ACADEMIC
PLATFORM

e-ISSN: 2717-8714

APJHAD

Academic Platform
Journal of Natural Hazards And Disaster Management

Volume: 5
Issue: 2
Year: 2024

Academic Platform Journal of Natural Hazards and Disaster Management (APJHAD)

Volume 5 Issue 2, June 2024

Contents

Research Articles

Review Articles

Academic Platform Journal of Natural Hazards and Disaster Management (APJHAD) Editorial Boards

Research Article
Academic Platform Journal of Natural Hazards and Disaster Management
5(2) 2024: 46-57, DOI: 10.52114/apjhad.1503020

Participation to Compulsory Earthquake Insurance System in the Southwestern Turkey After the 2023 Earthquake

Rahmiye Figen Ceylan[1*], Nihat Dipova[2]

[1] Department of Agricultural Economics, Faculty of Agriculture, Akdeniz University, Antalya, Türkiye
[2] Department of Civil Engineering, Faculty of Engineering, Akdeniz University, Antalya, Türkiye

Received: / Accepted: 21-June-2024 / 25-July-2024

Abstract

Earthquake is one of the foremost natural disasters for Turkey with its potential of occurrence and frequency. The recent Kahramanmaraş earthquake that took place in the southeastern Turkey in 2023 was catastrophic. This catastrophe reminded the necessity of having awareness of and getting prepared for potential awaited earthquakes. With this research, it was aimed to measure the intention of the society to get prepared for earthquakes in the southwestern region of Turkey that pose significant earthquake risk. The probability of having compulsory earthquake insurance (CEI) was estimated in Finike and Demre towns of Antalya, Turkey in 2023 after Kahramanmaraş earthquake. It was understood that with rising education, awareness and age, the probability of having insured rises in the representative districts. Yet, with ageing residency/building and random information, the probability declines. This early response emphasized the importance of scientific information of the society and better promotion of precautionary actions in the region and in Turkey.

Key words: Earthquake, Risk, Insurance, Logistic probability, Turkey

1. Introduction

Natural catastrophes are mostly inevitable. However, it is important to take precautions against their potential physical, financial, and health-related effects. Turkey has been historically known as a centre of periodic earthquake experiences. More than 90 % of country's lands that inhabit 95 % of the national population bear earthquake risks and it is known that 98 % of industrial centres and 93 % of energy producing dams are under direct earthquake risk [1]. Since the beginning of recorded history, Turkey witnessed many earthquakes and some of them were specifically devastating. The number of fatal earthquakes has been almost 20 in the last 100 years.

The recent Kahramanmaraş earthquake that took place in the southeastern region of Turkey in February 2023 was devastating with its mortality effect. Two earthquakes took place centred in two towns of the city in the same day, 6th of February, with magnitudes between 7.6 and 7.7. The earthquakes affected 11 provinces and more than 50 thousand people died. In addition, almost 2 million buildings got damaged, of which more than 500,000 were either collapsed or detected to be demolished afterwards [2]. Unfortunately, the earthquake reminded importance of preparations considering many aspects as health emergency systems, building structure

*Corresponding Author e-mail: ceylan.figen@gmail.com

reinforcement and post-encounter actions as physical and social recovery and reconstruction activities.

The public authorities make potential risk assessments for earthquakes and other natural disasters at least occasionally. The society has been informed continuously using different tools and with both scientific and social approaches. However, whether the society understands the importance of precautionary actions for earthquakes and similar natural disasters is still a question almost everywhere in the world. Kahramanmaraş earthquake was huge with its geographical dispersion and mortality effect. There were two previous devastating earthquakes that took place in Marmara Region in 1999, the industrial centre of Turkey. The magnitudes of the earthquakes were 7.8 and 7.5 and they led to high mortality of more than 18000 people. The loss of building stock was also more than 100000. Due to these catastrophes a need to increase societal awareness and level of preparation for potential earthquakes aroused [3]. Turkish Catastrophe Insurance Pool (the TCIP) was established in 2000 after Marmara earthquakes, to coordinate preparations for potential catastrophes. A Compulsory Earthquake Insurance (CEI) was issued at the end of 1999 to cover at least the material losses of the earthquakes and TCIP was appointed as the coordinator of insurance system [4]. The recent insurance records were overviewed to understand effectiveness of the system. The number of insurance certificates has risen steadily from 2.4 million in 2001 to 11,66 million of 20 million buildings in 2023 [5]. The rise observed in 2023 was 6.5 % but it was seen that the number of insurance certificates is still slightly above half of the existing national building stock. On the other hand, the total amount accumulated in the compulsory earthquake insurance pool has been fluctuating since its issuance on 1999/2000 as demonstrated in Figure 1.

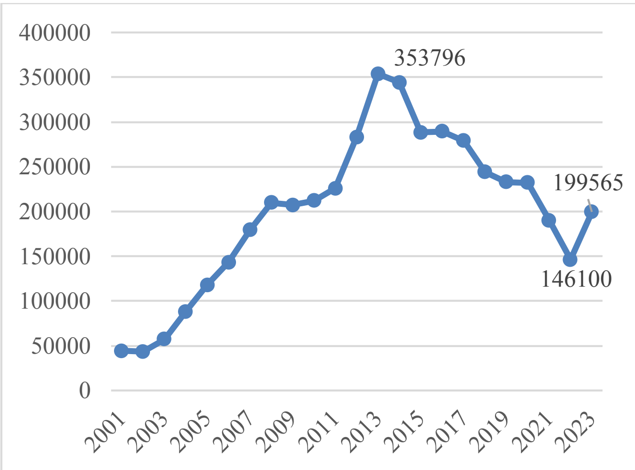

Figure 1. Value of certificates collected in TCIP – value in thousand $ (2001 – 2023)

While the total value was $ 44 million in 2001, the amount rose to almost $ 354 million in 2013 and reduced steadily afterwards. Following 2023 Kahramanmaraş earthquake, the total amount increased by 36 % from $ 146 to almost $ 200 million.

Therefore, the unfortunate 2023 Kahramanmaraş earthquake emphasized the need for assessing public awareness and individual preparedness to possible earthquakes countrywide. Accordingly, it was aimed with this study to detect the factors that affect individuals' earthquake insurance decisions. The insurance acceptance was analysed and interpreted for the Mediterranean region of Turkey with a representative sample of two touristic towns residing in southwestern costs of Antalya, that are Demre and Finike.

2. The Earthquake Risk in Antalya and Possible Causes

The research was focused on two Antalya towns and this focus needs to be explained. Earthquakes with high magnitudes were recorded in the region close to the Lycian coast throughout history and felt in Finike and Demre. The epicentre of the earthquake known as the Lycian Earthquake, which occurred in 141 AD, was predicted by Guidoboni and friends [6] to be between Rhodes island and Marmaris town. It is known that the damage was significant in a wide area from Limyra to Patara in this earthquake, and some of these damaged structures (especially public buildings) were repaired by Opramoas, a rich and benevolent person from Rhodiapolis [7]. A severe earthquake occurred in Finike on November 14th, 1886, and although there was no life loss record, it caused the walls of some buildings to split and a few furnace chimneys to collapse. The people of Finike left their homes due to fear and anxiety and spent the night in tents as recorded in Prime Ministry Ottoman Archives [8].

The region experienced many earthquakes during the 20th century as well. An earthquake having Mw=6.1 magnitude occurred near Finike on April 30th, 1911. An earthquake with an epicentre of 32 km south of Finike, at a depth of 10 km and a magnitude of Mw = 6.5 occurred on March 18th, 1926. The earthquake resulted in physical damage to 364 buildings and loss of life in the region between Kumluca and Fethiye as recorded by Ayhan and his friends in 1981 [9]. A recent earthquake took place on January 14th, 1969. This earthquake with a 6.3 magnitude occurred near Megisti Island, and although there was no loss of life, over 1000 buildings were damaged between Kumluca and Fethiye towns of southwestern region of Turkey. It was reported that half of the houses in Kalkan settlement had become uninhabitable due to this earthquake [10].

Residing on this historical background, the current situation of the region with regards to earthquake risk needs to be overviewed. When the focal points of earthquakes around Antalya are analysed in 3D, the earthquakes can be divided into two groups as Crustal earthquakes and Subduction zone earthquakes. In the region eleven source zones were defined for crustal earthquakes [11]. Among the crustal seismic zones, the C1 seismic zone is sourced by tectonic structure which is shown as TT in Figure 2.

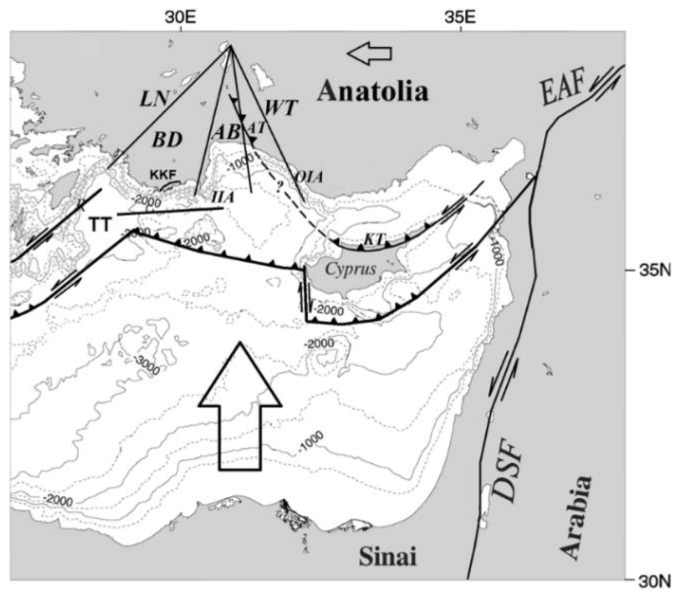

Figure 2. The earthquake sources of the region

This source zone demonstrated is particularly important as it is 25 km away from the current research area. In this region, there is a depression called Finike Trench, which is one of the deepest regions of the Mediterranean with a depth of 3064 meters [12]. Another tectonic structure among crustal resources is the Kekova and Kale faults (KKF) confirmed with different studies [13, 14]. These are two parallel faults between Demre and Kaş. These two faults demonstrated in Figure 2 have potential to produce an earthquake of magnitude Mw = 6.5.

The earthquake sources of the region are the Cyprus Arc and the Isparta Angle (Figure 2). The Cyprus Arc tectonic structure is a subduction fault between Cyprus and Rhodes, south of Antalya. This segment of the Cyprus Arc plunges northward, causing the Mediterranean Sea floor to subduct beneath Antalya region (Figure 3).

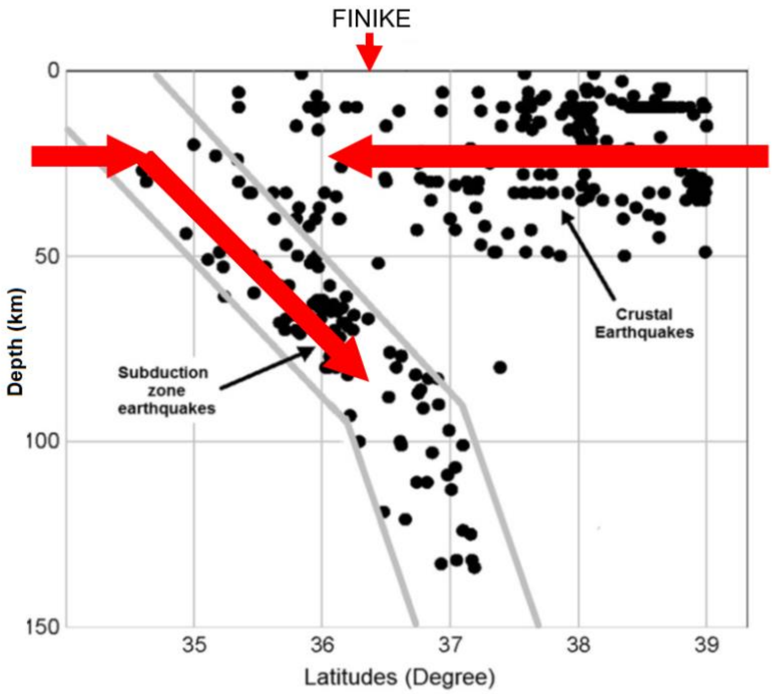

Figure 3. Northward subduction between Cyprus and Rhodes, beneath the Antalya region

When we look at the current research area, there are 3 active faults recognized within 50 km sphere of Finike and Demre towns. These faults have produced earthquakes up to Mw = 6.5 since 1900. It is predicted that the region should be prepared for an earthquake of Mw = 7 magnitude and a horizontal acceleration of 0.37g-0.42g in the future.

Finike and Demre soils are sand, and silt dominated alluvium, formed by the material transported via the streams reaching the coast filling the old bays. The groundwater table is approximately 2 m deep. There is susceptibility to liquefaction in the fine sand-dominated layers in the ground profile. In the liquefaction potential calculations made for Mw = 7 in these layers, the ground was found to be liquefiable. These records indicate that there is the possibility of witnessing earthquakes with high magnitudes and structures and endurability of current building stock in the region do pose mortality risk in contrast to the existent close history.

Accordingly, the awareness and preparation of the society in the targeted towns of Antalya province was considered as representative for the southwestern coasts of Turkey. The region and targeted towns are also important in terms of contribution to tourism and agricultural income of Turkey. These multidimensional characteristics of the region constituted the scientific and socio-economic bases of this research.

3. Materials and Method

The research objective was to estimate and interpret the tendency of individuals to have/purchase Compulsory Earthquake Insurance for earthquake preparation and factors affecting this decision within a logistic regression framework. Accordingly, primary data was retrieved via face-to-face surveys from 471 individuals, 232 in Demre and 239 in Finike towns of Antalya in June/July 2023.

With this primary data the probability of having Compulsory Earthquake Insurance (CEI) was estimated for the houseowners. There are many uninsured buildings, even if the insurance was announced as compulsory. The age and district of the building and having not changed the owner recently might be considered as effects of this limited insurance rate. However, the response - based evaluation was expected to provide more insights. Accordingly, the attitude related probability was estimated with logistic regression which was suggested by Berkson [15] in 1944. The probability function can be briefly reported as below.

$$log[Pr(Y = 1|x)] = \ln\left[\frac{Pr(Y = 1|x)}{1 - \Pr(Y = 1|x)}\right] = \sum \beta_i x_i + \sum \alpha_i D_i + u_i$$

The probability up to 100 % was estimated in a dichotomous framework and the positive and negative factors were detected with this methodology suggested by McFadden [16]. Therefore, the variable to be estimated (Y) referred to whether the house owner has CEI for his property (1) or not (0). The pre-detected potential factors, either continuous/discrete (x) or dummy (dichotomous/polytomous) were enlisted below.

Independent Variables

- **Age:** Age of the individual – scale (1: below 30 years old, 2:31-50 years old, 3:51+)
- **Edu:** Level of education – scale (1: elementary; 2: secondary; 3: BA/BSc; 4: MSc+)
- **PI:** Personal Income – scale (1: below minimum wage; 2: minimum wage; 3: 11.402-20000, 4: 2001-50000, 5: 50000+, 6: not mentioned, 7: no-income)
- **HHSE:** number of people employed in the household – discrete
- **A_B:** Age of the building & **A_R:** Years of residency – scale (1: 0-5 years. 2: 6-10 years, 3: 11-15 years, 4:15-20 years, 5: 21 years +
- **PRF:** The most important factor in apartment/house purchases is price – binary (1: Yes, 0: otherwise)
- **EQF:** The most important factor in apartment/house purchases is resistance to quakes– binary (1: Yes, 0: otherwise)
- **Info_CEI:** Knowledge on Insurance – binary (1: Yes, 0: No)
- **Info_OIV:** Knowledge on Private Communication Tax (OIV) and its relation to earthquake– binary (1: Yes, 0: No)
- **Prep_EQ:** Evaluation on public preparedness level – scale (1: completely ready, 2: ready, 3: no idea, 4: not ready, 5: definitely not ready)
- **Info_EQ:** Acceptance after proper information on reasons and results of earthquakes– scale (1: complete, 2: have idea, 3: no idea, 4: not ready, 5: definitely not ready)
- **Use_OIV:** Belief on Proper Use of Private Communication Tax – binary (1: Yes, 0: No)

- **Accept_CEI:** Insurance acceptance after proper information– scale (1: completely ready, 2: ready, 3: no idea, 4: not ready, 5: definitely not ready)
- **FD:** Residency – binary (1: Finike, 0: Demre)

Departing from this aggregate variable list, the probability was estimated via Python and using machine learning methodology of training and testing the data. After statistical fit tests the probability of odds or occurrence were determined from estimates of independent variables [17, 18].

4. Estimation of the Tendency to Have CEI

4.1. Estimation Results

A priory, it is important to mention that 105 individuals out of surveyed sample of 471 declared that they have CEI. This signed less than 25 % of insured buildings/apartments and very limited awareness for the target area that has earthquake risks. The number of insured individuals or buildings was 46 in Demre and 59 in Finike towns, with a slightly higher share in Finike. Existent awareness on CEI was portrayed with 127 out of 128 individuals' understanding of the Private Communication Tax (OIV) and its relevance to earthquake preparation. Therefore, the awareness and acceptance of the audience seemed to be closely related and low. Following this brief sample presentation, the reasoning behind this low level of insurance holding and factors that can be used to induce insurance capacity were detected and evaluated for the sample.

Afore mentioned independent list were estimated initially and checked with pseudo R^2 that refer to degree of explanation. As there were many potential determinants, there might be a multicollinear significance indicating correlation of the determinants. This collinearity level was checked with Variance Inflation Factor of each variable. The factors were demonstrated in the Table 1.

Table 1. Variance inflation factors of tendency to have CEI insurance

Estimator	VIF	Estimator	VIF
Age	7.38	Earthquake Awareness Preference	1.69
Education	9.13	CEI Knowledge	1.47
Personal Income	4.39	OIV Knowledge	1.57
HH Employment	4.35	Rising Public Preparation for Earthquakes	9.14
Age of Building	10.27	OIV Use	2.39
Years of Residency	6.27	Rising Information on Earthquakes	1.41
Price Preference	1.44	CEI Acceptance with Information	2.36
		Residency – F/D	3.23

The VIF score equal to 1 refers to inexistence of independent correlation between the relevant variable and other indicators. The value between 1 and 5 refers to low, 6 and 10 to moderate/high and above 10 extreme correlation levels. Depending on this information the number of variables were reduced, and three alternative models were estimated and evaluated. The model outputs were statistically evaluated with Likelihood Ratio [19] and Log-likelihood providing accurate inference on logistic estimation methodology [20].

In addition to the likelihood of the estimates, AIC [21] and BIC [22] statistics were used to compare models and the model with minimum values is suggested. Models including relevant independent variables and preferential statistics were demonstrated in Table 2.

Table 2. Alternative models that determine tendency to have CEI insurance

Model 1 – 15 independents	Model 2 – 11 independents	Model 3 – 10 independents
• Age &Edu &PI & HHSE • A_B & A_R & PRF & EQF • Info_OIV&Info_EQ • Prep_EQ&Use_OIV • Info_CEI&Accept_CEI • FD Residency	• Age &Edu &PI • A_B & A_R & EQF • Info_OIV& Info_EQ • Info_CEI&Accept_CEI • FD Residency	• Age &Edu &PI • A_R & EQF • Info_OIV& Info_EQ • Accept_CEI Info_CEI& • FD Residency
AIC: 481.04 BIC: 547.52	AIC: 473.73 BIC: 523.59	AIC: 491.40 BIC: 537.10
Pseudo R2: 0.11	Pseudo R2: 0.11	Pseudo R2: 0.07
Log-Likelihood: -224.52 LLR p-value: .351e-06	Log-Likelihood: -224.87 LLR p-value: 7.655e-08	Log-Likelihood: -234.70 LLR p-value: 0.0001083

According to this classification, the third model was selected to explain the probability with its higher Log-Likelihood value in absolute terms. Even if the AIC and BIC selection criteria of second model is better, the VIF of age of the building was high with a value above 10. This sign of high multicollinearity or inflation of the variance refers to existence of a relationship between the building age and other factors obviously [23] and it led us to consider the fit of the third model.

Prior to evaluating the parameter estimates and their contribution to the probability of having CEI, the fit of the data should be evaluated. Therefore, the accuracy score and classification report were checked for these logit estimates with confusion matrix. The selected factors were detected to explain the probability by 78 % due to accuracy score and the average significance of the probability to have CEI with the relevant variables was 87 %. Therefore, the model and estimates were found to be explanatory for the insurance holding probabilities of the sample.

In the final step, inverse logarithms of the estimates were calculated, and odds ratios of the factors were retrieved. The odds ratios of parameters that explain the directions of the effects were demonstrated in Table 3. Accordingly, it can be noted that the factors that appreciate the probability of having earthquake insurance were age, level of education and income, awareness on CEI and Private Communication Tax (OIV).

Table 3. Odds of the factors affecting compulsory earthquake insurance

Factor	Odds	Factor	Odds
Constant	1.01	Info_CEI	1.52
Age	1.85	Info_OIV	1.86
Edu	1.45	Info_EQ	0.87
PI	1.17	Accept_CEI	0.70
A_R	0.95	FD Residency	0.95
PRF	1.36		

With the rising age of the residency building there seemed to be a descending trend in insurance acceptance. Rising information on earthquakes in general terms and rising acceptance of CEI seemed to reduce the probability of having insurance. This finding can be related to widespread existence of word-of-mouth or random information in the society or reliance of individuals to non-scientific information.

