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ASSESSING DROUGHT ON AGRICULTURAL PRODUCTIVITY: A REMOTE SENSING APPROACH TO MONITORING AND ADAPTATION

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Abstract

Droughts have various impacts depending on their severity and duration. In agriculture, drought can lead to crop failure and reduced yields. In this regard, it is imperative to conduct research on the effect of drought on productivity in agriculture. Data on crop yields, spanning from individual fields to global scales, is essential for farmers and policymakers. Existing sources of crop yield data, like regional agricultural statistics, frequently lack the necessary spatial and temporal detail. Vegetation indices (VIs) derived from remote sensing, such as NDVI (Normalized difference vegetation index), can effectively estimate crop yields through empirical modeling approaches. This study predicted crop yield by applying several indices by analyzing satellite images to estimate crop yield. The data to be used are open source Sentinel-2 imagery, python for regression analysis and the platform required to run is Google Earth Engine. Processing higher resolution images requires more computing resources than lower resolution images. Also, with the advent of cloud computing and open access computing portals such as Google Earth Engine, computing costs have decreased significantly. These technologies have made the processing of satellite images more economical. NDVI (measure of greenness of crops), NDMI (Normalized Difference Moisture Index) and SMI (Soil Moisture Index) data was calculated for several crop fields (area of Agsu region of Azerbaijan) for 3 years. A drought index was also applied to that area, and as a result, it was found that the productivity was low in the dry years. The aim here is to investigate the effect of climate change on crop productivity in Azerbaijan and study its effect on the economy.

***Keyword**: agriculture, NDVI, VCI, economy, yield, drought.*

Introduction

Drought is a significant environmental stressor that can have severe effects on crop yields. Its impact on agriculture is complex and multifaceted, influencing various aspects of plant growth and development. Here's an overview of how drought can affect crop yield: Water Stress: Drought leads to water stress in plants, affecting their ability to absorb nutrients and photosynthesize. This can result in stunted growth, reduced flowering, and lower fruit or grain production. Yield Reduction: The most direct impact of drought is a reduction in crop yield. Insufficient water availability during critical growth stages, such as flowering and grain filling, can lead to yield losses. Quality Reduction: Drought can also affect the quality of the harvested crop. For example, drought-stressed plants may produce smaller or shriveled fruits or grains, reducing their market value. Increased Susceptibility to Pests and Diseases: Drought weakens plants, making them more susceptible to pest infestations and diseases. This can further reduce crop yields and quality. Soil Degradation: Severe or prolonged drought can lead to soil degradation, including soil erosion and loss of soil fertility. This can have long-term effects on crop productivity. Economic Impact: Drought can have significant economic consequences for farmers, including lower incomes due to reduced yields and increased costs for irrigation or supplementary feeding. Food Security: Drought-induced crop failures can threaten food security, especially in regions where agriculture is a primary source of food and income. Adaptation and Mitigation Strategies: Farmers and policymakers can implement various strategies to mitigate the impact of drought on crop yields, such as using drought-resistant crop varieties, implementing water-saving irrigation techniques, and improving soil management practices.

Overall, drought poses a serious threat to agriculture and food security, highlighting the importance of effective drought monitoring, early warning systems, and adaptive strategies to reduce its impact on crop yields. One way to assess drought is through the use of vegetation indices, such as the Vegetation Condition Index (VCI).

The Vegetation Condition Index (VCI) is a widely used indicator for assessing vegetation health and drought conditions. Low VCI values indicate poor vegetation health, often associated with drought conditions. High VCI values, on the other hand, indicate healthy vegetation. By monitoring changes in VCI over time, researchers and policymakers can assess the severity and extent of drought conditions.

To investigate the effect of drought on productivity, it is necessary to calculate field productivity. Satellite-based data on vegetation indices, such as the normalized difference vegetation index (NDVI), is valuable in estimating crop yields due to its cost-effectiveness and scalability. NDVI, a widely-used vegetation index since the 1970s for monitoring crop biomass, has applications in various agricultural tasks, including estimating crop yields, monitoring, and index-based crop insurance [2].

