslides, volcanic eruptions, earthquakes), it is essential to detect and monitor relevant LULC changes as soon as they occur, to identify and address their drivers and triggers through effective land/coastal planning and management policies.

Remote sensing (RS) change detection (CD) is commonly defined as a process to identify differences in geographical surface phenomena over time (Singh, 1989; Bruzzone and Bovolo, 2013). The CD is also defined as a process to identify significant differences in sequential pixel appearances due to object emergence, disappearance, movement, or shape alteration (Radke *et al.*, 2005). The detection process includes observing and evaluating differences over time to document biophysical and physical phenomena spectral and temporal progression (Mouat, Mahin, and Lancaster 1993).

The acceleration of change globally driven by naturogenic, and anthropogenic factors creates more significant variability of change processes. Hence, bitemporal, multitemporal, and time series CD techniques are needed to investigate heterogeneous change types, intensities, and process durations to suit the various purposes of studies. The era of freely accessible data, in parallel with the growth of non-proprietary toolboxes, should propagate doubly through RS communities and users (Panuju *et al.*, 2020).

The purpose of this paper is to perceive the research background reviewing the current state-of-the-art in multi-sensor LULC changes detection in RS datasets availability/complementarity, methodological approaches, techniques, and parameters. A systematic literature review was conducted using the PRISMA statement as a guideline to achieve this goal.

2. METHODS

A systematic literature review was carried out of academic articles indexed on the Web of Science database (https://www.webofscience.com/, accessed on 13 August 2022), using the PRISMA statement as a guideline (https://www.prisma-statement.org/, accessed on 13 August 2022), to identify the relevant scientific work already published on LULC change, estimation, and prediction in the oceanic island and/or coastal areas.

The PRISMA 2020 statement is beneficial when planning and performing systematic reviews to ensure that all necessary information is gathered. The PRISMA statement aims to increase the transparency and scientific validity of a reported systematic review or meta-analysis. Using the PRISMA statement and its extensions to write protocols or the completed review report, as well as to complete the PRISMA checklists, is likely to not only inform reviewers and readers about what authors did and discovered but also to improve the quality of reporting and make the peer review process more efficient (Swartz 2011; Sarkis-Onofre *et al.*, 2021). For these reasons, this methodology was selected to guide this systematic review.

A search was conducted utilizing nine combinations of relevant keywords and Boolean operators inside each study's title, abstract, and keywords (Figure 1). Review papers, conference papers, and articles written in non-English languages or non-open-access were excluded. The search was done between January 2010 and June 2022.

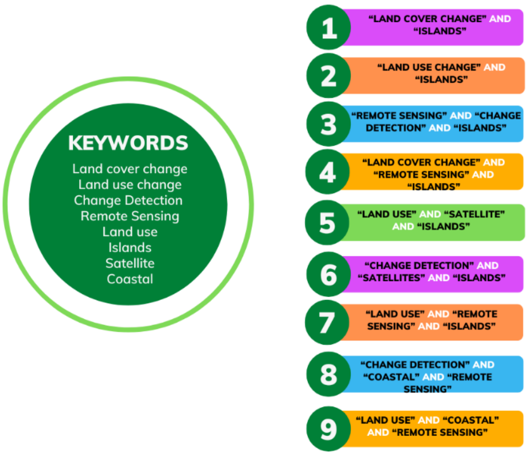

Figure 1. Search criteria adopted: keywords combinations.

The PRISMA approach is separated into three steps: (1) identification, (2) screening, and (3) inclusion. Figure 2 depicts the full literature search and subsequent filtering to identify the final articles for review.

In step 1 (identification), 670 studies were identified. The search obtained different results from each keyword combination (Figure 1). Search 6 got fewer results than the others (15 papers), and Search 9 presented the most results (285 articles). The first phase of the PRISMA process also includes removing duplicate research, which accounted for 112 of the totals.

In step 2 (screening), 391 papers from 558 were excluded based on the title and abstract review. It excluded (1) articles from non-RS sources that did not use CD methods as the primary approach; (2) articles in which the study area was not on islands or coastal areas, and (3) papers whose subject was not LULC-related. The last parameter represents a large number of excluded papers. It occurred due to the use of "islands" as a keyword generating results with "heat islands" subject papers, which is not the focus of this review paper.

In step 3 (inclusion), the remaining articles were selected for full-text analysis to extract relevant information. From 167 articles, the following information was extracted: (1) year of publication; (2) journal; (3) geographic location; (4) time range; (5) data source; (6) data type; (7) sensors; (8) RS-based approach; (9) data processing algorithm; (10) accuracy assessment approach and (11) spatial resolution (Table 1).

A list of abbreviations and acronyms used throughout the text is provided in Table 2 to aid in the readability of this paper.

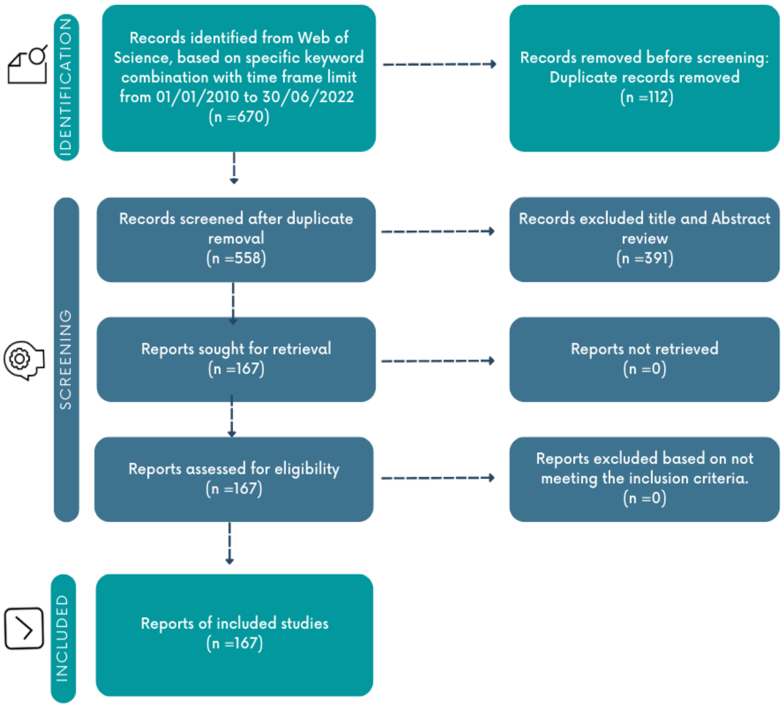

Figure 2. Workflow chart of the literature search process to identify relevant scientific articles about land use/land cover monitoring with RS data. An initial pool of publications was collected in Web of Science (n = 670). After screening each article's title, abstract, and keywords, 167 relevant articles remained.

Table 1. Structure of the file created to extract the data of interest.

Feature	**Data Type**	**Description**
Title	Free text	Article title
Author (s)	Free Text	Author's names
Year	Categorical	Published year
Journal	Free text	Published journal
DOI	Code	Article DOI
Keywords	Free Text	Article's keywords
Region	Categorical	The continent in which the study area is located
Country/countries	Free text	Country/countries in which the study area is/are located
Data Source	Free text	Data sources (e.g., literature review, historical data)
Data Type	Free text	Data type (e.g., multispectral, SAR, LiDAR)
Sensors	Free text	Sensor (e.g., Sentinel-2, Landsat 8)
RS-based Approach	Free text	RS-based approach (e.g., Vegetation Indices, Image Difference, Image Ratio, Principal Components Analysis)
Data Processing Algorithm	Free text	Algorithms (e.g., Random Forest)
Accuracy Assessment Approach	Free text	The approach applied to the data analysis to verify the accuracy of the results (e.g., Kappa Index)
Spatial Resolution	Free text	Pixel size (in meters)

Table 2. List of abbreviations and acronyms.

Abbreviation/ Acronym	**Meaning**
ALOS	Advanced Land Observing Satellite
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CD	Change Detection
CNN	Convolutional Neural Networks
DEM	Digital Elevation Model
ESA	European Space Agency
ISODATA	Iterative Self-Organizing Data Analysis Technique
KI	Kappa Index
LiDAR	Light Detection and Ranging
LULC	Land Use and Land Cover
MLCA	Maximum Likelihood Classifier Algorithm
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
OA	Overall Accuracy
OBC	Object-Based Classification
PA	Producer's Accuracy
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF	Random Forest
RS	Remote Sensing
SAR	Synthetic-Aperture Radar
SAVI	Soil-Adjusted Vegetation Index
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
UA	User's Accuracy
UAV	Unmanned Aerial Vehicle
VI	Vegetation Indices

3. RESULTS AND DISCUSSION

3.1. Year of publication

Analyzing the number of yearly scientific articles might indicate trends and patterns. It can assist in identifying whether a particular topic of study is growing or declining in popularity. The articles analyzed in this paper were published between January 1st, 2010, and June 30th, 2022. The number of studies varied over the years without an apparent pattern or trend (Figure 3).

The years 2020 and 2021 showed the highest number of studies published, namely 33 for each year (20%) (Norder *et al*., 2020; Xi *et al*., 2021; Abd & Hazem 2020; Magolan and Halls 2020; Dang *et al*., 2021; Zhu *et al*., 2021; Gray *et al*., 2021; Ren *et al*., 2020; Zheng *et al*., 2020; Xi *et al*., 2021) representing 40% of the papers in only two of the 12 years analyzed. An overall discussion identified increased publications in 2019, 2020, and 2021.

On the contrary, 2011 was the year with the lowest number of published works, with just two studies (1%) (Broich *et al*., 2011; Lyons, Phinn, and Roelfsema 2011) followed by 2012 with three papers (2%) (Gil *et al*., 2012; Hamylton and East 2012), 2010 with four articles (2%) (Chang *et al*., 2010; Vassilakis 2010; Wang *et al*., 2010; Berberoğlu *et al*., 2010); 2014 with five studies (3%) (Rapinel *et al*., 2014; Palacio-Aponte 2014; Du *et al*., 2014; Dusseux *et al*., 2014); 2015 with six papers (4%) (Tran, Tran, and Kervyn, 2015; Sanchez *et al*., 2015; Marlier *et al*., 2015; Singh, Engelbrecht, and Kemp 2015; Shapiro *et al*., 2015) and 2013 with seven studies (4%) (Chen *et al*., 2013; Cardoso *et al*., 2013; Cao and Gao 2013; Kaiser *et al*., 2013; Zhang *et al*., 2013; Welch *et al*., 2013). In 2019, 24 studies (14%) were published (Hou and Hou 2019; Austin *et al*., 2019; Villarreal *et al*., 2019; Saikia *et al*., 2019; Worrall *et al*., 2019; Tran *et al*., 2019; Liu and Hu 2019; Li *et al*., 2019; Zhao *et al*., 2019; Schubert *et al*., 2019; Fauzi *et al*., 2019; Xu *et al*., 2019; Oliveira *et al*., 2019; Ding *et al*., 2019; Matlhodi *et al*., 2019; Révillion, Attoumane, and Herbreteau 2019; Meilianda *et al*., 2019; Pelage *et al*., 2019; Ma *et al*., 2019; Nguyen *et al*., 2019; Ibarrola-Ulzurrun *et al*., 2019; Abdullah *et al*., 2019) followed by 2017 with 15 papers (9%) (Qiu *et al*., 2017). In 2016 and 2022 (until June 30th), 12 articles were published each year (7% each year) (Alom, Paque, and Maertens 2022; Wu *et al*., 2022; Nguyen *et al*., 2022; Zhao *et al*., 2022; Gameiro *et al*., 2022; Caballero *et al*., 2022; Roy *et al*., 2022; Brown *et al*., 2022; Morgan *et al*., 2022; Guo *et al*., 2022; Hernández, Morell, and Armstrong 2022) and in 2018, 11 studies (7%) were published (Bremer *et al*., 2018; Abdel-Hamid *et al*., 2018; Kefalas *et al*., 2018; Xu *et al*., 2018; Benítez, Mena, and Zurita-Arthos 2018; Lin *et al*., 2018; Sunwoo, Nguyen, and Choi 2018; Filipponi *et al*., 2018; Xu 2018).

3.2 Journals

Analyzing the journal publications statistics can provide valuable insights into the quality and impact of research being published in a particular journal, as well as trends over time, and can help inform decisions about resource allocation.

The “Remote Sensing Journal” published most publications on these selected topics (Figure 4). Forty-five papers (26%) were published in this open-access journal (Chen *et al*., 2022; Magolan and Halls 2020; Zhu *et al*., 2021; Gray *et al*., 2021; Ding *et al*., 2017; Tu *et al*., 2021; Peng *et al*., 2021; Elmahdy, Mohamed, and Ali 2020; Salgueiro, Marcello, and Vilaplana 2021; Wu *et al*., 2022; Muro *et al*., 2016; Vassilakis 2010; Tran, Tran, and Kervyn 2015; Hilgendorf *et al*., 2021). Numerous factors may have contributed, such as the (1) main focus on the RS topic; (2) the high journal rank and Impact Factor; (3)

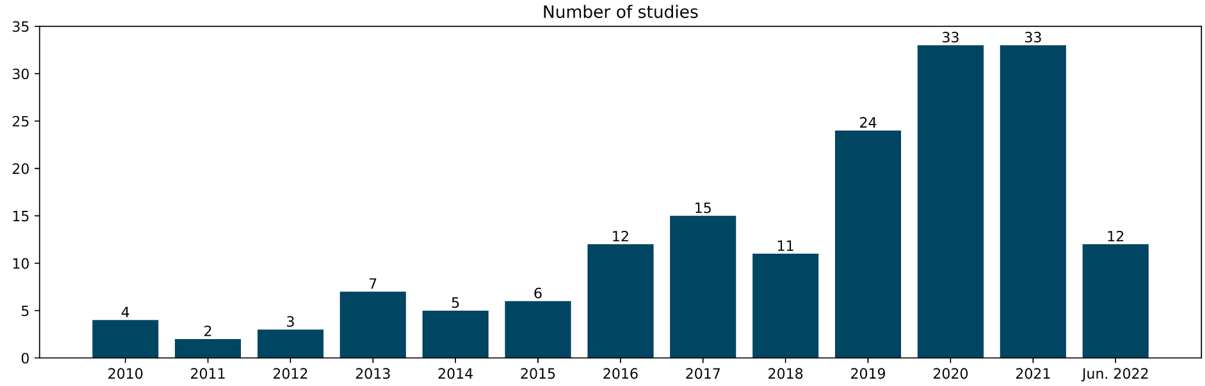

Figure 3. Distribution of the articles across the years (n=167).

the noteworthy visibility in several databases (e.g., Scopus, Web of Science, Ei Compendex, PubAg, GeoRef, Astrophysics Data System, etc.); and (4) open-access for readers; amongst other factors of author's interests.

