EUROPEAN Geographical Studies

Has been issued since 2014.
E-ISSN 2413-7197
2022. 9(1). Issued once a year

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Founder and Editor: Cherkas Global University

Release date 15.09.22.
Format 21 × 29,7/4.

Headset Georgia.

Order № 119.

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European Geographical Studies

2022

Is. 1

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Articles

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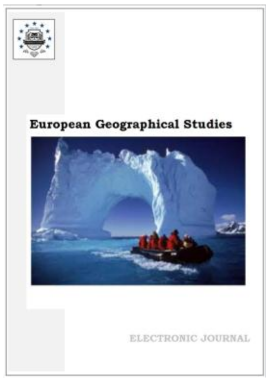
Published in the USA
European Geographical Studies
Has been issued since 2014.
E-ISSN: 2413-7197
2022. 9(1): 3-11

DOI: 10.13187/egs.2022.1.3
https://egs.cherkasgu.press



Articles

Forest Fire Risk Assessment and Mapping Using Support Vector Machine Algorithm, A Case Study in Nghe An Province, Vietnam

Thi Nam Phuong Doan [a, *], Van Trung Nguyen [a], Thi Thanh Hoa Pham [a], Thanh Ha Tran [a], Thi Thu Ha Le [a]

[a] Hanoi University of Mining and Geology, Hanoi, Vietnam

Abstract

In recent years, forest fires have occurred frequently in Vietnam due to the influence of climate change and human activities. This paper presents the results of modeling the risk of forest fires in the west of Nghe An province (north-central Vietnam) from remote sensing and GIS data. 09 factors affect the risk of forest fire, including vegetation cover (NDVI index), soil moisture (NMDI index), elevation, slope, aspect, wind speed, land surface temperature, average monthly precipitation and population density are used to build a model for mapping forest fire risk based on Suppor Vector Machine (SVM) algorithm. The past forest fire data is collected from the database of the Forest Protection Department (Vietnam Ministry of Agriculture and Rural Development) to evaluate the accuracy of the model. Different values of cost parameter (C) are tested to select the value with the highest accuracy in predicting forest fire risk. The results obtained in the study can be used effectively for monitoring and early warning of forest fire risk in the localities, helping to reduce damage caused by forest fires.

Keywords: forest fire risk, remote sensing, GIS, support vector machine algorithm, Nghe An province.

1. Introduction

A forest fire is a complex phenomenon that is difficult to model and manage. There are many factors that contribute to the ignition and spread of forest fires, such as human factors, topographic and meteorological variables. Development of forest fire risk prediction model and classification of forest fire risk is an urgent problem, providing timely information for the protection and development of forest resources. Geospatial technology, including remote sensing technology and geographic information system (GIS), has been widely and effectively used in building forest fire risk prediction models. Remote sensing and GIS allow the collection of data on forest cover for analysis, management, and modeling for early warning of the risk of forest fires.

Jaiswal et al. (2002) used analytical hierarchical method (AHP) to map forest fire risk in the Gorna Subwatershed area (Madhya Pradesh state, India) based on IRS satellite image database and GIS technology. The obtained results show that nearly 30 % of the study area is at "high" to "very

[*] Corresponding author
E-mail addresses: doanthinamphuong@humg.edu.vn (T.N.P. Doan)

high" forest fire risk, consistent with the locations where forest fires occur (Jaiswal et al., 2002). In the study (Wimberly et al., 2008), the authors used multi-temporal Landsat satellite image data to map the severity of forest fires in the southern Appalachians (North Carolina, USA). Normalized Burn Ration Index (NBR) calculated from near-infrared and short-wave infrared bands of Landsat imagery is used to evaluate the land cover change before and after the fire.

Many studies have used artificial intelligence techniques (artificial neural network, random forest, support vector machine) combined with AHP hierarchical analysis method to improve the accuracy of forest fire risk prediction models from remote sensing and GIS data (Vasilakos et al., 2009; Oliveira et al., 2012; Dieu Tien Bui et al., 2016, Dieu Tien Bui et al., 2017). Regression techniques such as multiple regression (Oliveira et al., 2012), logistic regression (Pourghasemi, 2015), geographically weighted regression (GWR) (Fernandez et al., 2012), data mining techniques (Arpaci et al., 2014) are also used to build forest fire risk prediction models based on assessing the relationship between natural-society factors and the possibility of forest fire occurrence.

In Vietnam, several studies have used land surface temperature data calculated from Landsat and MODIS thermal infrared images for early warning of areas with high risk of forest fires (Vuong Van Quynh, 2005; Doan Ha Phong, 2007; Tran Quang Bao et al., 2016). Thermal infrared remote sensing data is also used in the study (Trinh, Zablotskii, 2017) to detect subsurface coal fire in coal mines. Studies (Nguyen Ngoc Thach et al., 2015; Dang Ngo Bao Toan, 2021; Hoang et al., 2020) have also used remote sensing and GIS data for mapping forest fire risk in in different areas in Vietnam based on machine learning techniques. The obtained results show that machine learning techniques allow to classify forest fire risks with higher accuracy than traditional methods using hierarchical analysis technique (AHP). In general, the above studies have demonstrated the effectiveness of remote sensing and GIS technology to develop forest fire risk prediction model for monitoring and minimizing damage caused by forest fires.

2. Materials and methodology

Study area

The study area is located in the west of Nghe An province, in the north-central region of Vietnam, with geographical coordinates from 18°33' to 20°01'N, 103°52' to 105°48'E. This area has a diverse and complex topography, strongly divided by hills, mountains and a system of rivers and streams.

Nghe An has the largest area of forest and forestry land in the country, the forest coverage density in 2020 will reach 58.50 % according to the forest status report in 2020 of the Ministry of Agriculture and Rural Development of Vietnam. Although forest cover is high and tends to increase in recent years, most of the increased forest area in province is planted forest. The natural forest has a marked decrease in both quality and area.

The province is located in the tropical monsoon climate zone, with hot, humid and rainy summers (from May to October) and cold, less rainy winters (from November to April next year). The Feohn wind is most active in the western region of Nghe An province, causing a hot and dry climate, negatively affecting production activities as well as increasing the risk of forest fires.

Materials

In this study, the Sentinel 2 MSI and Landsat 8 multispectral images are used to calculate the land cover, soil moisture and land surface temperature factors. Remote sensing data is collected and processed directly on the Google Earth Engine (GEE) cloud computing platform.

65 Sentinel 2 MSI scenes, including Sentinel 2A and Sentinel 2B images taken from November 15, 2021, to January 16, 2022, are used to create cloudless image, and then calculate the Normalized Difference Vegetation Index (NDVI) and Normalized Multi-band Drought Index (NMDI). 15 Landsat 8 OLI_TIRS multispectral images with path/row of 127/047, 127/046 and 128/046 taken during the period from November 15, 2021, to 16 January 2022 were used to calculate the land surface temperature.

The Landsat 8 and Sentinel 2 MSI images in the western region of Nghe An province used in the study are shown in Figure 2.