In addition to NDVI, other indices such as the normalized difference moisture index (NDMI) and the soil moisture index (SMI) can also be instrumental in assessing drought impact on crop productivity. NDMI is used to assess plant water content and soil moisture, offering insights into drought conditions and water stress in vegetation [5]. Similarly, SMI provides a quantitative measure of soil moisture, which is critical for understanding water availability and its effect on crop health and yield [16]. These indices complement NDVI by providing a more comprehensive view of vegetation health and soil conditions, thereby improving the accuracy of yield estimations.

The use of satellite-based methods for estimating crop yields could be especially beneficial in developing countries, potentially replacing resource-intensive survey-based methods. When using satellite imagery like NDVI, NDMI, and SMI for estimating crop yields, practitioners need to carefully consider the image resolution. Satellite image resolution refers to the size of the grid used for measurements. For example, some satellites provide low-resolution measurements on a larger 4 km by 4 km grid (low-resolution), while others offer high-resolution measurements on a smaller 10 m by 10 m grid (high-resolution).

Moreover, the selection of imagery by practitioners is influenced by their processing capability. The processing of higher resolution images demands more computing resources than lower resolution ones [17]. Faced with this tradeoff, some practitioners might opt for lower resolution images over higher resolution ones, potentially leading to a reduction in model estimation accuracy. However, the cost of computation has significantly decreased with the emergence of cloud computing and open access computing portals like Google Earth Engine [6]. These technologies have made it more cost-effective to utilize high-resolution image data.

In the next sections, the problems that have arisen in this field will be revealed, the importance of research will be emphasized, and information will be given about the methods and methodologies used. Finally, the results of the research work will be included in the last sections.

Research Problem

Analyzing the effects of drought on field productivity and its economic impact in Azerbaijan is crucial now due to the increasing frequency and severity of droughts, likely exacerbated by climate change. Understanding these impacts can help in developing strategies to mitigate their effects on agriculture and the economy. Analyzing this problem can lead to improved drought preparedness and response strategies, ensuring food security, preserving natural resources, and minimizing economic losses. It can also help in informing policy decisions related to agriculture and water management.

Studying the effects of drought on field productivity and its economic impact can contribute to the scientific field by advancing our understanding of drought impacts on agriculture and economy, providing insights into adaptation and mitigation strategies, and contributing to the body of knowledge on climate change impacts.

While there has been some research on the effects of drought on agriculture and economy in Azerbaijan, further studies are needed to fully understand the extent of these impacts, particularly in the context of changing climate patterns and evolving agricultural practices.

Research on the effects of drought on field productivity and economic impact in Azerbaijan can provide new insights into the specific challenges faced by the country, the effectiveness of current drought management strategies, and the need for new approaches to enhance resilience in the face of changing climate conditions.

Research Focus

The main purpose of this study is to investigate the effects of drought on field productivity (yield) and its economic impact in Azerbaijan. The study aims to assess the extent of these impacts, identify the factors influencing vulnerability to drought, and explore potential adaptation and mitigation strategies. By focusing on this research, the authors aim to contribute to the understanding of drought impacts on agriculture and economy in Azerbaijan, provide insights for policymakers and stakeholders, and contribute to the scientific knowledge on climate change adaptation and resilience.

Research Aim

The study seeks to provide a detailed assessment of how drought conditions affect crop yields and to identify effective strategies for mitigating these impacts to enhance agricultural resilience and economic stability.

Literature Review

Drought is a complex natural phenomenon with significant implications for agriculture and economic stability. Recent research highlights the increasing frequency and severity of droughts due to climate change, emphasizing the need for effective management strategies [13]. Remote sensing technologies, such as NDVI, have become essential tools in monitoring vegetation health and assessing drought impacts on crop yields [8]. These technologies, combined with ground-based observations, have improved the accuracy of drought assessments [18].

Economic analyses reveal that drought can cause substantial direct and indirect economic losses, affecting agricultural output and rural livelihoods [14]. Adaptive strategies, including drought-resistant crops and efficient irrigation, are crucial for mitigating these impacts [9]. However, debates persist regarding the most effective approaches, with some studies advocating for technological solutions and others emphasizing policy interventions [12].