The "Sustainability Journal" has published 12 papers (7%) (Kefalas *et al*., 2018; Abdel-Hamid *et al*., 2018; Ren *et al*., 2020; Zheng *et al*., 2020; Xi *et al*., 2021; Schubert *et al*., 2019; Ballanti *et al*., 2017; Eshetu Yirsaw *et al*., 2017; Xu *et al*., 2016; Newman *et al*., 2020; Matlhodi *et al*., 2019). The "Land Journal", the "International Journal of Geo-Information", and the "Environmental Research Letters Journal" published six papers each (Benítez, Mena, and Zurita-Arthos 2018; Hou and Hou 2019; Broich *et al*., 2011), representing 3% of the total.

Figure 4. Distribution according to the journals where the papers analyzed were published (n=167) (top 5 highlighted).

The other 58% included journals such as the "Journal of Applied Remote Sensing", "PLOS One", "IEEE Access", and "Remote Sensing of Environment", with 2% each. In addition, the "Applied Ecology" and "Environmental, Ecology and Society", "Forest and Society", "Island Studies Journal", and the "South African Journal of Geomatics" represent 1% of the total.

3.3 Geographic Location

The 167 studies selected were distributed over six continents (Figure 5). Eighteen studies (11%) were conducted in North America, and nine studies (5%) in South America (Conti, de Araújo, and Cunha-Lignon 2016; Xu 2018; Chen, Ming, and Menenti 2020; Bremer *et al*., 2018; Cherrington *et al*., 2020; Hernández, Morell, and Armstrong 2022; Morgan *et al*., 2022; Mccarthy *et al*., 2020). Fourteen studies (8%) were conducted in Africa (Ramjeawon *et al*., 2020; Zanvo *et al*., 2021; Matlhodi *et al*., 2019; Singh, Engelbrecht, and Kemp 2015; Hamylton and East 2012; Eid *et al*., 2020), 28 studies (17%) in Europe (Tassi and Gil 2020; Wicki and Parlow 2017; Xie and Niculescu 2021; Dusseux *et al*., 2014; Ibarrola-Ulzurrun *et al*., 2019; Giza *et al*., 2021), 80 studies (48%) in Asia (Zhang *et al*., 2013; Guan *et al*., 2020; Meilianda *et al*., 2019; Ma *et al*., 2019), six studies (4%) in Oceania (Bell and Callow 2020; Lymburner *et al*., 2020; Zhu *et al*., 2021; Chamberlain, Phinn, and Possingham 2020; Lyons, Phinn, and Roelfsema 2011; Delevaux and Stamoulis 2022), and 12 studies (7%) have more than one study area (Bhatia and Cumming 2020; Hou and Hou 2019; Norder *et al*., 2020; Villarreal *et al*., 2019).

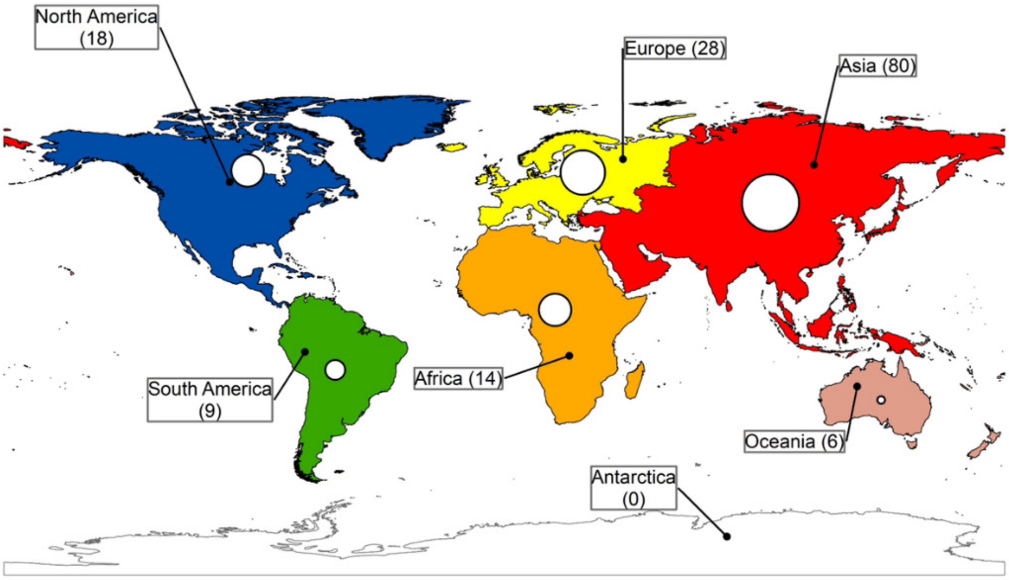

Figure 5. The geographical location of the analyzed studies. About 47% of all articles analyzed (n=167) have a study area in Asia, followed by Europe and America (16% each continent) and Africa (8%).

The studies covered more than 40 countries (Figure 6), such as Brazil (Pelage *et al*., 2019), Portugal (Tassi and Gil 2020), Mexico (Palacio-Aponte 2014), Tanzania, and Mozambique (Ferreira *et al*., 2012), among many others. China showcases the highest number of studies with 39 papers (23%) of the total (Hua *et al*., 2017; Chen *et al*., 2022) followed by the United States of America with 13 studies (7%) (Bremer *et al*., 2018; Villarreal *et al*., 2019), Vietnam with 11 studies (6%) (Tran *et al*., 2019; Nong *et al*., 2021), Portugal with ten studies (7%), and Indonesia with nine studies (5%).

3.4 Time Range

Time series analysis in RS refers to techniques and methods for extracting information about the landscape characterized by spectral and temporal variations. These are frequently applied to individual pixels independently (i.e., no interaction between pixels) (Rembold *et al*., 2015). Times series satellite imagery is utilized in diverse ways to monitor LULC dynamics. Given the availability of a diverse collection of satellite datasets (detailed in section 3.7 of this article), the frequency and length of time series analysis on papers that used RS approaches are being increased to identify, understand the triggers, and calculate damages and impacts (e.g., environmental and socioeconomic impacts) (Chen *et al*., 2021; Hasan *et al*., 2019).

Time series data is essential for several reasons. First, it allows researchers to identify patterns and trends in the data that may not be apparent from a single image. For example, changes in vegetation may only be evident over time as plants grow and mature (Huete *et al*., 2002). Second, time series data can help researchers understand how the Earth's surface changes over time due to natural or human-induced factors, such as climate change or LULC (Thapa 2022). Finally, time series data can be used to develop models predicting future changes (El-Hamid *et al*., 2022), which can be valuable for planning and management purposes.

In terms of the time range, 62 studies (37%) have analyzed more than 20 years (Figure 7) (Magolan and Halls 2020). It is critical to highlight the positive impact of the Landsat Mission (1970 to the present) and the data-free availability since 2008 (Abdel-Hamid *et al*., 2018) which consists of a relevant contribution to analyzing time series using RS approaches (Hemati *et al*., 2021).

Among the analyzed studies, 45 papers (27%) examined a time spanning 10 to 20 years (Alom, Paque, and Maertens 2022). Additionally, 15 studies (9%) investigated imagery covering 5 to 10 years (Tran *et al*., 2019) while 18 studies (11%) analyzed a time frame of one to 5 years (Rapinel *et al*., 2014). Finally, 16 studies (10%) focused on one year or less imagery (Qiu *et al*., 2017) and 11 studies (6%) did not mention the time range and/or the date of the satellite imagery used (Elhag and Boteva 2020). The duration of the time frame analyzed by each study varied, providing valuable insights into changes that occurred over time.

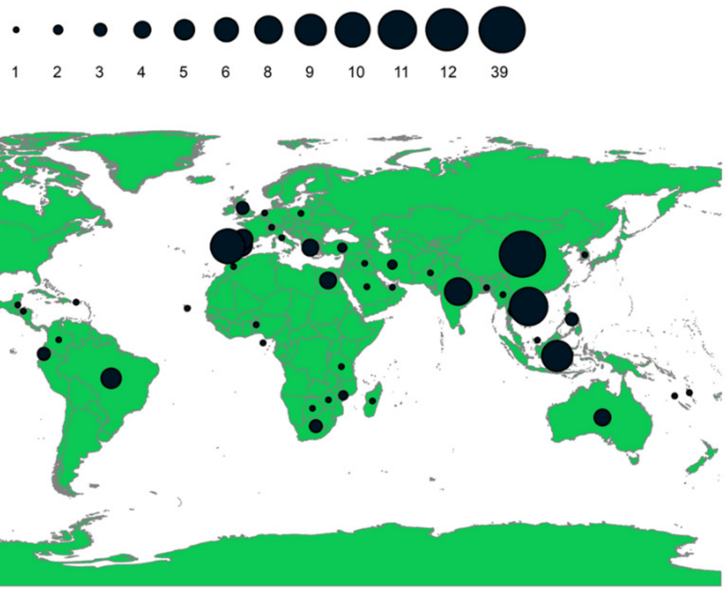

Figure 6. Map of the spatial distribution of study areas at the country level.

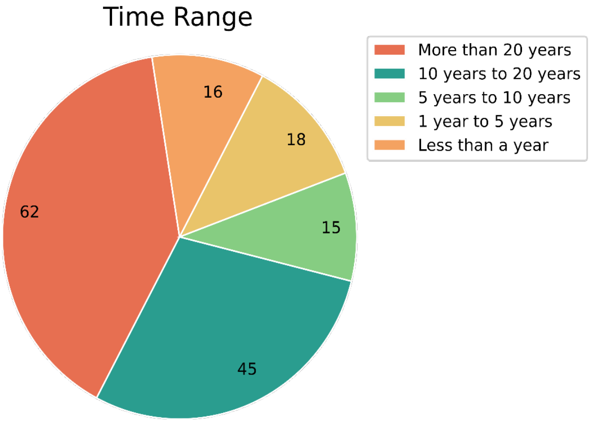

Figure 7. Overview of the time range analyzed in LULC change papers focused on small oceanic islands and/or coastal areas (n=167).

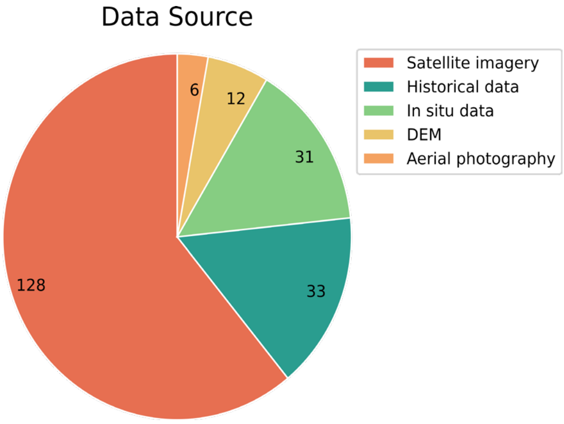

Figure 8. Distribution according to the data source used on the papers analyzed (top 5 highlighted).

3.5 Data Source

Identifying and informing on the availability of data sources used in RS studies focused on LULC change in coastal areas and oceanic islands is essential to assess and compare their effectiveness and reliability.

The most used data source was satellite imagery (Figure 8). This data was applied in 128 studies (77%). This data source includes different data types (e.g., Multispectral, SAR, LiDAR) and sensors (e.g., Landsat 8, Sentinel-2, Worldview-2) which will be described in topics 3.6 and 3.7 of this paper. The historical data was used in 33 studies, representing 20% of the papers analyzed. The historical data consists mainly of land cover datasets (e.g., NOAA C-CAP land cover, Corine land cover) (Ferrarini, Gustin, and Celada 2021; Grybas, Congalton, and Howard 2020). In situ data was applied in 32 papers (19%). This data source consists of field measurements (Zhang *et al.*, 2013; Magolan and Halls 2020; Tran *et al.*, 2019; Muro *et al.*, 2016; Kaiser *et al.*, 2013) and questionnaires to the community or stakeholders (Nong *et al.*, 2021). The Digital Elevation Model (DEM) was used in 12 studies (7%) (Yirsaw *et al.*, 2016; Ballanti *et al.*, 2017; Oliveira *et al.*, 2019; Dang *et al.*, 2020; Eid *et al.*, 2020; Oliveira, Disperati, and Alves 2021). Different DEM types were applied in those studies (e.g., Shuttle Radar Topography Mission (SRTM), Advanced Land Observing Satellite (ALOS), ASTER). The aerial photographs were used in six articles (4%) (Magolan and Halls 2020; Raynolds and Walker 2016; Ballanti *et al.*, 2017; Giza *et al.*, 2021; Berberoğlu *et al.*, 2010; Hamylton and East 2012). This data type was mainly applied to mapping land cover transitions.

3.6 Data Type

The data type consists of a relevant parameter in RS analysis since different types of data have different characteristics, which can affect the results and conclusions of the research. The multispectral data captures information about the reflectance of different wavelengths of light, which can be used to identify and classify different land cover types (Acción, Argüello, and Heras 2021). The radar data can be used for vegetation mapping by measuring the backscatter of radar signals from vegetation. The SAR data was recently made widely available after the Sentinel-1 launch and the open data policy by the European Space Agency (ESA) in 2014. The LiDAR data uses laser pulses to create highly detailed 3D maps of the Earth's surface, which can be used for terrain modeling, vegetation mapping, and other applications (Lopac *et al.*, 2022). The UAVs offer low-cost and swift data collection at a local scale, with the advantage of being fitted with cameras of very high spatial resolution (Elamin and El-Rabbany 2022).

The information on data type used in an RS study can help researchers understand the limitations and strengths of the data and methods used. It can also help other researchers replicate or build upon the study's findings and ensure that the appropriate data processing and analysis techniques are used to extract meaningful information from the data.

