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Examining the Impacts of Climate Variability on Agricultural Phenology: A Comprehensive Approach Integrating Geoinformatics, Satellite Agrometeorology, and Artificial Intelligence

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Abstract: The study on the impacts of climate variability on agricultural phenologydelves into the exploration of climate variability's influence on agricultural phenology through the synergistic utilization of geoinformatics, satellite agrometeorology, and AI techniques. Geoinformatics serves the purpose of identifying vulnerable locations, while satellite agrometeorology furnishes indispensable weather data crucial for crop production. By employing AI techniques to analyze extensive datasets, valuable patterns in crop phenology can be discerned, leading to significant insights into crop reactions to climate change. The integration of these methodologies enables researchers to develop a comprehensive comprehension of how climate variability impacts crop phenology, thereby facilitating the formulation of adaptation plans by policymakers and farmers. Ultimately, this research contributes to the promotion of sustainable farming practices and the enhancement of food security amidst the challenges posed by climate change.

Keywords: *Climate variability, crop phenology, geoinformatics, satellite agrometeorology, AI techniques, adaptation strategies, vulnerable areas, weather variables, crop growth and development.*

1. Introduction

Climate factors, including temperature, precipitation, and solar radiation, play a critical role in crop development and yield. With climate change, there has been an increase in temperature, altered precipitation patterns, and a rise in extreme weather events. Such changes are known to accelerate crop phenological development, shorten the growing period, and adversely impact crop productivity [1]. Drought caused by decreased precipitation poses a significant threat to crop development. Hence, understanding how crops respond to climate change is crucial for devising scientific methods to mitigate and adapt to climate change impacts.

Agricultural production is heavily dependent on the climatic conditions in which crops are grown. Climate variability, such as changes in temperature, precipitation, and extreme weather events, can have a significant impact on crop phenology, or the timing of planting, flowering, and harvesting. These changes in crop phenology can have severe consequences on food security and livelihoods, particularly in vulnerable communities. In underdeveloped countries, where agriculture is a primary source of revenue and subsistence, the consequences of climate unpredictability can be particularly detrimental. For instance, in Sub-Saharan Africa, where the majority of the population depends on agriculture for food and income, any adverse effects of climatic variability on crops can have a significant impact on the region's economy and people's quality of life. Develop efficient adaptation strategies to lessen the impact of climate variability on crop phenology to maintain food security and sustainable agricultural practices [2]. In this regard, geoinformatics, satellite agrometeorology, and artificial intelligence (AI) approaches can offer insightful details on how climatic variability affects crop phenology, enabling farmers and decision-makers to create effective adaptation strategies.

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Knowing how these changes will affect agricultural phenology and creating adaptation strategies are essential for reducing the dangers that climate variability poses. Artificial intelligence (AI), geoinformatics, and satellite agrometeorology are effective methods for illuminating how climatic variability influences agricultural phenology. Geoinformatics can offer a spatial understanding of the problem by identifying regions where crops are most susceptible to climatic change. Crop adaptation to changing climatic conditions can be studied using weather data from satellite agrometeorology. Researchers can more accurately forecast how crops will respond to climate change by utilising AI techniques to discover patterns and trends in agricultural phenology in large datasets. By combining these approaches, researchers will be able to create effective adaptation plans by thoroughly comprehending how climatic variability impacts crop phenology. To help farmers and decision-makers in developing countries make decisions about crop management practices and investments in agricultural infrastructure to boost their ability to withstand the effects of climate change, these technologies can provide them with relevant information [3].

Geographic information systems (GIS) are used in geoinformatics to analyse spatial data, such as crop distribution and land use patterns [4]. Researchers can identify sensitive locations where climate variability is anticipated to have the greatest impact on crop phenology by using GIS technologies to build maps that depict the distribution of crops and land use patterns. Researchers can focus their study on these areas and offer better solutions to the problems caused by climate variability by doing so. For instance, they might pinpoint regions where farmers might require enhanced soil fertility management techniques, greater access to irrigation systems, or better crop types that can survive shifting climatic conditions. To help policymakers comprehend the financial effects of these losses and create effective policies for dealing with them, geoinformatics can also give useful data on the scope and distribution of crop losses caused by climatic variability. Geoinformatics can be a potent tool for understanding the intricate relationships between climate variability and crop phenology and for creating effective adaptation strategies to ensure food security and sustainable agricultural practices. Geoinformatics can be used in conjunction with satellite agrometeorology and AI techniques.