Yet, having resided in Finike town seemed to be negatively correlated with the insurance acceptance. However, it is not accurate to conclude that there is a significant difference between towns. Rather than removing the negative factors from the system, understanding the reasoning behind was considered as more contributory.

4.2. Results and Discussion

It is visible that with age, the need for security rises. Besides, probability of residency ownership is mostly higher for older individuals almost everywhere in the world. There was a positive relationship between ageing population and tendency for earthquake preparation with insurance in New Zealand. However, the society seemed not to be sure about full recovery under disaster conditions [24].

In an attitude evaluation survey in Erzincan province of Turkey, which had witnessed mortality involving earthquakes and has future risk, the relationship between awareness and preparation level of 400 individuals were assessed in 2016 [25]. It was understood that rising income is directive for taking precaution for the sample and the awareness level contributes acceptance of the compulsory insurance. Willingness to pay for earthquake insurance was measured in South Korea following a moderately severe earthquake and it was found out that risk perception or awareness, level of income and house ownership status induce insurance demand [26]. In a public survey conducted with almost 1000 individuals in Iran in 2019, significant relationships were detected between preparation level and education and homeownership [27]. Income and awareness on earthquake seemed to contribute individual insurance purchases in a sample of 78 individuals from Turkey [28]. The researchers concluded that self-insurance mechanisms should be empowered, and urban renewal projects should be supported rather than compulsory contribution to TCIP.

Recalling the scope of OIV is also important to understand the relationship between the tax and insurance system. The Private Communication Tax (OIV) was introduced for Turkish society after the earthquakes of 1999 as a temporary funding tool. This tax is applied to cable TV, internet services and mobile use in minutes and messages. By the time, considerable shares of other permanent tax types as vehicle or housing taxes were devoted to recovery as well under the name of additive taxes. Those additive taxes were eliminated at the end of 2003, but OIV became permanent by 2003 [29]. The compulsory tax rate was 7.5 % until 2021 and rose to 10 % by then [30]. Yet, it was estimated that OIV collected from 1999 to 2022 had been around 39 billion Dollars in sum and 476 million Dollars in 2023 due to Ministry of Treasury and Finance records [31]. However, in contrast to its announcement objective, the tax revenues neither must be used solely for earthquake preparation due to tax regulations, nor were used for preparation [32]. For our research, the above 1 probability score inferred that with rising awareness on the earthquake tax and its uses, tendency to buy insurance plans would be affected positively.

Resistance of buildings to a potential earthquake is prioritized by some of the respondents in purchasing a house/apartment. For those people, the tendency of having their shelter insured seemed to be higher, signifying a correlation between awareness and preparation. However, rising information on earthquakes and acceptance of CEI after getting informed seemed to reduce the probability, in a contradictory way. The recent impacts may need further sociological evaluation. Over-information might be considered as a barrier against precautionary actions as well. In a phone survey with around 2000 individuals in California, the USA, it was seen that only 15 % of fully informed individuals seemed to have tendency to get prepared [33].

The detected factors affecting the probability of taking precautions against earthquakes with insurance in the sample towns were like earlier research findings. The factors related to the aggregate socio-economic awareness level like education, information on insurance and taxation tools and income appeared as probability rising factors. However, available random information on earthquakes and precautionary insurance/tax tools and derogations in residency structures seemed to deter the insurance ratio in the society.

5. Conclusion

There are many suggestions that can be derived from these findings. Rising insurance ratio due to rising education level is an expected outcome. But, even if there is endowed information in mass media or internet, the need for scientific information remains. Therefore, the first but not the least important suggestion is that the necessity of scientific information, its translation to daily wording and extension across society is still essential. However, considering the geological structure of the country, mass information and its detachment from earthquake experiences is also required. In other words, society should be kept awake continuously against earthquake risks.

Before concluding it is important to note that current research resides on personal responses of individuals in representative districts of a region of Turkey that pose important earthquake risk. Within the scope of limited sample and increased anxiety level after 2023 earthquake, intentions on getting insured in the future were higher. Accordingly, the mindset of people needs to be checked in normal condition. This rising interest and tendency was also observed in a sample that has higher education, income, total awareness than the national averages as the Mediterranean region and focused districts/towns has socio-economic endowments and advantages. This socio-economic inference solely is adequate to conclude on the need for informing larger audiences.

It is also important to note that follow-up of the awareness and preparation for earthquakes is essential for Turkey. Therefore, the audiences need to be surveyed and their preparation level should be evaluated by the public institutes and scientific organisations to form new precautionary actions in a persistent way. The detected rising insurance demand or tendency needs to be evaluated with different samples and followed up in time for policy and tool development to reach wider audiences. Besides, development of alternative insurance systems that would meet needs of individuals from different regions that have varied earthquake risk might be a persuasive act. The insurance companies or financial institutions that offer insurance plans can focus on new product development targeting audiences with different endowments and needs and may offer different payment plans. This sort of society-oriented policy making can be supported by national and regional public authorities. In this scope, scientific knowledge, financial evaluation and planning are expected to contribute to preparation for unwanted future occasions.

Conflict of Interest

Co-authors declare "no conflict of interest."

Author Contribution

R.F.C. and N.D designed the model and frame of the research together. N.D. guided the technical information sections on earthquake potential of the region and designed all technical questions of the survey. R.F.C. processed the socio-economic model. Co-authors contributed equally to the analysis and statistical interpretation. R.F.C. contributed socio-economic assessment of the findings. N.D. interpreted the findings to improve technical awareness and regional reflections of findings.

Acknowledgments

Municipalities of Demre and Finike towns (Antalya Türkiye) assited the survey implementation process. We would like to thank these regional authorities for their support.

References

[1] Ç. Ö. Incekara, “Assessment of compulsory earthquake insurance evaluations by loss adjusters under fuzzy logic”, *Euroasia Journal of Mathematics, Engineering, Natural & Medical Sciences* 9(21): 14-41. 2022.
[2] Anonymous, “Report of Kahramanmaraş and Hatay Earthquakes, Presidency of the Republic of Türkiye, Strategy and Budget Directorate”. url: https://www.sbb.gov.tr/wp-content/uploads/2023/03/2023-Kahramanmaras-ve-Hatay-Depremleri-Raporu.pdf. 2023a.
[3] A. F. Senol, A. Akbas and O. Caliskan, “Türkiye’de son yüzyılda (1923-2023) meydana gelen yıkıcı depremler ve kullanılan deprem yönetmelikleri - Destructive earthquakes occurred in Turkey in the last century (1923-2023) and earthquake regulations used”, In *2023: Mühendislikte yenilikçi çalışmalar - Innovative studies in engineering* edited by B Akdemir. ISBN: 978-625-6507-42-5, *4th section:* 75-97. 2023.
[4] Anonymous, “About the TCIP”. Republic of Türkiye Turkish Catastrophe Insurance Pool. url: https://dask.gov.tr/en/about-the-tcip. 2023b.
[5] Anonymous 2023c, “Number of insurance certificates”, Republic of Türkiye Turkish Catastrophe Insurance Pool.. url: https://dask.gov.tr/tr/police-uretim
[6] E. Guidoboni, G. Ferrari, D. Mariotti, A. Comastri, G. Tarabusi and G. Valensise, “Catalogue of Strong Earthquakes in Italy (461 BC-1997) and Mediterranean Area (760 BC-1500)”, National Institute of Geophysics and Volcanology – INGV. 2007.
[7] N. Cevik, “Rhodiapolis ve Kumluca sınırlarındaki antik yerleşmeler, arkeolojisi, tarihi, doğası ve tarımıyla Kumluca (Rhodiapolis) - Ancient settlements on the borders of Rhodiapolis and Kumluca, Kumluca with its archeology, history, nature and agriculture (Rhodiapolis)”, *Kumluca Municipality Publication*, Antalya, 13-72. 2008.
[8] Anonymous, BOA. Y. PRK. DH. nr.1/110. Lef.1., “Başbakanlık Osmanlı Arşivi Yıldız Perakende Evrakı Dahiliye Nezareti - Prime Ministry Ottoman Archives Yıldız Retail Documents Ministry of Internal Affairs”. (date unknown).
[9] E. E. Ayhan, N Alsan, SB Sancaklı & B Üçer, “Türkiye ve Dolayları Deprem Kataloğu (1881-1990) - Türkiye and Surroundings Earthquake Catalog 1881-1980”, *Bosphorus University Press*. 126 pp. 1981.
[10] T. M. P. Duggan, “The hidden history of Antalya Province, 300 B.C. to 2005, A chronology of plagues and earthquakes”, (translated. M. Oktan, Antalya'nın Gizli Tarihi: 2300 Yıl İçerisinde Bölgede Yaşanan Depremlerin ve Salgın Hastalıkların Kronolojisi). *Odin Publ*, Istanbul. 2011.
[11] N. Dipova and B. Cangir, “Probabilistic seismic hazard assessment for the two layer fault

system of Antalya (SW Turkey) area". *Journal of Seismology* 21:1067-1077. 2017.

[12] Anonymous. IOC International Oceanographic Commission, 1981, International bathymetric chart of the Mediterranean (1:1.000.000 scale), *Head Department of Navigation and Oceanography, Leningrad, USSR.* 1981.

[13] F. Saroglu, O. Emre and I. Kuşçu, "Türkiye Diri Fay Haritası - Active Fault Map of Turkey", Report. *MTA General Directorate of Mineral Research and Exploration*, Ankara. 1992.

[14] O. Emre, T. Y. Duman and S. Olgun, 1:250.000 Scale Active Fault Map Series Of TURKEY, *Fethiye (NJ 35-16) Quadrangle, Serial. No: 39. MTA General Directorate of Mineral Research and Exploration,* Ankara. 2012.

[15] J. Berkson, Application of the logistic function to bio-essay, *Journal of the American Statistical Association* 9: 357-365. 1944.

[16] D. McFadden, Conditional logit analysis of qualitative choice Be. *In: Zarembka, P., Ed., Frontiers in Econometrics.* Academic Press, New York, 105-142. 1973.

[17] B. Efron, Logistic regression, survival analysis, and the kaplan-meier curve, *Journal of the American Statistical Association,* 83(402): 414-425. 1988. https://doi.org/10.2307/2288857.

[18] D. R. Cox and E. J. Snell, *Analysis of Binary Data*. 2nd Edition, Chapman and Hall/CRC, London. 1989.

[19] D. N. Gujarati, *Basic Econometrics*. New York: McGraw Hill Book Co. pp: 545-546, 555. 2003.

[20] R. E. Crochiere, J. Tribolet and L. R. Rabiner, An interpretation of the log likelihood ratio as a measure of waveform coder performance. IEEE *Transactions on Acoustics, Speech, And Signal Processing*, 28(3): 318–323. 1980.

[21] H. Akaike, A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6): 716-723. December 1974. DOI: 10.1109/TAC.1974.1100705. 1974.

[22] M. Stone, Comments on model selection criteria of Akaike and Schwartz. *Journal of the Royal Statistical Society,* B 41; 276–278. 1979.

[23] R. M. O`Brian, A caution regarding rules of thumb for Variance Inflation Factors. *Quality & Quantity* 41: 673-690. 2007.

[24] J. A. Davey and J. Neale, Report prepared for the Earthquake Commission, with funding from the EQC 2012 Biennial Grants Programme. ISBN 978-0-477-10394-7 pp: 47-48. 2013.

[25] U. Yayla and T. Sahinoz, Preparedness for earthquake: knowledge and behavior. *Journal of International Health Sciences and Management* 6(11): 46-59. 2020.

[26] J-W. Moon, H. Hwang and J-B. Chung, Factors affecting awareness of preparedness after moderate earthquakes: An analysis of the Pohang earthquake in Korea. *Disaster Prevention and Management* 29(3): 405-420. 2020. https://doi.org/10.1108/DPM-07-2019-0209.

[27] M. Rostami-Moez, M. Rabiee-Yeganeh, M. Shokouhi & et al. Earthquake preparedness of households and its predictors based on health belief model. *BMC Public Health* 20 (646): 1-8. 2020. https://doi.org/10.1186/s12889-020-08814-2.

[28] O. D. Cavlak, O. Ozdemiz and B. B. Erkan, Preferences for earthquake risk–mitigation mechanisms: experimental evidence, *Natural Hazards Review* 19(3) (2018): 4018007.

[29] B. Hayrullahoglu, Analyzing of taxes which were implemented for financing of

earthquake expenditures in turkey. *Mehmet Akif Ersoy University Journal of Economics and Administrative Sciences Faculty* 9: 102-120. 2022.

[30] M. Miynat E. Keskin, Dijital çağda özel iletişim vergisinin yeri - Place of special communication tax in digital age. *Vergi Raporu,* 265: 107-119. 2021.

[31] Anonymous, General Administration and Budget Statistics. Republic of Türkiye Ministry of Treasury and Finance. 2024. https://muhasebat.hmb.gov.tr/genel-yonetim-butce-istatistikleri.

[32] S. Kurt, Evaluation of the special communications tax called as earthquake tax in accordance with the non-earmarking principle of the budget. *Institute of Public Administration Journal of Social Sciences* (4): 199-214. 2023.

[33] L. B. Bourque, Demographic characteristics, sources of information, and preparedness for earthquakes in California. *Earthquake Spectra* 31(4): 1909-1930. 2015. doi:10.1193/013014EQS024M.

Research Article
Academic Platform Journal of Natural Hazards and Disaster Management
5(2) 2024: 58-75, DOI: 10.52114/apjhad.1515787

Impacts of Earthquakes on Economic Growth and Income Inequality in Independent Turkic States

Burcu Türkcan[1*]

[1] Department of Economics, Faculty of Economics and Administrative Sciences, Ege University, Türkiye

Received: / Accepted: 13-July-2024 / 30-November-2024

Abstract

Earthquakes are major natural disasters that occur frequently worldwide. They have several socioeconomic impacts on countries. At first glance, it seems that as if they cause only large volumes of deaths, injuries and destruction. However, in the medium and long run, they cause several other impacts such as income, employment and production losses, increased government expenditures, inflation explosions and income distortions. All of these impacts are critical especially for developing countries that have more vulnerable economies than developed ones. In this respect, this study aims to analyse the impacts of massive earthquakes on economic growth and income inequality in independent Turkic states. With this purpose, two empirical models are estimated by the Generalized Method of Moments (GMM) with panel data covering the period from 1991 – 2022 for 6 countries. Empirical findings exhibit that major earthquakes do not have significant impacts on the economic growth processes of these countries. However, they have significant impacts on income distortions. In this manner, it seems that despite massive earthquakes, Turkic states have been able to sustain their economic growth processes. However, income inequality has increased as a by-product of these disasters. This evidence seems substantial for sustainable development policy formations of Turkic states.

Key words: Earthquakes, Economic growth, Income inequality, Turkic states

1. Introduction

The global climate crisis has been at the scene since the midst of the 20th century. Humanity is about reaching the limits of the globe. This fact has already been declared by The Limits to Growth Report published in 1972. Specifically, with the inefficient use of global resources, it would be impossible to sustain both population and production growth. Even it warns that this would cause drastic decreases in both [1]. Since that time, nothing has changed much in terms of humankind's production and consumption patterns. Global warming has accelerated and despite sustainability efforts, the problem has deepened. Beyond the Limits and The Limits to Growth: The 30-Year Update was published in 1992 and 2004, respectively. At their last update, they warned that 'Overshoot cannot be sustained without collapse.'. However, they have also pointed out that humanity could still reverse the collapse by taking the right actions on resource use and waste management [2].

With the rise of global warming and environmental degradation, the volume and severity of natural disasters have increased [3, 4]. Technological advancements have provided new tools [1]for forecasting natural disasters such as tsunamis, tornadoes and floods. However, there are

[*] Corresponding Author e-mail: burcu.turkcan@ege.edu.tr

still some disasters that cannot be truly foreseen like earthquakes. Fault zones have been discovered, their historical behaviours have been analysed and possible future earthquakes have been forecasted at all over the World. However, mankind has still inadequate tools to foreseen exactly when an earthquake will occur and at which magnitude will it happen. In this manner, it seems that we, as humankind, need to deeply understand the impacts of major earthquakes and take sustainable policy actions to minimize their socioeconomic costs.

Moreover, transformational changes in international system with the collapse of USSR (Union of Soviet Socialist Republics) in 1989, have reshaped the relationships of all countries across all over the World [5]. Some countries in the South Caucasus and Central Asia declared their independence in 1991. From that time on, historical and ethnic backgrounds of Turkic states have brought them together firstly in the Cooperation Council of Turkic-Speaking States and then in Organization of Turkic States [6]. All these efforts have been important due to creation of a power block in Central Asia. Moreover, the geographical area of these countries has critical importance [7]. With its wide range of landscape and climatic conditions, this area seems to be on the spotlight of climate crisis researchers in the near future. Moreover, this wide geographical area, which includes the main fault zones historically produced massive earthquakes. In this context, the main purpose of this study is to analyse the impacts of major earthquakes on economic growth and income inequality in independent Turkic states. However, there are still inadequate studies on the impacts of earthquakes in this country group. In this respect, the empirical results of this study are expected to make a significant contribution to the related literature. Hopefully, the empirical results will shed light on the socioeconomic impacts of earthquakes in this country group and the development of sustainable policy tools to decrease negative impacts. This country group has a special importance due to the fact that their independencies are relatively new (apart from Türkiye). Hence, their economies are more vulnerable than the similar developing countries. Also, their geography has an important role in the contemporary world. What is more, this role is expected to enhance by Turkic World Vision-2040. Organization of Turkic States has declared Turkic World Vision-2040 as an act focusing on economic and sectoral cooperation in transport. In particular, the use of the Trans-Caspian East-West Corridor has been targeted to widen and the new Zengezur Corridor has been targeted to be jointly built by Türkiye and Azerbaijan. The increase in transportation in the region is expected to increase the macroregional economic development in the near future. This will lead the region to have a more critical role in the global economy. In this respect, the examinations about independent Turkic states have critical importance in the contemporary world [8]. In this context, the first section of the study is devoted to the nexus between earthquakes and sustainable development in terms of economic growth and income inequality. The second section reviews the literature. The third section is devoted to the methodology and empirical results. Finally, in the conclusions, sustainable policy recommendations are proposed.

2. Earthquakes as a Natural Fact in Turkic States

Earthquakes are natural disasters that have several socioeconomic consequences in the short, medium and long-term. In the course of an earthquake, human, capital and infrastructure losses occur. However, this sudden impact is not the only one. From the occurrence of the earthquake through the first 6 months, inflation increases; investments in capital and infrastructure accelerate and government expenditures for disaster victims increase. From 6 months to 3 years, the volume of tourism decreases; foreign direct investments decrease; government expenditures increase and income inequality rises. Even after 3 years, structural changes still occur due to the earthquake [9]. All these impacts can also be classified as direct, indirect and induced impacts. The direct impacts include physical destruction of infrastructure, buildings, machinery and agricultural assets. However, indirect impacts imply that production and income decrease due to stock losses. Lastly, induced impacts indicate total effects on macroeconomic variables such as GDP (Gross Domestic Product), consumption and inflation [10]. All the aforementioned impacts are critical for all economies and nations. However, there is no doubt that they are more critical for developing countries in which GDP levels are lower and markets are more vulnerable [11].

Independent Turkic states (Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan, Türkiye and Uzbekistan) are developing countries that share the same ethnic historical background [12]. After the end of the 1st World War, Republic of Türkiye has been founded in 1923 in Anatolia. It had a great success against imperial countries and this new country was a secular bridge between Europe and Central Asia [13]. The fundamental notion behind the unity of citizens was the Turkic identity and nationalism as the mainstream policy. After the end of the Cold War, the USSR collapsed and Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan and Uzbekistan announced their liberties one by one in 1991. Hence, the number of independent Turkic states increased worldwide with the emergence of these new countries in Central Asia and the Caucasus [14]. After that time, independent Turkic states followed friendly foreign policies due to their ethno-historical background and linguistic unity. Organization of Turkic States which was first established with the heading of the Cooperation Council of Turkic-Speaking States, has been the most remarkable attempt to provide a union between independent Turkic states [6]. The founders of the organization were Azerbaijan, Kazakhstan, Kyrgyzstan and Türkiye. Then Uzbekistan and Turkmenistan joined the organization. The main object of this union has been declared as fostering comprehensive cooperation among Turkic states. It aims to enhance cooperation in terms of the economy, science, education, tourism and other fields [15]. Although all these efforts are remarkable, there is an underestimated and undiscussable area. Natural disasters are at the spotlight of the contemporary world. The magnitudes and frequencies of these events have increased because of the global climate crises [3]. More importantly, humanity will face more severe disasters. In this sense, it is critical to understand the impacts of these disasters on societies and economies.