The multispectral data was used in 129 articles (77% of the total) (Hua *et al.*, 2017; Magolan and Halls 2020) (Figure 9). There are strong reasons that may have supported this option, namely (1) the straightforward visual interpretation of the data acquired in the visible mode (Pirowski, Szypuła, and Marciak 2022); (2) the large number of multispectral sensors operating over the entire world since the 1970s (Lambin 2001); (3) the vast number of multispectral sensors with open access data. The combined use of multispectral and LiDAR data was used in five articles (3%) (Ballanti *et al*., 2017; Gray *et al*., 2021; Kefalas *et al*., 2018; Hilgendorf *et al*., 2021; Lymburner *et al*., 2020). The combination of multispectral and SAR data occurred in five papers (3%) (Abdel-Hamid *et al*., 2018; Tu *et al*., 2021; Muro *et al*., 2016; Howison *et al*., 2018; Dusseux *et al*., 2014), although only three papers (2%) used SAR data exclusively (Meilianda *et al*., 2019; Chen, Ming, and Menenti 2020; Li *et al*., 2021). Four articles (2%) used other data types of combinations (e.g., Multispectral, LiDAR, and UAV (Gray *et al*., 2021) and Multispectral and UAV (Miranda *et al*., 2020; Bremer *et al*., 2018). Twenty-one papers (13%) did not mention the data type, or the analysis was based on LULC maps and aerial photographs, among others, as mentioned in topic 3.5 of this paper.

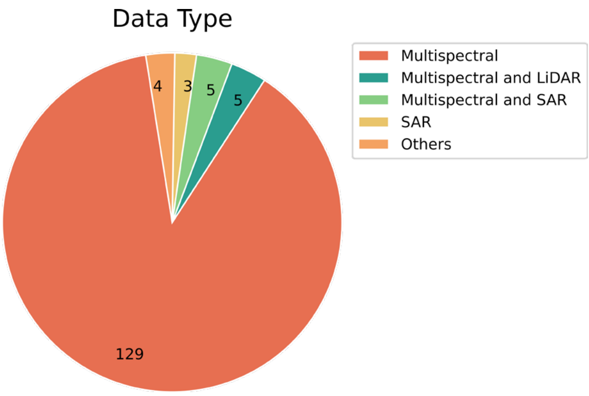

Figure 9. Distribution according to the data type used on the papers analyzed.

3.7 Sensors

The assessment of sensors used in the examined literature reveals a diverse spectrum of instruments and missions. Generally, sensors are classified as active (e.g., LiDAR and SAR) or passive (multispectral). In contrast to active sensors, passive RS sensors do not have their own energy source and do not produce radiation. Furthermore, passive sensors detect solar radiation reflected by items on the Earth's surface, such as vegetation (Kacic and Kuenzer 2022). The radiation being monitored is frequently detected in wavelengths ranging from visible light to shortwave infrared. Furthermore, passive sensors are susceptible to atmospheric factors (e.g., clouds), whereas active sensors emit radiation that is assessed again once an item returns. Active radar sensors in the X-band (2.5 to 3.75 cm wavelength), C-band (5.43 to 5.66 cm wavelength), L-band (20 to 60 cm wavelength), and P-band (60 to 120 cm wavelength) are relatively immune to atmospheric effects. LiDAR sensors, on the other hand, cannot penetrate clouds because they emit green or near-infrared light (Kacic and Kuenzer 2022).

The Landsat 5 data was included in 79 publications (47%) and is the most often used sensor (Figure 10) (Palacio-Aponte 2014; Villarreal *et al*., 2019; Ferreira *et al*., 2012). Landsat 8 was used in 58 publications (35%) (Benítez, Mena, and Zurita-Arthos 2018; Chamberlain, Phinn, and Possingham 2020; Caballero *et al*., 2022), Landsat 7 was used in 47 studies (28%) (Bhanage, Lee 2020; Hafyani *et al*., 2020; Wu *et al*., 2020), Sentinel-2 in 18 publications (11%) (Brown *et al*., 2022; Dang *et al*., 2020; Oliveira, Disperati, and Alves 2021; Davis and Douglass 2021; Nguyen *et al*., 2020; Haris *et al*., 2021), WorldView-2 in 12 papers (7%).

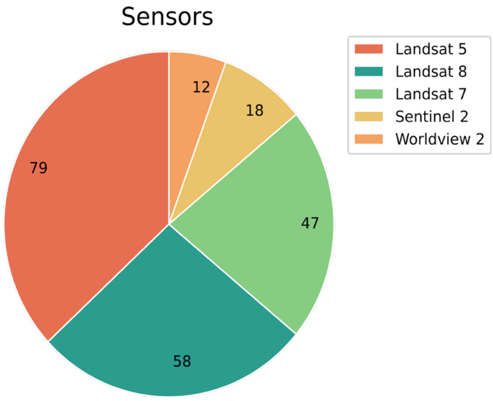

Figure 10. Overview of the different RS sensors used in the reviewed articles (top 5 highlighted).

A strong dominance of multispectral sensors (about 77% of all integrated sensors) is emphasized by the fact that sensors from the Landsat mission contribute to about 54% (91 papers) of the total number of selected articles (n = 167), namely by taking advantage of the continuous time-series from Landsat sensors (1972-onwards), provided by the Landsat archive since 2008 (USGS 2018; Woodcock *et al*., 2008). These datasets acquired from Landsat 1 to Landsat 9 have allowed researchers to study changes in land surface dynamics at a unique temporal scale and medium spatial resolution. Very high spatial resolution RS datasets comprise mainly commercial multispectral sensors, including WorldView-2.

3.8 Remote Sensing-based Approach

The RS-based approach analysis in the evaluated publications reveals a diverse set of methodological approaches employed (225 in total). The Vegetation Indices (VI), especially the Normalized Difference Vegetation Index (NDVI), have been widely used for assessing and monitoring vegetation. NDVI was used in 44 (26%) of the 167 studies analyzed (Figure 11) (Zhao *et al.*, 2022; Ren *et al.*, 2020; Chen *et al.*, 2022; Grybas, Congalton, and Howard 2020). This index uses the red channel information (radiances or reflectances), the most substantial chlorophyll absorption region. In contrast, the near-infrared channel is located in the higher reflectance plateau of vegetation canopies (Gao 1996).

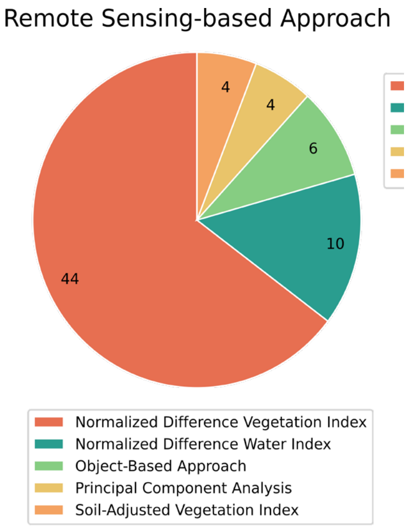

Figure 11. Distribution according to the approach used on the papers analyzed (top 5 highlighted).

The Normalized Difference Water Index (NDWI) is a vegetation index that assesses the leaf water content at the canopy level. This approach was used in 10 papers (6%) (Grybas, Congalton, and Howard 2020; Kefalas *et al.*, 2018; Dang *et al.*, 2021; Chen *et al.*, 2022; Xu *et al.*, 2018; Zhao *et al.*, 2021; Yasir *et al.*, 2020; Davis and Douglass 2021; Abdullah *et al.*, 2019; Xu 2018).

Object-Based Classification (OBC) was applied in six studies (4%) (Xie and Niculescu 2021). The OBC approach uses an image segmentation algorithm to group pixels with similar spectral characteristics into homogeneous image objects, which are then classified individually (Desheng and Xia 2010).

The Principal Component Analysis (PCA) is used for data compression, feature extraction, and image enhancement. PCA is a statistical method that can reduce the dimensionality of datasets without losing important information. It achieves this by creating new uncorrelated variables, called principal components, which are ordered to capture the most variance in the original data (Jolliffe and Cadima 2016; Machidon *et al.*, 2020). The PCA was applied in four studies (2%) of the total (Xu *et al.*, 2019). The Soil-Adjusted Vegetation Index (SAVI) is an RS approach that enables the measurement of vegetation density while reducing the impact of soil background reflectance. Unlike the widely used NDVI, which can be influenced by changes in background reflectance, SAVI incorporates a soil adjustment factor into its formula to provide a more accurate estimate of vegetation density (Huete 1988). This approach was applied in four papers representing 2% of the total.

3.9 Data Processing Algorithms

RS algorithms provide a way to automate the processing and analysis of RS data, allowing researchers to extract information rapidly and accurately about the Earth's surface, such as LULC patterns, vegetation health, water quality, and more. Without algorithms, processing and analyzing RS data would be a time-consuming task that could potentially lose important information (Zhang *et al.*, 2023; Valdivieso-Ros, Alonso-Sarria, and Gomariz-Castillo 2023). Algorithms can help standardize RS data analysis, making comparing data collected by different sensors and at different times easier. This standardization is important for monitoring changes in the Earth's surface over time, such as LULC changes, deforestation, and climate change impacts which is, in general, the focus of this review paper (Zhang *et al.*, 2023; Valdivieso-Ros, Alonso-Sarria, and Gomariz-Castillo 2023).

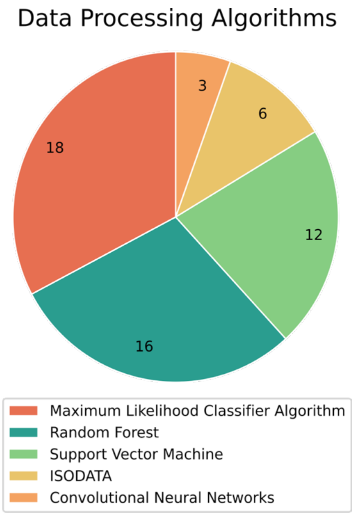

Figure 12. Distribution according to the algorithms used on the papers analyzed (n=167) (top 5 highlighted).

The Maximum Likelihood Classifier Algorithm (MLCA) was applied in 10% of the studies (Figure 12) (Rahman 2016; Dang *et al*., 2021; Nong *et al*., 2021; Rapinel *et al*., 2014). MLCA is based on the statistics for each class in each band and is normally distributed to calculate the probability that a given pixel belongs to a specific class (Ahmad, Quegan, and Quegan 2012).

RF is a statistical algorithm that Breiman first proposed in 2001 (Breiman 2001) to solve classification and regression problems. This algorithm is widely applied in LULC analyses (Gray *et al*., 2021; Tu *et al*., 2021; Dang *et al*., 2020; Abdel-Hamid *et al*., 2018; Peng *et al*., 2021; Chen *et al*., 2022; Zhao *et al*., 2021; Ramjeawon *et al*., 2020; Abdullah *et al*., 2019; Xie and Niculescu 2021) and was used in 16 studies (10%). RF principle consists of combining a large number of regression trees and applying sequentially from the root to the tree's leaves (Bu *et al*., 2022; Breiman 2001).

The SVM is based on statistics normally distributed for each class in each band and computes the likelihood that a given pixel belongs to a specific class (Pal and Mather 2005). The SVM was applied in 12 studies, representing 7% of the analyzed papers (Ballanti *et al*., 2017; Abdel-Hamid *et al*., 2018; Gray *et al*., 2021; Elmahdy, Mohamed, and Ali 2020; Lin *et al*., 2018; Ramjeawon *et al*., 2020; Dang *et al*., 2020; Morgan *et al*., 2022; Miranda *et al*., 2020).

The Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA) was applied in six papers (4%) (Rahman 2016; Sunwoo, Nguyen, and Choi 2018; Ma *et al*., 2019; El-Hattab 2016). This algorithm is one of the most popular variants of the K-means clustering algorithm. In this unsupervised classification, class means are calculated and dispersed evenly throughout the data, and the remaining pixels are iteratively clustered using minimum distance methods (Zhang *et al*., 2021).

Convolutional Neural Networks (CNNs) involve analyzing data collected from satellites or other remote sensors (e.g., UAV). CNNs have shown great promise in various RS applications, such as land use classification, vegetation monitoring, and object detection (Kattenborn, Eichel, and Fassnacht 2019; Guerrero *et al*., 2022). The CNNs were applied in three papers, representing 2% of the total (Gray *et al*., 2021).

3.10 Accuracy Assessment Approach

RS is an instrumental approach for monitoring changes in LULC over time. Nevertheless, the accuracy of the classification method must be assessed to assess whether the reported changes are real or just classification errors (Foody 2002). Comparisons are challenging because the accuracy of LULC categorization methodologies employed in one research may differ from that utilized in another. It is critical to understand the accuracy of the categorization system used when comparing the findings of different investigations (Foody 2002). To standardize the understanding of the different accuracy assessment approaches identified in this literature review process, the quantitative accuracy values resulting from applying different accuracy methods mentioned in the papers analyzed were classified as (1) low agreement; (2) moderate agreement; (3) good agreement, (4) excellent agreement and (5) almost perfect agreement. The parameters to classify the values in these categories were based on the methods' accuracy classification (Shivakumar and Rajashekararadhya 2018; Richards 2013; Okwuashi *et al*., 2012) and synthesized in Table 3.

Table 3. Accuracy assessment approach classification.

Accuracy Method	Low agreement	Moderate agreement	Good agreement	Excellent agreement	Almost perfect agreement
Kappa Index	Below 0.4	0.41 – 0.60	0.61 – 0.75	0.76 – 0.80	0.81 and above
Overall Accuracy User's Accuracy Producer's Accuracy	Below 40%	41% - 60%	61% - 75%	76% - 80%	Above 80%

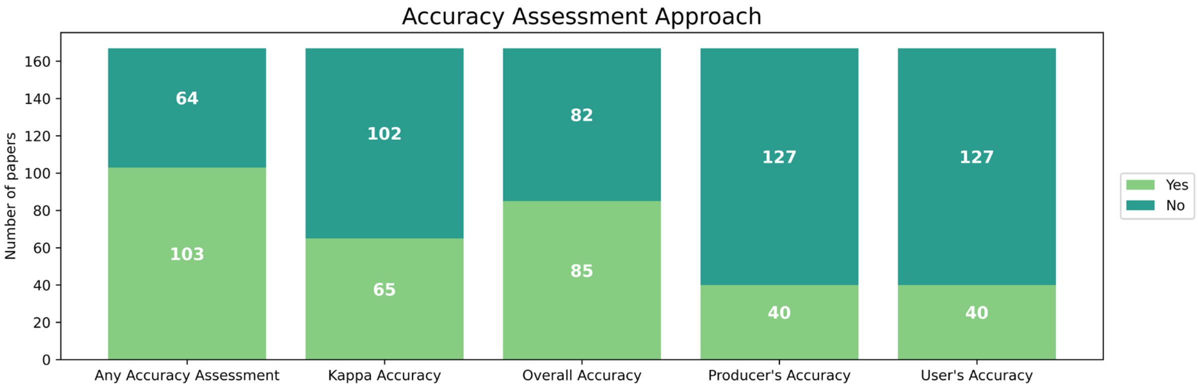

Figure 13. Accuracy assessment approach (n=167).