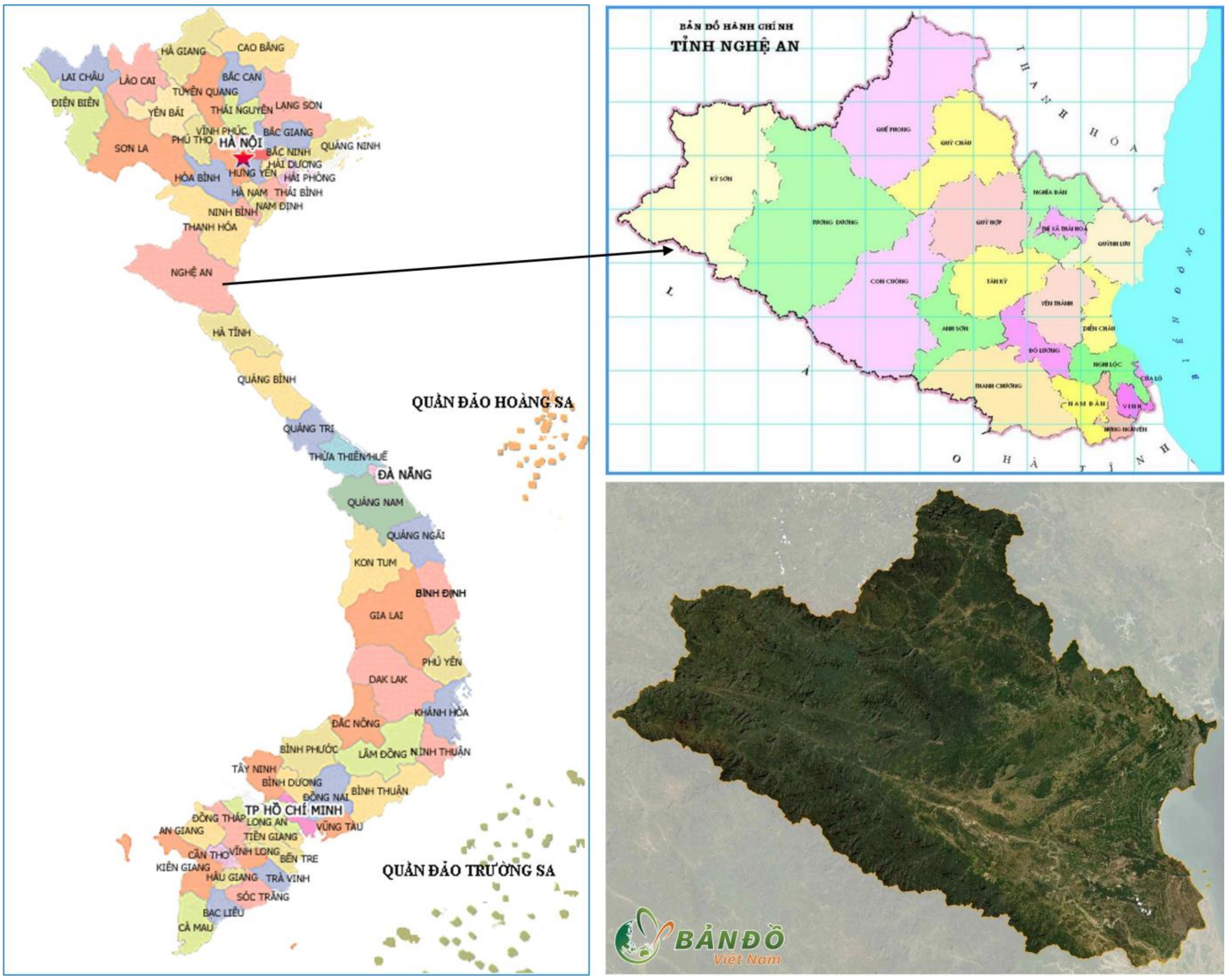


Fig. 1. The study area in the west of Nghe An province, Vietnam

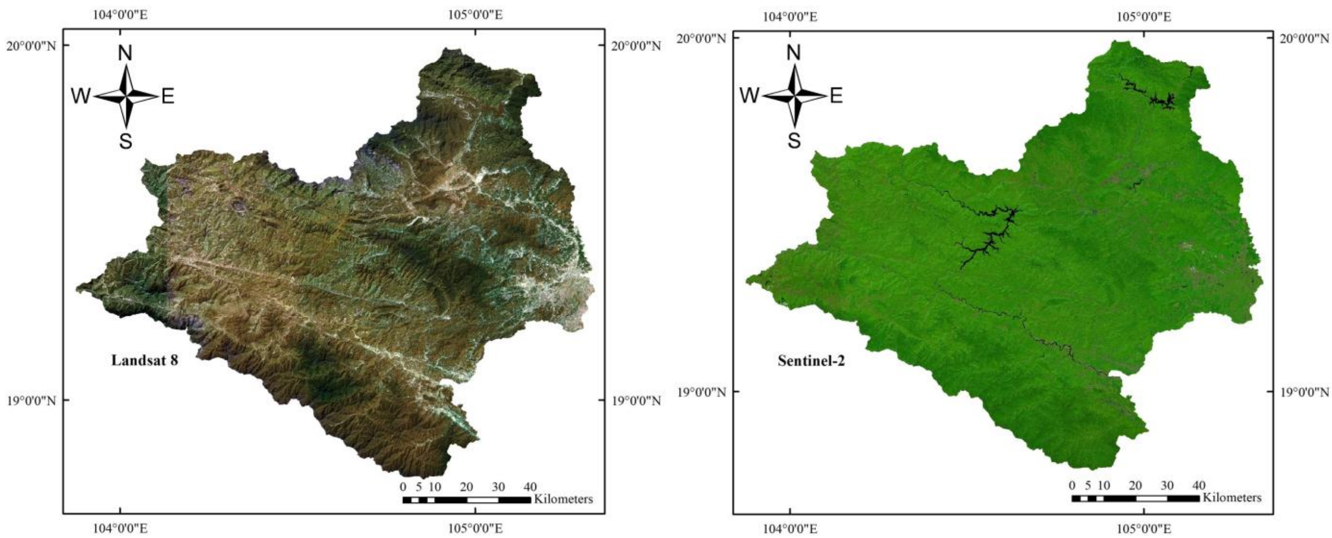


Fig. 2. Sentinel 2 MSI images in Lao Cai and Yen Bai provinces

The Shuttle Radar Topography Mission (SRTM) elevation data with 30 m spatial resolution is collected and processed to build the terrain factors for forest fire risk model, including elevation, aspect and slope.

Population density data is collected from the WorldPop database (Index). Meanwhile, wind speed and average monthly precipitation are collected from the WorldClim database (WorldClim).

Methodology

Based on the natural and social characteristics of the western region of Nghe An province, in this study, 09 factors are used to build the forest fire risk prediction model, including:

+ Population density
+ Vegetation cover (NDVI index)
+ Soil moisture (NMDI index)
+ Aspect
+ Slope
+ Wind speed
+ Elevation
+ Land surface temperature
+ Average monthly precipitation.

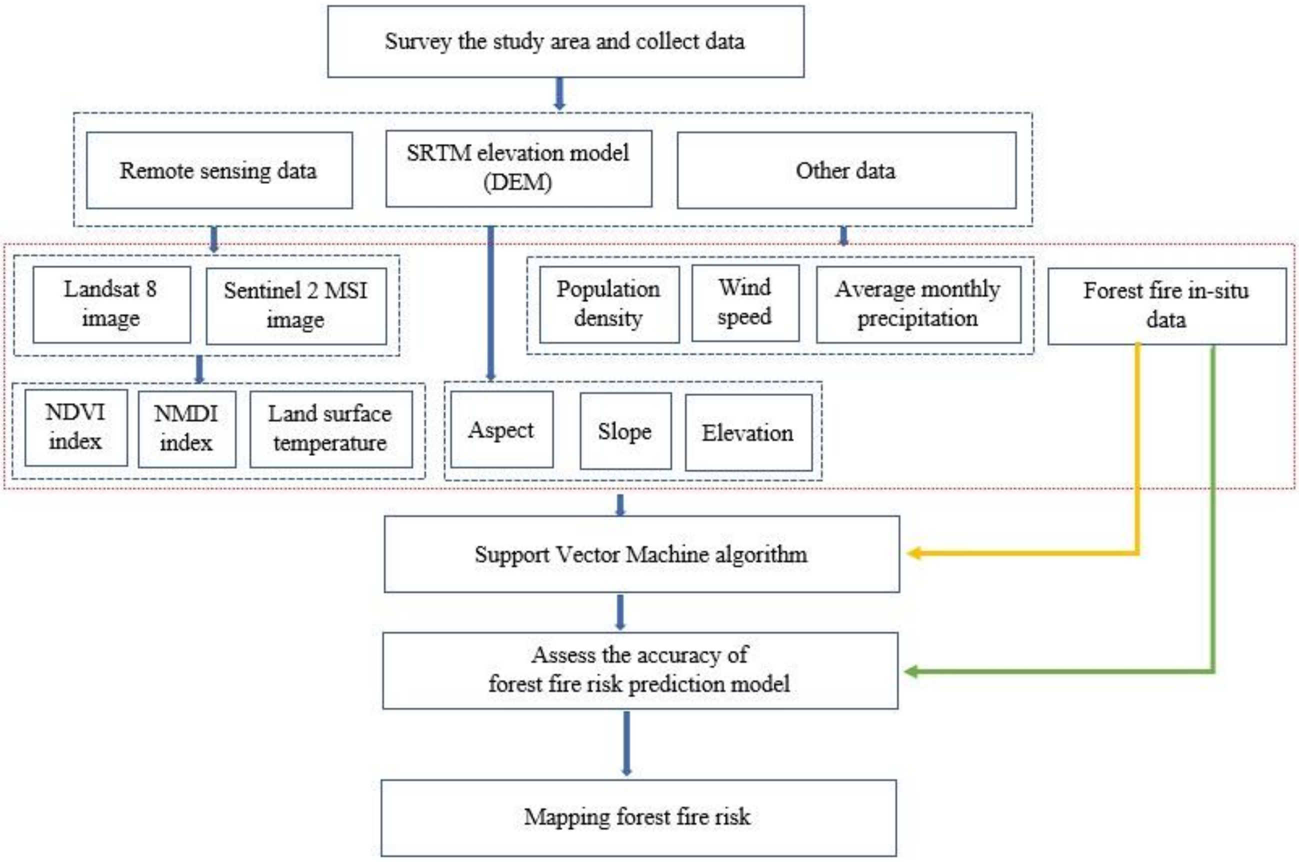


Fig. 3. Flowchart of the methodology for mapping forest fire risk using SVM algorithm from remote sensing and GIS data

The NDVI index is used to represent the vegetation cover factor in the forest fire risk prediction model. NDVI is calculated from the spectral reflectance value in the red and near-infrared channels of the Sentinel 2 MSI image following the equation (Rouse et al., 1973):

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

Where: ρ_{RED} and ρ_{NIR} are reflectance values of red (Band4) and near infrared (Band8) bands of Sentinel 2 MSI image.