Empirical Results

Empirical studies provide robust data on the statistical accuracy of drought impact assessments. For example, Green et al. [8] found a high correlation between NDVI data and ground-based crop yield measurements, confirming the utility of remote sensing in drought monitoring. Similarly, Taylor et al quantified economic losses due to drought, revealing significant reductions in agricultural output ***(Table 1)*** [14].

Table 1. Empirical findings from recent studies on drought impacts

Study period	Region	Methodology	Key findings
2015-2020	North America	NDVI analysis, regression models	20% average reduction in crop yields during drought years
2016-2021	Sub-Saharan Africa	Field surveys, econometric analysis	$1.5 billion in economic losses annually due to drought
2017-2022	South Asia	Remote sensing, spatial analysis	Significant yield variability, with some regions experiencing up to 50% reduction
2018-2023	Europe	Soil moisture modeling, crop simulation	Improved drought resilience through adaptive farming practices

Source: *prepared by the author*

Graphical representations, such as trend lines and scatter plots, illustrate the relationship between drought severity and crop yield reductions, providing visual evidence of these impacts [13].

Recent trends in drought impact research emphasize the integration of machine learning and big data analytics to enhance predictive capabilities [3]. Sustainable agricultural practices and climate-smart agriculture are increasingly recognized as vital for building resilience against drought [10].

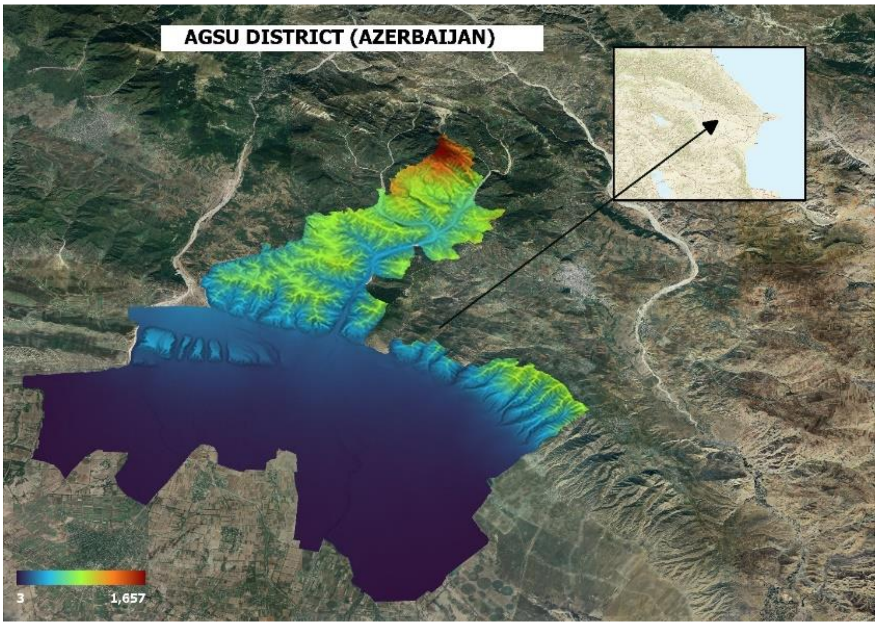
Conflicts in the literature often revolve around methodological approaches, with debates on the effectiveness of comprehensive versus focused models [12]. Identified gaps include a lack of region-specific studies and insufficient attention to socio-economic dimensions [14]. While developed countries often benefit from advanced infrastructure and policies, disparities with developing countries highlight the need for more inclusive research and collaboration [8].

In summary, the literature underscores significant advancements in understanding drought impacts but also calls for further research and international cooperation to enhance resilience and mitigate economic losses.