From the total of papers (n=167), 103 studies (62%) applied an accuracy assessment approach, and 64 papers (38%) did not mention any accuracy assessment approach (Figure 13).

The Kappa Index (KI) was used in 65 studies (39%) (Hafyani *et al.*, 2020; Gevana *et al.*, 2015; Chen *et al.*, 2020; Révillion, Attoumane, and Herbreteau 2019; Zanvo *et al.*, 2021; Ma *et al.*, 2019; Nguyen *et al.*, 2019; Abdullah *et al.*, 2019; Hong, Avtar, and Fujii 2019; Dewi and Bijker 2020; Abijith and Saravanan 2021) (Figure 13). The KI is a statistical measure of the extent to which two or more raters or observers agree in their judgments or evaluations of a given target. The KI considers the agreement expected by chance and provides a value ranging from 0 to 1, with higher values indicating greater agreement (Wang, Hu, and Feng 2022; Cohen 1960). The formula for calculating the KI, also known as Cohen's kappa, is as follows:

$$k = \frac{Po - Pe}{1 - Pe}$$

where Po corresponds to the proportion of observed agreement between raters and Pe to the proportion of expected agreement between raters by chance alone (Cohen 1960). The KI was calculated 94 times on the 65 papers that used this method. From the 94 assessment procedures, the KI showed an almost perfect agreement in 57 (61%), an excellent agreement in 21 (22%), and a good agreement in 12 (13%). Moderate agreement corresponds to 3%, and low agreement to 1% (Figure 14).

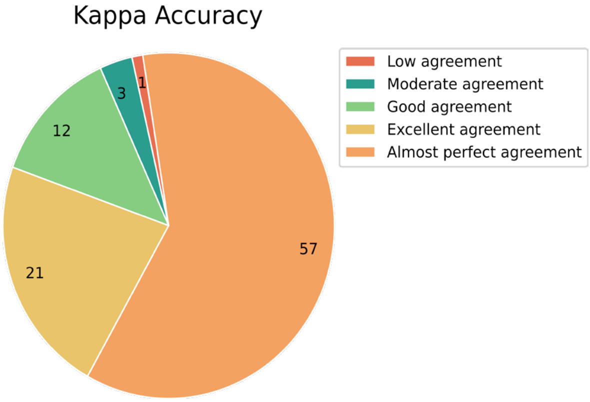

Figure 14. Overview of the Kappa Index accuracy assessment results (n=94).

The total accuracy of a classification model can be evaluated by a metric known as Overall Accuracy (OA), which was used in 85 studies (51%) of the total (Figure 13). The OA expresses the proportion of correctly classified cases out of all cases and is frequently utilized in assessing the performance of LULC classification models, image processing, and RS-based procedures (Congalton 1991). The OA was calculated 129 times on the 85 papers that used this approach. From the 129 assessment procedures, the OA showed an almost perfect agreement in 102 (79%), an excellent agreement in 16 proceedings (12%), and a good agreement in eight of them (6%). Moderate agreements were not identified using OA, and the low agreement corresponds to 2% (Figure 15).

The User's Accuracy (UA) was applied in 40 studies (24%) of the total (Figure 13). The approach measures the accuracy of a classification model that reflects the proportion of correctly classified samples in each class out of the total number of samples classified in that class (Patel and Kaushal 2010). In RS applications, the UA approach is particularly useful in identifying areas of commission errors where a pixel or sample is incorrectly classified as belonging to a certain class. By quantifying the proportion of samples that are incorrectly classified in each class, the UA approach can help improve the accuracy of classification models and reduce the likelihood of errors in decision-making based on the results (Patel and Kaushal 2010). The UA was calculated 54 times on the 40 papers that used this approach. From the 54 assessment procedures, the UA showed an almost perfect agreement in 42 (78%), an excellent agreement in seven procedures (13%), and a good agreement in five of them (9%). Moderate and low agreements were not identified using UA (Figure 16).

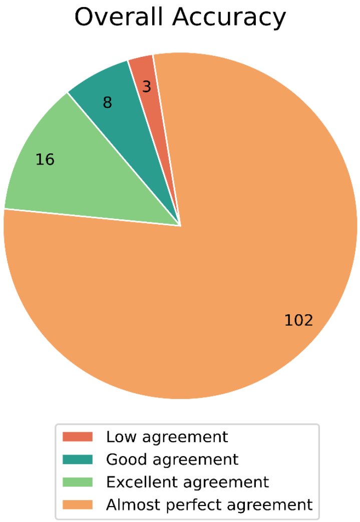

Figure 15. Overview of the Overall Accuracy assessment results (n=129).

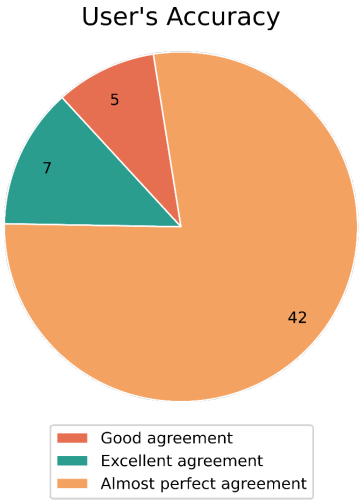

Figure 16. Overview of the User's Accuracy assessment results (n=54).

The Producer's Accuracy (PA) was applied in 40 studies (24%) of the total (Figure 13). The PA is a statistical metric used in RS and image classification that measures the proportion of correctly classified pixels of a specific land cover class in relation to the total number of pixels in that class. The PA approach measures the reliability of a classification algorithm or model in correctly identifying a particular land cover class (Rwanga and Ndambuki 2017; Congalton 1991). The PA was calculated 54 times on the 40 papers that used this approach. From the 54 procedures, the PA showed an almost perfect agreement in 38 (70%), an excellent agreement in nine assessments (17%), and a good agreement in seven of them (13%). Moderate and low agreements were not identified using PA (Figure 17).

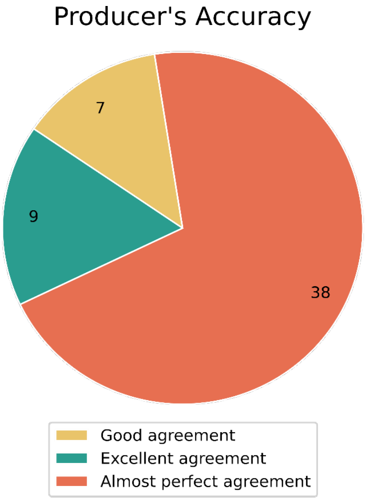

Figure 17. Overview of the Producer's Accuracy assessment results (n=54).

3.11 Spatial Resolution

Spatial resolution is an essential factor in RS-based analysis because it determines the level of detail that can be extracted from an image. The spatial resolution consists of the measurement of an object by a satellite. This measurement occurs on a geographical area on the ground and refers to the size of each pixel in the image or the area on the ground that each pixel represents. Images with higher spatial resolution have smaller pixels and can capture more detailed information about the Earth's surface, while images with lower spatial resolution have larger pixels and provide a more generalized landscape view.

Most of the work analyzed in this research (69%) used data with a resolution of 30 meters (Figure 19), which represents 116 articles (Li *et al.*, 2019; Zhao *et al.*, 2019; Tran, Tran, and Kervyn 2015; Zareie *et al.*, 2016). It is mainly due to Landsat data, which also provides panchromatic data with a spatial resolution of 15 meters, which has been used in 32 articles (19%) (Hernández, Morell, and Armstrong 2022; Pervez *et al.*, 2016; Dewi and Bijker 2020; Elmahdy, Mohamed, and Ali 2020). Twenty-eight articles (17%) used 10 meters of spatial resolution RS data (e.g., Sentinel-1, Sentinel-2) (Tu *et al.*, 2021; Muro *et al.*, 2016). Only 11 papers (7%) used RS data with a very high spatial resolution – 2 meters or higher (e.g., QuickBird 2, WorldView-2) (Vassilakis 2010; Rapinel *et al.*, 2014; Schubert *et al.*, 2019; Lyons, Phinn, and Roelfsema 2011), and eight articles (5%) used data with 20 meters of spatial resolution (Wang *et al.*, 2016; Davis and Douglass 2021; Wang *et al.*, 2016).

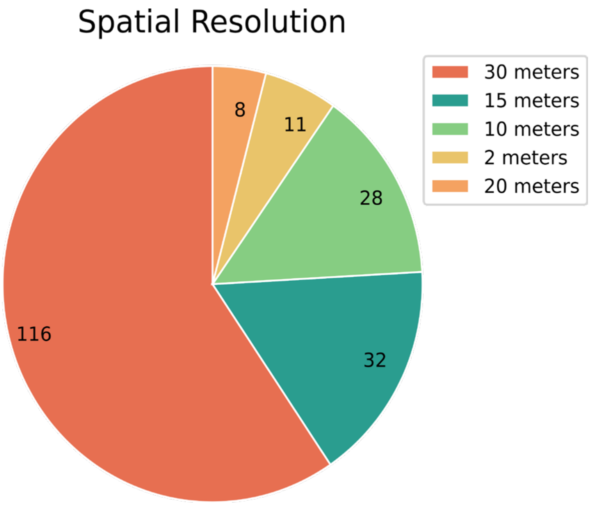

Figure 19. Distribution according to the spatial resolution of the RS data used on the papers analyzed (top 5 highlighted).

4. CONCLUSIONS

This review covered the 167 open-access articles published from January 2010 to June 2022 on remote sensing-based LULC change detection in islands and/or coastal areas. To the best of our knowledge, this is the first review paper focused on this specific and relevant topic. As an overall conclusion, this systematic literature review has revealed several important insights. The number of studies published varied over the years without an apparent pattern or trend, but it was possible to note a considerable increase from 2019 to June 2022. The “Remote Sensing Journal” published most of the studies on this topic and the geographic location of the study areas showed that the continent with more case studies was Asia, with China being the most productive country in this field. The time range parameter showed that most papers analyzed more than 20 years of time span and regarding data sources, satellite imagery was used in most papers analyzed in this review. It is essential to consider the relevance of the historical data (e.g., land cover maps) in this analysis. This data source was mighty used and is relevant because it provides a baseline for understanding changes in LULC over time. By analyzing historical data, we can identify trends and patterns and evaluate the effectiveness of land management practices and policies. The multispectral data were extensively used in the analyzed papers. In contrast to multispectral data, the SAR data was hardly used. The SAR data can penetrate the clouds and measure the canopy trees, which is relevant for small oceanic islands because these areas face intense and recurrent cloud cover scenarios. Therefore, SAR data constitutes a high potential data type for LULC CD in oceanic islands and can be intensively explored in future studies. The most used sensors were from the Landsat Mission. This mission has provided open data acquired over half a century and supports this field’s most robust time series analysis. The NDVI was the most used remote sensing-based methodological. Regarding data processing algorithms, the MLCA and the RF are the ones the research community is putting more effort into. On the other hand, OA is the most applied accuracy assessment approach in this field. Most studies used RS data with 30 meters or higher spatial resolution. As oceanic islands are usually small territories, higher spatial resolution data can better distinguish between different LULC classes and consequently improve change detection. The main constraints identified in the analyzed papers include the non-existence of information in several articles regarding spatial resolution and the cloud coverage percentage of the RS data. Furthermore, most papers do not clarify which RS data preprocessing procedures were developed, namely atmospheric corrections. These parameters are critical and directly impact the accuracy and reliability of the results. They provide essential contextual information for the optimal use and interpretation of RS data, especially in insular contexts where the landscape and environmental conditions can be highly variable and complex, and LULC change can occur rapidly. This literature review has contributed to a deeper understanding of the complex remote sensing-based procedures used to detect LULC changes in coastal and insular areas. The results of this review may have relevant implications in future studies in this field, as they clearly indicate the current leading practices and information gaps in these procedures, allowing for novel approaches to be developed, namely methodological frameworks using multi-sensor data (*e.g.*, SAR, LiDAR, UAV) and Machine Learning-based data processing techniques to improve the accuracy and reliability of LULC change monitoring. These advanced approaches may provide more detailed, updated, and accurate information on LULC change, which is essential for supporting cost-effective decision-making and policy development.

CONTRIBUTION

Rafaela Tiengo: Methodology development, data collection and analysis, and manuscript writing.
Alicia Palácios-Orueta: Review of data analysis, work suggestions, and study advisor.
Jéssica Uchôa: Data collection, review of data analysis, and manuscript writing.
Artur Gil: Review of data analysis, work suggestions, and study advisor.
All authors contributed to the writing (reviewing and editing) of the manuscript.

REFERENCES

Abd El-Hamid, Hazem T. 2020. 'Geospatial Analyses for Assessing the Driving Forces of Land Use/Land Cover Dynamics Around the Nile Delta Branches, Egypt'. Journal of the Indian Society of Remote Sensing 48 (12): 1661–74. https://doi.org/10.1007/s12524-020-01189-2.

Abdel-Hamid, Ayman, Olena Dubovyk, Islam Abou El-Magd, and Gunter Menz. 2018. 'Mapping Mangroves Extents on the Red Sea Coastline in Egypt Using Polarimetric SAR and High Resolution Optical Remote Sensing Data'. Sustainability (Switzerland) 10 (3): 1–22. https://doi.org/10.3390/su10030646.

Abdullah, Abu Yousuf Md, Arif Masrur, Mohammed Sarfaraz Gani Adnan, Md Abdullah Al Baky, Quazi K. Hassan, and Ashraf Dewan. 2019. 'Spatio-Temporal Patterns of Land Use/Land Cover Change in the Heterogeneous Coastal Region of Bangladesh between 1990 and 2017'. Remote Sensing 11 (7). https://doi.org/10.3390/rs11070790.

Abijith, Devanantham, and Subbarayan Saravanan. 2021. 'Assessment of Land Use and Land Cover Change Detection and Prediction Using Remote Sensing and CA Markov in the Northern Coastal Districts of Tamil Nadu, India'. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-021-15782-6.

Acción, Álvaro, Francisco Argüello, and Dora B. Heras. 2021. 'A New Multispectral Data Augmentation Technique Based on Data Imputation'. Remote Sensing 13 (23): 4875. https://doi.org/10.3390/rs13234875.

Ahmad, Asmala, S Quegan, and Shaun Quegan. 2012. 'Analysis of Maximum Likelihood Classification on Multispectral Data'. Applied Mathematical Sciences. Vol. 6. https://www.researchgate.net/publication/279541271.