In this study, the NMDI moisture index (Wang, Qu, 2007) was used to represent the surface moisture information of the study area. The NMDI index is also determined from optical remote sensing images according to the following formula:

$$NMDI = \frac{R_{860nm} - (R_{1610nm} - R_{2150nm})}{R_{860nm} + (R_{1610nm} - R_{2150nm})} \quad (2)$$

In which, R_{860nm}, R_{1610nm} and R_{2150nm} are spectral reflectances from near-infrared (band 8), short-wave infrared (band 11 and band 12) bands of Sentinel 2 MSI satellite images.

Land surface temperatures were extracted from Landsat 8 thermal infrared remote sensing data using NASA model (Trinh, 2014).

The elevation, slope, and aspect data layers are calculated from the SRTM elevation digital model with a spatial resolution of 30 m. All 9 data layers of the forest fire risk prediction model are interpolated to a spatial resolution of 10m for consistency with Sentinel 2 MSI image data. Finally, the SVM algorithm is used to classify forest fire risk levels from 9 input data layers and forest fire data in the western region of Nghe An province.

The flowchart of the methodology for mapping forest fire risk using SVM algorithm from remote sensing and GIS data is shown in Figure 3.

3. Results and discussion

To build topographic data layers such as slope, elevation, and aspect, the SRTM model with spatial resolution of 30 m was used in this study. The collection and processing are done on the Google Earth Engine (GEE) platform. DEM SRTM data of the study area is presented in Figure 4. The slope, elevation and aspect data layers in the western region of Nghe An province built from the SRTM model are shown in Figure 5.

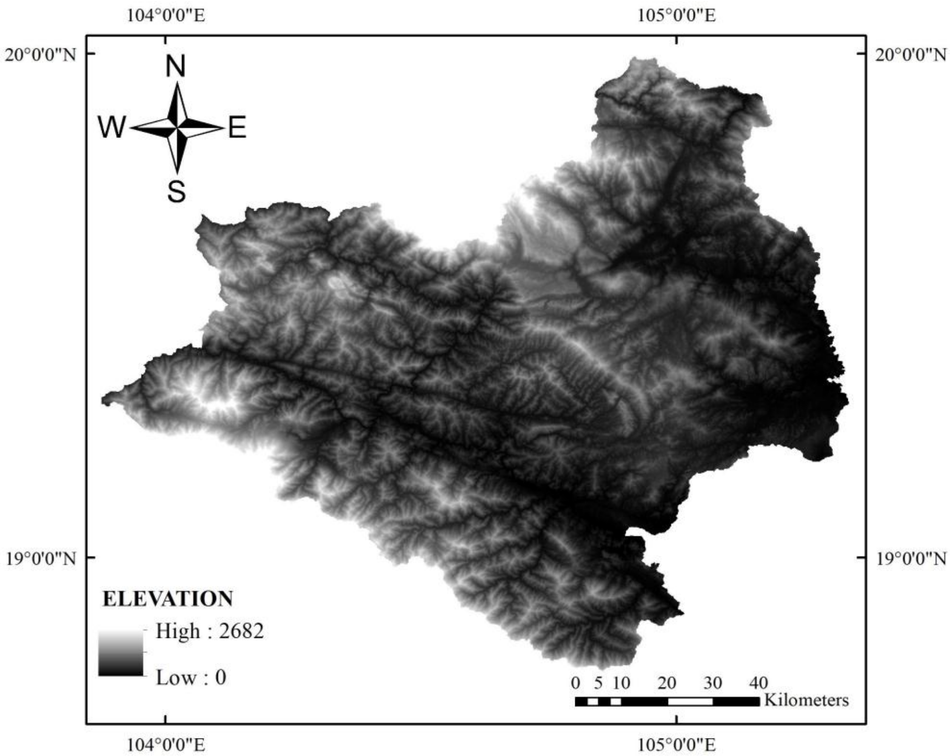


Fig. 4. The SRTM model of study area

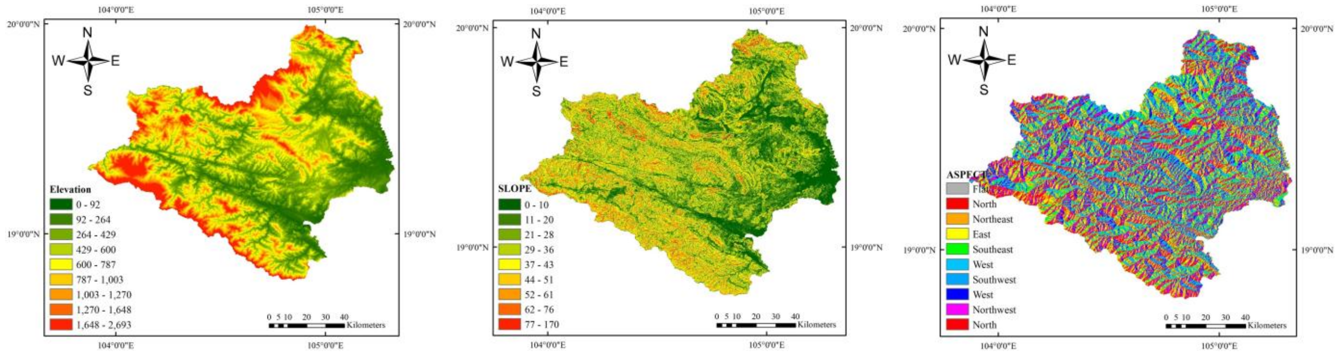


Fig. 5. Elevation, Slope and Aspect data layers for forest fire risk prediction model

Sentinel 2 MSI images after collection and pre-processing were used to calculate the vegetation index NVDI (formula 1) and the drought index NMDI (formula 2). Meanwhile, the Landsat 8 image is used to calculate the land surface temperature according to the NASA model. The results of mapping vegetation cover (NDVI index), soil moisture (NMDI index) and land surface temperature data layers in the western region of Nghe An province from remote sensing data are presented in Figure 6. The surface temperature of the study area ranges from 10,15°C to 35,47°C. Areas with low land surface temperature are concentrated in mountainous areas with dense vegetation cover, while areas with high land surface temperatures are concentrated in residential and bare land. For visualization, in the study, the land surface temperature is divided into 9 ranges: less than 18°C, 18-19°C, 19-20°C, 20-21°C, 21-22°C, 22-23°C, 23-24°C, 24-30°C and greater 30°C (Figure 6). Land surface temperature determined from Landsat 8 image has spatial resolution of 30m, to be consistent with NDVI and NMDI data, in the study the land surface temperature is interpolated to 10 m pixel size.