It's known that there are several fault zones in Central Asia, the South Caucasus and Anatolia. Although the main earthquake area across these countries is Türkiye, other countries have also experienced massive earthquakes in their histories. The examples include the Azerbaijan Shemakha Earthquake in 1667 (6.9); the Azerbaijan Shemakha Earthquake in 1902 (6.9); the Turkmenistan Ashgabat Earthquake in 1929 (7.4); the Turkmenistan Ashgabat Earthquake in 1948 (7.3); the Turkmenistan Nebitday – Turkmenbashi Earthquake in 2000 (7.0); the Uzbekistan Tashkent Earthquake in 1937 (6.5); the Uzbekistan Tashkent Earthquake in 1966 (6.9); the Uzbekistan Gazli – Bukhara Earthquake in 1976 (7.0); the Uzbekistan Gazli Earthquake in 1984 (7.0); the Kazakhstan Vernensk Earthquake in 1887 (7.3); the Kazakhstan Alma-Ata Earthquake in 1889 (8.3); the Kazakhstan Alma-Ata Earthquake in 1911 (7.7); the Kazakhstan Alma-Ata Earthquake in 1978 (7.1); the Kyrgyzstan Belovodskoje Earthquake in 1885 (6.9); the Kyrgyzstan Earthquake in 1946 (7.6); the Kyrgyzstan Toluk Earthquake in 1992 (7.5). As underlined before, Türkiye is an earthquake country because of its geographical features. Several massive earthquakes have occurred in Turkish history such as the Türkiye Erzincan Earthquake in 1939 (7.9); the Türkiye Samsun Earthquake in 1943 (7.2); the Türkiye Van Earthquake in 1976 (7.5); the Türkiye Golcuk-Kocaeli Earthquake in 1999 (7.8); the Türkiye Van Earthquake in 2011 (7.2) and the Türkiye Kahramanmaras Earthquakes in 2023 (7.8 and 7.6). The values in parentheses are the magnitudes of earthquakes. Table 1 summarizes the main active faults across independent Turkic states. All information in Table 1 were collected from AFEAD [16].

Table 1. Main active faults across independent Turkic States

Country	Fault
Azerbaijan	Main Thrust of Great Caucasus Fault
	Malkamude Thrust Fault
	Kodjashen Fault
	Saliany – Liangabiz Fault
	Apsheron Threshold Fault
	Vandam Fault
Kazakhstan	Chingiz – Tarbagatay Fault
	Tarbagatai Fault
	Chingis – Narym Fault
	Karatau Fault
	Kendaktas Fault
	Sarkand Fault
	Main Dzhungarian Fault
Kyrgyzstan	Talas – Fergana Fault
	Arslanbob Fault
	Issyk – Ata Fault
	Frontal Terskey Fault
	South Chongkemin Fault
	Chonkurchak Fault
	North Naryn Fault
Türkiye	North Anatolian Fault
	East Anatolian Fault
	North Marmara Fault
	Gediz Graben
	Southeast Hellenic Trench
	Great Menderes Graben
	Salt Lake Fault
	Edremit Fault
	Akdag Graben Fault
	Cyprus Trench Fault
Turkmenistan	Main Kopet Dagh Fault
	Kum Dagh Fault
	Isak – Cheleken Fault
	Ghiaur Dagh Fault
Uzbekistan	North Kuldjuktau Fault
	South Atoynok Fault
	Kulkuduk Fault
	Central Ustiurt Fault

All these active faults have produced massive earthquakes in historical manner. Despite providing some examples of massive earthquakes in the history of Turkic states, Table 2 summarizes them with their times and places between 1991 and 2023. This time period was selected due to the independence declaration dates of Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan and Uzbekistan.

Table 2. Massive earthquakes in Independent Turkic States, 1991 – 2023

Date	Place	Magnitude
	Azerbaijan	
04.06.1999	Agdas, Ucar, Agali	5.4
25.11.2000	Baku	6.8
07.05.2012	Zagatala	5.7
11.05.2017	Iran-Ardabil	5.1
05.06.2018	Shaki-Zaqatala	5.3
05.02.2019	Shemakha	5.0
	Kazakhstan	
13.06.2009	Tekeli	6.3
	Kyrgyzstan	
15.05.1992	Osh	6.2
19.08.1992	Toluk	7.5
09.01.1997	Dzhergetal, Koshtebe,Kazarman	5.8
05.09.2002	Not known	5.5
15.12.2006	Kochkor	5.8
08.01.2007	Isfaria	6.0
01.01.2008	Osh	5.6
05.10.2008	Nora	6.6
17.11.2015	Osh	5.6
	Turkmenistan	
06.12.2000	Nebitday – Turkmenbashi	7.0
	Uzbekistan	
15.05.1992	Andızhan	6.2
19.07.2011	Fargona, Violyati	6.1
	Türkiye	
13.03.1992	Erzincan	6.9
01.10.1995	Dinar, Evciler	6.4
27.06.1998	Adana, Ceyhan	6.3
17.08.1999	Istanbul, Kocaeli, Sakarya	7.6
12.11.1999	Bolu, Duzce, Adapazarı	7.2
06.06.2000	Cerkes, Cubuk, Orta	6.0
15.12.2000	Afyon - Bolvadin	6.0
03.02.2002	Afyon	6.5
27.01.2003	Saglamtas, Pulumur	6.1
05.01.2003	Bingol	6.4
08.03.2010	Elazig	6.1
23.10.2011	Ercis, Van	7.1
10.06.2012	Fethiye	6.1
20.07.2017	Bodrum, Datca	6.6
24.01.2020	Elazig, Malatya	6.7
30.10.2020	Izmir	7.0
06.02.2023	Kahramanmaras	7.8 - 7.6
20.02.2023	Kahramanmaras, Malatya	6.3

Note: Since numerous massive earthquakes occurred after 1991, only earthquakes greater than 6.0 in magnitude in Türkiye region are included in the table.

When the magnitudes of earthquakes, number of massive earthquakes and number of active faults are compared, Türkiye is the riskiest country across Turkic states. However, Kyrgyzstan and Azerbaijan are also observed as high risk countries in terms of earthquakes. Given this, earthquakes should be one of the main discussion themes of independent Turkic states. In this context, it is critical to understand the socioeconomic impacts of earthquakes.

3. Literature Analysis

Natural disasters and their impacts received increasing attention in the literature due to the increase in both their frequency and magnitude in parallel with the global climate crises. However, although the socioeconomic impacts of natural disasters have been discussed in more detail over the last 25 years, the macroeconomic impacts of earthquakes have not yet been deeply analysed [17, 18]. It is observed from the literature that natural disasters are discussed as a general phenomenon in most studies, without examining in greater detail the type of disaster. Only few studies have separated these disasters into climatic and geological disasters (please see: [19, 20, 21, 22]).

When the socioeconomic impacts of natural disasters are taken into account, most related studies have focused on the impacts of natural disasters on economic growth (such as [3, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36]). However, very few studies have focused on the income inequality impacts of these disasters (such as; [19, 34, 37, 38]). Moreover, the number of studies focusing on the earthquakes' macroeconomic impacts is very low. These studies can be found in [19, 23, 26, 27, 30, 31, 33, 34, 38, 39, 40, 41].

Another important point in the related literature is the investigations of the studies. It follows from the literature that the most of the related studies have investigated negative impacts of disasters on economic growth (please see: [23, 3; 25, 39, 27, 28, 29; 31, 42, 34, 41, 35, 43, 9, 21, 36, 44]). However, some studies have also investigated positive impacts resulting from different time periods and country groups (please see: [24, 45, 30; 40, 20, 23]). Even some studies have found no significant relationship between natural disasters and economic growth (please see: [26, 46, 32]). Lastly, the studies analysing the impacts of disasters on income inequality have investigated that disasters increase income inequality (please see: [19, 34, 37]).

Since this study focuses on the impacts of earthquakes, it is important to examine the studies having the same axis. In this vein, Huang et al. [23] reported that in Chinese cities, only moderate and strong earthquakes had negative impacts on economic growth from 1999 to 2014. However, Fisker [33] underlined that earthquakes decrease the growth levels of regions where they exist. But when it comes to the nation-level, other regions' growths may neutralize the negative impact at the national level. Similarly, Onuma et al. [39] analysed 173 countries between 1960 and 2010 and they found that earthquakes have negative impacts only in the midterm. Similarly, Skidmore and Toya [22] explored the relationships between natural disasters and macroeconomic indicators. They found that climatic disasters are positively correlated with economic growth, while geological disasters are negatively correlated. Noy [21] analysed different country sets as to their development levels and the results showed that disaster shocks on macroeconomy are handled better in developed countries. Wu and Guo [26] conducted an analysis of 31 Chinese provinces between 2000 and 2010. They found that earthquakes have no significant impact on economic growth in Chinese provinces. However, Best and Burke [27] conducted an analysis of Haiti between 2004 and 2014 and they have investigated that earthquake had negative impact on economic growth. Loayza et al. [20] used a cross-country panel data set for the 1961 – 2005 period and they investigated significant impacts of disasters on economic growth. But they underlined that effects are not always negative. Lackner [30] conducted an analysis for 195 countries between years of 1973 – 2015. Empirical results showed that earthquakes have negative long-run impacts on economic growth in low- and middle-income countries. However, they have positive impacts in high income countries. Zhao et al. [31] conducted a panel data analysis of 181 county-level cities in Sichuan Province in China between 2003 and 2013. They underlined that the Wenchuan Earthquake had a negative impact on economic growth. However, the recovery period may neutralize this negative impact. Sahin and Yavuz [40] also conducted an analysis of 4 OECD (Organisation for Economic Cooperation and Development) countries between 2005 and 2014 and they found that earthquakes positively affect production in Canada, Chile and Greece. However, they have no impact on Türkiye. Yamamura [19] investigated for 86 countries and the 1965 – 2004 period that natural disasters increase income inequality in short-term. However, this impact disappears in the long-term. Felbermayr and Gröschl [41] conducted an analysis of 108 countries between 1979 and 2010 years and they detected that poor countries are mainly (and negatively) affected by strong earthquakes. Barone and Mocetti [34] analysed impacts of earthquakes occurred in Italy in 1976 and 1980. They underlined that earthquakes may decrease growth and increase inequality in cases of weak institutions and the lack of financial aid. Anbarci et al. [38] estimated a panel data model for 26 countries and the 1960 – 2002 period and they found that developed countries are affected less by earthquakes.

When the aforementioned studies are examined, it seems that there is no study analyzing independent Turkic states in the context of macroeconomic impacts of earthquakes. Although there are several studies in spite of massive earthquakes in this country group (such as [47, 48, 49, 50]), they neither examine their impacts on economic growth and income inequality, nor analyse the related countries as a group. In this context, this paper is the first study analyzing independent Turkic states in terms of macroeconomic impacts of massive earthquakes. Moreover, this paper contributes to the literature on the point that it analyses the period after 1991 for this country group. This starting date was determined as to the independence declarations of Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan and Uzbekistan. Consequently, the empirical findings may have critical importance for policy formation in these countries.

4. Methodology

4.1. Data and Models

Three different types of data sets can be used in econometric analyses as time series data set, cross-sectional data set and panel data set. Panel data has some superiorities over two other data sets. First, they provide more efficient estimations due to higher degrees of freedom [51]. Second, they decrease the possibility of multicollinearity between independent variables. Third, by taking into account both time and cross section dimensions, they make it possible to deepen the analyses [52]. In this study, a panel data set covering the 1991 – 2022 period and 6 independent Turkic states, are used. This time period has been selected due to the declaration of independence of 5 Turkic states (Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan and Uzbekistan).

Two different models are estimated in this panel data context. The first model tries to estimate the determinants of economic growth and the second model tends to estimate the determinants of income inequality. In this sense, the dependent variable of the first model is the economic growth rate and the dependent variable of the second model is the GINI coefficient. The independent variables of the first model are gross fixed capital formation, labour force participation rate, earthquakes and the lagged value of the economic growth rate. Additionally, the independent variables of the second model are the economic growth rate, inflation, unemployment and earthquakes. Table 3 summarizes the variables and their notations.

Table 3. Variables and their notations

Model 1		Model 2	
Notation	**Variable**	**Notation**	**Variable**
GROWTH	Economic Growth Rate	GINI	GINI Index
GFCF	Gross Fixed Capital Formation Rate	GROWTH	Economic Growth Rate
LFPR	Labor Force Participation Rate	INF	Inflation Rate
GROWTH(-1)	One Year Lagged Value of Economic Growth	UNEMP	Unemployment Rate
QUAKE	Earthquakes	QUAKE	Earthquakes
RD	Research and Development		

In the first model, GROWTH is the annual percentage growth of Gross Domestic Product (GDP) and GFCF is the gross fixed capital formation as a percentage of GDP. LFPR is the labor force as a percentage of total population between the ages 15 and 64. RD is research and development expenditures as a percentage of GDP. QUAKE is a dummy variable expressing the earthquakes greater than the magnitude 5.0. Dummy variables are dichotomous variables that are constructed with a qualitative approach. In this sense, they are formed from 1s and 0s [52]. They provide ease to measure the impacts of qualitative variables and hence increase the explanatory power of the regression [53]. In our model, the existence of massive earthquakes is demonstrated by QUAKE dummy variable. In this manner, if at least one earthquake with a magnitude greater than 5.0, has occurred in a year, then it's marked as 1 in the series. Finally, GROWTH(-1) is the one-year lagged value of economic growth rate. This variable is added to the model because the economic growth process expresses path dependency [3, 29, 55, 56, 57]. The first model can be expressed as follows:

$$GROWTHit = \beta 0 + \beta 1GFCFit + \beta 2LFPRit + \beta 3RDit + \beta 4QUAKEit + \beta 5GROWTH(-1)it + eit \qquad (1)$$

where, i expresses the cross section dimension and t expresses the time dimension. Finally, e is the error term.

In the second model, GINI refers to the GINI coefficient indicating income inequality. It measures the distribution of income across a nation. As much it deviates from 0, income inequality increases so much [57]. Moreover, GROWTH variable is the annual percentage growth of GDP as in the first model. INF is the annual percentage increase in consumer prices. UNEMP is the unemployment rate as a percentage of total laborforce. And lastly, QUAKE is the earthquake dummy as in the first model. Apart from earthquakes data, all other data have been retrieved from World Development Indicators Database [77]. However, earthquakes data have been retrieved from NOAA (National Centers for Environmental Information) [76] and KOERI BOUN (Bogazici University Kandilli Observatory and Earthquake Research Institute) [75]. The expression of the second model where i expressing cross section dimension, t expressing time dimension and e expressing error term, is expressed as follows:

$$GINIit = \beta 0 + \beta 1GROWTHit + \beta 2INFit + \beta 3UNEMPit + \beta 4QUAKEit + eit \qquad (2)$$

Both models were constructed following the related literature. The first model is a basic Solow Growth Model based on Cobb-Douglas Production Function Approach. In this approach, output level is determined mainly by physical capital, labor force and production technology. This model is enhanced by the addition of natural disasters (please see: [24, 3, 30, 41, 33, 20, 21, 59]). However, there are different results in terms of the impacts of earthquakes on economic growth process. Although most of the studies have found negative impacts of earthquakes on economic growth [3, 30, 41, 33, 21], some of them have found no impact [20] and even some studies have found positive impacts due to the recovery affords in the long-run [24]. Across all these studies, some evidences have pointed out that impacts change as to countries/country groups and time span [24, 20, 59].

The second model is based on the sustainability approach in terms of income inequality (please see: [60, 61; 19, 37, 38, 62, 63]). In this context, following the related literature, the main determinants of the Gini coefficient have been taken into account and earthquakes have been added as another factor affecting income inequality in the model. Again there are contradicting empirical results in the literature. As an example, Keerthiratne and Tol [60] found that earthquakes decrease income inequality in Sri Lanka. However, Yamamura [19] underlined that earthquakes may increase income inequality in the short-run, but this effect may disappear in the long-run.

4.2. Empirical Methods and Results

In this study, two models are estimated via panel data analysis methods to test the impacts of earthquakes on economic growth and income inequality. In this respect, firstly, cross section dependencies of series were checked. This is an important step because if cross sectional dependency exists, then second generation unit root tests should be applied to check the validity of stationarity. First generation unit root tests produce erroneous results when cross sectional dependency ignorance [64, 65]. While checking the cross section dependency, it is critical to select a suitable test for the related data set. There are frequently used different tests as Breush-Pagan LM Test, Pesaran Scaled LM Test, Bias-Corrected Scaled LM Test and Pesaran CD Test. When cross section dimension is low (i=6) and time dimension is long enough (t= 31), Breusch – Pagan LM Test is suitable to apply [66, 67]. Null hypothesis of this test assumes no cross section dependency. Since QUAKE is a dummy variable set, cross section dependency test was not conducted for this series. Table 4 expresses Breusch – Pagan LM Test results for the series in the first model.

Table 4. Breusch – Pagan LM Test results for the growth model

Series	t Statistic	Probability	Evidence
GROWTH	167.5007	0.0000	Cross section dependency
GFCF	33.37421	0.0042	Cross section dependency
LFPR	170.2333	0.0000	Cross section dependency
RD	120.4142	0.0000	Cross section dependency

The Breusch-Pagam LM Test results show that all four series have cross section dependency. In this case, second generation unit root tests should be applied to check the validity of stationarity. Pesaran [67] has proposed the CIPS unit root test which has built upon IPS (Im, Pesaran and Shin) Test and aimed to improve its performance in panel data. The CIPS Test is especially effective when the time dimension is relatively large [68]. Table 5 summarizes the results of the CIPS Unit Root Test.

Table 5. CIPS Unit Root Test results for the growth model

Series	t Statistic	Probability	Evidence
GROWTH	-3.02329	<0.01	Stationary
GFCF	-2.55220	<0.05	Stationary
LFPR	-2.22270	<0.10	Stationary
RD	-1.18906	>=0.10	Not stationary

Table 5 exhibits that GROWTH has no unit root problem at 1% significance level. GFCF and LFPR do not also have unit root problems at the 5% and 10% significance levels respectively. However, RD has unit root problem. In this sense, first difference of the series has been taken and then the CIPS test was applied again. The test results showed that t statistic is 3.73702 indicating stationarity at 1% significance level. Hence, the first difference of RD has been used in our model. After detecting the stationarity of series, the next step is determining the type of the model to estimate. In this manner, a panel data model may either be fixed effects model or random effects model and Hausman Test expresses true type of model to be estimated. The null hypothesis of this test assumes the validity of fixed effects, while the alternative hypothesis assumes random effects [69]. Table 6 exhibits the Hausman Test results for the first model.

Table 6. Hausman Test results for the growth model

Model	Chi-Sq. Statistic	Probability	Evidence
Growth Model	1.647824	0.8954	Random Effects

After determining the type of the model, the GMM technique was used to estimate the first model. The GMM Technique which has a superiority over Maximum Likelihood, has been a widely used technique in panel data [70]. It is widely accepted that Least Squares Procedure produces large biases in panel data and what is more is that Maximum Likelihood Method is also insufficient to estimate true model [71]. Lagged values of the independent variables have been used as instrumental variables. Lag selection were made through AIC criteria [71]. Table 7 shows the GMM estimation results.

Table 7. GMM estimation results of the growth model

Variable	Coefficient	t-Statistic	Probability
Constant	-16.64984	-1.925621	0.0568*
GFCF	0.172461	1.934909	0.0557*
LFPR	0.171951	0.171951	0.0743*
QUAKES	8.140416	8.140416	0.1194
GROWTH(-1)	0.810792	0.810792	0.0000***

Note: * stands for 10% significance level; ** stands for 5% significance level and * stands for 1% significance level.**

The estimation results show that as expected, gross fixed capital formation, the labour force participation rate and one-year lagged value of economic growth are all statistically significant and have positive impact on economic growth rate. However, earthquakes greater than 5.0

magnitude has no statistically significant impact on the economic growth rate. This evidence is consistent with the findings of [24], [20] and [59].

For a more in-depth analysis, the second model is conducted. This model assumes that the existence of massive earthquakes is a determinant of income inequality. Again, the Breusch-Pagan LM Test was conducted as the first step. Since the GINI is an index series and QUAKE is a dummy variable series, their cross section dependencies have not been detected. Table 8 summarizes the results for the series.

Table 8. Breusch – Pagan LM Test results for the income inequality model

Series	t Statistic	Probability	Evidence
INF	65.76880	0.0000	Cross section dependency
UNEMP	217.5324	0.0000	Cross section dependency
GROWTH	167.5007	0.0000	Cross section dependency

Since all the series have cross section dependency, the next step is to check the validity of the stationarity. In this manner, CIPS unit root test was conducted. Table 9 summarizes the results.

Table 9. CIPS Unit Root Test results for the income inequality model

Series	t Statistic	Probability	Evidence
INF	-1.26983	>=0.10	Not stationary
UNEMP	-1.32631	>=0.10	Not stationary
GROWTH	-3.02329	<0.01	Stationary

It is observed from the results that while inflation and unemployment are not stationary at the level, growth is stationary. Therefore, the first difference of both series have been taken and stationarity has been detected. CIPS results have proved that both series are stationary at their fisrt differenced forms. INF had -2.418 t-statistic value and UNEMP had -3.508 t-statistic value indicating statistical significances at 10% and 1% respectively. After handling stationary series, the Hausman Test has been applied to determine the type of the model. Table 10 exhibits the results.

Table 10. Hausman Test results for the income inequality model

Model	Chi-Sq. Statistic	Probability	Evidence
Income Inequality Model	5.144645	0.2728	Random Effects

The Hausman Test Results indicate that Income Inequality Model has also the form of random effects. In this manner, GMM estimation has been conducted with random effects in our model. Table 11 shows the empirical results.