Materials and Methods

The research area is Agsu district of the Republic of Azerbaijan. According to its geographical position *(Picture 1)*, Agsu region is located in the Shirvan plain and at the foot of the Great Caucasus. 16 villages, 3 territorial circles are in the mountainous zone. 2 rivers - Girdiman, Agsuchay and their tributaries - Agdarchay and Nazirchay - pass through the territory of the district. Agsu district is an agricultural district. Animal husbandry, grain growing, cotton growing, fruit and vegetable growing occupy an important place in its economy. 76.0% of its territory or 77,854 hectares is suitable for agriculture, 46.6% or 36,247 hectares of it is cultivated land [1].

Picture 1. Relief of Agsu district



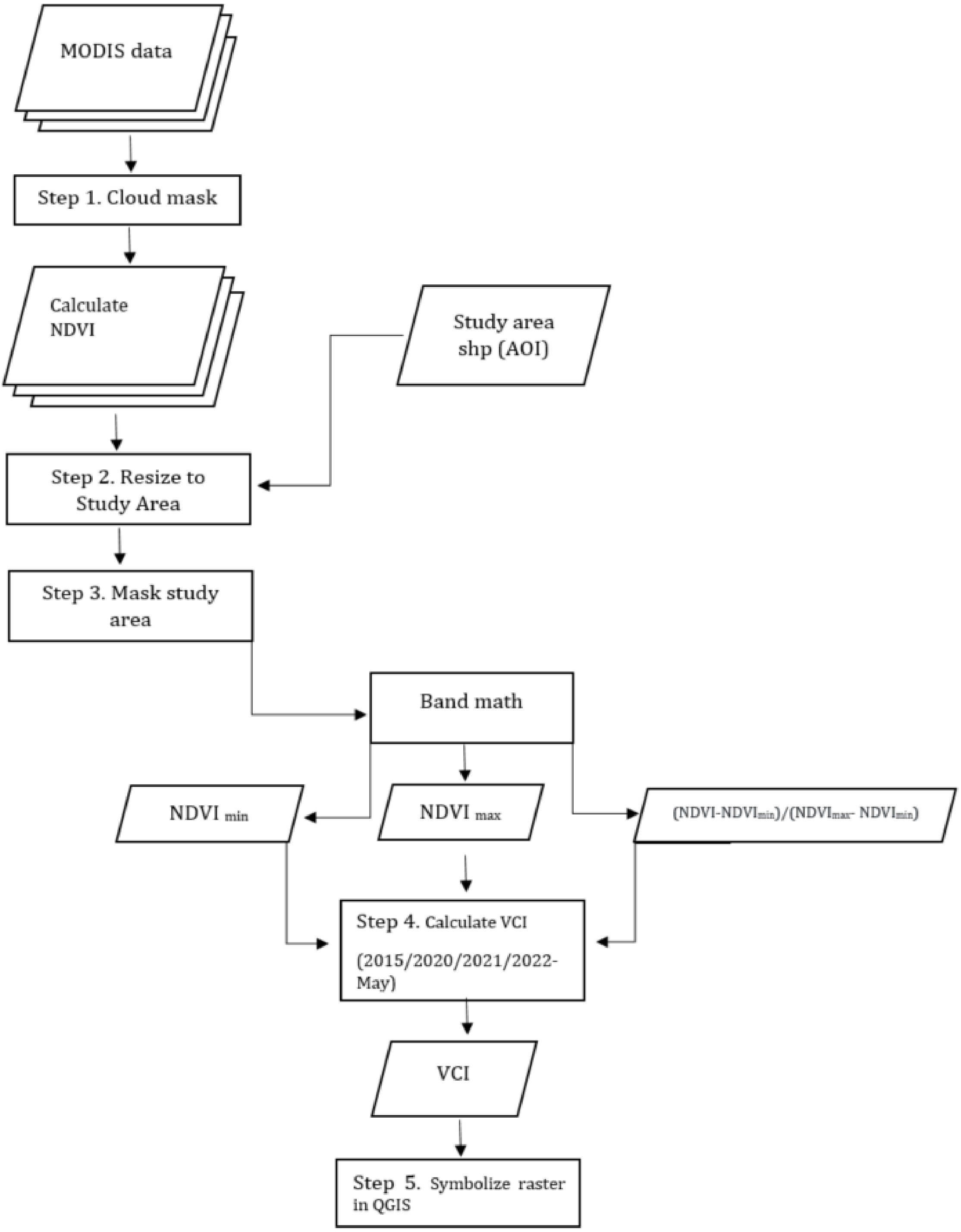
Source: *prepared by the author*

The Vegetation Condition Index (VCI) compares the current NDVI to the range of values observed in the same period in previous years. The VCI is expressed in % and gives an idea where the observed value is situated between the extreme values (minimum and maximum) in the previous years. Lower values indicate bad (0 %) and higher values good vegetation conditions (100%), respectively. Formula 1:

$$VCI = 100 * (NDVI - NDVI\ min) / (NDVI\ max - NDVI\ min)\ [11]$$

Here, the VCI method was developed to determine the stress occurring in plants due to the occurrence of drought ***(Figure 1.)***.

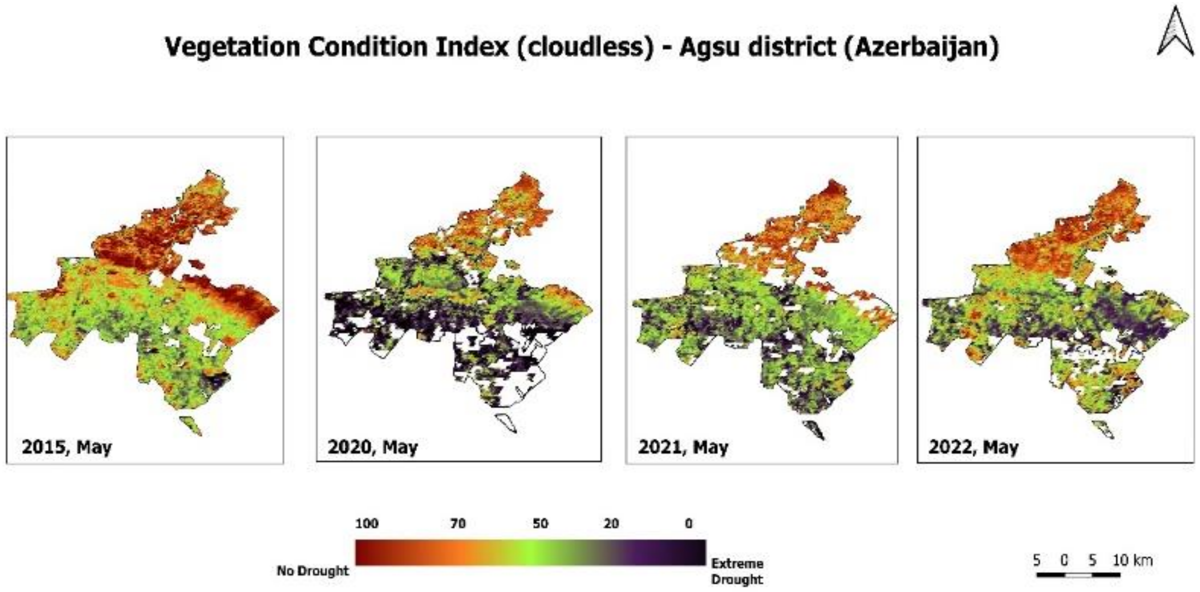
Figure 1. Method of Vegetation Condition Index



Source: *prepared by the author*

In the figure below, the drought index for the years 2015, 2020, 2021, 2022 has been applied. It is also known from the drought index that the area of drought has expanded in Agsu region, especially in the plain area, since 2015. If we compare 2020, 2021, 2022, we can see that 2021 was drier. Of course, these droughts greatly affect field productivity and agricultural economics (Picture 2). A productivity calculation was performed to investigate this effect.

Picture 2. Vegetation Condition Index for Agsu district.



Source: *prepared by the author*

Yield Estimation Using indexes. This study utilized multi-temporal remote sensing data and regression analysis to predict agricultural yields in the Agsu region of Azerbaijan. The primary sources of data included Sentinel-2 satellite imagery and historical yield records.