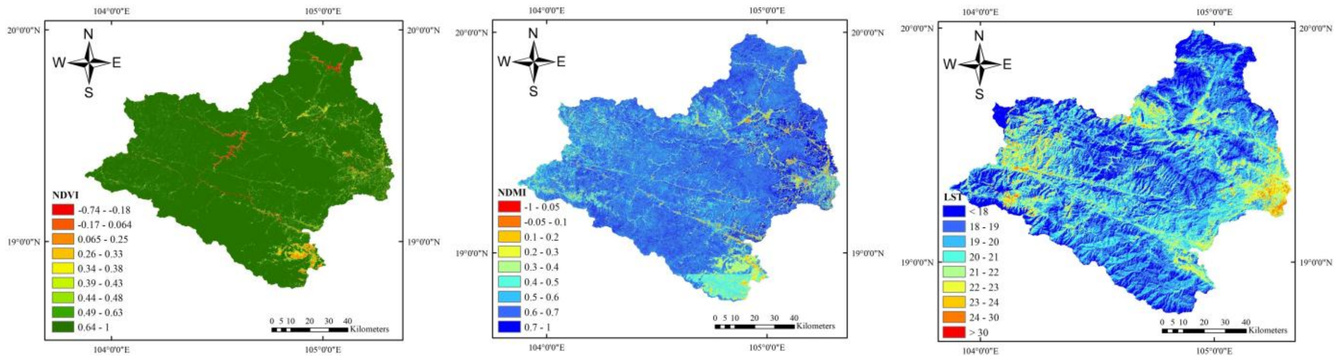


Fig. 6. NDVI, NMDI and Land surface temperature data layers for forest fire risk prediction model

Figure 7 presents the results of building data layers on wind speed, average monthly precipitation and population density in the western region of Nghe An province. Since the resolution of data collected from WorldPop and WorldClime databases is 1000m, to be consistent with other data layers of forest fire risk prediction model, these data layers are interpolated to 10m pixel size.

To evalute the forest fire risk using the SVM algorithm, this study has tested with different values of cost parameter (C). The parameter C tells the SVM algorithm how to balance the two competing objectives which are to maximize the margin between the two classes and to not allow any samples to be misclassified. If C = 0 then the algorithm does not allow any samples to be misclassified. If your data is not linearly separable then the algorithm will not be able to find a separating hyperplane. If C > 0 then the algorithm can trade-off some misclassified samples in-order to find a margin that better separates the remaining points.

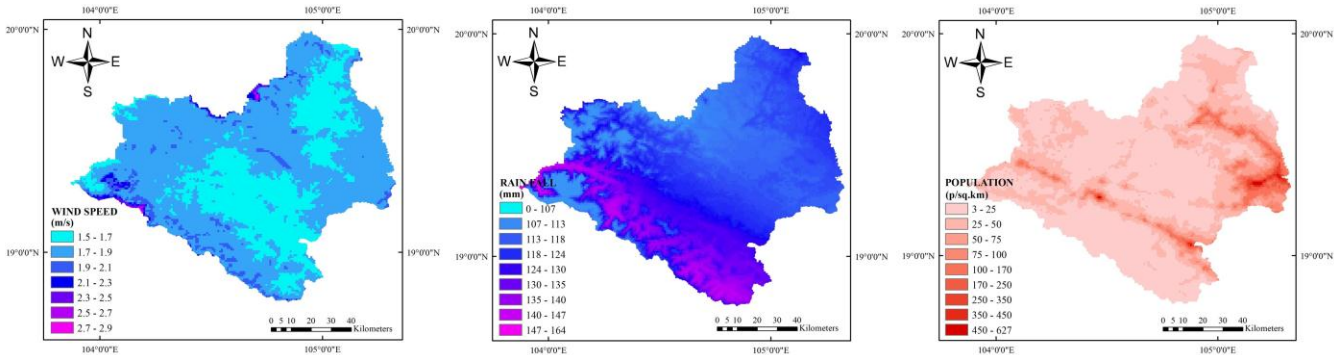


Fig. 7. Wind speed, Average monthly precipitation, and Population density data layers for forest fire risk prediction model

From analyzing the distribution of forest fire data, the parameter C = 25 allows forecasting the risk of forest fire in the study area with the highest accuracy. Out of 36 points where forest fires have occurred, 18/36 fire points are distributed in areas with a «high» level of forest fire risk, 3 points in areas with «very high» level; 4 fire points distributed in the area with «very low» and «low» level. The forest fire hazard zoning map in the western region of Nghe An province based on SVM algorithm is presented in Figure 8, in which the forest fires risk is divided into 5 levels: very high, high, medium, low and very low.

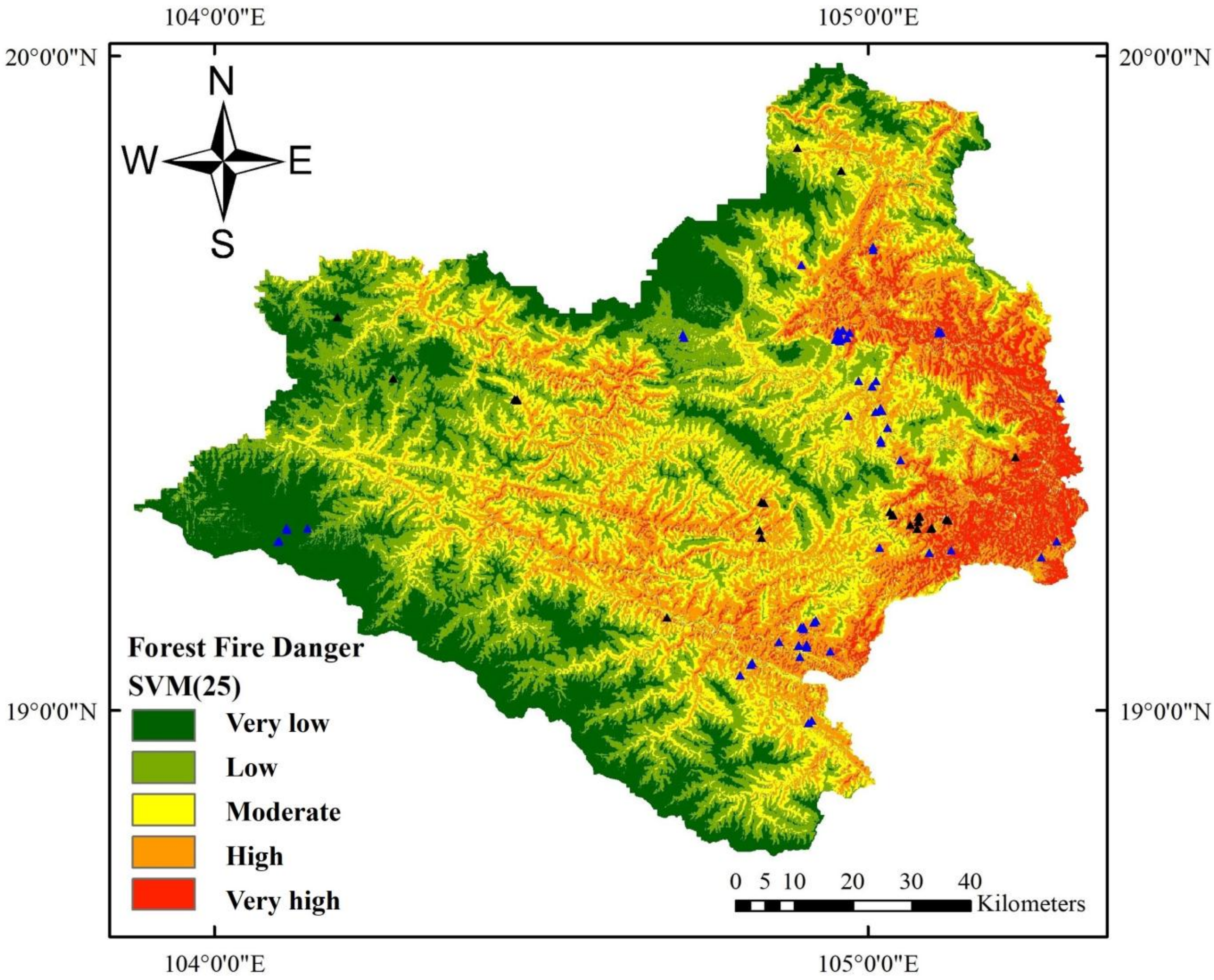


Fig. 8. Result of mapping forest fire risk in the western region of Nghe An province

4. Conclusion

In this study, 09 factors affect the risk of forest fire, including vegetation cover (NDVI index), soil moisture (NMDI index), elevation, slope, aspect, wind speed, land surface temperature, average monthly precipitation and population density are used for mapping forest fire risk based on Suppor Vector Machine (SVM) algorithm. Sentinel 2 MSI and Landsat 8 images data are used to create the vegetation cover, soil moisture and land surface temperature data layer. Topographic data layers, including slope, elevation and aspect are built from the SRTM model with a spatial resolution of 30 m. The population density, average monthly precipitation, and wind speed factors were built from the WorldPop and WorldClim databases. The obtained results show that the SVM algorithm allows forecasting the risk of forest fires with high accuracy. From the analysis of 36 points where fires have occurred in the past, 21/36 points are distributed in areas with a high and very high fire risk level. The results obtained can be used effectively for monitoring and early warning of forest fire risk and helping to reduce damage caused by forest fires.