Table 11. GMM estimation results for the income inequality model

Variable	Coefficient	t-Statistic	Probability
Constant	23.29859	8.909452	0.0000***
INF	0.401101	0.784368	0.4366
UNEMP	7.617754	3.222919	0.0023**
GROWTH	1.161668	2.590098	0.0126**
QUAKES	11.90413	5.024242	0.0000***

Note: * stands for 10% significance level; ** stands for 5% significance level and * stands for 1% significance level.**

The estimation results show that unemployment, economic growth and earthquakes are the determinants of GINI coefficients in Turkic states. However, it seems that inflation has no statistically significant effect on income inequality. Moreover, all the significant determinants have positive impacts on the dependent variable. For the sake of clarity, it is important to remember that the higher the GINI coefficient means the higher distortions in income inequality. In this manner, it is observed that as unemployment and economic growth rate increase, income inequality increases, too. Also, the occurrence of massive earthquakes increases income inequality in this country group.

5. Conclusions

Earthquakes are natural disasters of that existences cannot be foreseen all the time and impacts are great in both fatalities and damages. Since the global climate crisis began, the number and magnitude of natural disasters have increased. Recently, two devastating earthquakes occurred in Türkiye on February 6, 2023. This has caused thousands of people to die and numerous buildings and infrastructure to collapse. Other independent Turkic states have also experienced massive earthquakes in recent years. With their destructive results, earthquakes seem critical for all these countries. Moreover, all independent Turkic states are classified as developing countries. Such countries are characterized with less developed industrial structures and lower human development levels.2 Azerbaijan, Kazakhstan, Kyrgyzstan, Turkmenistan and Uzbekistan have gained their independences in 1991. Since they had been under the control of the USSR for a long time period, it is critical for them to establish appropriate public policies for sustainable development. Also, their geography has a strategic role in the contemporary world. Organization of Turkic States has declared Turkic World Vision-2040 for the extended use of the Trans-Caspian East-West Corridor and for the joint construction of new Zengezur Corridor. It's expected that higher transportation rates will lead to higher strategic importance of this region in the near future. In this respect, the examinations about independent Turkic states have critical importance [8].

Following all these facts, this study tries to shed light on the impacts of massive earthquakes on economic growth and income inequality in Turkic states. Empirical findings suggest that earthquakes have no statistically significant impact on economic growth. However, these findings are in line with the literature. Most of the empirical studies have investigated that earthquakes have no significant impact or they have positive impacts in the long run. This result occurs due to high investments on the earthquake region. If these investments are supported by structural reforms, excellent planning and strong institutions, it is possible to overcome short-run negative impacts [32, 46, 35]. However, economic growth is a quantitative notion and cannot tell us everything about the sustainability. In this manner, it is important to research the sustainability facts behind the earthquakes. At this point, a basic question arises. What if earthquakes do not affect the growth process but detoriate income distribution? Empirical analyses of this study investigated that the existence of massive earthquakes in Turkic states between 1991 and 2022, causes higher income inequality. Again this result is in the same line with the related literature. Although there are only few studies examining this relationship, the existed ones have underlined that massive earthquakes increase income inequality [37]. However, here there is an important explanation in the literature, too. Nearly all studies examining the impacts of natural disasters on income inequality have underlined that less developed and developing countries have been affected more from disasters [45, 30, 36]. In this sense, there is a policy dilemma for developing countries as choosing to invest in structural reforms in terms of disaster-resilient societies or choosing to invest in growth-oriented policies. The first is probably time-consuming and costly but the latter means greater fatalities and damage in the case of a massive earthquake. Growth-oriented policies may increase GDP per capita in the short-run but it will not sustain welfare in the long-run. In this case, societal well-being would be underestimated and sustainable development would be laid aside.

In summary, massive earthquakes seem critical for the sustainable development journeys of independent Turkic states. Historically, devastating earthquakes have been experienced several times in each country and it seems that the frequency of natural disasters will increase in the near future. In this manner, it is important to take right policy actions in terms of sustainability. Precautions seem critical for earthquake-resilient societies and economies.

Notes

1. In these studies, there is an implicit assumption that earthquakes are independent of the global climate crisis. However, since the world is an integrated complex system [72], actually it is impossible to think earthquakes apart from the climate crisis.

2. For the list of developing countries, please visit [73].

Conflict of Interest

No potential conflicts of interest were reported by the author(s).

Author Contribution

B. T. collected the data, designed the models and wrote the whole manuscript.

References

[1] D. H. Meadows, D. L. Meadows, J. Randers, and W. W. III. Behrens. The limits to growth. Universe Books, First Edition, New York, 1972.

[2] D. H. Meadows, D. L. Meadows and J. Randers. Beyond the limits. Chelsea Green Publications, First Edition, USA, 1992.
[3] M. T. I. Kahn, S. Anwar, S. A. Sarkodie, M. R. Yaseen, and A. M. Nadeem. "Do natural disasters affect economic growth? The role of human capital, foreign direct investment, and infrastructure dynamics". *Heliyon*, 9, 1- 19, 2023. https://doi.org/10.1016/J.HELIYON.2023.E12911
[4] J. Guo, H. Liu, X. Wu, J. Gu, , S. Song and Y. Tang. "Natural disasters, economic growth and sustainable development in China—an empirical study using provincial panel data". *Sustainability,* 7(12), 16783 – 16800, 2015. https://doi.org/10.3390/su71215847
[5] O. Sander. "Turkey and the Turkic world". *Central Asian Survey*, 13(1), 37 – 44, 1994. https://doi.org/10.1080/02634939408400849
[6] Y. Sapiyev. "Turkey and Turkic-speaking states". *Journal of Anadolu Strategy*, 3(2), 1 – 31, 2022.
[7] A. Penck. "Central Asia". *The Geographical Journal*, 76(6), 477 – 487, 1930. https://doi.org/10.2307/1783689
[8] M. Mustofaev. "The Organization of Turkic States: A New Approach to Global and Regional Challenges". *Perceptions,* 27(1), 105 – 120, 2022.
[9] C. R. Jaramillo. "Do natural disasters have long-term effects on growth?" Documento CEDE 2007 – 14, 2007.
[10] R. Mechler. "Macroeconomic impacts of natural disasters". *World Bank*. 2003 http://info.worldbank.org/etools/docs/library/
[11] A. Coburn, and R. Spence. *Earthquake protection*. John Wiley and Sons. 1992.
[12] A. Tokmak, and I. Kara. "Türk devletleri teşkilatı ülkelerinin yurtdışında yerleşik yaşayan vatandaşlarına yönelik uygulamalarının analizi". *MANAS Journal of Social Studies*, 12(2), 677 – 690, 2023. https://doi.org/10.33206/mjss.1251578
[13] I. Bal. "The Turkish model and the Turkic republics". *New Trends in Turkish Foreign Affairs.* Ed. Vedat Yucel and Salomon Ruysdael. Writers Club Press. USA. PP. 211 – 234, 2002.
[14] K. Cinar. "Turkey and Turkic nations: a post-cold war analysis of relations". *Turkish Studies,* 14(2), 256 – 271, 2013. https://doi.org/10.1080/14683849.2013.802925

[15] OTS (Organization of Turkic States). Organization of Turkic States. https://www.turkicstates.org (Accessed 10 November 2023).
[16] AFEAD (Active Faults of Eurasia Database) http://neotec.ginras.ru/index/english/database_eng.html (Accessed 08 October 2023).
[17] M. Cruse. "Place in Haitian literature since the 2010 earthquake". *Geographical Review*, 103(4), 469 – 483, 2013.
[18] B. J. Godfrey. "Urban development and redevelopment in San Francisco". *Geographical Review*, 87(3), 309-333, 1997.
[19] E. Yamamura. "The impact of natural disasters on income inequality: analysis using panel data during the period 1970 to 2004". *International Economic Journal*, 29(3), 359 – 374, 2015. https://doi.org/10.1080/10168737.2015.1020323
[20] N. V. Loayza, E. Olaberria, J. Rigolini, and L. Christiaensen. "Natural disasters and growth: going beyond the averages". *World Development*, 40(7), 1317 – 1336, 2012.

https://doi.org/10.1016/j.worlddev.2012.03.002

[21] I. Noy. "The macroeconomic consequences of disasters". *Journal of Development Economics*, 88, 221 – 231, 2009. https://doi.org/10.1016/j.jdeveco.2008.02.005

[22] M. Skidmore, and H. Toya. "Do natural disasters promote long-run growth?" *Economic Inquiry*, 40(4), 664 – 687, 2002. https://doi.org/10.1093/ei/40.4.664

[23] L. Huang, Q. Liu, and Y. Tang. "Long-term economic impact of disasters: evidence from multiple earthquakes in China". *World Development*, 174, 106446, 2024. https://doi.org/10.1016/j.worlddev.2023.106446

[24] G. M. Idroes, I. Hardi, M. Nasir, E. Gunawan, P. Maulidar, and A. R. R. Maulana. "Natural disasters and economic growth in Indonesia". *Ekonomikalia Journal of Economics*, 1(1), 33 – 39, 2023. https://doi.org/10.60084/eje.v1i1.55

[25] G. S. Atsalakis, E. Bouri, and F. Pasiouras. "Natural disasters and economic growth: a quantile on quantile approach". *Annual Operations Research*, 306, 83–109, 2021. https://doi.org/10.1007/s10479-020-03535-6

[26] X. Wu, and J. Guo. "Natural disasters and economic growth—an empirical study using provincial panel data of China". In: *Economic Impacts and Emergency Management of Disasters in China.* Springer, Singapore. 2021.

[27] R. Best, and P. J. Burke. "Macroeconomic impacts of the 2010 earthquake in Haiti". *Empirical Economics*, 56, 1647 – 1681, 2019. https://doi.org/10.1007/s00181-017-1405-4

[28] N. Baig, S. Khan, N. G. Gilal, and A. Qayyum. "Do natural disasters cause economic growth? An ARDL bound testing approach". *Studies in Business and Economics*, 13(1), 5-20, 2018. https://doi.org/10.2478/sbe-2018-0001

[29] Y. T. Hee, K. V. Kalimuthu, L. C. Yu, C. S. Pong, and F. C. Chew. "Do natural disasters affect economic growth in Bangladesh?" *International Journal of Business and Society*, 19(3), 781 – 792, 2018.

[30] S. Lackner. "Earthquakes and economic growth". *FIW Working Paper*. No. 190. Pp. 1-61, 2018.

[31] R. Zhao, Z. Shihu, and H. Aiping. "Disaster impact, national aid, and economic growth: evidence from the 2008 Wenchuan earthquake". *Sustainability,* 10(12), 4409, 2018. https://doi.org/10.3390/su10124409

[32] E. Cavallo, S. Galiani, I. Noy, and J. Pantano. "Catastrophic natural disasters and economic growth". *The Review of Economics and Statistics*, 95(5), 1549–1561, 2013. https://doi.org/10.1162/REST_a_00413

[33] P. S. Fisker. "Earthquakes and economic growth. Institute for Advanced Development Studies". *Development Research Working Paper Series*. No: 01/2012.

[34] G. Barone, and S. Mocetti. "Natural disasters, growth and institutions: a tale of two earthquakes". *Journal of Urban Economics*, 84, 52 – 66, 2014. https://doi.org/10.1016/j.jue.2014.09.002

[35] K. J. Thomas, F. B. McDermott, and S. J. T. Richard. "Disasters and development: natural disasters, credit constraints, and economic growth". *Oxford Economic Paper,* 66(3), 750–773, 2014. https://doi.org/10.1093/oep/gpt034

[36] M. E. Kahn. "The death toll from natural disasters: the role of income, geography, and institutions". *The Review of Economics and Statistics*, 87 (2), 271–284, 2005.

https://doi.org/10.1162/0034653053970339
[37] E. Yamamura. "Impact of natural disasters on income inequality: analysis using panel data during the period 1965 to 2004". *MPRA Paper No*. 45623, 2013.
[38] N. Anbarci, M. Esceleras, and C. A. Register. "Earthquake fatalities: the interaction of nature and political economy". *Journal of Public Economics*, 89, 1907 – 1933, 2005. https://doi.org/10.1016/j.jpubeco.2004.08.002
[39] H. Onuma, K. J. Shin, and S. Managi. "Short-, medium-, and long-term growth impacts of catastrophic and non-catastrophic natural disasters". *Economics of Disasters and Climate Change*, 5, 53 – 70, 2021. https://doi.org/10.1007/s41885-020-00074-z
[40] I. Sahin, and O. Yavuz. "Econometric analysis of natural disasters' macro-economic impacts: an analysis on selected four OECD countries". *Journal of Business, Economics and Finance*, 4(3), 430 – 442, 2015. https://doi.org/10.17261/Pressacademia.2015313064
[41] G. Felbermayr, and J. Gröschl. "Naturally negative: the growth effects of natural disasters". *Journal of Development Economics*, 111, 92 – 106, 2014. https://doi.org/10.1016/j.jdeveco.2014.07.004
[42] N. Benali, and K. Saidi. "A robust analysis of the relationship between natural disasters, electricity and economic growth in 41 countries". *Journal of Economic Development*, 42(3), 89 – 100, 2017. https://doi.org/10.35866/CAUJED.2017.42.3.005
[43] S. Hochrainer. "Assessing the macroeconomic impacts of natural disasters: are there any?" *World Bank Policy Research Working Papers*. No. 4968, 2009.
[44] T. N. Rasmussen. "Macroeconomic implications of natural disasters in the Caribbean". *IMF Working Paper.* No: 04/224, 2004.
[45] E. A. Asyahid, and I. S. Pekerti. "Economic impact of natural disasters, spillovers, and role of human development: Case of Indonesia". *Letters in Spatial and Resource Sciences*, 15, 493 – 506, 2022. https://doi.org/10.1007/s12076-022-00307-7
[46] Y. Okuyama. Disaster and economic growth: theoretical perspectives. In: Okuyama, Y., Rose, A. (eds) Advances in Spatial and Economic Modeling of Disaster Impacts. *Advances in Spatial Science*. Springer, Cham, 2019.
[47] T. C. Zajicek. "The seismic colony: earthquakes, empire and technology in Russian-ruled Turkestan, 1887–1911". *Central Asian Survey*, 41(2), 322 – 346, 2021. https://doi.org/10.1080/02634937.2021.1919056
[48] R. Umaraliev, R. Moura, H – B. Havenith, F. Almeida, and A. G. Nizamiev. "Disaster risk in central asia: socio-economic vulnerability context and pilot-study of multi-risk assessment in a remote mountain area of the Kyrgyz Republic". *European Journal of Engineering Research and Science*, 5(3), 234 – 244, 2020.
[49] D. Iakubowskii, N. Komendantova, E. Rovenskaya, D. Krupenev, and D. Boyarkin. "Impacts of earthquakes on energy security in the Eurasian economic union: resilience of the electricity transmission networks in Russia, Kazakhstan, and Kyrgyzstan". *Geosciences*, 9(1), 54, 2019. https://doi.org/10.3390/geosciences9010054
[50] E. Durukal, and M. Erdik. "Physical and economic losses sustained by the industry in the 1999 Kocaeli, Turkey earthquake". *Natural Hazards,* 46, 153 – 178, 2008. https://doi.org/10.1007/s11069-008-9218-6
[51] J. P. Elhorst. Spatial panel data models. *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications.* M.M. Fischer ve A. Getis (Eds). Springer-Verlag

Berlin Heidelberg, 2010.

[52] C. Hsiao. “Panel data analysis – advantages and challenges”. *Test*, 16(1), 1 – 22, 2007. https://doi.org/10.1007/s11749-007-0046-x

[53] M. A. Hardy. *Regression with dummy variables.* Sage Publications. California. USA, 1993.

[54] D. B. Suits. “Use of dummy variables in regression equations”. *Journal of the American Statistical Association*, 52(280), 548 – 551, 1957. https://doi.org/10.1080/01621459.1957.10501412

[55] J. Bellaiche. “On the path-dependence of economic growth”. *Journal of Mathematical Economics*, 46(2), 163 – 178, 2010. https://doi.org/10.1016/j.jmateco.2009.11.002

[56] T. Harada. “Path-dependent economic growth with technological trajectory”. *Economics of Innovation and New Technology*, 19(6), 521 – 538, 2010.

[57] A. K. Dutt. Path dependence, equilibrium and economic growth. in Arestis, P., Sawyer,M. (eds): *Path Dependency in Macroeconomics*. International Papers in Political Economy, Macmillan Palgrave, Houndmills and New York, 2009.

[58] EUROSTAT. (2023). Glossary: Gini coefficient. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Gini_coefficient (Accessed 04 October 2023).

[59] J. M. Albala-Bertrand. “Natural disaster situations and growth: a macroeconomic model for sudden disaster impacts”. *World Development*, 21(9), 1417 – 1434, 1993. https://doi.org/10.1016/0305-750X(93)90122-P

[60] S. Keerthiratne, and R. S. J. Tol. “Impact of natural disasters on income inequality in Sri Lanka”. *World Development*, 105, 217 – 230, 2018. https://doi.org/10.1016/j.worlddev.2018.01.001

[61] M., Mehrara, and M. Mohammadian. “The determinants of gini coefficient in Iran based on bayesian model averaging”. *Hyperion Economic Journal*, 1(3), 20 – 28, 2015.

[62] E. Abounoori. “Unemployment, inflation and income distribution: A Cross-Country Analysis”. *Iranian Economic Review*, 8(9), 1 – 11, 2003. https://doi.org/10.22059/IER.2003.30925

[63] T. P. Schultz. “Secular trends and cyclical behaviour of income distribution in the United States: 1944 – 1965”. In Six papers on the size distribution of wealth and income. *NBER*. Pp. 75 – 106, 1967.

[64] M. H. Pesaran. “General diagnostic tests for cross section dependence in panels”. *Cambridge Working Papers in Economics*, 435, 2004.

[65] M. H. Pesaran. “A simple panel unit root test in the presence of cross section dependency”. *Cambridge Working Papers in Economics*, 0346, 2006.

[66] M. H. Pesaran. “General diagnostic tests for cross-sectional dependence in panels”. *Empirical Economics*, 60, 13 – 50, 2021. https://doi.org/10.1007/s00181-020-01875-7

[67] T. S. Breusch, and A. R. Pagan. “The lagrange multiplier test and its application to model specifications in econometrics”. *Review of Econometric Studies*, 47, 239–253, 1980. https://doi.org/10.2307/2297111

[68] M. H. Pesaran. “A simple panel unit root test in the presence of cross-section dependence”. *Journal of Applied Econometrics*, 22, 265 – 312, 2007. https://doi.org/10.1002/jae.951

[69] J. A. Hausman. “Specification tests in econometrics”. *Econometrica*, 46(6), 1251 – 1271,

1978. https://doi.org/10.2307/1913827

[70] D. Harris, and L. Matyas. “Introduction to the generalized method of moments estimation. Ed. Laslozo Matyas. Generalized Method of Moments Estimation”. USA: Cambridge University Press, 1999.

[71] J. D. Sargan. “The estimation of economic relationships using instrumental variables”. *Econometrica*, 26, 393 – 415, 1958. https://doi.org/10.2307/1907619

[72] C. A. Hidalgo, and R. Hausmann. “The building blocks of economic complexity”. *PNAS*, 106(26), 10570 – 10575, 2009. https://doi.org/10.1073/pnas.0900943106

[73] IMF. https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates (Accessed 10 November 2023).

[74] EM-DAT. The International Disaster Database. https://public.emdat.be/ (Accessed 04 October 2023).

[75] KOERI BOUN (Bogazici University Kandilli Observatory and Earthquake Research Institute). http://www.koeri.boun.edu.tr/new/ (Accessed 11 November 2023).

[76] NOAA (National Centres for Environmental Information). https://www.ngdc.noaa.gov/hazard/earthqk.shtml (Accessed 10 November 2023).

[77] WDI (World Development Indicators). https://databank.worldbank.org/source/world-development-indicators (Accessed 10 November 2023).

Review Article
Academic Platform Journal of Natural Hazards and Disaster Management
5(2) 2024: 76-100, DOI: 10.52114/apjhad.1557231

Time Series Analysis from 1984 to 2023 of Earth Observation Satellites Data for Evaluating Changes in Vegetation Cover and Health at Flaring Sites in the Niger Delta, Nigeria

Barnabas O. Morakinyo[1*]

Department of Surveying & Geoinformatics, Faculty of Environmental Sciences, BAZE University, Abuja, Nigeria

Received: / Accepted: 27-September-2024 / 17-December-2024

Abstract

Normalized Difference Vegetation Index (NDVI) is the most popular vegetation index used to address the challenges of multi-spectral imagery, such as the evaluation of vegetation. The data (11 Landsat 5 TM, 49 Landsat 7 ETM+, 27 Landsat 8 OLI-TIRS, and 15 Landsat 9 OLI-TIRS) dated from 10/10/1984 to 17/12/2023 with < 3 % cloud cover was used to study 11 flaring sites in Rivers State, Nigeria. Data processing and analysis were carried out using MATLAB code. For Landsat 5 and 7, NDVI was determined from the atmospherically corrected multispectral bands (1-4) and for Landsat 8 and 9, bands (2-5) in the N, E, S and W directions at distances 60m, 90m, 120m and 240m from the flare. Generally, the results show that the NDVI at 60m are the lowest. NDVI increases as distance increases to 90m, 120m and 240m from the flare for all the sites. NDVI for all sites decreases as each year passes. However, Onne station shows an unsteady pattern for the years (1984-2007) before the station was built. The lowest mean NDVI (0.290) obtained from all the 11 sites is recorded at Umudioga 60m E from the flare stack, followed by Obigbo with (0.300) at 60m E from the flare. Standard deviation (SD) for each site is small with a range value (5.0786×10^{-5} - 2.0689×10^{-4}). Therefore, it can be concluded that Landsat sensors can be used to evaluate the changes in vegetation cover and health at the flaring sites in the Niger Delta.