Allen, M, P Antwi-Agyei, F Aragon-Durand, M Babiker, P Bertoldi, M Bind, S Brown, and M Buckeridge. 2019.

Alom, Ilia, Rose Paque, and Michiel Maertens. 2022. 'History of Land Cover Change on Santa Cruz Island, Galapagos'.

Austin, Kemen G., Amanda Schwantes, Yaofeng Gu, and Prasad S. Kasibhatla. 2019. 'What Causes Deforestation in Indonesia?' Environmental Research Letters 14 (2). https://doi.org/10.1088/1748-9326/aaf6db.

Ballanti, Laurel, Kristin B. Byrd, Isa Woo, and Christopher Ellings. 2017. 'Remote Sensing for Wetland Mapping and Historical Change Detection at the Nisqually River Delta'. Sustainability (Switzerland) 9 (11). https://doi.org/10.3390/su9111919.

Bell, Rose Anne, and J. Nikolaus Callow. 2020. 'Investigating Banksia Coastal Woodland Decline Using Multi-Temporal Remote Sensing and Field-Based Monitoring Techniques'. Remote Sensing 12 (4): 14–16. https://doi.org/10.3390/rs12040669.

Benítez, Fátima L., Carlos F. Mena, and Leo Zurita-Arthos. 2018. 'Urban Land Cover Change in Ecologically Fragile Environments: The Case of the Galapagos Islands'. Land 7 (1). https://doi.org/10.3390/land7010021.

Berberoğlu, S., A. Akin, P. M. Atkinson, and P. J. Curran. 2010. 'Utilizing Image Texture to Detect Land-Cover Change in Mediterranean Coastal Wetlands'. International Journal of Remote Sensing 31 (11): 2793–2815. https://doi.org/10.1080/01431160903111077.

Bhatia, Nitin, and Graeme S. Cumming. 2020. 'Deforestation and Economic Growth Trends on Oceanic Islands Highlight the Need for Meso-Scale Analysis and Improved Mid-Range Theory in Conservation'. Ecology and Society 25 (3): 1–14. https://doi.org/10.5751/ES-11713-250310.

Breiman, Leo. 2001. 'Random Forests'. Machine Learning 45 (1): 5–32. https://doi.org/10.1023/A:1010933404324.

Bremer, Leah L., Lisa Mandle, Clay Trauernicht, Pua'ala Pascua, Heather L. McMillen, Kimberly Burnett, Christopher A. Wada, *et al*., 2018. 'Bringing Multiple Values to the Table: Assessing Future Land-Use and Climate Change in North Kona, Hawai'i'. Ecology and Society 23 (1). https://doi.org/10.5751/ES-09936-230133.

Broich, Mark, Matthew Hansen, Fred Stolle, Peter Potapov, Belinda Arunarwati Margono, and Bernard Adusei. 2011. 'Remotely Sensed Forest Cover Loss Shows High Spatial and Temporal Variation across Sumatera and Kalimantan, Indonesia 2000-2008'. Environmental Research Letters 6 (1). https://doi.org/10.1088/1748-9326/6/1/014010.

Brown, Christopher F, Steven P Brumby, Brookie Guzder-williams, Tanya Birch, Samantha Brooks Hyde, Joseph Mazzariello, Wanda Czerwinski, *et al.*, 2022. 'Dynamic World , Near Real-Time Global 10 m Land Use Land Cover Mapping', 1–17. https://doi.org/10.1038/s41597-022-01307-4.

Bruzzone, Lorenzo, and Francesca Bovolo. 2013. 'A Novel Framework for the Design of Change-Detection Systems for Very-High-Resolution Remote Sensing Images'. Proceedings of the IEEE 101 (3): 609–30. https://doi.org/10.1109/JPROC.2012.2197169.

Bu, Lingxin, Quan Lai, Song Qing, Yuhai Bao, Xinyi Liu, Qin Na, and Yuan Li. 2022. 'Grassland Biomass Inversion Based on a Random Forest Algorithm and Drought Risk Assessment'. Remote Sensing 14 (22): 5745. https://doi.org/10.3390/rs14225745.

Caballero, Isabel, Mar Roca, Juan Santos-echeand, and Patricia Bern. 2022. 'Use of the Sentinel-2 and Landsat-8 Satellites for Water Quality Monitoring : An Early Warning Tool in the Mar Menor Coastal Lagoon'.

Calado, Helena, Ana Braga, Fabiana Moniz, Artur Gil, and Marta Vergílio. 2015. 'Spatial Planning and Resource Use in the Azores'. Mitigation and Adaptation Strategies for Global Change 20 (7): 1079–95. https://doi.org/10.1007/s11027-013-9519-2.

Cardoso, Pedro, François Rigal, Simone Fattorini, Sofia Terzopoulou, and Paulo A.V. Borges. 2013. 'Integrating Landscape Disturbance and Indicator Species in Conservation Studies'. PLoS ONE 8 (5): 1–10. https://doi.org/10.1371/journal.pone.0063294.

Chamberlain, Debbie, Stuart Phinn, and Hugh Possingham. 2020. 'Remote Sensing of Mangroves and Estuarine Communities in Central Queensland, Australia'. Remote Sensing 12 (1). https://doi.org/10.3390/RS12010197.

Chang, Ni-Bin, Min Han, Wei Yao, Liang-Chien Chen, and Shiguo Xu. 2010. 'Land Use and Land Cover Classification with SPOT-5 Images and Partial Lanczos Extreme Learning Machine (PL-ELM)'. Earth Resources and Environmental Remote Sensing/GIS Applications 7831: 783110. https://doi.org/10.1117/12.863827.

Chen, Chao, Huixin Chen, Weimin Liao, Xinxin Sui, Liyan Wang, Jianyu Chen, and Yanli Chu. 2020. 'Dynamic Monitoring and Analysis of Land-Use and Land-Cover Change Using Landsat Multitemporal Data in the Zhoushan Archipelago, China'. IEEE Access 8: 210360–69. https://doi.org/10.1109/ACCESS.2020.3036128.

Chen, Chi Farn, Nguyen Thanh Son, Ni Bin Chang, Cheng Ru Chen, Li Yu Chang, Miguel Valdez, Gustavo Centeno, Carlos Alberto Thompson, and Jorge Luis Aceituno. 2013. 'Multi-Decadal Mangrove Forest Change Detection and Prediction in Honduras, Central America, with Landsat Imagery and a Markov Chain Model'. Remote Sensing 5 (12): 6408–26. https://doi.org/10.3390/rs5126408.

Chen, Dong, Yafei Wang, Zhenyu Shen, Jinfeng Liao, Jiezhi Chen, and Shaobo Sun. 2021. 'Long Time-Series Mapping and Change Detection of Coastal Zone Land Use Based on Google Earth Engine and Multi-Source Data Fusion'. Remote Sensing 14 (1): 1. https://doi.org/10.3390/rs14010001.

Chen, Yu, Zutao Ming, and Massimo Menenti. 2020. 'Change Detection Algorithm for Multioral Remote Sensing Images Based on Adaptive Parameter Estimation'. IEEE Access 8: 106083–96. https://doi.org/10.1109/ACCESS.2020.2993910.

Cohen, Jacob. 1960. 'A Coefficient of Agreement for Nominal Scales'. Educational and Psychological Measurement 20 (1): 37–46. https://doi.org/10.1177/001316446002000104.

Congalton, Russell G. 1991. 'A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data'. Remote Sensing of Environment 37 (1): 35–46. https://doi.org/10.1016/0034-4257(91)90048-B.

Conti, Luis Américo, Carlos Alberto Sampaio de Araújo, and Marília Cunha-Lignon. 2016. 'Spatial Database Modeling for Mangrove Forests Mapping; Example of Two Estuarine Systems in Brazil'. Modeling Earth Systems and Environment 2 (2). https://doi.org/10.1007/s40808-016-0129-3.

Dang, An T.N., Lalit Kumar, Michael Reid, and Ho Nguyen. 2021. 'Remote Sensing Approach for Monitoring Coastal Wetland in the Mekong Delta, Vietnam: Change Trends and Their Driving Forces'. Remote Sensing 13 (17). https://doi.org/10.3390/rs13173359.

Dang, Kinh Bac, Manh Ha Nguyen, Duc Anh Nguyen, Thi Thanh Hai Phan, Tuan Linh Giang, Hoang Hai Pham, Thu Nhung Nguyen, Thi Thuy Van Tran, and Dieu Tien Bui. 2020. 'Coastal Wetland Classification with Deep U-Net Convolutional Networks and Sentinel-2 Imagery: A Case Study at the Tien Yen Estuary of Vietnam'. Remote Sensing 12 (19): 1–26. https://doi.org/10.3390/rs12193270.

Davis, Dylan S., and Kristina Douglass. 2021. 'Remote Sensing Reveals Lasting Legacies of Land-Use by Small-Scale Foraging Communities in the Southwestern Indian Ocean'. Frontiers in Ecology and Evolution 9 (September): 1–14. https://doi.org/10.3389/fevo.2021.689399.

Delevaux, Jade M.S., and Kostantinos A. Stamoulis. 2022. 'Prioritizing Forest Management Actions to Benefit Marine Habitats in Data-Poor Regions'. Conservation Biology 36 (2): 1–12. https://doi.org/10.1111/cobi.13792.

Desheng Liu, and Fan Xia. 2010. 'Assessing Object-Based Classification: Advantages and Limitations'. Remote Sensing Letters 1 (December): 187–94.

Dewi, Ratna Sari, and Wietske Bijker. 2020. 'Dynamics of Shoreline Changes in the Coastal Region of Sayung, Indonesia'. Egyptian Journal of Remote Sensing and Space Science 23 (2): 181–93. https://doi.org/10.1016/j.ejrs.2019.09.001.

Ding, Zhi, Xiaohan Liao, Fenzhen Su, and Dongjie Fu. 2017. 'Mining Coastal Land Use Sequential Pattern and Its Land Use Associations Based on Association Rule Mining'. Remote Sensing 9 (2): 116. https://doi.org/10.3390/rs9020116.

Ding, Zhi, Fenzhen Su, Junjue Zhang, Yu Zhang, Shuchang Luo, and Xuguang Tang. 2019. 'Clustering Coastal Land Use Sequence Patterns along the Sea-Land Direction: A Case Study in the Coastal Zone of Bohai Bay and the Yellow River Delta, China'. Remote Sensing 11 (17). https://doi.org/10.3390/rs11172024.

Du, Peijun, Pei Liu, Junshi Xia, Li Feng, Sicong Liu, Kun Tan, and Liang Cheng. 2014. 'Remote Sensing Image Interpretation for Urban Environment Analysis: Methods, System and Examples'. Remote Sensing 6 (10): 9458–74. https://doi.org/10.3390/rs6109458.

Dusseux, Pauline, Thomas Corpetti, Laurence Hubert-Moy, and Samuel Corgne. 2014. 'Combined Use of Multi-Temporal Optical and Radar Satellite Images for Grassland Monitoring'. Remote Sensing 6 (7): 6163–82. https://doi.org/10.3390/rs6076163.

Elamin, Ahmed, and Ahmed El-Rabbany. 2022. 'UAV-Based Multi-Sensor Data Fusion for Urban Land Cover Mapping Using a Deep Convolutional Neural Network'. Remote Sensing 14 (17): 4298. https://doi.org/10.3390/rs14174298.

Elhag, Mohamed, and Silvena Boteva. 2020. 'Quantitative Analysis of Different Environmental Factor Impacts on Land Cover in Nisos Elafonisos, Crete, Greece'. International Journal of Environmental Research and Public Health 17 (18): 1–17. https://doi.org/10.3390/ijerph17186437.

El-Hamid, Hazem T. Abd, Hoda Nour-Eldin, Nazih Y. Rebouh, and Ahmed M. El-Zeiny. 2022. 'Past and Future Changes of Land Use/ Land Cover and the Potential Impact on Ecosystem Services Value of Damietta Governorate, Egypt'. Land 11 (12): 2169. https://doi.org/10.3390/land11122169.

El-Hattab, Mamdouh M. 2016. 'Applying Post Classification Change Detection Technique to Monitor an Egyptian Coastal Zone (Abu Qir Bay)'. Egyptian Journal of Remote Sensing and Space Science 19 (1): 23–36. https://doi.org/10.1016/j.ejrs.2016.02.002.

Elmahdy, Samy, Mohamed Mohamed, and Tarig Ali. 2020. 'Land Use/ Land Cover Changes Impact on Groundwater Level and Quality in the Northern Part of the United Arab Emirates'. Remote Sensing 12 (11). https://doi.org/10.3390/rs12111715.

Fauzi, Adam, Anjar Sakti, Lissa Yayusman, Agung Harto, Lilik Prasetyo, Bambang Irawan, Muhammad Kamal, and Ketut Wikantika. 2019. 'Contextualizing Mangrove Forest Deforestation in Southeast Asia Using Environmental and Socio-Economic Data Products'. Forests 10 (11): 1–18. https://doi.org/10.3390/f10110952.

Ferrarini, Alessandro, Marco Gustin, and Claudio Celada. 2021. 'Twenty-Three Years of Land-Use Changes Induced Considerable Threats to the Main Wetlands of Sardinia and Sicily (Italy) along the Mediterranean Bird Flyways'. Diversity 13 (6). https://doi.org/10.3390/d13060240.

Ferreira, Maria Adelaide, Francisco Andrade, Ricardo Nogueira Mendes, and José Paula. 2012. 'Use of Satellite Remote Sensing for Coastal Conservation in the Eastern African Coast: Advantages and Shortcomings'. European Journal of Remote Sensing 45 (1): 293–304. https://doi.org/10.5721/EuJRS20124526.

Filipponi, Federico, Emiliana Valentini, Alessandra Nguyen Xuan, Carlos A. Guerra, Florian Wolf, Martin Andrzejak, and Andrea Taramelli. 2018. 'Global MODIS Fraction of Green Vegetation Cover for Monitoring Abrupt and Gradual Vegetation Changes'. Remote Sensing 10 (4). https://doi.org/10.3390/rs10040653.

Foody, Giles M. 2002. 'Status of Land Cover Classification Accuracy Assessment'. Remote Sensing of Environment 80 (1): 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4.

Gameiro, Samuel, Victor Nascimento, Douglas Facco, Giuliana Sfredo, and Jean Ometto. 2022. 'Multitemporal Spatial Analysis of Land Use and Land Cover Changes in the Lower Jaguaribe Hydrographic Sub-Basin, Ceará, Northeast Brazil'. Land 11 (1). https://doi.org/10.3390/land11010103.