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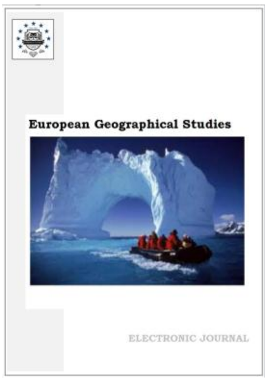
Published in the USA
European Geographical Studies
Has been issued since 2014.
E-ISSN: 2413-7197
2022. 9(1): 12-20

DOI: 10.13187/egs.2022.1.12
https://egs.cherkasgu.press



Shoreline Changes and Their Impacts on Tourism: A Case Study of Sam Son City, Thanh Hoa Province, Vietnam

Kim Dung Le [a], Thi Lan Pham [b, *]

[a] Hong Duc University, Vietnam
[b] Hanoi University of Mining and Geology, Vietnam

Abstract

Sam Son has over 17 kilometers of coastline, making it advantageous for marine tourism and resort tourism. However, various types of research have confirmed that climate change has impacted on tourism activities. The change in shoreline can have a significant impact on tourism infrastructure, as it can alter the accessibility, safety, and attractiveness of coastal destinations. The aim of the paper is to analyze the shoreline change rate over 33 years (1989–2022) and its impacts on tourism in Sam Son. Multi-temporal satellite images were used to extract shorelines, and Digital Shoreline Analysis Systems (DSAS) was used to detect the rate of shoreline change. The results indicated that the shoreline change of Sam Son can be divided two parts, including the Hoi estuary zone and the Do River estuary area. In the Hoi estuary, the erosion rates range from -2.22 m/yr to -40.32 m/yr. Buiding FLC Sam Son for tourism is one of the causes of loss of sedimentation in this area. Additionally, in the Do River estuary, the rate of accretion has significantly increased, reaching to 9.7 m/yr. This phenomenon of sediment accumulation is the foundation for building resorts to serve tourism in Sam Son.

Keywords: shoreline change, tourism, DSAS, and Sam Son.

1. Introduction

Coastal areas are some of the most popular tourist destinations worldwide, attracting millions of visitors every year. However, climate change is causing significant and ongoing changes to coastlines (Duong, 2021), which are having a range of impacts on tourism in these areas. Climate change is also leading to an increase in the frequency and severity of extreme weather events, such as hurricanes, tropical storms, and flooding, which can cause significant property damage and disrupt tourism activities. This can have serious economic consequences for tourism-based communities and small businesses.

Moreover, changing weather patterns and temperatures can also have indirect effects on tourism activities, such as water sports, hiking, and wildlife viewing, which may become less predictable, more difficult to access, or be impacted by changes in wildlife behavior due to changes in the environment.

The sea level rise caused by global warming, and coastal erosion (Zhang et al., 2004) is leading to the loss of shoreline infrastructure. This loss can make it more difficult for visitors to enjoy the beach and can reduce the overall attractiveness of coastal areas as tourist destinations.

* Corresponding author
E-mail addresses: phamthilan@humg.edu.vn (T. Lan Pham)

Additionally, coastal erosion can damage businesses that rely on tourism, such as hotels and restaurants, and can make it harder for them to operate effectively. (Paterson et al., 2010). In the erosion studies, there is a persistent debate regarding the extent to which coastline erosion is influenced by natural versus human factors, including tourism development and urban growth (Nguyen et al., 2020).

Thanh Hoa is a province located in the North Central Coast of Vietnam, and it is home to a well-known seaside resort called Sam Son. The resort is situated approximately 15 km from the provincial capital (Nguyen Xuan Hai, Thanh, 2020). Despiteits popularity as a tourist destination, Sam Son's beach tourism industry is facing major challenges due to unsustainable exploitation and development practices, compounded by the effects of climate change. According to a study by Cong Quan Nguyen and V.H. Pham in 2016, the cumulation rate along the northern and southern coast of Hoi river mouth reaches 5 to 10 m/year, while the erosion at the Hoi estuary is weaker, only about 3-5 m/year (Cong Quan Nguyen, Pham, 2016). The narrowing of Sam Son town's administrative boundaries caused by coastal erosion has resulted in direct impacts on human life, tourism resources, infrastructure, historical and cultural relics, seasonality, and all tourism activities in the area (Nguyen Xuan Hai, Thanh, 2020).

This study addresses the current status of coastal erosion and accretion for the beaches of Sam Son, which were selected for their popularity as tourist destinations and the likelihood of significant anthropogenic influence on shoreline change. The shoreline changes were detected using Landsat images. Remote sensing techniques for shoreline detection include extracting the ratio Green/Near Infrared (Lan et al., 2013), Histogram thresholding on band 5 (Alesheikh et al., 2007), and NDWI (Kuleli et al., 2011). In this paper, the NDWI was used to extract shorelines, and continuing coastal erosion and accretion rates were calculated using the Digital Shoreline Analysis System (DSAS) (Baig et al., 2020).

2. Study area

Sam Son City is a coastal city situatedin Thanh Hoa province, located in the North Central Coast region of Vietnam (Figure 1). It is located approximately 16 kilometers from the center of Thanh Hoa City and 170 kilometers from Hanoi, the capital city of Vietnam. Sam Son City is well-known for its beautiful beaches, which attract many tourists from both Vietnam and other countries. Sam Son has several attractions, including Truong Le Mountain, which offers a beautiful panoramic view of the city and surrounding areas. Additionally, there is Hon Trong Mai and Doc Cuoc Temple, both of which are situated at the top of Doc Cuoc Mountain.

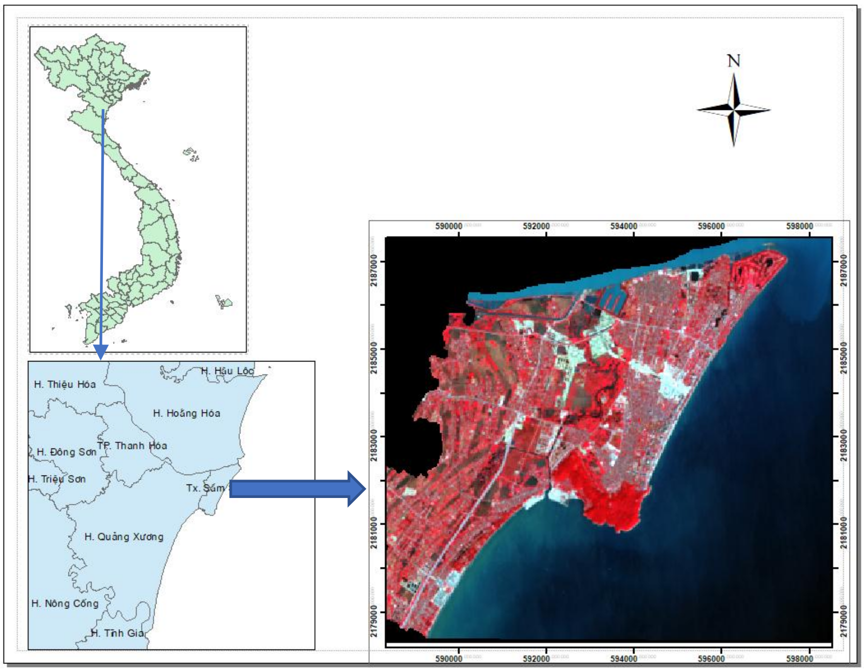


Fig. 1. Study area

The shoreline of Sam Son Cityhas experienced significant changes in recent years due to natural and human-induced factors. Coastal erosion, sea level rise, land subsidence, as well as human activities like sand mining and coastal development have all contributed to alterations in the shoreline. The loss of beach area and changes to the shoreline can significantly impact tourism in Sam Son City since the area's beaches are a major attraction for tourists. Furthermore, coastal erosion can cause damage to infrastructure and properties along the coast, resulting in economic losses.

In conclusion, shoreline change in Sam Son City is a complex issue that requires a multifaceted approach to address. It is crucial to monitor the the shoreline continually and implement appropriate measures to ensure the long-term sustainability of the coastal environment and the local economy.

3. Materials and methods

Multi-temporal Landsat satellite data were downloaded from the USGS website (https://earth explorer.usgs.gov/) for 1989, 2001, 2013 and 2022. The satellite images that have been downloaded are in UTM projection, specifically in zone 48N and using the WGS 84 datum. The details of the satellite data used and its details are shown in Table 1.