Key words: Time series, Evaluating, Changes, Vegetation cover and health, Environmental science

1. Introduction

Flaring is a great factor contributing to the ongoing climate change in the entire world with the Niger Delta, Nigeria, not an exception. Several authors have studied the impacts of gas flaring in the environment worldwide which include increase in temperature [1, 2]; environmental pollution [1, 3, 4, 5]; contamination of vegetation [6]; destruction of vegetation and agricultural pursuits [7, 8, 9]. The negative impacts of flaring in the Niger Delta include stunted growth and/or death of farm produce, reduction and destruction of agricultural activities and vegetation [2, 3, 4, 7, 10, 11, 12, 13, 14].

Normalized Difference Vegetation Index (NDVI) is one of the primaries and the most well received vegetation index used for the vegetation assessment through remote sensing technology. The evaluation of vegetation helps in land use studies, land cover changes, commercial agriculture etc. NDVI which has a long history and simplicity can easily be obtained from any multispectral sensor with a visible and a near Infra-Red band, hence the reason for its general application [15].

[*] Corresponding Author e-mail: barnabas.ojo@bazeuniversity.edu.ng

Globally, research has shown that NDVI is successful to distinguish non-forest, sparse forest, dense forest, agricultural fields and savannah. For example, assessments of the impact of climate on vegetation dynamics over East Africa from 1982 to 2015 [16]; drought monitoring in the Hetao plain, Mongolia of Northwest China [17, 18], in North America [19], and in Turkey [20]; forest health and vegetation changes in Germany [21, 22], in China [23], and in Greece [24]. Also, for monitoring land cover dynamics of the United Kingdom [25]; ecological environmental change in China [26]; land use land cover (LULC) changes of Pakistan's Southern Punjab Province [27]; systematic planning of urban environment [28, 29]; and global vegetation monitoring [30].

Additionally, evergreen forests are determined against seasonal forest types by the NDVI [31], and vegetation properties of various kinds are also estimated by the same NDVI, including the leaf area index (LAI) [32]. Other areas of applications of NDVI include but are not limited to the study of chlorophyll concentration in leaves [33]; productivity of plants [34] and plant stress [35]. The robustness of the NDVI-related models is directly determined by the reliability of the NDVI [36].

The consistent use of NDVI among different sensors and platforms is the primary factor for the promotion of its effectiveness for the assessment of vegetation [37]. However, atmospheric effect, NDVI susceptibility to saturation, and the quality of sensor are the major difficulties facing NDVI [15]. The problem of the effects of scattered radiation in the atmosphere is reduced by using the reflectance for retrieval of NDVI [38]. NDVI values of -1 to 1 are the range of values of NDVI whether radiance, reflectance, or digital number (DN) is used as input. Water bodies give negative NDVI [3, 4], rocks, sands, or concrete surfaces give close to zero [3, 2], and vegetation, including crops, shrubs, grasses, and forests give positive NDVI values [38]. The higher values of NDVI suggest healthy vegetation [2, 3, 4].

For the past four decades NDVI products from Advanced Very High-Resolution Radiometer (AVHRR) and MODerate Resolution Imaging Spectroradiometer (MODIS) have used time-series analysis [3, 4, 7, 15]. The applications of time-series NDVI includes monitoring change in vegetation [39, 6, 40], land cover types classification [2], simulation of environmental dynamics [41], extraction of vegetation phenology [42] etc.

Many studies have been carried out on the policies regarding gas flaring globally. For example [43] found out that in Canada, the United Kingdom, Saudi Arabia, and Norway strict regulatory measures for flaring gas were put in place. It is required for oil companies to submit their environmental impact assessments on expected emissions and discharges from gas flaring; and to provide the comprehensive precautionary measures put in place for mitigating the environmental impacts of their activities [43]. Also, the advanced countries such as United States of America, Canada, United Kingdom, Norway etc. employed modern technologies for capturing flared gas for electricity generation which in turn eliminates gas flaring in the sector [43]. In Nigeria, policy coherence around gas flaring has been slowed by political partisanship, poor governance, lack of regulatory compliance, and policy conflict between environmental protection and economic development priorities [44].

In addition, in Nigeria weak enforcement of the existing anti-gas-flaring laws, and lack of efficient regulatory legal framework for gas flare management are other challenges confronting zero flare policy that leads to oil companies continuing to flare gas [45]. A policy-specific approach toward reducing natural gas flaring and improving government quality in Nigeria is not less desirable. A gas flaring price targeting natural gas companies should be more effective in mitigating gas flaring than the wider ‘carbon price’ or pollution price/tax policy [46]. Olujobi (2020) [43] concluded that low human capacity and poor funding of anti-flaring gas policies are contributing factors to continuous flaring of gas in Nigeria.

Furthermore, several studies have been carried out on the strategies for mitigating the effects of gas flaring worldwide. Firstly, the application of Carbon Capture Utilization and Storage (CCUS) technologies which enable capturing at the source, transportation, and secure storage of Carbon dioxide (CO_2) emissions from oil and gas sectors processes [47, 48]. Also, advanced drilling such as horizontal drilling which involves drilling wells parallel to the Earth's surface, allowing for the extraction of oil and gas from multiple locations using a single wellbore [49]. This technique enables companies to access hard-to-reach reserves and increase production efficiency while reducing the environmental footprint of drilling operations [49]. Horizontal drilling reduces surface disturbance and habitat fragmentation, thereby mitigating the impact on ecosystems [50, 51].

In addition, reinjection technique is another method used for curbing the impacts of gas flaring. This technique is generally employed to maintain the presence of gas for the future use and increases the efficiency of oil production in enhanced oil recovery (EOR) activities [52]. Flare utilization methods include the application of gas turbine generator (GTG), pipeline natural gas (PNG), liquefied petroleum gas (LPG), liquefied natural gas (LNG), compressed natural gas (CNG), natural gas hydrates (NGH), gas to liquid (GL) [53].

Evaluation of the changes in the vegetation cover and health at the flaring sites in the Niger Delta using NDVI data from the Earth Observation Satellites (EOS) (Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), Landsat 8 and Landsat 9 Operational Land Imager and Thermal Infrared Sensor (OLI-TIRS)); and the time series analysis represents the knowledge gap in this research. The crucial importance of this research is that it helps to know the range of changes in the vegetation cover and health; and also, to evaluate the extent of damages that have occurred within the period at each flaring site.

There are three (3) principal research questions for this study: (1) How correctly can Landsat Earth Observation data be used to evaluate changes in vegetation cover and health over a long period at gas flaring sites in the Niger Delta? (2) What is the rate of changes in vegetation cover and health at the specific flaring site in the Niger Delta? (3) How accurately can time series analysis be used for the assessment of the changes in vegetation cover and health at the flaring sites in the Niger Delta? Hence, the examination of the ability of Landsat 5, 7, 8 and 9 sensors to evaluate the changes in vegetation cover and health at gas flaring sites in the Niger Delta is the overall aim of the study. The following are the objectives for this research: (1) Derivation of NDVI from atmospherically corrected Landsat data in the North (N), East (E), South (S), and West (W) directions at the flaring sites; (2) Classification of land surface cover (LSC) at the flaring sites; (3) Ground validation of the satellite data to improve the results; (4) Application of time series analysis for evaluating the rate of changes in vegetation cover and health.

2. Materials and Method

2.1. Study area

Eleven (11) flaring sites including two (2) refineries (Eleme 1 and Eleme 2); seven (7) flow stations (Onne, Umurolu, Alua, Rukpokwu, Obigbo, Chokocho and Umudioga); one (1)

Liquefied Natural Gas (LNG) plant (Bonny) and one (1) oil well (Sara) all from Rivers State, Niger Delta region (Figure 1) were studied for evaluation of the changes in the vegetation cover and health from 1984 to 2023 in the Niger Delta. The size of the area examined around the flare stacks with Landsat data is 12 × 12 km, in order to include sufficient data for detailed mapping of each site so that processes not related to flaring could also be resolved.

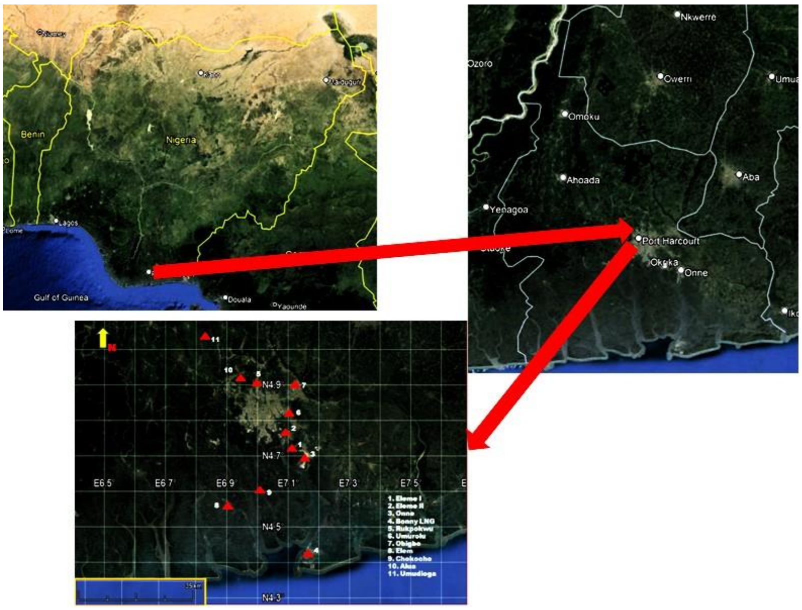

Figure 1. Top left: map of Nigeria; top right: map of Rivers State; bottom: 11 gas flaring studied sites [54].

2.2. Data used

Eleven (11) Landsat 5 TM data, forty-nine (49) Landsat 7 ETM+ data, twenty-seven (27) Landsat 8 OLI-TIRS data, and fifteen (15) Landsat 9 OLI-TIRS data dated from 10/10/1984 to 17/12/2023 with < 3 % cloud cover was used for this study. The USGS website where these data were downloaded is https://earthexplorer.usgs.gov/.

2.3. Data Analysis

2.3.1. Processing of Landsat data

1. Geo-location points were verified: Ten (10) ground control points (GCPs) were selected over the Niger Delta using Google Earth (Table 1). Twenty (20) images with five (5) images each from Landsat 5, 7**,** 8 and 9 were uploaded into the ArcGIS and the selected GCPs were identified. In Table 1, the coordinates (latitude and longitude) of the selected 10 ground control points through the Google Earth were presented in the columns 2 and 3. Columns 4 and 5 show the coordinates of the same selected 10 ground control points through Landsat 5, 7, 8 and 9 data. Column 6 provides the descriptive remarks for each of the selected points. The comparison of the coordinates of these controls obtained from the Google Earth and ArcGIS was carried out with a negligible difference found (1.0×10^{-6} to 7.3×10^{-6} m) (Table 1). This was taken as an acceptable error range for the geo-location of the imagery.

2. Removal of zero and out of range values from the data using MATLAB code, and their replacement with not a number (nan) in order to avoid divide by zero errors in calculations. Values at the upper and lower limits of the 8-bit, 12-bit and 14-bit data range which cannot be distinguished from noise were all removed.

Table 1. Geo-location point verification for Landsat 5, 7, 8 & 9 data

S/N	Google Earth Latitude (θ)	Google Earth Longitude (λ)	Landsat 5, 7, 8 & 9 Latitude (θ)	Landsat 5, 7, 8 & 9 Longitude (λ)	Remarks
1	04 24 35.42	07 09 36.00	04 24 35.40	07 09 36.00	An edge of a two storey building
2	04 25 48.34	07 11 15.41	04 25 48.34	07 11 15.39	A point on a tower
3	04 44 18.04	06 46 26.03	04 44 18.04	06 46 26.00	A two-point road junction
4	04 58 17.09	06 37 51.89	04 58 17.01	06 37 51.23	Edge of a fence.
5	04 52 59.09	06 52 09.95	04 52 59.09	06 52 09.00	A point on a LNG terminal
6	04 51 40.12	06 57 57.93	04 51 40.00	06 57 57.00	A three-point road junction
7	05 03 08.89	06 55 15.91	05 03 08.10	05 55 15.21	A three-point road junction
8	05 00 59.28	06 57 15.5	05 00 59.20	06 57 15.30	Edge of a building at Rivers International Airport
9	04 45 26.24	07 07 04.29	04 45 26.20	07 07 04.30	Edge of Eleme II fence
10	04 47 56.02	07 03 26.73	04 47 56.01	07 03 26.50	Edge of a building

3. The radiometric calibration of the multispectral bands of the data was performed. The Digital Number (DN) values were converted to the top of atmosphere (TOA) radiance values based on the sensor calibration parameters provided within the metadata files from USGS according to the Landsat 5 [55], Landsat 7 [56], Landsat 8 and Landsat 9 Science Data User's Handbooks [57] using equations 1, 2 and 3.

$$L_\lambda = G_{rescale} \times QCAL + B_{rescale} \quad (1)$$

Equation (1) is also expressed as;

$$L_\lambda = ((LMAX_\lambda - LMIN_\lambda) / (QCALMAX - QCALMIN)) \times (QCAL - QCALMIN) + LMIN_\lambda \quad (2)$$

Where:

L_λ= Spectral radiance at the sensor's aperture ($Wm^{-2}sr^{-1}\mu m^{-1}$);

$G_{rescale}$= Rescaled gain (Data product "gain" contained in the Level 1 product header or ancillary data record) ($Wm^{-2}sr^{-1}\mu m^{-1}$)/ DN;

$B_{rescale}$= Rescaled bias (Data product "offset" contained in the Level 1 product header or ancillary data record) ($Wm^{-2}sr^{-1}\mu m^{-1}$);

$QCAL$ = The quantized calibrated pixel value in DN;

$LMIN_\lambda$= The spectral radiance that is scaled to QCALMIN ($Wm^{-2}sr^{-1}\mu m^{-1}$);

$LMAX_\lambda$= The spectral radiance that is scaled to QCALMAX ($Wm^{-2}sr^{-1}\mu m^{-1}$);

$QCALMIN$ = The minimum quantized calibrated pixel value (corresponding to $LMIN_\lambda$) in DN = 1 for LPGS (a processing software version) products;

$QCALMAX$ = The maximum quantized calibrated pixel value (corresponding to $LMAX_\lambda$) in DN = 255.

For Landsat 8 and 9, the DN can be converted to spectral radiance using equation 3

$$L_\lambda = (M_L \times Q_{cal}) + A_L \ [57] \quad (3)$$

Where:

L_λ= Spectral radiance ($Wm^{-2}sr^{-1}\mu m^{-1}$);

M_L= Radiance multiplicative scaling factor for the band from the metadata;

A_L= Radiance additive scaling factor for the band from the metadata;

Q_{cal} = Level 1 pixel value in DN.

4. Computation of TOA reflectance for multispectral bands 1 to 4 for Landsat 5 and 7 including the application of simple sun angle correction is done with equation (4) which assumes Lambertian surface reflectance [56, 58]:

$\rho_p = (\pi \times L_\lambda \times d^2) / (ESUN_\lambda \times \cos \theta s)$ (4)

Where:

ρ_p = Unitless effective at-satellite planetary reflectance;

L is measured per unit solid angle;

πL = Upwelling radiance over a full hemisphere;

d = Earth-Sun distance in astronomical units;

$ESUN_\lambda$= Mean solar exo-atmospheric irradiances;

θs = Solar zenith incident angle in degrees [55].

For Landsat 8 and 9, Level 1 DN of multispectral bands 2-5 can be converted to TOA uncorrected reflectance for solar elevation angle using equation 5.

$\rho_\lambda' = (M_\rho \times Q_{cal}) + A_\rho$ [57] (5)

Where:

ρ_λ' = TOA Planetary Spectral Reflectance, without correction for solar angle(Unitless);

M_ρ= Reflectance multiplicative scaling factor for the band from the metadata;

A_ρ= Reflectance additive scaling factor for the band from the metadata;

Q_{cal} = Level 1 pixel value in DN.

The Landsat 8 and 9 corrected reflectance for solar elevation angle is as follows:

$\rho_\lambda = \rho_\lambda' / \cos(\theta_{SZ}) = \rho_\lambda' / \sin(\theta_{SE})$ [57] (6)

Where:

$\rho\lambda$ = TOA planetary reflectance

θ_{SZ} = Local sun elevation angle; the scene centre sun elevation angle in degrees is provided in the metadata;

θ_{SE} = Local solar zenith angle; θ_{SZ}=90°− θ_{SE}.

5. Atmospheric correction method: Dark Object Subtraction (DOS) method [59, 60] was adopted. The basic assumption is that within the image some pixels are in complete shadow and their radiances received at the satellite are due to atmospheric scattering “path radiance”. This assumption is combined with the fact that very few targets on the Earth’s surface are absolute black, so an assumed 1 % minimum reflectance is better than 0 % [61]. MODIS and Medium Resolution Imaging Spectroradiometer (MERIS) atmospheric correction algorithms [61] are based on this principle. However, this method assumes that this error is the same over the whole image.

DOS processes applied to this study mean that pixels corresponding to the darkest location (Atlantic Ocean) were selected for bands 1-4 for Landsat 5 and 7, and bands 2-5 for Landsat 8 and 9. The number of pixels obtained varies depending on the size of the darkest spot (Table 2). In Table 2, column 1 shows the image identification number of parts of Landsat 5, 7, 8 and 9 data (3 each) used for the study where the coordinates (latitude and longitude) of darkest pixels for each image for bands 1-4 for Landsat 5 and 7, and bands 2-5 for Landsat 8 and 9 were retrieved. Then, columns 2-5 presented the coordinates of darkest points for each image and for each multispectral band. The reflectance for these dark pixels was computed for each band and the minimum value obtained for each band was used as an estimate of the atmospheric reflectance for the respective band. These small errors were subtracted from the computed reflectance for each pixel of the whole image to reduce the atmospheric effects.

Table 2. Latitude and longitude of selected dark pixels over Atlantic Ocean (L5, L7, L8 & L9)

Image ID	Band 1 (Lat/Long.)	Band 2 (Lat/Long.)	Band 3 (Lat/Long.)	Band 4 (Lat/Long.)
LT51880571986017AAA04	04 20 02.07 07 15 03.13	04 20 11.21 07 15 58.84	04 21 36.79 07 15 51.34	04 21 25.05 07 16 22.45
LT51880571987004XXX04	04 10 00.26 07 04 43.95	03 48 04.22 07 42 00.92	03 49 09.90 07 42 01.96	03 51 01.14 07 42 23.63
LT51880571986353XXX10	04 16 48.94 07 21 40.25	04 11 40.48 07 39 48.02	04 10 16.93 07 21 20.77	04 08 08.69 07 09 02.10
LE71880571999333AGS00	03 40 37.29 06 35 44.23	03 41 14.57 06 35 31.92	03 45 10.61 06 34 32.91	03 43 54.41 06 32 27.08
LE71880572000352EDC00	03 57 55.38 06 24 15.44	04 17 17.76 08 09 37.65	04 18 50.68 08 10 15.89	04 19 24.42 08 11 31.37
LE71880572003008SGS00	04 18 00.97 07 26 14.16	03 36 14.95 07 57 22.38	03 38 15.29 07 57 45.13	03 41 09.19 07 58 49.59
	Band 2 (Lat/Long.)	Band 3 (Lat/Long.)	Band 4 (Lat/Long.)	Band 5 (Lat/Long.)
LC81880572018361LGN00	04 22 38.41 07 04 41.30	04 22 43.01 07 04 26.11	04 22 39.58 07 04 48.01	04 22 36.42 07 04 15.20
LC81880572019364LGN00	04 16 36.71 08 10 10.49	04 18 54.00 08 10 32.05	04 17 22.05 08 10 47.00	04 16 49.02 08 10 19.67
LC81880572021353LGN00	03 35 25.09 07 56 24.71	03 34 22.50 07 56 12.06	03 35 44.80 07 55 31.42	03 34 19.28 07 55 37.52
LC09L1TP18805720211211	04 22 37.00 07 04 41.13	04 23 00.05 07 04 23.05	04 22 49.61 07 04 37.01	04 22 26.08 07 04 43.59
LC09L1T18805720220317	04 06 42.08 06 38 18.60	04 06 06.59 06 48 45.38	04 06 43.39 06 49 22.24	04 04 52.90 06 46 54.80
LC09L1T18805720231225	03 58 05.19 06 23 32.19	03 58 42.27 06 25 23.40	03 58 57.30 06 25 41.18	03 59 11.23 06 25 59.42

6. Atmospherically corrected reflectance: This is the result obtained after the application of the DOS method in section 5 above.
7. Classification of Land Surface Cover (LSC): The atmospherically corrected reflectance bands 1-4 for Landsat 5 and 7, and bands 2-5 for Landsat 8 and 9 using the K-means function [2, 3, 4, 7, 8,10, 11, 13, 63] of the MATLAB tool were used for the first unsupervised cluster analysis for the land cover types classification. Three (3) classes of land cover (LC) types with cloud classified as the fourth class was obtained. Any of the 3 LC (Vegetation, water, soil and built up area) and the cloud as the fourth class was identified. Also, MATLAB codes were used for the elimination of the cloud class by masking. The cloud-masked reflectance was used for the second cluster analysis and 4 LC retrieved are vegetation, soil, built-up area and water [2, 6, 11, 64]. However, Landsat SWIR bands 5 and 7 (Landsat 5 and 7), and bands 6 and 7 (Landsat 8 and 9) were also employed for the classification of land cover types but they could not give useful results as the bands used, therefore, they were dropped for further analysis. Furthermore, Visual examination of Worldview-1 and 2, and IKONOS pseudo-true color images (RGB) from Google Earth and Digital Global (http://browse.digitalglobe.com/imagefinder/public.do) were also used to study and clarified the LC obtained. Results obtained from LC classification were used to summarize the LC types around each site.