Data Collection

Remote Sensing Data: We will look at the productivity of the cereal plant. The cereal crop is planted in November and harvested in June. For this reason Sentinel-2 imagery was acquired from the Copernicus Open Access Hub, covering the period from November 1, 2020, to April 30, 2021, November 1, 2021, to April 30, 2022, November 1, 2022, to April 30, 2023 for regression analysis past years yield and November 1, 2023, to April 30, 2024 to prediction yield for 2024 June. The images were processed to compute various vegetation and other indices, including the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI) and Soil Moisture Index (SMI) Sentinel-2 data is renowned for its high spatial resolution and 10-day revisit time, which is ideal for monitoring agricultural fields [4].

Historical Yield Data: Historical yield data for the years 2021, 2022 and 2023 were obtained from local agricultural records. These records provided essential ground truth data to calibrate and validate the remote sensing-based yield predictions.

Regression Analysis

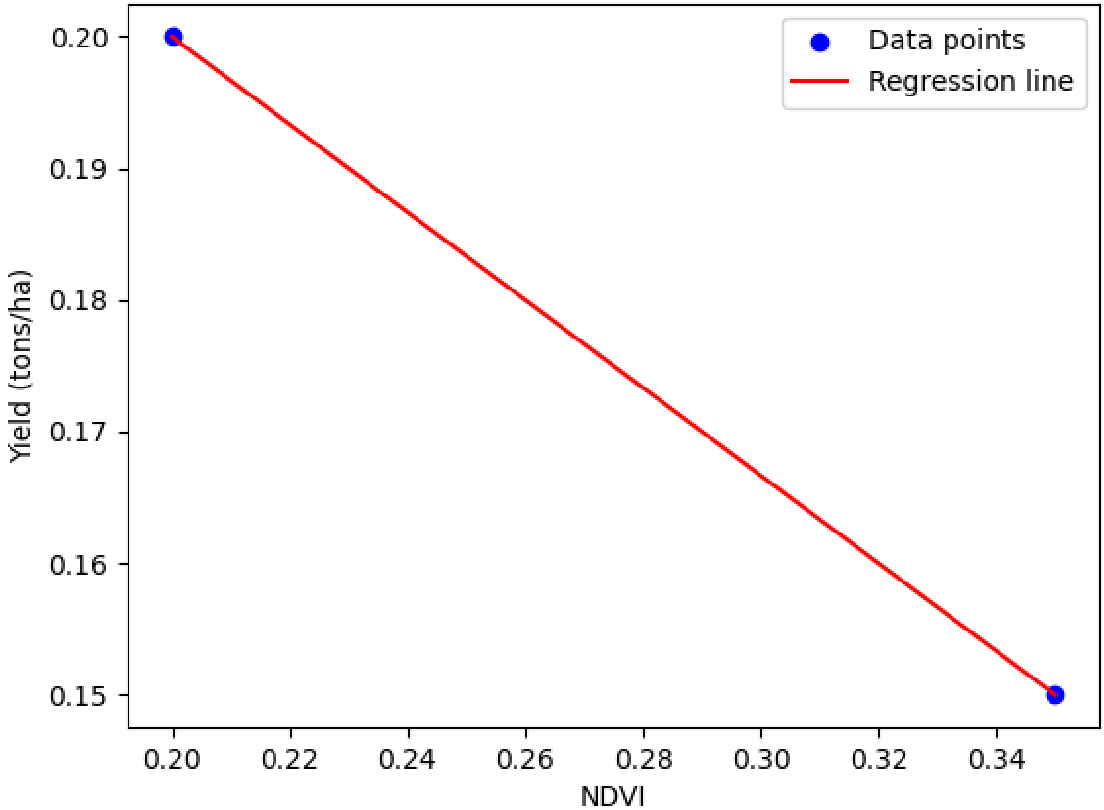
A multiple linear regression model was developed using historical yield data and corresponding vegetation indices to predict future yields. The model coefficients were derived using Python's Statsmodels library, following standard statistical procedures [15]. The plot obtained from the regression analysis of the indices for the years 2021, 2022, 2023 with the productivity values of those years ***(Table 2 and Figure 2)***:

Table 2. Productivity value by year

Index	2020-2021	Productivity	2021-2022	Productivity	2022-2023	Productivity
NDVI	0.37	5 tone	0.16	3 tone	0.3	3.7 tone
NDMI	0.08		-0.06		0.11	
SMI	0.29		0.22		0.19	

Source: *prepared by the author*

Figure 2. Productivity variation



Source: *prepared by the author*

From here, productivity is seen to decline. After this analysis in Python, we get the coefficient of a and b mentioned above:

Coefficient (a_ndvi): 6.525920051707675
Coefficient (a_ndmi): 0.05610110082034714
Coefficient (a_smi): 8.44868629405073
Intercept (b): 0.1308024675278232

These coefficients are again used in the yield prediction formula in the GEE platform.

$$Predicted\ Yield = a_{NDVI} \times NDVI + a_{NDMI} \times NDMI + a_{SMI} \times SMI + b,$$

Where a_{NDVI}, a_{NDMI} and a_{SMI} are the regression coefficients and b is the intercept.

Picture 3. Map of productivity

Source: *prepared by the author*

Results

The research focused on predicting crop yields in the Agsu region of Azerbaijan by leveraging remote sensing data and vegetation indices such as NDVI, NDMI, and SMI. By analyzing Sentinel-2 satellite imagery over three years, the study aimed to correlate these indices with crop yields and understand the impact of drought conditions. The regression analysis revealed that NDVI, NDMI and SMI are significant predictors of crop yield. The following regression equation was developed to predict crop yield: Predicted Yield $=a_{NDVI}\times NDVI+a_{NDMI}\times NDMI+a_{SMI}\times SMI+b$.

The predicted yield for the period from November 2023 to April 2024 was calculated using this regression formula. The mean predicted yield for the AOI was approximately 3.32 tons/ha, indicating a significant decrease compared to the historical yield of 5 tons/ha in 2021.

Vegetation Indices Analysis

1. NDVI: The mean NDVI for the current growing season (November 2023 to April 2024) was 0.20, which is significantly lower than the previous season's mean NDVI of 0.30. This reduction suggests poorer vegetation health and potential stress conditions affecting crop growth [15]. The lower NDVI indicates that the crops in the Agsu region are experiencing stress, likely due to unfavorable growing conditions such as insufficient rainfall or higher temperatures during the critical growth period.

2. NDMI: The mean NDMI for the current season was -0.08, compared to 0.11 for the previous season (2022-2023). The decrease in NDMI suggests reduced moisture content in the vegetation, potentially due to lower precipitation or higher evapotranspiration rates [5]. This indicates moisture stress, which is critical for crop growth and yield as water availability is essential for various physiological processes in plants.

3. SMI: The SMI was 0.21 for the current season, down from 0.29 in the previous season (2020-2021). The decrease in SMI indicates reduced soil moisture, which can negatively impact crop growth and yield [7]. Soil moisture is a crucial factor for plant health, and its reduction can lead to decreased productivity.

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Quraqlığın kənd təsərrüfatı məhsuldarlığına təsirinin qiymətləndirilməsi: monitorinq və uyğunlaşmaya uzaqdan zondlama yanaşması