Table 1. Landsat image list (L7 – Landsat 7 ETM+; L8 – Landsat 8; L5 – Landsat 5 TM)

Sensor	Acquisition date	Tidal level (m)
L8	20221017	3.21
L8	20131227	3.01
L5	20010929	2.61
L5	19891123	2.5

To analyze the shoreline change along the coastal tract of Sam Son, a process has been followed as given in Figure 1. The shorelines were extracted from Landsat in 1989, 2001, 2013 and 2022. The multi-date shoreline was also given as input in Digital Shoreline Analysis System (DSAS) tool to calculate the shoreline change statistics.

3.1. Shoreline extraction

Shoreline extraction using satellite images is a process that involves separating land and water bodies. One of the indicators that is sensitive to changes in water content and can be used to detect water-related objects is the normalized difference water index (NDWI), which is derived from the near-infrared (NIR) and short-wave infrared (SWIR) channels of remote sensing data (Gao, 1996). The NDWI can also be derived from NIR and green channels in remote sensing data (McFeeters, 2007). The NDWI is considered one of the most commonly utilized water indices for extracting shorelines (Liu et al., 2017). In this study, the NDWI value was derived by Gao (1996) for Equation 1.

$$NDWI = \frac{NIR-SWIR}{NIR+SWIR} \quad (1)$$

Where NIR is the near-infrared band of Landsat; SWIR is the short-wave infrared channel of Landsat.

Multi-temporal satellite imageries areíused to extract shoreline data through online visual digitization in vector format using ArcGIS10.1. Shorelines are manually and individually digitized from each satellite image for the purpose of extraction. The shorelines were added to a personal geodatabase with following five attributes: ObjectID, Shape, Shape_Length, Date_, and Uncertainty. The shorelines extracted at different times were combined into a single feature in the attribute table, resulting in a single shapefile.

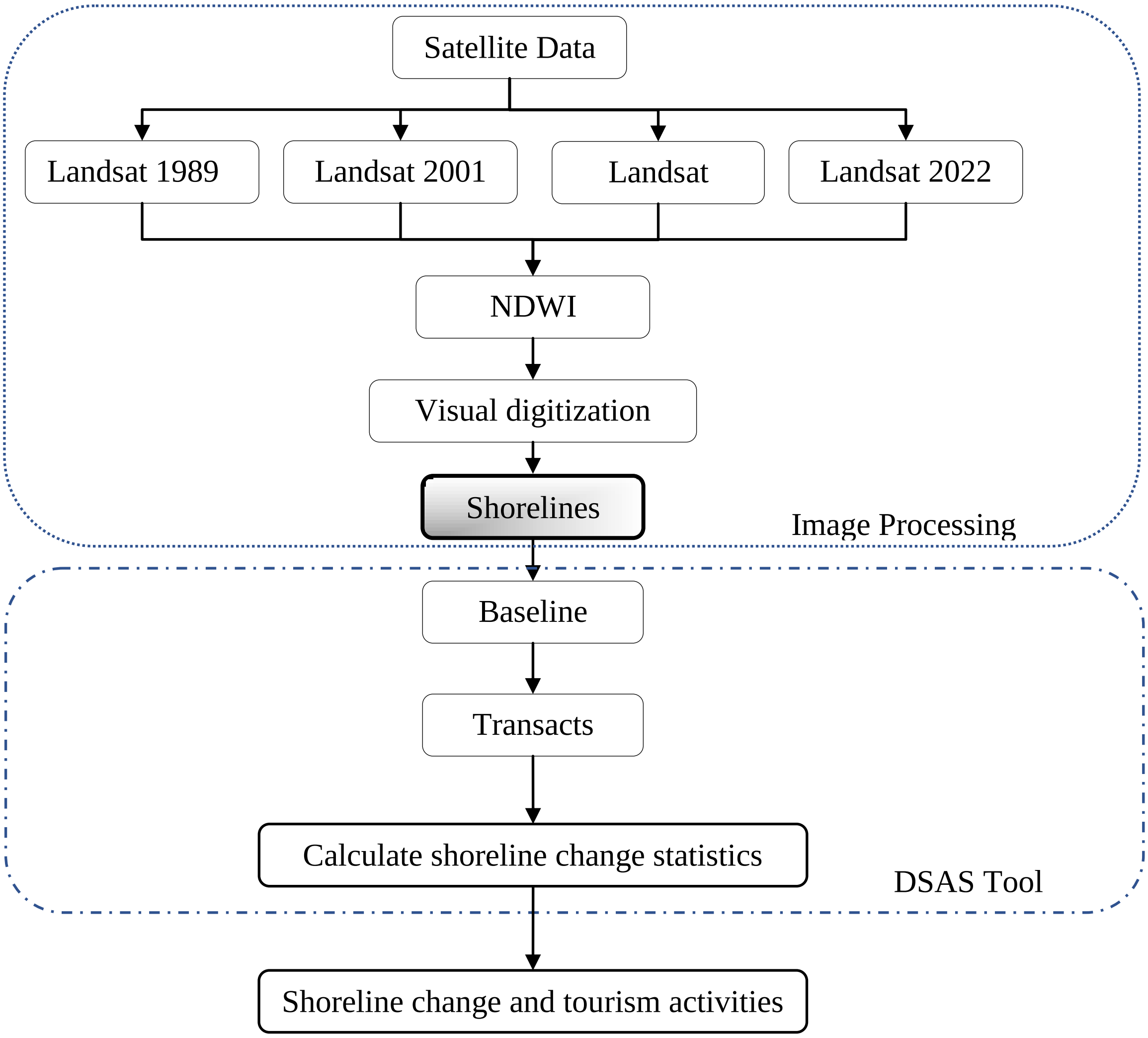


Fig. 1. Flow chart of the methodology

3.2. Shoreline change

In this study, the DSAS tool was used to estimate shoreline change. The changes to the shoreline were determined by incorporating the shoreline positions referenced to the established baseline. The variation in the coastline was determined by the intersections of transects oriented perpendicular to the shoreline (Kuleli et al., 2011). It is essential to establish the baseline adjacent to the series of shoreline positions. Transects should be cast perpendicular to this baseline at a spacing defined by the user to intersect the shorelines and establish measurement points. The position of the baseline plays a significant role in determining the orientation of the transect through the shorelines.

In this study, 521 transverse transects, each 1700 meters long and perpendicular to the offshore baseline, were generated at 50-meter intervals along the coastline (Figure 2). The DSAS methodology was used to evaluate the erosion and accretion rates of shoreline positions by utilizing the end point rate (EPR) and linear regression (LRR) techniques. To determine the end point rate (EPR), the distance of shoreline movement is divided by the time elapsed between the oldest and most recent shoreline positions. The LRR approach has encountered issues when fitting a least squares regression line to all shoreline points along a specific transect to determine the slope of the line, which represents the rate of shoreline change. The LRR method assumes a linear trend between the earliest and latest shoreline dates to calculate the rate of shoreline change. The metadata files for long- and short-term transects contain information about the two fields associated with the linear regression rate calculation. Instead of a single shoreline point, the LRR method involves fitting a least squares regression line to multiple shoreline position points for a particular transect (Figure 3).

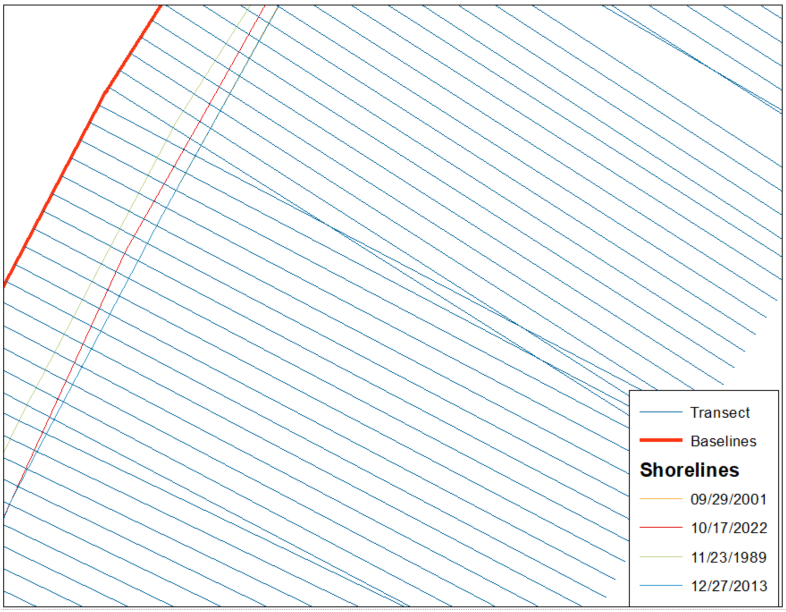


Fig. 2. Launching of transects from the baseline parallel to the shoreline vectors