8. Retrieval of NDVI in the N, E, S and W directions: The cloud-masked reflectance bands 3 and 4 for Landsat 5 and 7, and bands 4 and 5 for Landsat 8 and 9 were used for the retrieval of NDVI [3, 4]. For Landsat 5 and 7, band 3 is Red (R) and band 4 is Near Infra-Red (NIR) while for Landsat 8 and 9, band 4 is R and band 5 is NIR. The mathematical formula for NDVI is as stated in equation (7) [65].

   $$NDVI = (NIR - R)/(NIR + R) \tag{7}$$

   Where,
   NIR = Near Infra-Red reflectance;
   R = Red reflectance.

A summary of stages for the processing of Landsat 5, 7, 8 and 9 is shown in Figure 2.

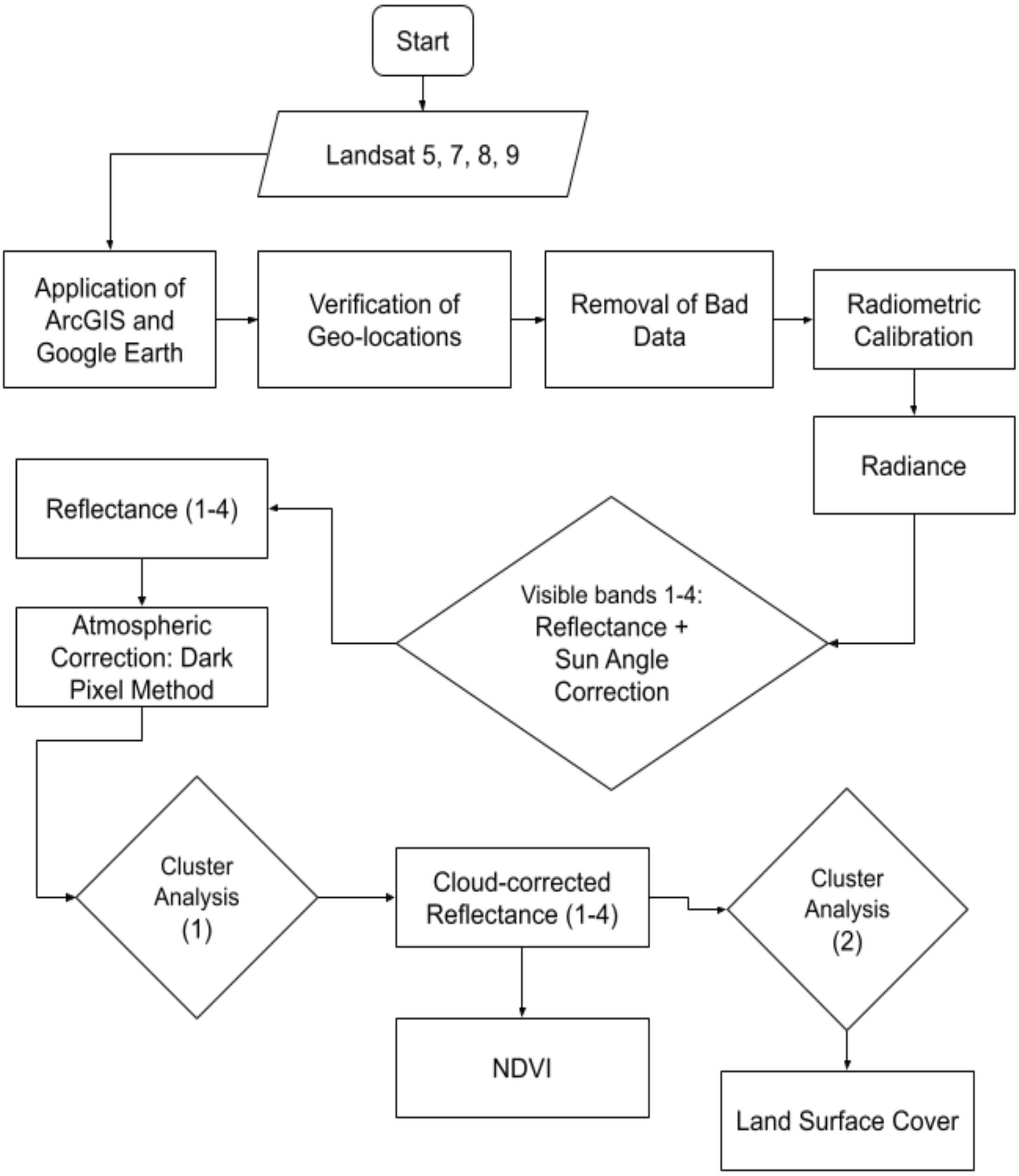

Figure 2. Methodology for processing of Landsat 5, 7, 8 and 9 data.

2.3.2. Ground validation of Landsat data

Methods and processes for the evaluation of satellite data in order to check if such data meet their stated accuracy requirements and objectives are referred to as the validation of satellite products. For this study, the validation measurements were carried out at Eleme Refineries I and II, and Onne, Alua, Chokocho and Obigbo Flow Stations on 27/07/2012 for reconnaissance activities. From 04/08/2012 to 21/09/2012[6], the first ground measurements and observations took place, which were also repeated from 05/08/2019 to 22/09/2019 [11]. The third field measurement conducted from 05/08/2023 to 22/09/2023. The in-situ data acquired are coordinates of features and points, relative humidity, air temperature, and photographs of features and locations. In addition, fieldwork activities at these 6 flaring sites confirmed that their LC (vegetation, some buildings, open land and water bodies) types are similar; and that they are the same with as other remaining flaring sites examined due to the similarity of the topography of the Niger Delta.

3. Results

3.1. Time series analysis of NDVI

Satellite data from 1984 to 2023 were used for time series analysis for this study. Generally, the results obtained presented yearly changes for all the 11 flaring sites. The NDVI values were retrieved using four cardinal points i.e., in the N, E, S and W directions at 60 m, 90 m, 120 m and 240 m from the flare stack which was at the centre of the site (0 m) 12 × 12 km. The pixels adjacent to the flare stack were used as the starting point. All Landsat data used were processed individually with NDVI for each pixel within the site retrieved. The NDVI at 60 m, 90 m, 120 m and 240 m from the flare in the N, E, S and W were retrieved for each year. Mean value for each year from the available data was computed and the range (Maximum and minimum) values of NDVI for the computed years were finally retrieved (Tables 3-6). In Table 3-6, columns 1-3 present the names of the facilities, their build time and date of available Landsat data for each site. Columns 4-7 show the mean range of NDVI values at 60 m, 90 m, 120 m and 240 m recorded for each site in the four cardinal directions.

Tables 7-17 present NDVI results at 60 m, 90 m, 120 m and 240 m from the flare in the N, E, S and W for each specific site when the entire available data for each site were processed at once. Columns 1-3 give the name of the facility for the specific site, its build date and the available Landsat data for the site in the archive. Columns 4-7 shows the NDVI results recorded in the four cardinal directions. The changes in the values of NDVI from 1984 to 2023 are presented in Figures 3-13. The results show similar trends for points between 60-120 m with a yearly reduction in the NDVI. However, at 240 m, throughout the year the NDVI results fluctuate for all the stations. Furthermore, unlike the values from 60-120 m where the highest NDVI values for all sites were recorded for the early years, the NDVI obtained for a distance of 240 m in 2023 is almost equivalent to that of the early years and even greater for some sites. For 60-120 m distance from the flare, the photosynthetic activity has been reduced to a little and/or dead with the vegetation cover and its health being negatively affected [3, 7, 11, 12, 2, 66] as shown by the results obtained. The in-situ data from ground validation activities also supported the results from the satellite data. The time of build for Eleme Refinery II, Onne Flow Station and Bonny LNG facilities are shown by a red line in the Figures 4, 5 and 7.

Table 3. Mean annual NDVI range for flaring sites at 60 m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme I	1965	1986-2023	0.20-0.69	0.36-0.75	0.54-0.84	0.23-0.78
Eleme II	1988	1984-2023	0.23-0.70	0.23-0.74	0.21-0.76	0.33-0.78
Onne	2010	1984-2023	0.48-0.82	0.51-0.79	0.48-0.82	0.51-0.79
Umurolu	Unknown	1984-2023	0.15-0.79	0.39-0.78	0.48-0.88	0.48-0.77
Bonny	1989	1986-2023	0.23-0.68	0.23-0.68	0.27-0.70	0.27-0.68
Alua	Unknown	1984-2023	0.25-0.71	0.28-0.75	0.40-0.80	0.28-0.75
Rukpokwu	Unknown	1986-2023	0.25-0.73	0.25-0.73	0.22-0.67	0.39-0.80
Obigbo	Unknown	1986-2023	0.15-0.61	0.25-0.71	0.40-0.80	0.25-0.73
Chokocho	Unknown	1986-2023	0.25-0.71	0.31-0.81	0.40-0.88	0.40-0.83
Umudioga	Unknown	1984-2023	0.40-0.74	0.46-0.76	0.23-0.78	0.18-0.78
Sara	Unknown	1986-2023	0.34-0.82	0.25-0.71	0.34-0.81	0.34-0.84

Table 4. Mean annual NDVI range for flaring sites at 90 m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme I	1965	1986-2023	0.30-0.64	0.45-0.75	0.54-0.77	0.23-0.75
Eleme II	1988	1984-2023	0.23-0.74	0.32-0.76	0.34-0.76	0.23-0.74
Onne	2010	1984-2023	0.51-0.83	0.49-0.81	0.39-0.71	0.44-0.74
Umurolu	Unknown	1984-2023	0.28-0.77	0.37-0.76	0.41-0.78	0.37-0.76
Bonny	1989	1986-2023	0.23-0.66	0.23-0.66	0.22-0.67	0.25-0.70
Alua	Unknown	1984-2023	0.26-0.74	0.22-0.74	0.19-0.72	0.38-0.84
Rukpokwu	Unknown	1986-2023	0.29-0.77	0.26-0.74	0.31-0.75	0.26-0.74
Obigbo	Unknown	1986-2023	0.31-0.75	0.26-0.74	0.23-0.74	0.21-0.74
Chokocho	Unknown	1986-2023	0.26-0.74	0.26-0.74	0.35-0.88	0.31-0.84
Umudioga	Unknown	1984-2023	0.48-0.77	0.48-0.72	0.24-0.78	0.20-0.75
Sara	Unknown	1986-2023	0.35-0.88	0.26-0.74	0.31-0.79	0.21-0.76

Table 5. Mean annual NDVI range for flaring sites at 120 m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme I	1965	1986-2023	0.49-0.72	0.55-0.82	0.41-0.62	0.50-0.72
Eleme II	1988	1984-2023	0.32-0.59	0.31-0.70	0.34-0.64	0.28-0.62
Onne	2010	1984-2023	0.32-0.62	0.39-0.64	0.35-0.59	0.34-0.70
Umurolu	Unknown	1984-2023	0.46-0.72	0.29-0.52	0.48-0.70	0.37-0.65
Bonny	1989	1986-2023	0.37-0.51	0.53-0.65	0.38-0.52	0.32-0.44
Alua	Unknown	1984-2023	0.30-0.62	0.35-0.64	0.32-0.59	0.33-0.70
Rukpokwu	Unknown	1986-2023	0.44-0.70	0.16-0.54	0.32-0.65	0.28-0.64
Obigbo	Unknown	1986-2023	0.24-0.65	0.16-0.44	0.33-0.70	0.36-0.64
Chokocho	Unknown	1986-2023	0.44-0.70	0.16-0.54	0.32-0.65	0.28-0.64
Umudioga	Unknown	1984-2023	0.48-0.70	0.16-0.42	0.32-0.57	0.33-0.64
Sara	Unknown	1986-2023	0.42-0.72	0.25-0.52	0.44-0.70	0.32-0.65

Table 6. Mean annual NDVI range for flaring sites at 240 m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme I	1965	1986-2023	0.50-0.62	0.85-0.86	0.77-0.80	0.48-0.54
Eleme II	1988	1984-2023	0.60-0.70	0.65-0.71	0.60-0.64	0.45-0.54
Onne	2010	1984-2023	0.45-0.53	0.62-0.64	0.60-0.70	0.65-0.69
Umurolu	Unknown	1984-2023	0.50-0.58	0.48-0.56	0.75-0.78	0.50-0.59
Bonny	1989	1986-2023	0.55-0.59	0.50-0.53	0.48-0.52	0.51-0.53
Alua	Unknown	1984-2023	0.45-0.53	0.61-0.64	0.60-0.65	0.69-0.70
Rukpokwu	Unknown	1986-2023	0.75-0.79	0.74-0.81	0.48-0.59	0.51-0.53
Obigbo	Unknown	1986-2023	0.45-0.52	0.65-0.69	0.65-0.67	0.81-0.84
Chokocho	Unknown	1986-2023	0.75-0.79	0.73-0.74	0.52-0.61	0.42-0.50
Umudioga	Unknown	1984-2023	0.75-0.78	0.66-0.69	0.61-0.69	0.42-0.50
Sara	Unknown	1986-2023	0.50-0.60	0.48-0.54	0.75-0.78	0.50-0.61

Table 7. Mean NDVI for Eleme I at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme I (60 m)	1965	1986-2023	0.445	0.555	0.529	0.490
Eleme I (90 m)		1986-2023	0.470	0.600	0.655	0.510
Eleme I (120 m)		1986-2023	0.605	0.685	0.685	0.610
Eleme I (240 m)		1986-2023	0.660	0.855	0.785	0.645

Table 8. Mean NDVI for Eleme II at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Eleme II (60 m)	1988	1984-2023	0.485	0.485	0.485	0.445
Eleme II (90 m)		1984-2023	0.485	0.505	0.550	0.450
Eleme II (120 m)		1984-2023	0.555	0.540	0.490	0.485
Eleme II (240 m)		1984-2023	0.650	0.680	0.620	0.495

Table 9. Mean NDVI for Onne at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Onne (60 m)	2010	1984-2023	0.490	0.630	0.515	0.520
Onne (90 m)		1984-2023	0.570	0.515	0.550	0.590
Onne (120 m)		1984-2023	0.605	0.650	0.570	0.610
Onne (240 m)		1984-2023	0.670	0.685	0.650	0.670

Table 10. Mean NDVI for Umurolu at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Umurolu (60 m)	Unknown	1984-2023	0.525	0.405	0.590	0.510
Umurolu (90 m)		1984-2023	0.540	0.405	0.595	0.545
Umurolu (120 m)		1984-2023	0.560	0.565	0.765	0.565
Umurolu (240 m)		1984-2023	0.590	0.855	0.785	0.695

Table 11. Mean NDVI for Bonny at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Bonny (60 m)	1989	1986-2023	0.455	0.455	0.445	0.380
Bonny (90 m)		1986-2023	0.445	0.445	0.450	0.475
Bonny (120 m)		1986-2023	0.540	0.515	0.468	0.494
Bonny (240 m)		1986-2023	0.570	0.590	0.500	0.520

Table 12. Mean NDVI for Alua at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Alua (60 m)	Unknown	1984-2023	0.460	0.480	0.600	0.515
Alua (90 m)		1984-2023	0.460	0.495	0.455	0.512
Alua (120 m)		1984-2023	0.480	0.515	0.455	0.610
Alua (240 m)		1984-2023	0.500	0.625	0.625	0.695

Table 13. Mean NDVI for Rukpokwu at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Rukpokwu (60 m)	Unknown	1986-2023	0.490	0.350	0.445	0.460
Rukpokwu (90 m)		1986-2023	0.530	0.490	0.485	0.500
Rukpokwu (120 m)		1986-2023	0.570	0.500	0.530	0.520
Rukpokwu (240 m)		1986-2023	0.770	0.775	0.535	0.5595

Table 14. Mean NDVI for Obigbo at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Obigbo (60 m)	Unknown	1986-2023	0.380	0.300	0.485	0.475
Obigbo (90 m)		1986-2023	0.445	0.480	0.515	0.490
Obigbo (120 m)		1986-2023	0.485	0.500	0.606	0.500
Obigbo (240 m)		1986-2023	0.530	0.670	0.660	0.825

Table 15. Mean NDVI for Chokocho at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Chokocho (60 m)	Unknown	1986-2023	0.480	0.350	0.485	0.460
Chokocho (90 m)		1986-2023	0.500	0.500	0.565	0.463
Chokocho (120 m)		1986-2023	0.570	0.560	0.615	0.575
Chokocho (240 m)		1986-2023	0.770	0.735	0.640	0.615

Table 16. Mean NDVI for Umudioga at (60, 90, 120 and 240) m from the stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Umudioga (60 m)	Unknown	1984-2023	0.570	0.290	0.445	0.460
Umudioga (90 m)		1984-2023	0.590	0.600	0.505	0.475
Umudioga (120 m)		1984-2023	0.625	0.610	0.510	0.480
Umudioga (240 m)		1984-2023	0.765	0.675	0.650	0.485

Table 17. Mean NDVI for Sara at (60, 90, 120 and 240) m from the flare stack

Facility	Build time	Data dates	N (m)	E (m)	S (m)	W (m)
Sara (60 m)	Unknown	1986-2023	0.550	0.385	0.550	0.485
Sara (90 m)		1986-2023	0.580	0.480	0.570	0.495
Sara (120 m)		1986-2023	0.612	0.500	0.575	0.555
Sara (240 m)		1986-2023	0.655	0.510	0.765	0.590

At Eleme Refinery I (Figure 3), NDVI at 60 m from the flare in the 4 directions shows slow and stable decrease in values until 2001 when there was a gradual reduction in its values. At 60 m from the flare in the W direction, the NDVI value reduced from 0.42 m in 2022 to 0.24 m in 2023. Figure 4 presents NDVI for Eleme Refinery II which gives a yearly reduction of its values. However, at 240 m NDVI values were almost sustained from 1984 to 2008; and from 2008 to 2023 values of NDVI increase slowly. This is due to the damage of the Refinery II since 2008 that led to reduction in the production capacity to about 10 %. From Figure 5 (Onne), there were no changes in the value of NDVI (1984-2008). However, at 60 and 90 m for the 4 directions from 2008 and 2015 NDVI fluctuated. In 2008, at 120 m, NDVI reduced from 0.62 m to (0.52-0.48) m in 2009. Furthermore, Umurolu (Figure 6) show slow increase in the NDVI values (0.50-0.59) m from 1984 to 2023 with the maximum value recorded in 2009.