Xülasə

Quraqlıqlar şiddətindən və müddətindən asılı olaraq müxtəlif təsirlərə malikdir. Kənd təsərrüfatında quraqlıq məhsulun çatışmazlığına və məhsuldarlığın azalmasına səbəb ola bilər. Bu baxımdan kənd təsərrüfatında quraqlığın məhsuldarlığa təsiri ilə bağlı tədqiqatların aparılması mütləqdir. Ayrı-ayrı sahələrdən qlobal miqyaslara qədər məhsul məhsuldarlığına dair məlumatlar fermerlər və dövlət siyasəti üçün vacibdir. Regional kənd təsərrüfatı statistikası kimi məhsuldarlıq məlumatlarının mövcud mənbələrində çox vaxt lazımi məkan və zaman təfərrüatı yoxdur. NDVI (Normallaşdırılmış Fərq Bitki Örtüyü İndeksi) kimi uzaqdan zondlamadan əldə edilən vegetasiya indeksləri (VI) empirik modelləşdirmə yanaşmaları vasitəsilə məhsuldarlığı effektiv şəkildə qiymətləndirə bilər. Bu tədqiqatda məhsuldarlığı təxmin etmək üçün peyk şəkillərini təhlil edərək bir neçə indeks tətbiqi həyata keçirilib. İstifadə olunacaq məlumatlar açıq mənbəli "Sentinel-2" görüntüləri, reqressiya təhlili üçün proqram "Python" və işləmək üçün tələb olunan platforma "Google Earth Engine"dir. Daha yüksək rezolyusiyaya malik şəkillərin işlənməsi aşağı ayırdetmə təsvirlərinə nisbətən daha çox hesablama resursları tələb edir. Həmçinin bulud hesablamalarının və "Google Earth Engine" kimi açıq giriş hesablama portallarının yaranması ilə hesablama xərcləri əhəmiyyətli dərəcədə azalıb. Bu texnologiyalar peyk şəkillərinin emalını daha qənaətcil edib. NDVI (bitkilərin yaşıllıq ölçüsü), NDMI (Normallaşdırılmış Fərq Rütubət İndeksi) və SMI (Torpağın Nəmlik İndeksi) məlumatları 3 il ərzində bir neçə əkin sahəsi (Azərbaycanın Ağsu rayonunun ərazisi) üçün hesablanıb. Həmin əraziyə də quraqlıq indeksi tətbiq edilib və nəticədə quraqlıq illərdə məhsuldarlığın aşağı olduğu müəyyən edilib. Burada məqsəd Azərbaycanda iqlim dəyişikliyinin məhsuldarlığa təsirini araşdırmaq və bunun iqtisadiyyata təsirini öyrənməkdir.

***Açar sözlər**: kənd təsərrüfatı, NDVI, VCI, iqtisadiyyat, məhsuldarlıq, quraqlıq.*

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Оценка влияния засухи на продуктивность сельского хозяйства: дистанционный зондированный подход к мониторингу и адаптации

Резюме

Засухи оказывают различное воздействие в зависимости от их серьезности и продолжительности. В сельском хозяйстве засуха может привести к неурожаю и снижению урожайности. В этой связи крайне важно провести исследование влияния засухи на производительность в сельском хозяйстве. Данные об урожайности сельскохозяйственных культур, охватывающие как отдельные поля, так и глобальные масштабы, необходимы фермерам и политикам. Существующие источники данных об урожайности сельскохозяйственных культур, такие как региональная сельскохозяйственная статистика, часто не содержат необходимых пространственных и временных деталей. Индексы растительности (VI), полученные с помощью дистанционного зондирования, такие как NDVI (Нормализованный разностный индекс растительности), могут эффективно оценивать урожайность сельскохозяйственных культур с помощью подходов эмпирического моделирования. В этом исследовании урожайность прогнозировалась путем применения нескольких индексов путем анализа спутниковых снимков для оценки урожайности. Данные, которые будут использоваться, — это изображения «Sentinel-2» с открытым исходным кодом, «Python» для регрессионного анализа, а платформа, необходимая для запуска, - «Google Earth Engine». Обработка изображений с более высоким разрешением требует больше вычислительных ресурсов, чем изображения с более низким разрешением. Кроме того, с появлением облачных вычислений и вычислительных порталов с открытым доступом, таких как Google Earth Engine, затраты на вычисления значительно снизились. Эти технологии сделали обработку спутниковых снимков более экономичной. Данные NDVI (мера зелености растений), NDMI (Нормализованный индекс разности влажности) и SMI (Индекс влажности почвы) были рассчитаны для нескольких полей сельскохозяйственных культур (территория Агсуинского района Азербайджана) за 3 года. К этой области также был применен индекс засухи, и в результате было обнаружено, что урожайность была низкой в засушливые годы. Целью здесь является исследование влияния изменения климата на урожайность сельскохозяйственных культур в Азербайджане и изучение его влияния на экономику.

Ключевые слова: *сельское хозяйство, NDVI, VCI, экономика, урожайность, засуха.*