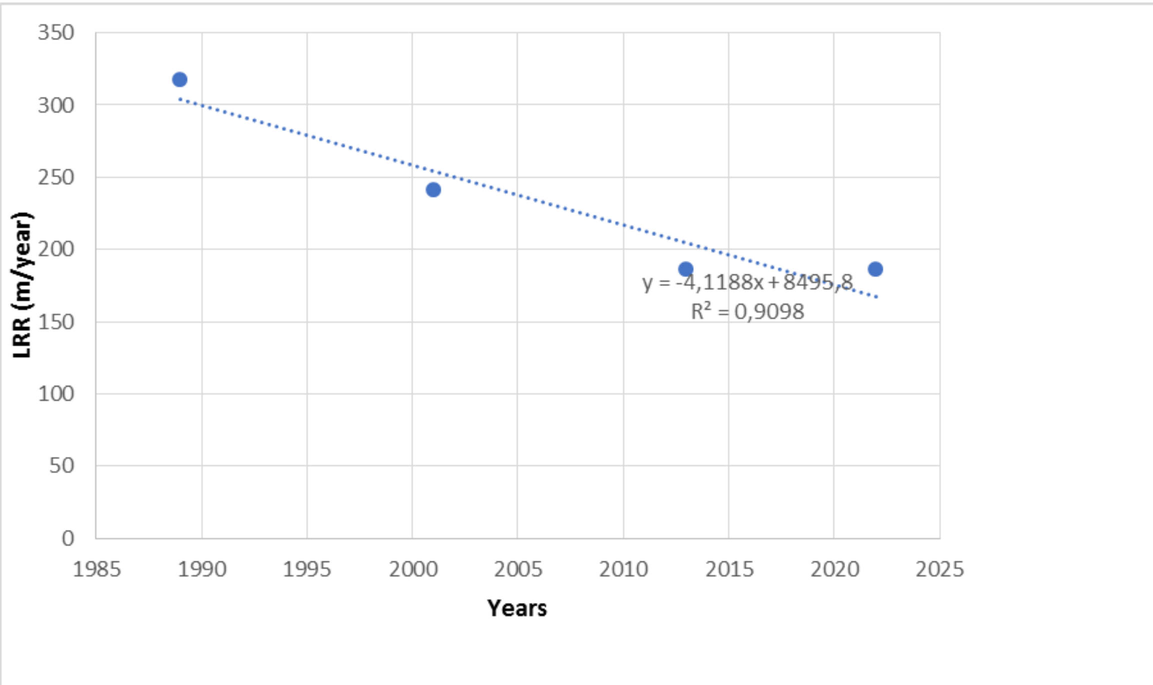


Fig. 3. Representation of a typical cross-plot showing LRR for shoreline change in Sam Son City

4. Results and discussion

4.1. Shoreline state

The geomorphological features of the coastline play a crucial role in detecting beach conditions, specifically those related to coastal erosion. The shoreline is a dynamic system that responds quickly and continuously evolves, with trends monitored through mapping on various dates through data collection in the field or satellite imaging (Mendonça et al., 2020). The rate of shoreline change for Sam Son has been analyzed using the LRR method. The study shows that Sam Son experienced both erosion and accretion. The rate over 521 transects, erosion rates ranged from

-0.77 m/year to -40.32 m/year, while the accretion rate along the coast ranged from 0.68 m/year to 9.7 m/year. Moreover, the LRR indicates that stable and insignificantly changing shoreline areas are concentrated in the Trung Son, Bac Son, Truong Son, Quang Vinh, Quang Hung, and Quang Dai regions (Figure 4).

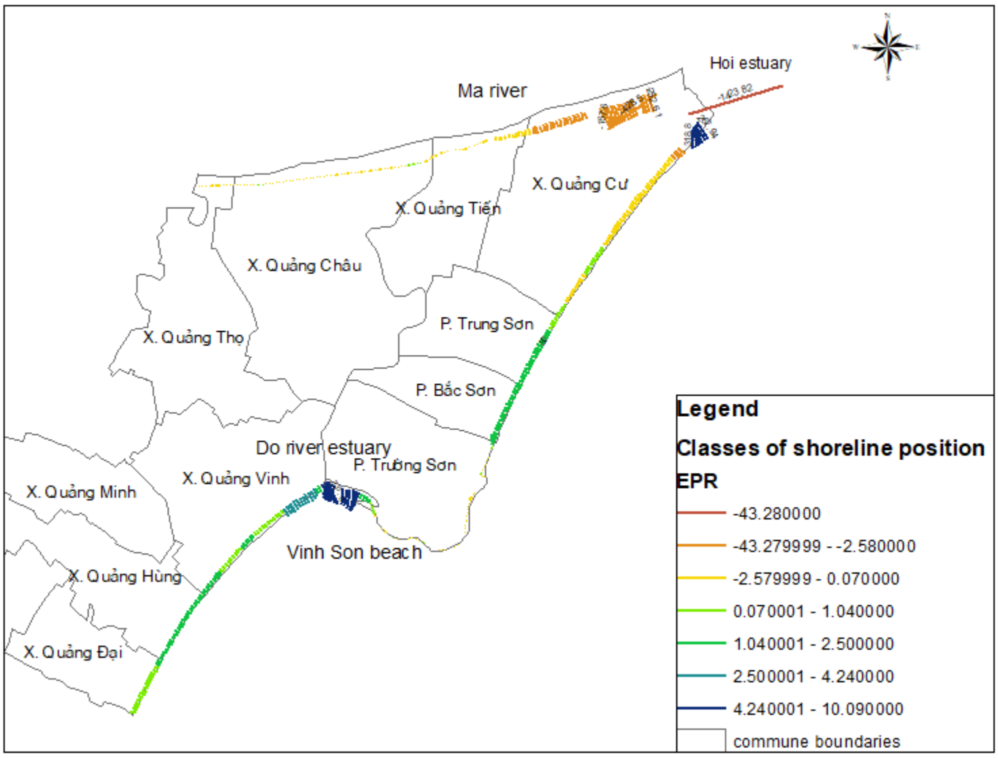


Fig. 4. Shoreline accretions and erosion of Sam Son coast with LRR

4.2. Shoreline change and tourism

Sam Son is one of the beautiful beaches in Vietnam that attracts many tourists. However, in recent years, Sam Son has been strongly affected by climate change, which has significantly impacted tourism activities. Climate change affects various tourism activities, including tourism resources, infrastructure and technical facilities serving tourism activities, and touristic operations. Specifically, climate change indirectly impacts tourism resources (20 %), tourism infrastructure (30 %), and tourism technical infrastructure (15 %) and affects seasonality in marine tourism (35 %). Additionally, climate change indirectly impacts tourism services, such as resorts, passenger transfers, and sightseeing activities, as entertainment depends heavily on weather conditions (Nguyen Xuan Hai, Thanh, 2020). Due to the impact of climate change, Sam Son City in Thanh Hoa Province has experienced unusual patterns of activity, such as an increased frequency and intensity of storms. These storms arrive earlier and last longer than average in many years, which has seriously affected the overall tourism development, as well as the technical infrastructure and tourism facilities of Sam Son City in particular (Le, 2022). One of the impacts on the technical infrastructure material factor for tourism in Sam Son is shoreline change and tourist accommodation facilities.

The rate of shoreline changes is strongest in two areas, namely the Hoi estuary (Figure 5) and the Do river estuary (Figure 6).

The accretion process is concentrated only in the southern part of Hoi estuary with rates ranging from 4.97 to 9.7 meters per year. Hoi estuary is the downstream area of the Ma River system, which annually discharges millions (approximately 5.17 million) of tons of sediment into the sea (Van Cu Nguyen, Pham, 2003). The amount of sediment is formed through the process of accumulation at river mouths, such as that of the Hoi estuary. On the other hand, the area to the north of the Hoi estuary experiences severe erosion, with erosion rates ranging from -2.22 m/yr to -40.32 m/yr. The strongest erosion, which reaches a rate of -40.32 m/yr, is associated with the most complex erosion-accretion activity. In this area, coastal erosion is caused by both natural factors and land exploitation activities. The natural factors include climate events such as storms, rising sea levels, and waves (Viet Cuong Ho, Le, 2012; Manh Hung Le, Ho, 2013). The activities of land exploitation cause depletion of sediment supply, leading to erosion. One of the most prominent land exploitation activities is the construction of tourism accommodation facilities such as Sam Son FLC complex and Van Chai resort. 8. As a result, sand mining in this tourism area has led to the loss of the source of sediment deposition and this activity also creates a swirling current of waves that washes away the sediment, leading to coastal erosion.