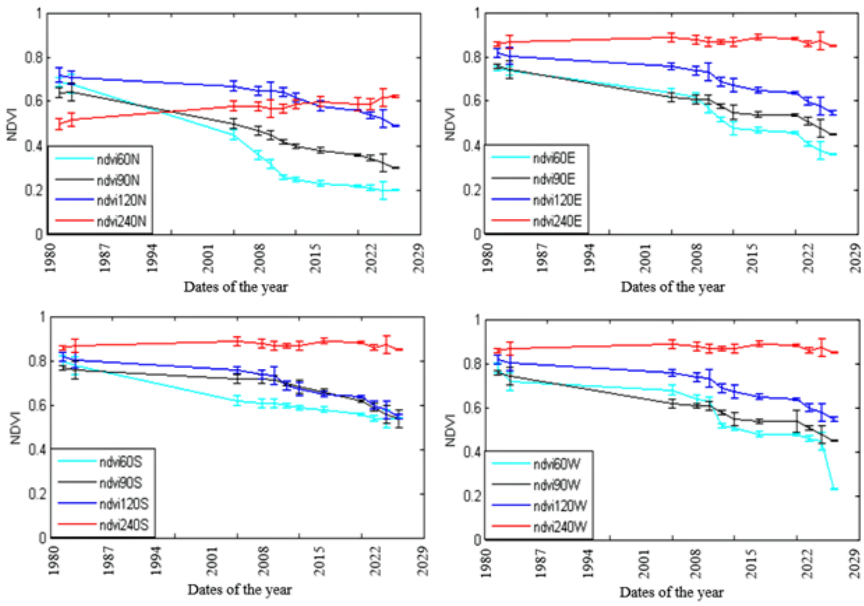

Figure 3. NDVI value changes over time in Eleme refinery I (1986-2023)

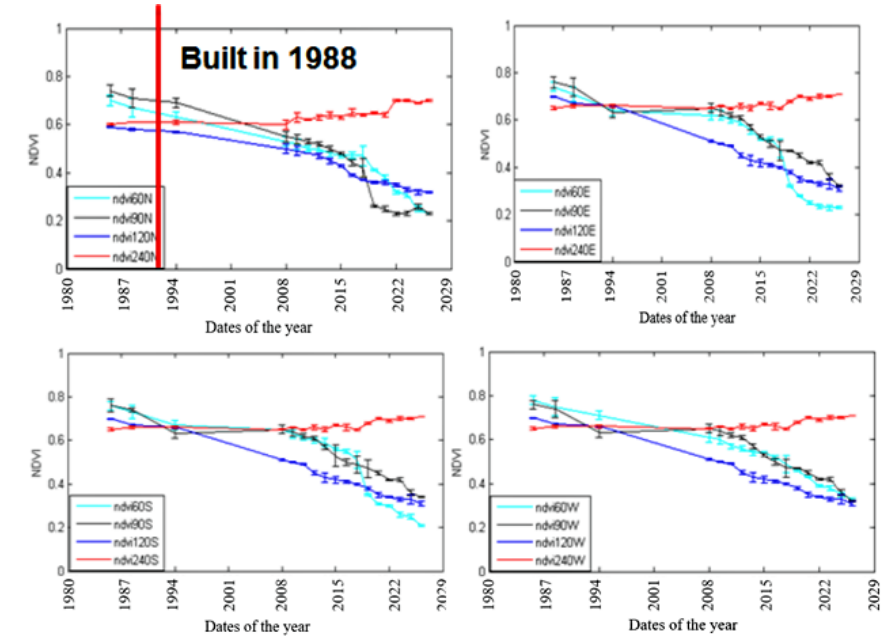

Figure 4. NDVI value changes over time in Eleme refinery II (1984-2023)

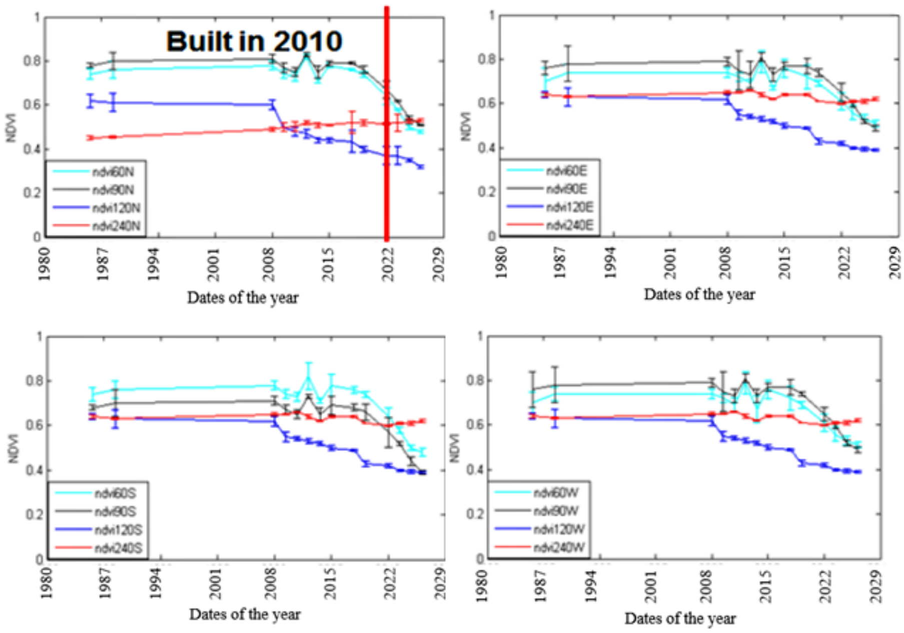

Figure 5. NDVI value changes over time in Onne (1984-2023)

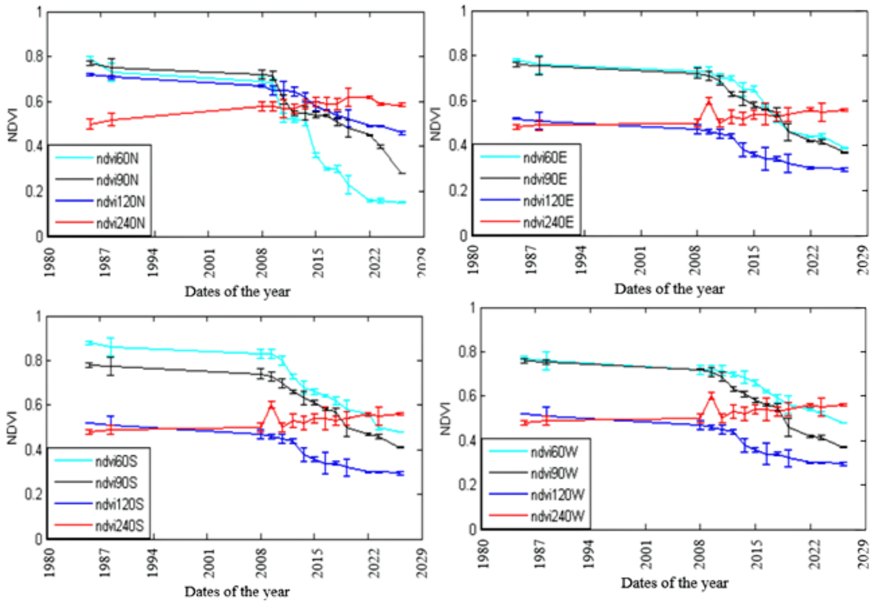

Figure 6. NDVI value changes over time in Umurolu (1984-2023)

From (2008-2023) NDVI reduced at 60 m N for Bonny LNG (Figure 7) but at 90 m there was a great reduction in 2006. At 120 m NDVI values were almost constant (1986-2004), and from here the NDVI steadily reduced until 2023. However, at 240 m NDVI values increased from (0.5) m in 2001 to 0.55 m and above in 2023. General annual reductions of NDVI were recorded for Alua (Figure 8), Rukpokwu (Figure 9), Obigbo (Figure 10), Chokocho (Figure 11), Umudioga (Figure 12) and Sara (Figure 13) in the N, E, S, and W directions. However, for Alua, at 240 m NDVI slowly increased for all directions. For Obigbo, at a distance of 240 m, the NDVI gave the same values for all directions. For Umudioga N, NDVI reduced from 2008 to 2023 (0.5-0.7). For Sara at 240 m NDVI increased from 1990 to 2002 (0.48-0.71), reduced in 2005 (0.58) and then slowly increased until 2023. The lowest mean NDVI (0.290) obtained from all the 11 sites is recorded at Umudioga 60 m E of the flare stack, followed by Obigbo with (0.300) at 60 m East of the flare. Finally, both Rukpokwu and Chokocho recorded (0.350) at 60 m East of the stack.

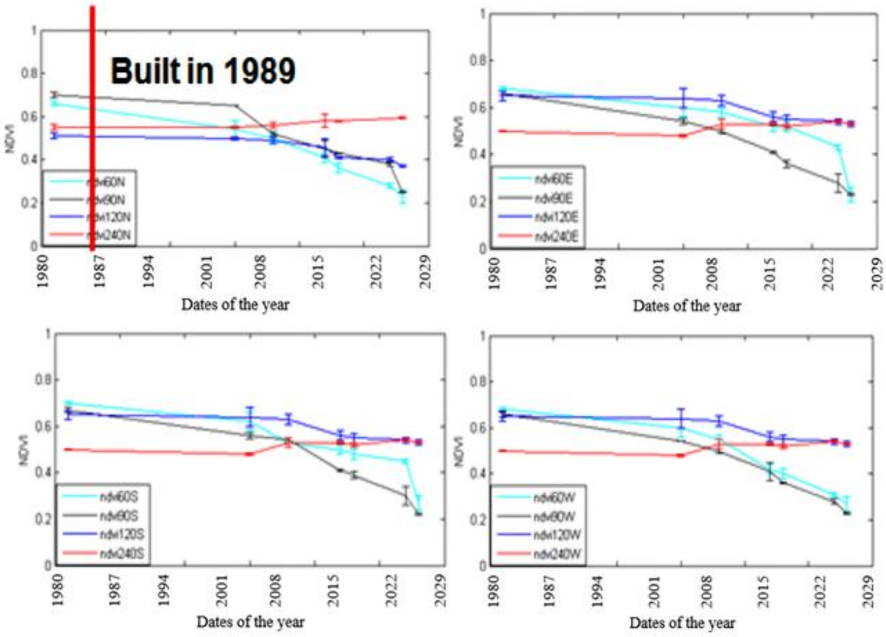

Figure7. NDVI value changes over time in Bonny LNG (1986-2023)

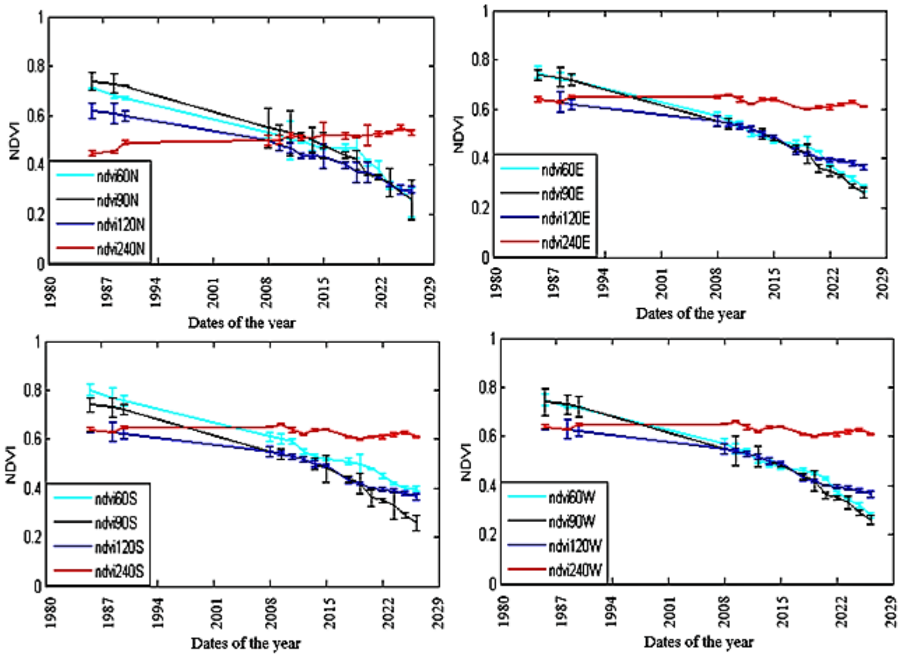

Figure 8. NDVI value changes over time in Alua (1984-2023)

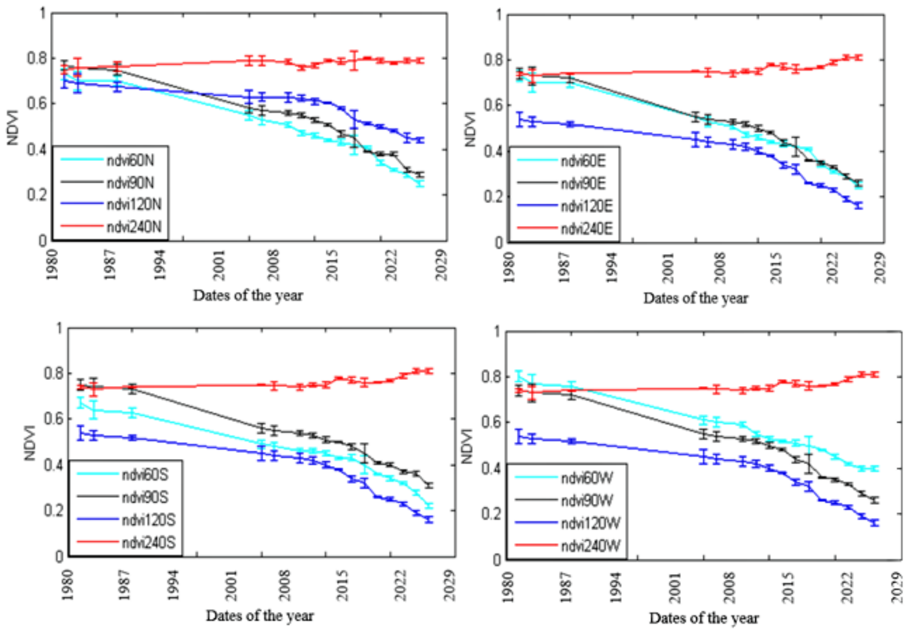

Figure 9. NDVI value changes over time in Rukpokwu (1986-2023)

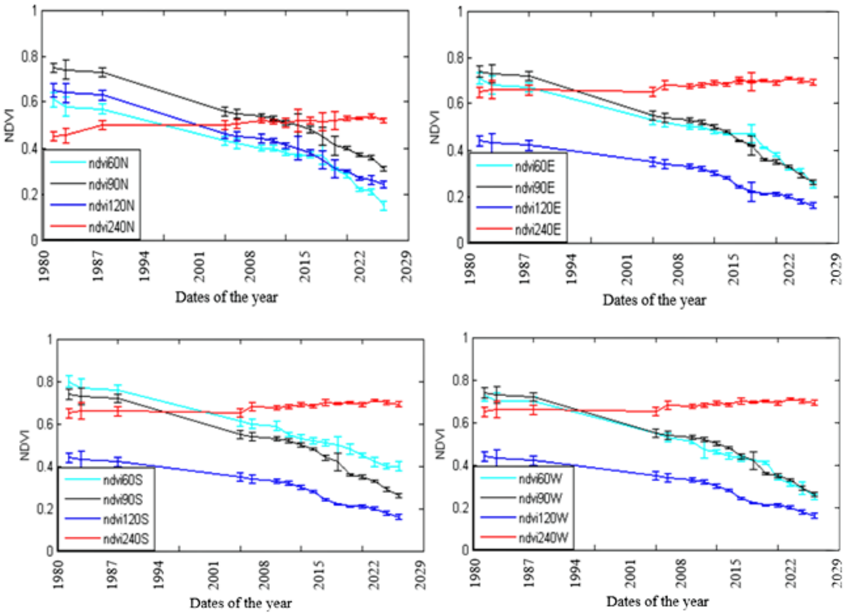

Figure 10. NDVI value changes over time in Obigbo (1986-2023)

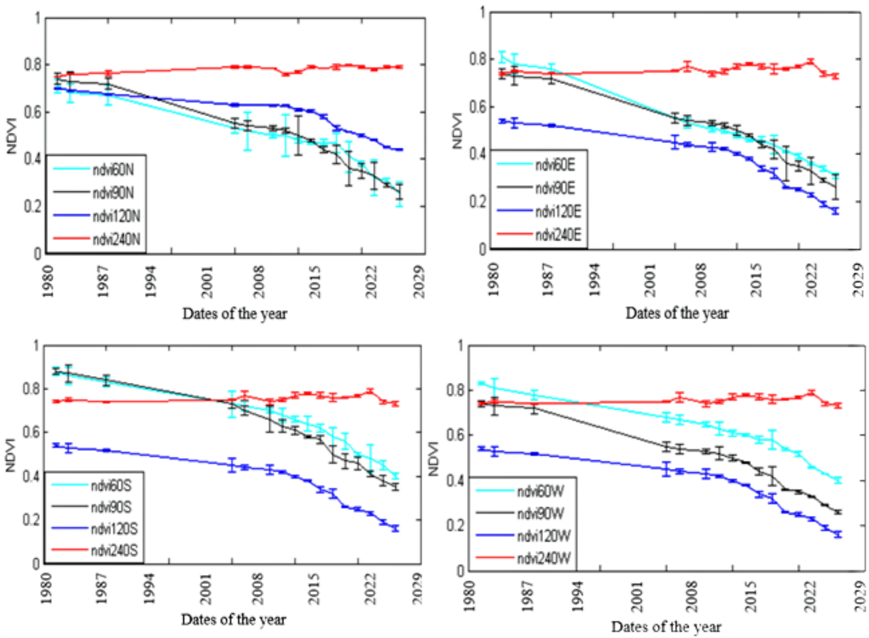

Figure 11. NDVI value changes over time in Chokocho (1986-2023)

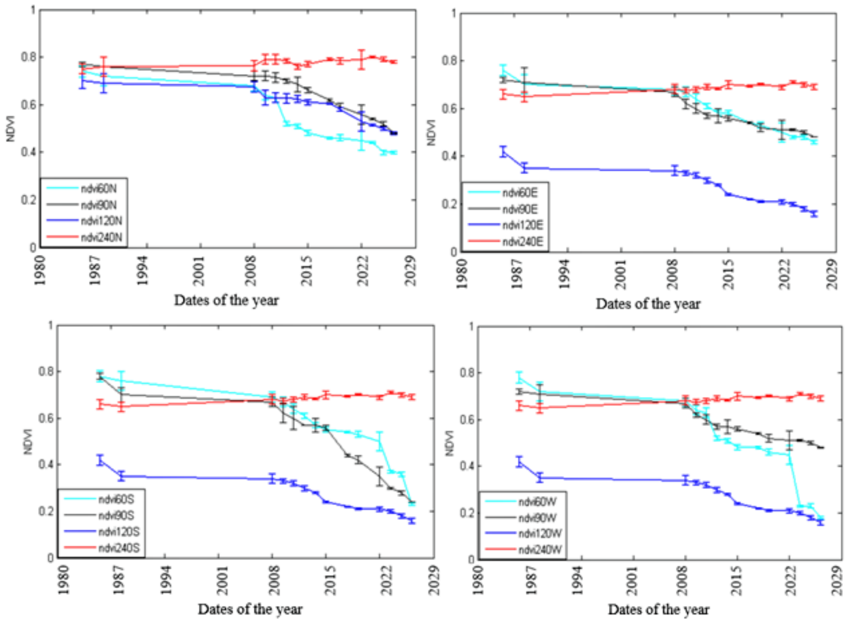

Figure 12. NDVI value changes over time in Umudioga (1984-2023)

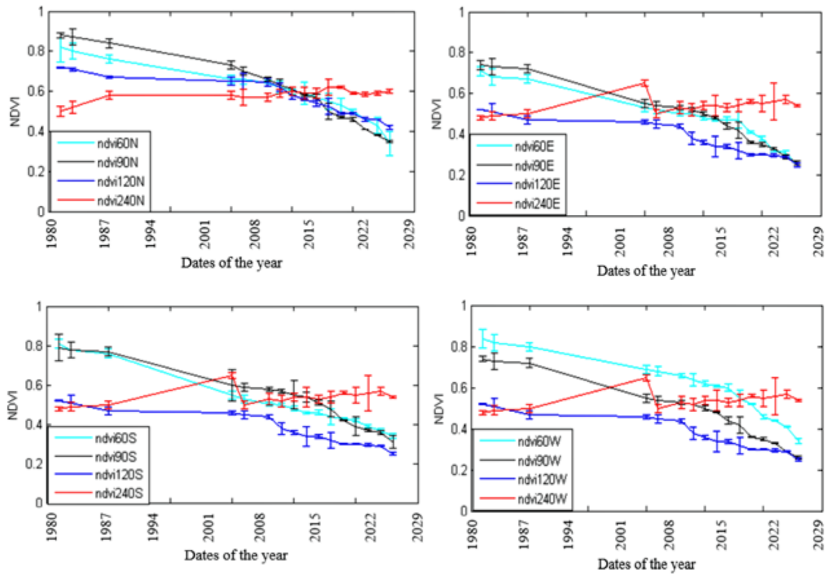

Figure 13. NDVI value changes over time in Sara (1986-2023)

3.2. Statistical analysis

The NDVI results for each pixel in each subscene from 1984 to 2023 were linearly regressed against time. The mean and standard deviation of NDVI trend values were calculated in each case for NDVI trend values. The significance level adopted for the analysis is α >0.05. Table 18 presents the mean and standard deviation (SD) for all the NDVI values at each flaring site. Column 1 gives the list of the 11 flaring sites studied, columns 2 and 3 shows the computed mean and standard deviation of NDVI recorded for all pixels within 12 × 12 km of each site.

Table 18. Mean and SD for NDVI values for the study sites (Change in NDVI/ year)

Flaring sites	Mean (All pixels)	SD (All pixels)
Eleme I	1.9166×10^{-5}	2.0689×10^{-4}
Eleme II	1.5010×10^{-5}	1.3596×10^{-4}
Onne	2.2849×10^{-6}	7.9515×10^{-5}
Umurolu	5.8057×10^{-5}	7.4988×10^{-5}
Bonny	2.1294×10^{-5}	8.2903×10^{-5}
Alua	8.7469×10^{-5}	1.4516×10^{-4}
Rukpokwu	7.3986×10^{-5}	6.2093×10^{-5}
Obigbo	7.8273×10^{-5}	1.1192×10^{-4}
Chokocho	1.0520×10^{-4}	5.0786×10^{-5}
Umudioga	-3.0408×10^{-5}	1.0120×10^{-4}
Sara	1.4015×10^{-5}	7.6382×10^{-5}

Mean gives a central value in the distribution; however, it does not indicate how far the data points fall from the center. SD value summarizes the variability in a dataset; and also represents the typical distance between each data point and the mean. A smaller value of SD shows that the data points cluster closer to the mean which is an indication that the values in the dataset are relatively consistent. In contrast, higher values show that the values spread out further from the mean. The results presented in Table 18 show that SD for each site is small with a range value (5.0786×10^{-5} - 2.0689×10^{-4}). Chokocho site recorded the lowest SD (5.0786×10^{-5}) and the highest value is for Eleme refinery 1. The NDVI results obtained for all sites are directly opposite to the temperature which is supported by the previous literature [1, 5, 9, 14]. The higher the temperature around the flare source, the lower NDVI retrieved. Hence, contamination of vegetation, destruction of farm produce, stunted growth and/or death of vegetation and agricultural products, environmental pollution etc. at each site is inevitable.