Gao, Bo-cai. 1996. 'NDWI—A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water from Space'. Remote Sensing of Environment 58 (3): 257–66. https://doi.org/10.1016/S0034-4257(96)00067-3.

García-Romero, Leví, Antonio I. Hernández-Cordero, Elisabeth Fernández-Cabrera, Carolina Peña-Alonso, Luis Hernández-Calvento, and Emma Pérez-Chacón. 2016. 'Urban-Touristic Impacts on the Aeolian Sedimentary Systems of the Canary Islands: Conflict between Development and Conservation'. Island Studies Journal 11 (1): 91–112. https://doi.org/10.24043/isj.336.

Gevana, Dixon, Leni Camacho, Antonio Carandang, Sofronio Camacho, and Sangjun Im. 2015. 'Land Use Characterization and Change Detection of a Small Mangrove Area in Banacon Island, Bohol, Philippines Using a Maximum Likelihood Classification Method'. Forest Science and Technology 11 (4): 197–205. https://doi.org/10.1080/21580103.2014.996611.

Gil, Artur, Catarina Fonseca, and José Benedicto-Royuela. 2018. 'Land Cover Trade-Offs in Small Oceanic Islands: A Temporal Analysis of Pico Island, Azores'. Land Degradation & Development 29 (2): 349–60. https://doi.org/10.1002/ldr.2770.

Gil, Artur, Catarina Fonseca, Agustín Lobo, and Helena Calado. 2012. 'Linking GMES Space Component to the Development of Land Policies in Outermost Regions - The Azores (Portugal) Case-Study'. European Journal of Remote Sensing 45 (1): 263–81. https://doi.org/10.5721/EuJRS20124524.

Gil, Artur, Qian Yu, Mohamed Abadi, and Helena Calado. 2014. 'Using Aster Multispectral Imagery for Mapping Woody Invasive Species in Pico Da Vara Natural Reserve (Azores Islands, Portugal)'. Revista Árvore 38 (3): 391–401. https://doi.org/10.1590/S0100-67622014000300001.

Giza, Andrzej, Paweł Terefenko, Tomasz Komorowski, and Paweł Czapliński. 2021. 'Determining Long-Term Land Cover Dynamics in the South Baltic Coastal Zone from Historical Aerial Photographs'. Remote Sensing 13 (6): 1–20. https://doi.org/10.3390/rs13061068.

Gray, Patrick Clifton, Diego F. Chamorro, Justin T. Ridge, Hannah Rae Kerner, Emily A. Ury, and David W. Johnston. 2021. ‘Temporally Generalizable Land Cover Classification: A Recurrent Convolutional Neural Network Unveils Major Coastal Change through Time’. Remote Sensing 13 (19). https://doi.org/10.3390/rs13193953.

Grybas, Heather, Russell G. Congalton, and Andrew F. Howard. 2020. ‘Using Geospatial Analysis to Map Forest Change in New Hampshire: 1996-Present’. Journal of Forestry 118 (6): 598–612. https://doi.org/10.1093/jofore/fvaa039.

Guan, Yuwei, Yanru Zhou, Binbin He, Xiangzhuo Liu, Hongguo Zhang, and Shilei Feng. 2020. ‘Improving Land Cover Change Detection and Classification with BRDF Correction and Spatial Feature Extraction Using Landsat Time Series: A Case of Urbanization in Tianjin, China’. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 13: 4166–77. https://doi.org/10.1109/JSTARS.2020.3007562.

Guerrero Tello, José Francisco, Mauro Coltelli, Maria Marsella, Angela Celauro, and José Antonio Palenzuela Baena. 2022. ‘Convolutional Neural Network Algorithms for Semantic Segmentation of Volcanic Ash Plumes Using Visible Camera Imagery’. Remote Sensing 14 (18): 4477. https://doi.org/10.3390/rs14184477.

Guo, Tianci, Tao He, Shunlin Liang, Jean Louis Roujean, Yuyu Zhou, and Xin Huang. 2022. ‘Multi-Decadal Analysis of High-Resolution Albedo Changes Induced by Urbanization over Contrasted Chinese Cities Based on Landsat Data’. Remote Sensing of Environment 269: 112832. https://doi.org/10.1016/j.rse.2021.112832.

Hafyani, Mohammed El, Ali Essahlaoui, Anton Van Rompaey, Meriame Mohajane, Abdellah El Hmaidi, Abdelhadi El Ouali, Fouad Moudden, and Nour Eddine Serrhini. 2020. ‘Assessing Regional Scale Water Balances through Remote Sensing Techniques: A Case Study of Boufakrane River Watershed, Meknes Region, Morocco’. Water (Switzerland) 12 (2). https://doi.org/10.3390/w12020320.

Hamylton, Sarah, and Holly East. 2012. ‘A Geospatial Appraisal of Ecological and Geomorphic Change on Diego Garcia Atoll, Chagos Islands (British Indian Ocean Territory)’. Remote Sensing 4 (11): 3444–61. https://doi.org/10.3390/rs4113444.

Haris, Nurul Afdal, Sandiaga Swahyu Kusuma, Sanjiwana Arjasakusuma, and Pramaditya Wicaksono. 2021. ‘Comparison of Sentinel-2 and Multitemporal Sentinel-1 SAR Imagery for Mapping Aquaculture Pond Distribution in the Coastal Region of Brebes Regency, Central Java, Indonesia’. Geographia Technica, no. Special Issue (September): 128–37. https://doi.org/10.21163/GT_2021.163.10.

Hasan, Sarah, Wenzhong Shi, Xiaolin Zhu, and Sawaid Abbas. 2019. ‘Monitoring of Land Use/Land Cover and Socioeconomic Changes in South China over the Last Three Decades Using Landsat and Nighttime Light Data’. Remote Sensing 11 (14): 1658. https://doi.org/10.3390/rs11141658.

Hemati, Mohammadali, Mahdi Hasanlou, Masoud Mahdianpari, and Fariba Mohammadimanesh. 2021. ‘A Systematic Review of Landsat Data for Change Detection Applications: 50 Years of Monitoring the Earth’. Remote Sensing 13 (15). https://doi.org/10.3390/rs13152869.

Hernández, William J., Julio M. Morell, and Roy A. Armstrong. 2022. ‘Using High-Resolution Satellite Imagery to Assess the Impact of Sargassum Inundation on Coastal Areas’. Remote Sensing Letters 13 (1): 24–34. https://doi.org/10.1080/2150704X.2021.1981558.

Hilgendorf, Zach, M. Colin Marvin, Craig M. Turner, and Ian J. Walker. 2021. ‘Assessing Geomorphic Change in Restored Coastal Dune Ecosystems Using a Multi-Platform Aerial Approach’. Remote Sensing 13 (3): 1–34. https://doi.org/10.3390/rs13030354.

Hong, Huynh Thi Cam, Ram Avtar, and Masahiko Fujii. 2019. ‘Monitoring Changes in Land Use and Distribution of Mangroves in the Southeastern Part of the Mekong River Delta, Vietnam’. Tropical Ecology 60 (4): 552–65. https://doi.org/10.1007/s42965-020-00053-1.

Hou, Wan, and Xiyong Hou. 2019. ‘Data Fusion and Accuracy Analysis of Multi-Source Land Use/Land Cover Datasets along Coastal Areas of the Maritime Silk Road’. ISPRS International Journal of Geo-Information 8 (12). https://doi.org/10.3390/ijgi8120557.

Howison, Ruth A., Theunis Piersma, Rosemarie Kentie, Jos C.E.W. Hooijmeijer, and Han Olff. 2018. ‘Quantifying Landscape-Level Land-Use Intensity Patterns through Radar-Based Remote Sensing’. Journal of Applied Ecology 55 (3): 1276–87. https://doi.org/10.1111/1365-2664.13077.

Hua, Lizhong, Xinxin Zhang, Xi Chen, Kai Yin, and Lina Tang. 2017. ‘A Feature-Based Approach of Decision Tree Classification to Map Time Series Urban Land Use and Land Cover with Landsat 5 TM and Landsat 8 OLI in a Coastal City, China’. ISPRS International Journal of Geo-Information 6 (11): 1–18. https://doi.org/10.3390/ijgi6110331.

Huete, A, K Didan, T Miura, E.P Rodriguez, X Gao, and L.G Ferreira. 2002. ‘Overview of the Radiometric and Biophysical Performance of the MODIS Vegetation Indices’. Remote Sensing of Environment 83 (1–2): 195–213. https://doi.org/10.1016/S0034-4257(02)00096-2.

Huete, A.R. 1988. ‘A Soil-Adjusted Vegetation Index (SAVI)’. Remote Sensing of Environment 25 (3): 295–309. https://doi.org/10.1016/0034-4257(88)90106-X.

Ibarrola-Ulzurrun, Edurne, Javier Marcello, Consuelo Gonzalo-Martín, and José Luis Martín-Esquivel. 2019. ‘Temporal Dynamic Analysis of a Mountain Ecosystem Based on Multi-Source and Multi-Scale Remote Sensing Data’. Ecosphere 10 (6). https://doi.org/10.1002/ecs2.2708.

Jolliffe, Ian T., and Jorge Cadima. 2016. ‘Principal Component Analysis: A Review and Recent Developments’. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 374 (2065): 20150202. https://doi.org/10.1098/rsta.2015.0202.

Kacic, Patrick, and Claudia Kuenzer. 2022. 'Forest Biodiversity Monitoring Based on Remotely Sensed Spectral Diversity—A Review'. Remote Sensing 14 (21): 5363. https://doi.org/10.3390/rs14215363.

Kaiser, G., B. Burkhard, H. Römer, S. Sangkaew, R. Graterol, T. Haitook, H. Sterr, and D. Sakuna-Schwartz. 2013. 'Mapping Tsunami Impacts on Land Cover and Related Ecosystem Service Supply in Phang Nga, Thailand'. Natural Hazards and Earth System Sciences 13 (12): 3095–3111. https://doi.org/10.5194/nhess-13-3095-2013.

Kattenborn, Teja, Jana Eichel, and Fabian Ewald Fassnacht. 2019. 'Convolutional Neural Networks Enable Efficient, Accurate and Fine-Grained Segmentation of Plant Species and Communities from High-Resolution UAV Imagery'. Scientific Reports 9 (1): 17656. https://doi.org/10.1038/s41598-019-53797-9.

Kefalas, George, Konstantinos Poirazidis, Panteleimon Xofis, and Stamatis Kalogirou. 2018. 'Mapping and Understanding the Dynamics of Landscape Changes on Heterogeneous Mediterranean Islands with the Use of OBIA: The Case of Ionian Region, Greece'. Sustainability (Switzerland) 10 (9). https://doi.org/10.3390/su10092986.

Lambin, E.F. 2001. 'Remote Sensing and Geographic Information Systems Analysis'. In International Encyclopedia of the Social & Behavioral Sciences, 13150–55. Elsevier. https://doi.org/10.1016/B0-08-043076-7/04200-5.

Li, Humei, Mingquan Wu, Dinghui Tian, Lianxi Wu, and Zheng Niu. 2019. 'Monitoring and Analysis of the Expansion of the Ajmr Port, Davao City, Philippines Using Multi-Source Remote Sensing Data'. PeerJ 2019 (8): 1–23. https://doi.org/10.7717/peerj.7512.

Li, Peng, Zhenhong Li, Keren Dai, Yasir Al-Husseinawi, Wanpeng Feng, and Houjie Wang. 2021. 'Reconstruction and Evaluation of DEMs from Bistatic Tandem-X SAR in Mountainous and Coastal Areas of China'. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 14: 5152–70. https://doi.org/10.1109/JSTARS.2021.3073782.

Lin, Qingying, Jinyun Guo, Jinfeng Yan, and Wang Heng. 2018. 'Land Use and Landscape Pattern Changes of Weihai, China Based on Object-Oriented SVM Classification from Landsat MSS/TM/OLI Images'. European Journal of Remote Sensing 51 (1): 1036–48. https://doi.org/10.1080/22797254.2018.1534532.

Lira, C., M. Lousada, A. P. Falcão, A. B. Gonçalves, S. Heleno, M. Matias, M. J. Pereira, *et al*., 2013. 'The 20 February 2010 Madeira Island Flash-Floods: VHR Satellite Imagery Processing in Support of Landslide Inventory and Sediment Budget Assessment'. Natural Hazards and Earth System Sciences 13 (3): 709–19. https://doi.org/10.5194/nhess-13-709-2013.

Liu, Manqing, and Deyong Hu. 2019. 'Response of Wetland Evapotranspiration to Land Use/Cover Change and Climate Change in Liaohe River Delta, China'. Water (Switzerland) 11 (5). https://doi.org/10.3390/w11050955.

Lopac, Nikola, Irena Jurdana, Adrian Brnelić, and Tomislav Krljan. 2022. 'Application of Laser Systems for Detection and Ranging in the Modern Road Transportation and Maritime Sector'. Sensors 22 (16): 5946. https://doi.org/10.3390/s22165946.

Lymburner, Leo, Peter Bunting, Richard Lucas, Peter Scarth, Imam Alam, Claire Phillips, Catherine Ticehurst, and Alex Held. 2020. 'Mapping the Multi-Decadal Mangrove Dynamics of the Australian Coastline'. Remote Sensing of Environment 238 (March 2019): 111185. https://doi.org/10.1016/j.rse.2019.05.004.

Lyons, Mitchell, Stuart Phinn, and Chris Roelfsema. 2011. 'Integrating Quickbird Multi-Spectral Satellite and Field Data: Mapping Bathymetry, Seagrass Cover, Seagrass Species and Change in Moreton Bay, Australia in 2004 and 2007'. Remote Sensing 3 (1): 42–64. https://doi.org/10.3390/rs3010042.

Ma, Chunlei, Bin Ai, Jun Zhao, Xiaoping Xu, and Wei Huang. 2019. 'Change Detection of Mangrove Forests in Coastal Guangdong during the Past Three Decades Based on Remote Sensing Data'. Remote Sensing 11 (8): 921. https://doi.org/10.3390/rs11080921.

Machidon, Alina L., Fabio del Frate, Matteo Picchiani, Octavian M. Machidon, and Petre L. Ogrutan. 2020. 'Geometrical Approximated Principal Component Analysis for Hyperspectral Image Analysis'. Remote Sensing 12 (11): 1698. https://doi.org/10.3390/rs12111698.