In addition, based on consultations with stakeholders in the field, it has been identified that the severe impact of evaluation results has affected tourism infrastructure (Nguyen Xuan Hai, Thanh, 2020), such as shoreline change. The services in marine tourism that are affected by shoreline change (erosion) in Sam Son are shown in Table 2.

Table 2. Matrix analysis of limitation, and factors affecting marine tourism in Sam Son

Areas	Tourism activities	Limitations
Along the coast of Ho Xuan Huong	Hotels, Public swimming beaches, Shopping, Restaurant	Infrastructure has not fully invested, Sea level rise, Planning is not synchronized
Quang Cu commune		Natural disaster risks; erosion; Environmental pollution; Infrastructure is low; Services are not yet developed; Landslide.

Source: Nguyen, Tran, 2020

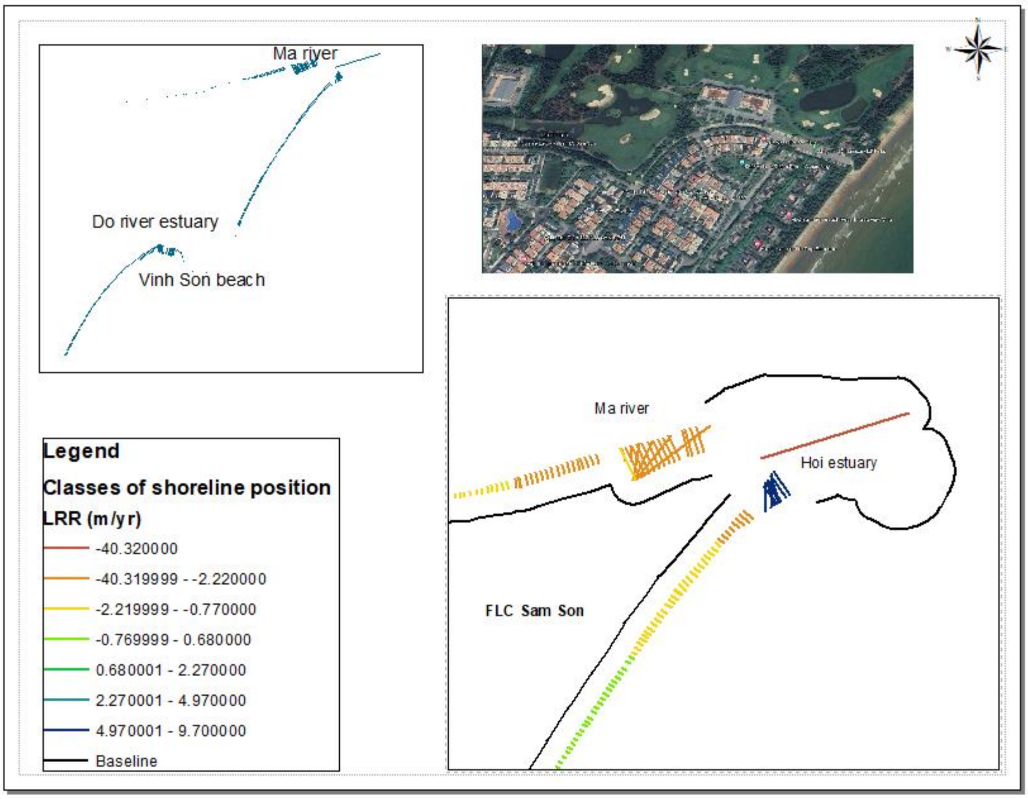


Fig. 5. The rate of shoreline change in Hoi estuary (LRR)

The Do river estuary is where the process of sedimentation and formation of Vinh Son Beach and Nam Sam Son Beach take place. This area is located to the west of the Truong Le mountain range.

Therefore, sediment and sand are deposited by the action of waves and tides. Leading to accumulation rate of up to 9.7 m/yr (Figure 6). The deposition of sediment at the mouth of the Do River serves as the foundation for developing resort areas that cater to tourism. Currently, this area has been filled with additional sand and built boundaries for the purpose of building resorts and hotels.

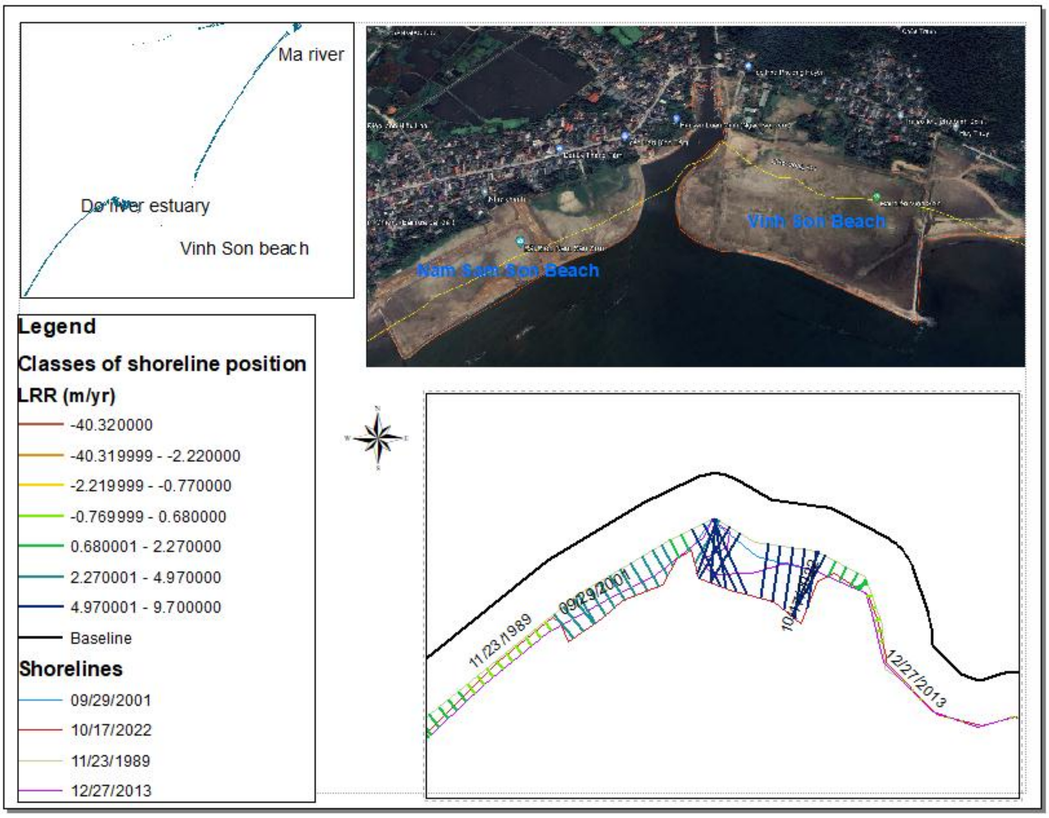


Fig. 6. The rate of shoreline change in Do river estuary

5. Conclusion

The impact of shoreline change on tourism in Sam Son City has been significant. The city's beautiful beaches are a major attraction for tourists, and any changes to the shoreline can have an adverse effect on the tourism industry in the area.

Coastal erosion and land subsidence have caused the loss of some beach areas, potentially reducing the number of tourists visiting Sam Son City. This could have a negative impact on the local economy, as tourism is a significant source of income for the area. In addition, the shoreline changes can also impact the availability of recreational activities, such as swimming and sunbathing, thereby decreasing the area's appeal to tourists.

To address the adverse effects of shoreline changes on tourism in Sam Son, Thanh Hoa, it is crucial to adopt sustainable and eco-friendly tourism practices. This can encompass initiatives like beach nourishment projects, the promotion of ecotourism, and the integration of measures to mitigate the effects of climate change. Furthermore, it is essential to involve the local community in tourism development and management to ensure that tourism benefits the local economy and promotes the preservation of natural resources.

Overall, addressing the problem of shoreline changes in Sam Son City is crucial to ensuring the sustainability of the local economy and the long-term viability of the region as a favored tourist destination.

6. Acknowledgments

The authors thank the Ministry of Education and Training and Hong Duc University for providing financial support (B2021.HDU.04.TT). All authors approved the version of the manuscript to be published.

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