4. Discussion

The lowest values of NDVI were obtained at 60 m and the values increase as distance from the flare increases to 90 m, 120 and 240 m for all the 11 sites throughout the years of analysis. However, before the construction of Onne (1984-2008) NDVI fluctuated which could be attributed to the vegetation density, vegetation types and their photosynthetic rate as no flare was present. The results also recorded yearly reduction in NDVI within 120 m from the stack; and that the impacts of the flare after 120 m are very little. Also, the results from the statistical analysis give smaller SD which means that the data cluster to the mean i.e. the dataset values is consistent. The implication of the results is that vegetation closer to the flare is sparse, unhealthy and some of it is dead. The lowest mean NDVI (0.290) obtained from all the 11 sites is recorded at Umudioga 60 m E of the flare stack. Therefore, it can be concluded that Landsat sensors can be used to evaluate the changes in vegetation cover and its health at the flaring sites in the Niger Delta.

Lack of data on vegetation types, and the rate and volume of the gas burning at flaring sites are two major challenges to this research. Therefore, a further study needs to be carried out using these two datasets in order to improve on the results obtained for this study.

Gas flaring is a major problem in Nigeria that has not yet received 100 % attention of the Government on how to solve it. Hence, the following recommendations are made:

- Nigerian Government should carry out the stringent enforcement of the Nigerian Petroleum Industry Act of 2021.

- Nigerian Environmental protection laws should have adequate provisions for combating oil and gas pollution, degradation, and gas flaring. The National Environmental Standard Regulation Enforcement Agency (Establishment) Act (NESREA), 2007, should be amended to widen its scope to oil and gas sector activities.
- The Nigerian Constitution should be amended to make environmental infringements justiciable in order to guarantee a healthy and sustainable environment.
- Enactment of the comprehensive regulatory framework governing gas utilization and development of gas pipeline networks to all the six (6) geo-political zones in Nigeria for proper gas distribution.
- The Nigerian Government should increase generation of electricity in Nigeria through the use of gas.
- Oil companies should update their equipment to modern technologies and methods to be in accordance with the international standards.
- Nigerian Government should encourage investors in the energy sector by providing the enabling environment.
- A gas flaring price targeting natural gas companies should be more effective in mitigating gas flaring than the wider ‘carbon price’ or pollution price/tax policy.
- The Federal Government should provide alternative energy source to mitigate the effect of gas flaring on the people and preserve the environment.

Acknowledgements

The Author is grateful to the USGS for the provision of Landsat data and ATMCORR Calculator. Many thanks to Jill Schwarz for MATLAB coding and guidance.

Conflict of Interest

The Author declares no conflict of interest.

Author Contribution

B. M. performed the research and analysis and wrote the whole manuscript.

References

[1] Lu, W., Liu, Y., Wang, J., Xu, W., Wu, W., Liu, Y., Zhao, B., Li, H., & Pei Li. “Global proliferation of offshore gas flaring areas”. *Journal of Maps*, 16(2), 396-404, 2020. DOI: 10.1080/17445647.2020.1762773

[2] Morakinyo, B. O., Lavender, S., Schwarz, J & Abbott, V.. “Mapping of land cover and estimation of their emissivity values for gas flaring sites in the Niger Delta”. *British Journal of Environmental Sciences,* 7(2), 31-58, 2019.

[3] Morakinyo, B. O., Lavender, S & Abbott, V.. “Detection of potentially gas flaring related pollution on vegetation cover and its health using remotely sensed data in the Niger Delta, Nigeria”. *Asian Review of Environmental and Earth Sciences,* 10(1), 1-13, 2023a. https://doi.org/10.20448/arees.v10i1.4407

[4] Morakinyo, B. O.. “Assessments of the impacts of environmental factors on vegetation cover at gas flaring sites in the Niger Delta, Nigeria”. *Review of Environment and Earth Sciences*, 10(1), 8-18, 2023b.

[5] Umbugala, U. D & Morakinyo, B. O.. “Detection of Oil and Gas Platforms in the Niger Delta, Nigeria: Role of Digital Technology in Facilities Management”. *BAZE University Journal of Entrepreneurship and Interdisciplinary Studies,* 2(2), 11-22, 2023.

[6] Morakinyo, B. O.. “Flaring and pollution detection in the Niger Delta using remote sensing”. PhD Thesis, University of Plymouth, Plymouth, United Kingdom. 2015.

[7] Morakinyo, B. O., Lavender, S &Abbott, V.. “Investigation of potential prevailing wind impact on land surface temperature at gas flaring sites in the Niger Delta, Nigeria”. *International Journal of Environment and Geoinformatics,* 9(1), 179-190, 2022a. https://doi.org/10.30897/ijegeo.968687

[8] Morakinyo, B. O., Lavender, S & Abbott, V.. “Evaluation of factors influencing changes in land surface temperature at gas flaring sites in the Niger Delta, Nigeria”. *BAZE University Journal of Entrepreneurship and Interdisciplinary Studies,* 1(2), 1-19, 2022b.

[9] Nwaogu, L. A & Onyeze, G. O. C.. “Environmental Impacts of Gas Flaring on Ebocha-Egbema, Niger Delta, Nigeria”. *Energy and Environmental Research,* 8(1), 1-11, 2020.

[10] Morakinyo, B. O.. “Detection of Impacts of Gas Flaring in the Environment: Application of Landsat Earth Observation Data”. *BAZE University Journal of Entrepreneurship and Interdisciplinary Studies,* 2(1), 74-89, 2023c.

[11] Morakinyo, B. O., Lavender, S & Abbott, V.. “The methodology and results from ground validation of satellite observations at gas Flaring Sites in Nigeria”. *International Journal of Environment and Geoinformatics,* 8(3), 290-300, 2021. https://doi.org/10.30897/ijegeo.749664

[12] Morakinyo, B. O., Lavender, S & Abbott, V.. “Assessment of uncertainties in the computation of atmospheric correction parameters for Landsat 5 TM and Landsat 7 ETM+ thermal band from atmospheric correction parameter (ATMCORR calculator)”. *British Journal of Environmental Sciences,* 8(1), 20-30, 2020a.

[13] Morakinyo, B. O., Lavender, S & Abbott, V.. “Retrieval of land surface temperature from Earth observation satellites for gas flaring sites in the Niger Delta, Nigeria”. *International Journal of Environmental Monitoring and Analysis.* 8(3), 59-74, 2020b. https://doi.org/10.11648/j.ijema.20200803.13

[14] Musa, D. G., Oruonye, E. D., Anger, R. T., Ojeh, V. N & Delphine, D.. “Effect of Gas Flaring on Human Well-Being and Environment in Obodo-Ugwa, Ndokwa West, Local Government Area, Delta State, Nigeria”. *Journal of Engineering & Environmental Science 2024, 2(1): 000108),* 2024.

[15] Huang, S., Tang, L., Hupy, P., Wang, Y & Shao, G.. “A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing”. *Journal of Forestry Research* 32(1), 1-6, 2020. https://doi.org/10.1007/s11676-020-01155-1

[16] Kalisa, W., Igbawua, T., Henchiri, M., Ali, S., Zhang, S., Bai, Y & Zhang, J.. “Assessment of climate impact on vegetation dynamics over East Africa from 1982 to 2015”. *Scientific Reports,*9:16865, 2019. https://doi.org/10.1038/s41598-019-53150-0

[17] Hua, X., Rena, H., Tansey, K., Zhenga, Y., Ghent, D., Liu, X & Yan, L.. “Agricultural drought monitoring using European Space Agency Sentinel 3A land surface temperature and normalized difference vegetation index imageries”. *Agricultural and Forest Meteorology*, 279, 107707, 2019.

[18] Wei., W., Zhang, H., Zhou, J., Zhou, L., Xie, B. & Li, C. "Drought monitoring in arid and semi-arid region based on multi-satellite datasets in Northwest China". *Environmental Science and Pollution Research*, vol. 28, pages 51556-51574, 2021.

19] Karnieli, A., Agam, N., Pinker, R. T., Anderson, M., Imhoff, M. L., Gutman, G. G., Panov, N & Goldberg, A.. "Use of NDVI and Land Surface Temperature for Drought Assessment: Merits and Limitations". *Journal of Climate*, 23: 618-633, 2010.

[20] Polat, A. B., Akcay, O & Kontas, F.. "Drought monitoring in Burdur Lake, Turkey using multi-sensor remote sensing data sets". *Advances in Geodesy and Geoinformation (formerly Geodesy and Cartography)*, Vol. 73, no. 1, article no. e47, 2024. https://doi.org/10.24425/agg.2023.146159

[21] Gessner, U.; Reinermann, S., Asam, S & Kuenzer, C. "Vegetation Stress Monitor-Assessment of Drought and Temperature-Related Effects on Vegetation in Germany Analyzing MODIS Time Series over 23 Years". Remote Sensing, 15, 5428, 2023. https://doi.org/10.3390/rs15225428

[22] Kloos, S., Yuan, Y., Castelli, M & Menzel, A.. "Agricultural Drought Detection with MODIS Based Vegetation Health Indices in Southeast Germany". Remote Sensing, 13, 3907, 2021. https://doi.org/10.3390/rs13193907

[23] Chang, J., Liu, Q., Wang, S & Huang, C. "Vegetation Dynamics and Their Influencing Factors in China from 1998 to 2019". Remote Sensing, 14, 3390, 2022. https://doi.org/10.3390/rs14143390

[24] Chrysopolitou, V., Apostolakis, A., Avtzis, D., Avtzis, N., Diamandis, S., Kemitzoglou, D., Papadimos, D., Perlerou, C., Tsiaoussi, V & Dafis, S.. "Studies on forest health and vegetation changes in Greece under the effects of climate changes". Biodiversity Conservation, 22:1133-1150, 2013. DOI 10.1007/s10531-013-0451-2.

[25] Lavender, S. J.. "Monitoring land cover dynamics at varying spatial scales using high to very high resolution optical imagery". *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLI-B8, XXIII ISPRS Congress, 12-19 July 2016, Prague, Czech Republic.

[26] Jiang, L., Liu, Y., Wu, S & Yang, C.. "Analyzing ecological environment change and associated driving factors in China based on NDVI time series data". *Ecological Indicators*, 129, 107933, 2021.

[27] Hu, Y., Raza, A., Syed, N. R., Acharki, S., Ray, R. L., Hussain, S., Dehghanisanij, H., Zubair, M & Elbeltagi, A.. "Land Use/Land Cover Change Detection and NDVI Estimation in Pakistan's Southern Punjab Province". *Sustainability*, 15, 3572, 2023. https://doi.org/10.3390/su15043572

[28] Guha, S.. "A long-term monthly assessment of land surface temperature and normalized difference vegetation index using Landsat data". *urbe. Revista Brasileira de Gestão Urbana*, v.13, e20200345, 2021. https://doi.org/10.1590/2175-3369.013.e20200345

[29] Guha, S., Govil, H & Diwan, P.. "Monitoring LST-NDVI Relationship Using Premonsoon Landsat Datasets". *Advances in Meteorology*, Volume 2020, Article ID 4539684, 15 pages, 2020. https://doi.org/10.1155/2020/4539684

[30] Roßberg, T & Schmitt, M.. "A Globally Applicable Method for NDVI Estimation from Sentinel-1 SAR Backscatter Using a Deep Neural Network and the SEN12TP Dataset". PFG, 91: 171-188, 2023.

[31] Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J. M., Tucker, C. J & Stenseth, N. C.. "Using the satellite-derived NDVI to assess ecological responses to environmental change". *Trends of Ecological Evolution,* 20(9), 503-510, 2005.

[32] Tian, J., Wang, L., Li, X., Gong, H., Shi, C., Zhong, R & Liu, X.. "Comparison of UAV and WorldView-2 imagery for mapping leaf area index of mangrove forest". *International Journal of Applied Earth Observation and Geoinformatics,* 61, 22-31, 2017.

[33] Pastor-Guzman, J., Atkinson, P., Dash, J & Rioja-Nieto, R.. "Spatio-temporal variation in mangrove chlorophyll concentration using Landsat 8". *Remote Sensing of Environment,* 7(11), 14530-14558, 2015.

[34] Vicente-Serrano, S. M., Camarero, J. J., Olano, J. M., Martín-Hernández, N., Peña-Gallardo, M., Tomás-Burguera, M., Gazol, A., Azorin-Molina, C., Bhuyan, U & El-Kenawy, A.. "Diverse relationships between forest growth and the normalized difference vegetation index at a global scale". *Remote Sensing of Environment,* 187, 14-29, 2016.

[35] Chavez, R. O., Clevers, J. G. P. W., Decuyper, M., De Bruin, S & Herold, M.. "50 years of water extraction in the Pampa del Tamarugal basin: Can Prosopis tamarugo trees survive in the hyper-arid Atacama Desert (Northern Chile)?". *Journal of Arid Environment,* 124, 292-303, 2016.

[36] Butt, B.. "Environmental indicators and governance". *Current Opinion on Environmental Sustainability* 32, 84-89, 2018.

[37] Grant, B. G.. "UAV imagery analysis: Challenges and opportunities. In: Proceedings of the long-range imaging II". Anaheim, CA, vol 10204, p 1020406, 2017.

[38] Jones, H. G & Vaughan, R. A.. "Remote sensing of vegetation: Principles, techniques and applications". Oxford University Press, New York, p 353, 2010.

[39] Chu, H. S., Venevsky, S., Wu, C & Wang, M. H.. "NDVI-based vegetation dynamics and its response to climate changes at Amur-Heilongjiang River Basin from 1982 to 2015". *Sci. Total Environ*. 650, 2051-2062, 2019. https://doi.org/10.1016/j. scitotenv.2018.09.115

[40] Mao, D., Wang, Z., Luo, L & Ren, C.. "Integrating AVHRR and MODIS data to monitor NDVI changes and their relationships with climatic parameters in Northeast China". *International Journal of Applied Earth Observation and Geoinformatics,* 18, 528-536, 2012. https://doi.org/10.1016/j. jag.2011.10.007

[41] Zhao, J., Huang, S., Huang, Q., Wang, H., Leng, G & Fang, W.. "Time-lagged response of vegetation dynamics to climatic and teleconnection factors". *Catena,* 189, 104474, 2020. https://doi.org/10.1016/j.catena.104474

[42] Buyantuyev, A & Wu, J.. "Urbanization diversifies land surface phenology in arid environments: Interactions among vegetation, climatic variation, and land use pattern in the Phoenix metropolitan region, USA". *Landscape Urban Plan,* 105 (1-2), 149-159, 2012. https://doi.org/10.1016/j.landurbplan.2011.12.013

[43] Olujobi, O. J.. "Analysis of the Legal Framework Governing Gas Flaring in Nigeria's Upstream Petroleum Sector and the Need for Overhauling". *Social Science,*9, 132, 2020.

[44] Aigbe, G. O., Cotton, M & Stringer, L. C.. "Global gas flaring and energy justice: An empirical ethics analysis of stakeholder perspectives". *Energy Research & Social Science* 99, 103064, 2023.

[45] Olujobi, O. J., Yebisi, T. E., Patrick, O. P & Ariremako, A. I.. "The Legal Framework for

Combating Gas Flaring in Nigeria's Oil and Gas Industry: Can It Promote Sustainable Energy Security?". *Sustainability*, 14, 7626, 2022. https://doi.org/10.3390/su1413762.

[46] Alola, A. A., Onifade, S. T., Magazzino, C & Obekpa, H. O.. "The effects of gas flaring as moderated by government quality in leading natural gas flaring economies". *Scientific Reports*,13: 14394, 2023. https://doi.org/10.1038/s41598-023-38032-w.

[47] Sandunika, D.M.I., Dilka, S.H.S., Alwis, M.K.S.D., Siriwardhana, S.M.G.T., M. S, N., Perera, W.A.V.T., Sandeepa, R.A.H.T., Panagoda, L.P.S.S., Chamara, N.N., & Kumarasiri, K.A.C.S.. "Assessing the effectiveness and sustainability of carbon capture and storage (ccs) technologies for mitigating greenhouse gas emissions". 2020.

[48] Thepsaskul, W., Wongsapai, W., Sirisrisakulchai, J., Jaitiang, T., Daroon, S., Raksakulkan, V., Muangjai, P., Ritkrerkkrai, C., Suttakul, P., & Wattakawigran, G.. "Potential business models of carbon capture and storage (CCS) for the oil refining industry in Thailand". *Energies*, *16*(19), p.6955, 2023.

[49] Ekemezie, I. O & Digitemie, W. N,. "Climate change mitigation strategies in the oil and gas sector. A review of practices and impact". *Engineering Science & Technology Journal*, Volume 5, Issue 3, 935-948, 2024.

[50] Van Oort, E., Chen, D., Ashok, P., & Fallah, A.. "Constructing deep closed-loop geothermal wells for globally scalable energy production by leveraging oil and gas ERD and HPHT well construction expertise". In SPE/IADC Drilling Conference and Exhibition (p. D021S002R001). SPE. 2021, March.

[51] Lyons, W. C., Stanley, J. H., Sinisterra, F. J., & Weller, T.. "Air and Gas Drilling Manual: Applications for Oil, Gas, Geothermal Fluid Recovery Wells, Specialized Construction Boreholes, and the History and Advent of the Directional DTH". *Gulf Professional Publishing*. 2020.

[52] Elvidge, C. D., Bazilian, M. D., Zhizhin, M., Ghosh, T., Baugh, K & Hsu, F. (2018). The potential role of natural gas flaring in meeting greenhouse gas mitigation targets. Energy Strategy Reviews 20 (2018) 156-162.

[53] Zolfaghari, M., Pirouzfar, V and Sakhaeinia, H.. "Technical characterization and economic evaluation of recovery of flare gas in various gas-processing plants". *Energy* 124481-491, 2017.

[54] ESRI.. "Map of Nigeria, map of Rivers State and map of 11 gas flaring studied sites". 2024.

[55] Chander, G & Markham, K.. "Revised Landsat 5 TM Radiometric Calibration Procedures and Post Calibration Ranges". *IEEE Transaction of Geosciences and Remote Sensing* 41(11): 2674-2677, 2003.

[56] NASA.. "National Aeronautics and Space Administration. Landsat 7 ETM+ Science Data Users Handbook". [Online]. Available: http://www.landsathandbook.gsfc.nasa.gov/data_prod/prog_sect11_3.html [Accessed 23rd January 2022].

[57] Ihlen, V.. "Landsat 8 (L8) Data Users Handbook", Version 5.0. Department of the Interior, U.S. Geological Survey. 2019.

[58] Markham, B. L &Barker, J. L.. "Landsat MSS and TM post-calibration dynamic ranges, exoatmospheric reflectances and at-satellite temperature". *EOSAT Landsat Technical Notes*: 3-8, 1986.

[59] Lavender, S. J.. "Monitoring land cover dynamics at varying spatial scales using high to very high resolution optical imagery". *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume XLI-B8, XXIII ISPRS Congress, 12-19 July 2016, Prague, Czech Republic.

[60] Liang, S., Fang, H &Chen, M.. "Atmospheric Correction of Landsat ETM+ Land Surface Imagery - Part I: Methods". *IEEE Transactions on Geoscience and Remote Sensing* 39(11): 2490-2498, 2001.

[61] Chavez, P. S.. "Image-based Atmospheric Corrections-Revisited and Improved". *Photogrammetry Engineering and Remote Sensing* 62(9): 1025-1036, 1996.

[62] Santer, R., Carrere, V., Dubuisson, P & Roger, J. C.. "Atmospheric correction over land for MERIS". *International Journal of Remote Sensing* 20: 1819-1840, 1999.

[63] Şatır, O & Berberoğlu, S. (2012). Land Use/Cover Classification Techniques Using Optical Remotely Sensed Data in Landscape Planning, Landscape Planning, Dr. Murat Ozyavuz (Ed.), ISBN: 978-953-51-0654-8, InTech. [Online]. Available: http://www.intechopen.com/books/landscape-planning/land-use-cover-classificationtechniques-using-optical-remotely-sensed-data-in-landscape-plannin [Accessed 15th May 2023]

[64] Maaharjan, A.. "Land use/land cover of Katrimandu valley by using Remote Sensing and GIS. M.Sc. Dissertation submitted to Central Department of Environmental Sciences", Institute of Science and Technology, Tribhuvan University, Kirtipur, Kathmandu, Nepal. 2018.

[65] Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X & Ferreira, L.G.. "Overview of the radiometric and biophysical performance of the MODIS vegetation indices". *Remote Sensing of Environment,* 83 (1-2), 195-213, 2002. https://doi.org/10.1016/S0034-4257(02) 00096-2

[66] Goward, S. N., Tucker, C. J. &Dye, D. G.. "North American vegetation patterns observed with the NOAA-7 Advanced Very High-Resolution Radiometer". *Vegetation*, 64, 3-14, 1985.