Magolan, Jessica Lynn, and Joanne Nancie Halls. 2020. 'A Multi-Decadal Investigation of Tidal Creek Wetland Changes, Water Level Rise, and Ghost Forests'. Remote Sensing 12 (7). https://doi.org/10.3390/rs12071141.

Marlier, Miriam E., Ruth S. DeFries, Patrick S. Kim, Shannon N. Koplitz, Daniel J. Jacob, Loretta J. Mickley, and Samuel S. Myers. 2015. 'Fire Emissions and Regional Air Quality Impacts from Fires in Oil Palm, Timber, and Logging Concessions in Indonesia'. Environmental Research Letters 10 (8). https://doi.org/10.1088/1748-9326/10/8/085005.

Matlhodi, Botlhe, Piet K. Kenabatho, Bhagabat P. Parida, and Joyce G. Maphanyane. 2019. 'Evaluating Land Use and Land Cover Change in the Gaborone Dam Catchment, Botswana, from 1984-2015 Using GIS and Remote Sensing'. Sustainability (Switzerland) 11 (19). https://doi.org/10.3390/su11195174.

Mccarthy, Matthew J., Brita Jessen, Michael J. Barry, Marissa Figueroa, Jessica Mcintosh, Tylar Murray, Jill Schmid, and Frank E. Muller-Karger. 2020. 'Automated High-Resolution Time Series Mapping of Mangrove Forests Damaged by Hurricane Irma in Southwest Florida'. Remote Sensing 12 (11). https://doi.org/10.3390/rs12111740.

Meilianda, Ella, Biswajeet Pradhan, Syamsidik, Louise K. Comfort, Dedy Alfian, Romy Juanda, S. Syahreza, and Khairul Munadi. 2019. 'Assessment of Post-Tsunami Disaster Land Use/Land Cover Change and Potential Impact of Future Sea-Level Rise to Low-Lying Coastal Areas: A Case Study of Banda Aceh Coast of Indonesia'. International Journal of Disaster Risk Reduction 41 (August): 101292. https://doi.org/10.1016/j.ijdrr.2019.101292.

Miranda, Vasco, Pedro Pina, Sandra Heleno, Gonçalo Vieira, Carla Mora, and Carlos E.G.R. Schaefer. 2020. 'Monitoring Recent Changes of Vegetation in Fildes Peninsula (King George Island, Antarctica) through Satellite Imagery Guided by UAV Surveys'. Science of the Total Environment 704: 135295. https://doi.org/10.1016/j.scitotenv.2019.135295.

Morgan, Grayson R., Cuizhen Wang, Zhenlong Li, Steven R. Schill, and Daniel R. Morgan. 2022. 'Deep Learning of High-Resolution Aerial Imagery for Coastal Marsh Change Detection: A Comparative Study'. ISPRS International Journal of Geo-Information 11 (2). https://doi.org/10.3390/ijgi11020100.

Mouat, D.A, G.G Mahin, and J Lancaster. 1993. 'Remote Sensing Techniques in the Analysis of Change Detection'. Geocarto International, 39–50.

Muro, Javier, Morton Canty, Knut Conradsen, Christian Hüttich, Allan Aasbjerg Nielsen, Henning Skriver, Florian Remy, Adrian Strauch, Frank Thonfeld, and Gunter Menz. 2016. 'Short-Term Change Detection in Wetlands Using Sentinel-1 Time Series'. Remote Sensing 8 (10): 1–14. https://doi.org/10.3390/rs8100795.

Newman, Rebecca Jo Stormes, Claudia Capitani, Colin Courtney-Mustaphi, Jessica Paula Rose Thorn, Rebecca Kariuki, Charis Enns, and Robert Marchant. 2020. 'Integrating Insights from Social-Ecological Interactions into Sustainable Land Use Change Scenarios for Small Islands in Thewestern Indian Ocean'. Sustainability (Switzerland) 12 (4): 1–22. https://doi.org/10.3390/su12041340.

Nguyen, Giang Cong, Khac Vu Dang, Tuan Anh Vu, Anh Khac Nguyen, and Christiane Weber. 2022. 'Ha Long—Cam Pha Cities Evolution Analysis Utilizing Remote Sensing Data'. Remote Sensing 14 (5): 1–24. https://doi.org/10.3390/rs14051241.

Nguyen, Hai Hoa, Lan Thi Ngoc Tran, An Thanh Le, Nghia Huu Nghia, Linh Vo Khanh Duong, Hien Thi Thu Nguyen, Simone Bohm, and Charles Finny Sathya Premnath. 2020. 'Monitoring Changes in Coastal Mangrove Extents Using Multi-Temporal Satellite Data in Selected Communes, Hai Phong City, Vietnam'. Forest and Society 4 (1): 256–70. https://doi.org/10.24259/fs.v4i1.8486.

Nguyen, Long Duc, Cuong Trong Nguyen, Hoa Sy Le, and Bao Quang Tran. 2019. 'Mangrove Mapping and Above-Ground Biomass Change Detection Using Satellite Images in Coastal Areas of Thai Binh Province, Vietnam'. Forest and Society 3 (2): 248–61. https://doi.org/10.24259/fs.v3i2.7326.

Nong, Duong H., An T. Ngo, Hoa P.T. Nguyen, Thuy T. Nguyen, Lan T. Nguyen, and Summet Saksena. 2021. 'Changes in Coastal Agricultural Land Use in Response to Climate Change: An Assessment Using Satellite Remote Sensing and Household Survey Data in Tien Hai District, Thai Binh Province, Vietnam'. Land 10 (6). https://doi.org/10.3390/land10060627.

Norder, Sietze J., Ricardo F. de Lima, Lea de Nascimento, Jun Y. Lim, José María Fernández-Palacios, Maria M. Romeiras, Rui Bento Elias, *et al*., 2020. 'Global Change in Microcosms: Environmental and Societal Predictors of Land Cover Change on the Atlantic Ocean Islands'. Anthropocene 30. https://doi.org/10.1016/j.ancene.2020.100242.

Okwuashi, Onuwa, Mfon Isong, Etim Eyo, Aniekan Eyoh, Okey Nwanekezie, Dupe Nihinlola Olayinka, Daniel Okon Udoudo, and Beulah Ofem. 2012. 'GIS Cellular Automata Using Artificial Neural Network for Land Use Change Simulation of Lagos, Nigeria'. Journal of Geography and Geology, May. https://doi.org/10.5539/jgg.v4n2p94.

Oliveira, Eduardo R., Leonardo Disperati, and Fátima L. Alves. 2021. A New Method (Minded-Ba) for Automatic Detection of Burned Areas Using Remote Sensing. Remote Sensing. Vol. 13. https://doi.org/10.3390/rs13245164.

Oliveira, Eduardo R., Leonardo Disperati, Luca Cenci, Luísa Gomes Pereira, and Fátima L. Alves. 2019. 'Multi-Index Image Differencing Method (MINDED) for Flood Extent Estimations'. Remote Sensing 11 (11): 1–29. https://doi.org/10.3390/rs11111305.

Palacio-Aponte, Gerardo. 2014. 'Land Cover Modification Geoindicator Applied in a Tropical Coastal Environment'. Revista de Biologia Tropical 62 (3): 1111–28. https://doi.org/10.15517/rbt.v62i3.12215.

Panuju, Dyah R., David J. Paull, and Amy L. Griffin. 2020. 'Change Detection Techniques Based on Multispectral Images for Investigating Land Cover Dynamics'. Remote Sensing 12 (11): 1781. https://doi.org/10.3390/rs12111781.

Patel, Nilanchal, and Brijesh Kaushal. 2010. 'Improvement of User's Accuracy through Classification of Principal Component Images and Stacked Temporal Images'. Geo-Spatial Information Science 13 (4): 243–48. https://doi.org/10.1007/s11806-010-0380-0.

Pelage, Latifa, Gilles Domalain, Alex S. Lira, Paulo Travassos, and Thierry Frédou. 2019. 'Coastal Land Use in Northeast Brazil: Mangrove Coverage Evolution Over Three Decades'. Tropical Conservation Science 12. https://doi.org/10.1177/1940082918822411.

Peng, Jianwei, Shuguang Liu, Weizhi Lu, Maochou Liu, Shuailong Feng, and Pifu Cong. 2021. 'Continuous Change Mapping to Understand Wetland Quantity and Quality Evolution and Driving Forces: A Case Study in the Liao River Estuary from 1986 to 2018'. Remote Sensing 13 (23). https://doi.org/10.3390/rs13234900.

Pervez, Wasim, Vali Uddin, Shoab Ahmad Khan, and Junaid Aziz Khan. 2016. 'Satellite-Based Land Use Mapping: Comparative Analysis of Landsat-8, Advanced Land Imager, and Big Data Hyperion Imagery'. Journal of Applied Remote Sensing 10 (2): 026004. https://doi.org/10.1117/1.jrs.10.026004.

Pirowski, Tomasz, Bartłomiej Szypuła, and Michał Marciak. 2022. 'Interpretation of Multispectral Satellite Data as a Tool for Detecting Archaeological Artifacts (Navkur Plain and Karamleis Plain, Iraq)'. Archaeological and Anthropological Sciences 14 (9): 166. https://doi.org/10.1007/s12520-022-01637-9.

Qiu, Shuangshuang, Wenze Yue, Huan Zhang, and Jiaguo Qi. 2017. 'Island Ecosystem Services Value, Land-Use Change, and the National New Area Policy in Zhoushan Archipelago, China'. Island Studies Journal 12 (2): 177–98. https://doi.org/10.24043/isj.20.

Shivakumar, and Rajashekararadhya. 2018. 'An Investigation on Land Cover Mapping Capability of Classical and Fuzzy Based Maximum Likelihood Classifiers'. International Journal of Engineering & Technology 7 (2): 939. https://doi.org/10.14419/ijet.v7i2.10743.

Radke, R.J., S. Andra, O. Al-Kofahi, and B. Roysam. 2005. 'Image Change Detection Algorithms: A Systematic Survey'. IEEE Transactions on Image Processing 14 (3): 294–307. https://doi.org/10.1109/TIP.2004.838698.

Rahman, Muhammad Tauhidur. 2016. 'Detection of Land Use/Land Cover Changes and Urban Sprawl in Al-Khobar, Saudi Arabia: An Analysis of Multi-Temporal Remote Sensing Data'. ISPRS International Journal of Geo-Information 5 (2). https://doi.org/10.3390/ijgi5020015.

Ramjeawon, Manish, Molla Demlie, Michele L. Toucher, and Susan Janse van Rensburg. 2020. 'Analysis of Three Decades of Land Cover Changes in the Maputaland Coastal Plain, South Africa'. Koedoe 62 (1): 1–12. https://doi.org/10.4102/koedoe.v62i1.1642.

Rapinel, Sébastien, Bernard Clément, Sylvie Magnanon, Vanessa Sellin, and Laurence Hubert-Moy. 2014. 'Identification and Mapping of Natural Vegetation on a Coastal Site Using a Worldview-2 Satellite Image'. Journal of Environmental Management 144: 236–46. https://doi.org/10.1016/j.jenvman.2014.05.027.

Raynolds, Martha K., and Donald A. Walker. 2016. 'Increased Wetness Confounds Landsat-Derived NDVI Trends in the Central Alaska North Slope Region, 1985-2011'. Environmental Research Letters 11 (8). https://doi.org/10.1088/1748-9326/11/8/085004.

Rembold, Felix, Michele Meroni, Ferdinando Urbano, Antoine Royer, Clement Atzberger, Guido Lemoine, Herman Eerens, and Dominique Haesen. 2015. 'Remote Sensing Time Series Analysis for Crop Monitoring with the SPIRITS Software: New Functionalities and Use Examples'. Frontiers in Environmental Science 3 (July). https://doi.org/10.3389/fenvs.2015.00046.

Ren, Zhouqiao, Wanxin Zhan, Qiaobing Yue, and Jianhua He. 2020. 'Prioritizing Agricultural Patches for Reforestation to Improve Connectivity of Habitat Conservation Areas: A Guide to Grain-to-Green Project'. Sustainability (Switzerland) 12 (21): 1–17. https://doi.org/10.3390/su12219128.

Révillion, Christophe, Artadji Attoumane, and Vincent Herbreteau. 2019. 'Homisland-Io: Homogeneous Land Use/Land Cover over the Small Islands of the Indian Ocean'. Data 4 (2): 1–10. https://doi.org/10.3390/data4020082.

Richards, John A. 2013. Remote Sensing Digital Image Analysis. Edited by John A. Richards. 5th, 494p ed. Vol. 978-3-642-30062-2. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-30062-2.

Rietbergen, Simon, Tom Hammond, Chucri Sayegh, Frits Hesselink, and Kieran Mooney. 2007. 'Island Voices-Island Choices Developing Strategies for Living with Rapid Ecosystem Change in Small Islands World Headquarters International Union for Conservation of Nature Ecosystem Management Series No. 6. IUCN. 40pp.

Roy, Parth Sarathi, Reshma M. Ramachandran, Oscar Paul, Praveen K. Thakur, Shirish Ravan, Mukunda Dev Behera, Chandan Sarangi, and Vijay P. Kanawade. 2022. 'Anthropogenic Land Use and Land Cover Changes—A Review on Its Environmental Consequences and Climate Change'. Journal of the Indian Society of Remote Sensing 0123456789. https://doi.org/10.1007/s12524-022-01569-w.

Rwanga, Sophia S., and J. M. Ndambuki. 2017. 'Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS'. International Journal of Geosciences 08 (04): 611–22. https://doi.org/10.4236/ijg.2017.84033.

Saffache, P, and P Angelelli. 2010. 'Integrated Coastal Zone Management in Small Islands: A Comparative Outline of Some Islands of the Lesser Antilles'. Journal of Integrated Coastal Zone Management, 255–79.

Saikia, Lalit, Chandan Mahanta, Abhijit Mukherjee, and Suranjana Bhaswati Borah. 2019. 'Erosion–Deposition and Land Use/Land Cover of the Brahmaputra River in Assam, India'. Journal of Earth System Science 128 (8). https://doi.org/10.1007/s12040-019-1233-3.

Salgueiro, Luis, Javier Marcello, and Verónica Vilaplana. 2021. 'Single-Image Super-Resolution of Sentinel-2 Low Resolution Bands with Residual Dense Convolutional Neural Networks'. Remote Sensing 13 (24): 1–20. https://doi.org/10.3390/rs13245007.

Sanchez, Antonio, Dania Abdul Malak, Anis Guelmami, and Christian Perennou. 2015. 'Development of an Indicator to Monitor Mediterranean Wetlands'. PLoS ONE 10 (3): 1–19. https://doi.org/10.1371/journal.pone.0122694.

Sarkis-Onofre, Rafael, Ferrán Catalá-López, Edoardo Aromataris, and Craig Lockwood. 2021. 'How to Properly Use the PRISMA Statement'. Systematic Reviews 10 (1): 117. https://doi.org/10.1186/s13643-021-01671-z.

Schubert, Henry, Markus Rauchecker, Andrés Caballero Calvo, and Brigitta Schütt. 2019. 'Land Use Changes and Their Perception in the Hinterland of Barranquilla, Colombian Caribbean'. Sustainability (Switzerland) 11 (23): 1–21. https://doi.org/10.3390/su11236729.

Shapiro, Aurélie, Carl Trettin, Helga Küchly, Sadroddin Alavinapanah, and Salomão Bandeira. 2015. 'The Mangroves of the Zambezi Delta: Increase in Extent Observed via Satellite from 1994 to 2013'. Remote Sensing 7 (12): 16504–18. https://doi.org/10.3390/rs71215838.

Singh, Ashbindu. 1989. 'Review Article Digital Change Detection Techniques Using Remotely-Sensed Data'. International Journal of Remote Sensing 10 (6): 989–1003. https://doi.org/10.1080/01431168908903939.

Singh, RG, J Engelbrecht, and J Kemp. 2015. 'Change Detection of Bare Areas in the Xolobeni Region, South Africa Using Landsat NDVI.' South African Journal of Geomatics 4 (2): 138. https://doi.org/10.4314/sajg.v4i2.6.

Sunwoo, Wooyeon, Hoang Hai Nguyen, and Minha Choi. 2018. 'Coastal Wetland Change Detection Using High Spatial Resolution KOMPSAT-2 Imagery'. Terrestrial, Atmospheric and Oceanic Sciences 29 (5): 509–21. https://doi.org/10.3319/TAO.2018.05.18.01.

Swartz, Martha Kirk. 2011. 'The PRISMA Statement: A Guideline for Systematic Reviews and Meta-Analyses'. Journal of Pediatric Health Care 25 (1): 1–2. https://doi.org/10.1016/j.pedhc.2010.09.006.

Tassi, Andrea, and Artur Gil. 2020. 'A Low-Cost Sentinel-2 Data and Rao's Q Diversity Index-Based Application for Detecting, Assessing and Monitoring Coastal Land-Cover/Land-Use Changes at High Spatial Resolution'. Journal of Coastal Research 95 (sp1): 1315–19. https://doi.org/10.2112/SI95-253.1.

Thapa, Pawan. 2022. 'The Relationship between Land Use and Climate Change: A Case Study of Nepal'. In The Nature, Causes, Effects and Mitigation of Climate Change on the Environment. IntechOpen. https://doi.org/10.5772/intechopen.98282.

Tran, Hanh, Thuc Tran, and Matthieu Kervyn. 2015. 'Dynamics of Land Cover/Land Use Changes in the Mekong Delta, 1973-2011: A Remote Sensing Analysis of the Tran Van Thoi District, Ca Mau Province, Vietnam'. Remote Sensing 7 (3): 2899–2925. https://doi.org/10.3390/rs70302899.

Tran, Hoa Thi, James B. Campbell, Randolph H. Wynne, Yang Shao, and Son Viet Phan. 2019. 'Drought and Human Impacts on Land Use and Land Cover Change in a Vietnamese Coastal Area'. Remote Sensing 11 (3): 1–23. https://doi.org/10.3390/rs11030333.

Tu, Ying, Bin Chen, Wei Lang, Tingting Chen, Miao Li, Tao Zhang, and Bing Xu. 2021. 'Uncovering the Nature of Urban Land Use Composition Using Multi-Source Open Big Data with Ensemble Learning'. Remote Sensing 13 (21). https://doi.org/10.3390/rs13214241.

USGS. 2018. 'Free Open Landsat Data Unleashed Power Remote Sensing Decade Ago'. 17 April 2018.

Valdivieso-Ros, Carmen, Francisco Alonso-Sarria, and Francisco Gomariz-Castillo. 2023. 'Effect of the Synergetic Use of Sentinel-1, Sentinel-2, LiDAR and Derived Data in Land Cover Classification of a Semiarid Mediterranean Area Using Machine Learning Algorithms'. Remote Sensing 15 (2): 312. https://doi.org/10.3390/rs15020312.

Vassilakis, Emmanuel. 2010. 'Remote Sensing of Environmental Change in the Antirio Deltaic Fan Region, Western Greece'. Remote Sensing 2 (11): 2547–60. https://doi.org/10.3390/rs2112547.

Villarreal, Miguel L., Sandra L. Haire, Jose M. Iniguez, Citlali Cortés Montaño, and Travis B. Poitras. 2019. 'Distant Neighbors: Recent Wildfire Patterns of the Madrean Sky Islands of Southwestern United States and Northwestern Mexico'. Fire Ecology 15 (1). https://doi.org/10.1186/s42408-018-0012-x.

Wang, De, Bojie Fu, Kangshou Lu, Luxiang Xiao, Yuxin Zhang, and Xiaoming Feng. 2010. 'Multifractal Analysis of Land Use Pattern in Space and Time: A Case Study in the Loess Plateau of China'. Ecological Complexity 7 (4): 487–93. https://doi.org/10.1016/j.ecocom.2009.12.004.

Wang, Hao, Yunfeng Hu, and Zhiming Feng. 2022. 'Fusion and Analysis of Land Use/Cover Datasets Based on Bayesian-Fuzzy Probability Prediction: A Case Study of the Indochina Peninsula'. Remote Sensing 14 (22): 5786. https://doi.org/10.3390/rs14225786.

Wang, Qing, Shaoyun Zhong, Xueyan Li, Chao Zhan, Xin Wang, and Peng Liu. 2016. 'Supratidal Land Use Change and Its Morphodynamic Effects along the Eastern Coast of Laizhou Bay during the Recent 50 Years'. Journal of Coastal Research 2016-Sprin (Special Issue 74): 83–94. https://doi.org/10.2112/SI74-008.1.

Welch, James R., Eduardo S. Brondízio, Scott S. Hetrick, and Carlos E.A. Coimbra. 2013. 'Indigenous Burning as Conservation Practice: Neotropical Savanna Recovery amid Agribusiness Deforestation in Central Brazil'. PLoS ONE 8 (12). https://doi.org/10.1371/journal.pone.0081226.

Wicki, Andreas, and Eberhard Parlow. 2017. 'Multiple Regression Analysis for Unmixing of Surface Temperature Data in an Urban Environment'. Remote Sensing 9 (7). https://doi.org/10.3390/rs9070684.

Woodcock, Curtis E., Richard Allen, Martha Anderson, Alan Belward, Robert Bindschadler, Warren Cohen, Feng Gao, *et al*., 2008. 'Free Access to Landsat Imagery'. Science 320 (5879): 1011–1011. https://doi.org/10.1126/science.320.5879.1011a.

Worrall, Fred, Ian M. Boothroyd, Rosie L. Gardner, Nicholas J.K. Howden, Tim P. Burt, Richard Smith, Lucy Mitchell, Tim Kohler, and Ruth Gregg. 2019. 'The Impact of Peatland Restoration on Local Climate: Restoration of a Cool Humid Island'. Journal of Geophysical Research: Biogeosciences 124 (6): 1696–1713. https://doi.org/10.1029/2019JG005156.

Wu, Qi, Shiqi Miao, Haili Huang, Mao Guo, Lei Zhang, Lin Yang, and Chenghu Zhou. 2022. 'Quantitative Analysis on Coastline Changes of Yangtze River Delta Based on High Spatial Resolution Remote Sensing Images'. Remote Sensing 14 (2). https://doi.org/10.3390/rs14020310.

Wu, Yizhou, Shuai Wang, Jiacheng Yang, Siqin Wu, Heyuan You, and Yue Wang. 2020. 'Impact of Land Use on Coastline Change of Island Cities: A Case of Zhoushan Island, China'. Island Studies Journal 15 (2): 335–52. https://doi.org/10.24043/isj.125.

Xi, Henghui, Wanglai Cui, Li Cai, Mengyuan Chen, and Chenglei Xu. 2021. 'Evaluation and Prediction of Ecosystem Service Value in the Zhoushan Islands Based on LUCC'. Sustainability (Switzerland) 13 (4): 1–13. https://doi.org/10.3390/su13042302.

Xie, Guanyao, and Simona Niculescu. 2021. 'Mapping and Monitoring of Land Cover/Land Use (LCLU) Changes in the Crozon Peninsula (Brittany, France) from 2007 to 2018 by Machine Learning Algorithms (Support Vector Machine, Random Forest, and Convolutional Neural Network) and by Post-Classification c'. Remote Sensing 13 (19). https://doi.org/10.3390/rs13193899.

Xu, Caiyao, Lijie Pu, Ming Zhu, Jianguo Li, Xinjian Chen, Xiaohan Wang, and Xuefeng Xie. 2016. 'Ecological Security and Ecosystem Services in Response to Land Use Change in the Coastal Area of Jiangsu, China'. Sustainability (Switzerland) 8 (8). https://doi.org/10.3390/su8080816.

Xu, Hanqiu, Yifan Wang, Huade Guan, Tingting Shi, and Xisheng Hu. 2019. 'Detecting Ecological Changes with a Remote Sensing Based Ecological Index (RSEI) Produced Time Series and Change Vector Analysis'. Remote Sensing 11 (20): 1–24. https://doi.org/10.3390/rs11202345.

Xu, Nan. 2018. 'Detecting Coastline Change with All Available Landsat Data over 1986-2015: A Case Study for the State of Texas, USA'. Atmosphere 9 (3). https://doi.org/10.3390/atmos9030107.

Xu, Nan, Dongzhen Jia, Lei Ding, and Yan Wu. 2018. 'Continuously Tracking the Annual Changes of the Hengsha and Changxing Islands at the Yangtze River Estuary from 1987 to 2016 Using Landsat Imagery'. Water (Switzerland) 10 (2). https://doi.org/10.3390/w10020171.

Yasir, Muhammad, Hui Sheng, Hong Fan, Shah Nazir, Abdoul Jelil Niang, Md Salauddin, and Sulaiman Khan. 2020. 'Automatic Coastline Extraction and Changes Analysis Using Remote Sensing and GIS Technology'. IEEE Access 8: 180156–70. https://doi.org/10.1109/ACCESS.2020.3027881.

Yirsaw, E., W. Wu, H. Temesgen, and B. Bekele. 2016. 'Effect of Temporal Land Use/Land Cover Changes on Ecosystem Services Value in Coastal Area of China: The Case of Su-Xi-Chang Region'. Applied Ecology and Environmental Research 14 (3): 409–22. https://doi.org/10.15666/aeer/1403_409422.

Yirsaw, Eshetu, Wei Wu, Xiaoping Shi, Habtamu Temesgen, and Belew Bekele. 2017. 'Land Use/Land Cover Change Modeling and the Prediction of Subsequent Changes in Ecosystem Service Values in a Coastal Area of China, the Su-Xi-Chang Region'. Sustainability (Switzerland) 9 (7): 1–17. https://doi.org/10.3390/su9071204.

Zareie, Sajad, Hassan Khosravi, Abouzar Nasiri, and Mostafa Dastorani. 2016. 'Using Landsat Thematic Mapper (TM) Sensor to Detect Change in Land Surface Temperature in Relation to Land Use Change in Yazd, Iran'. Solid Earth 7 (6): 1551–64. https://doi.org/10.5194/se-7-1551-2016.

Zhang, Xiaoping, Delu Pan, Jianyu Chen, Yuanzeng Zhan, and Zhihua Mao. 2013. 'Using Long Time Series of Landsat Data to Monitor Impervious Surface Dynamics: A Case Study in the Zhoushan Islands'. Journal of Applied Remote Sensing 7 (1): 073515. https://doi.org/10.1117/1.jrs.7.073515.

Zhang, Xiaoyuan, Kai Liu, Shudong Wang, Xin Long, and Xueke Li. 2021. 'A Rapid Model (COV_PSDI) for Winter Wheat Mapping in Fallow Rotation Area Using MODIS NDVI Time-Series Satellite Observations: The Case of the Heilonggang Region'. Remote Sensing 13 (23): 4870. https://doi.org/10.3390/rs13234870.

Zhang, Yuzhen, Jingjing Liu, Wenhao Li, and Shunlin Liang. 2023. 'A Proposed Ensemble Feature Selection Method for Estimating Forest Aboveground Biomass from Multiple Satellite Data'. Remote Sensing 15 (4): 1096. https://doi.org/10.3390/rs15041096.

Zhao, Dongmiao, Xuefei Li, Xingtian Wang, Xiang Shen, and Weijun Gao. 2022. 'Applying Digital Twins to Research the Relationship Between Urban Expansion and Vegetation Coverage: A Case Study of Natural Preserve'. Frontiers in Plant Science 13 (February). https://doi.org/10.3389/fpls.2022.840471.

Zhao, Wenzhen, Zenglin Han, Xiaolu Yan, and Jingqiu Zhong. 2019. 'Land Use Management Based on Multi-Scenario Allocation and Trade-Offs of Ecosystem Services in Wafangdian County, Liaoning Province, China'. PeerJ 2019 (9): 1–24. https://doi.org/10.7717/peerj.7673.

Zhao, Yinghui, Ru An, Naixue Xiong, Dongyang Ou, and Congfeng Jiang. 2021. 'Spatio-temporal Land-use/Land-cover Change Dynamics in Coastal Plains in Hangzhou Bay Area, China from 2009 to 2020 Using Google Earth Engine'. Land 10 (11). https://doi.org/10.3390/land10111149.

Zheng, Weiheng, Feng Cai, Shenliang Chen, Jun Zhu, Hongshuai Qi, Shaohua Zhao, and Jianhui Liu. 2020. 'Ecological Suitability of Island Development Based on Ecosystem Services Value, Biocapacity and Ecological Footprint: A Case Study of Pingtan Island, Fujian, China'. Sustainability (Switzerland) 12 (6). https://doi.org/10.3390/su12062553.

Zhu, Bozhong, Yan Bai, Xianqiang He, Xiaoyan Chen, Teng Li, and Fang Gong. 2021. 'Long-Term Changes in the Land–Ocean Ecological Environment in Small Island Countries in the South Pacific: A Fiji Vision'. Remote Sensing 13 (18): 1–24. https://doi.org/10.3390/rs13183740.