In satellite agrometeorology, crop growth and development are tracked using satellite data. Information on temperature, precipitation, and other environmental factors are included in this data, which is essential for comprehending crop growth and development. Researchers can learn more about how crop phenology is impacted by climate variability by keeping an eye on these variables. For instance, temperature variations can impact when crops flower and mature, while variations in precipitation can impact soil moisture and crop yields. Researchers can spot patterns and trends in crop growth and development using satellite data, which can offer a complete perspective of various weather factors over wide areas. Satellite agrometeorology can be a potent tool for evaluating the impact of climate variability on crop phenology when combined with geoinformatics and AI approaches, allowing researchers to make more precise predictions about how crops will react to changing climatic circumstances. The adoption of enhanced irrigation techniques, the introduction of drought-tolerant crops, or the creation of new management techniques can all be done with the use of this knowledge to assist farmers adapt to the consequences of climate change.

To find patterns and trends in large datasets of crop phenology data, artificial intelligence approaches like machine learning algorithms can be used. These methods can help in the creation of adaptation strategies by forecasting how crops will respond to climatic changes. To train machine learning algorithms to detect connections between meteorological variables like temperature and precipitation, for example, agricultural phenology data, such as the date of planting and harvesting, can be employed. By studying these associations, researchers can develop more successful adaptation strategies by making more accurate predictions of how crops would respond to changing climatic conditions.

Machine learning algorithms can also be used to assess data from multiple sources, like satellite data and ground-based observations, to give a more complete picture of crop growth and development. Using this methodology, researchers can identify the underlying factors that influence crop phenology, such as soil moisture, nutrient availability, and insect pressure, and develop more effective management strategies to deal with them.

Researchers can get a thorough understanding of how climate variability is affecting crop phenology by combining geoinformatics, satellite agrometeorology, and AI approaches. This understanding can help guide farmers' and policymakers' adaptation efforts. In the face of climate change, this knowledge can support sustainable farming practices and assist ensure food security.

In light of this, the goal of this article is to investigate the possibilities of integrating geoinformatics, satellite agrometeorology, and artificial intelligence (AI) tools for determining how climate variability affects crop phenology. The paper will go through the benefits and drawbacks of these methods as well as how they could advance our knowledge of how climatic variability influences crop phenology. The ultimate objective of this research is to offer policymakers and farmers insights on how to create effective adaptation strategies, increasing food security and environmentally friendly agricultural methods in the face of climate change.

2. Related Work

Numerous studies have demonstrated that crop phenology is significantly impacted by climate change at various scales. Crop development and yield are significantly influenced by climate variables such as temperature, precipitation, and sun radiation [5]. Crop productivity is at risk due to rising global temperatures and changed precipitation patterns. Numerous studies have shown how climate change affects both annual and perennial crops [6]. For instance, rising air temperatures have been linked to earlier apple tree blossoming and budding in Japan as well as earlier phenological phases of natural vegetation in Germany. It has been discovered that perennial plants respond more strongly to rising temperatures than annual plants [1]. While most winter cereal phenophases in the Iberian Peninsula were advanced due to rising temperatures, wheat heading and flowering dates were earlier in the US Great Plains. Due to a shorter growing season, dates for winter wheat's green-up, anthesis, and maturity were sooner in China. A common indication for determining how climate and environmental factors affect crop development and yield is crop phenology. To offer a scientific basis for adaptation to and mitigation of the effects of climate change, it is crucial to have a better understanding of how crops respond to climate change [7].

According to Zhang et al. [8], investigating the connection between local climate and land use and land cover (LULC) is necessary to increase agricultural production. Changes in LULC are a significant contributor to local climate change, and vice versa, changes in LULC and vegetation cover can be caused by climate change [9]. For instance, farmers may change the crops they grow in response to shifting economic conditions and local meteorological conditions. Increased land surface temperatures (LST) can have an impact on the amount of plants and water required for irrigation [10]. Even though our comprehension of the interaction between LULC and the local climate is growing, further scientific investigation is required to fully comprehend this intricate interplay.

Changing temperatures and precipitation amounts are the main contributors to climate change, which has resulted in considerable changes in Land Use and Land Cover (LULC) throughout the world [11]. Understanding the effects of different growth pathways and developing scientific solutions to protect natural resources and maintain ecosystem services depend on these shifts [12][13]. Globally, the importance of sustainable ecosystem services is rising, and there is serious worry over the direct link between LULC and the fundamental characteristics and processes of the Earth, including the water cycle, the ecological environment, and land degradation and productivity. LULC changes constitute a quick and symbolic process driven by anthropogenic activities, and they are a crucial tool for evaluating changes in the world at different temporal and spatial dimensions. Humans are frequently impacted by these changes, and anthropogenic activity has drastically altered the status of the Earth's surface [14].

The author of [15] used a GIS-based segmentation technique to address climate change-related challenges in coastal zones and identify vulnerable locations at the regional level. The study compared two sets of coastal vulnerability indicators, one for global studies and the other for regional studies. Both sets of indicators took into account the same characteristics of coastal systems, including topography and slope, geomorphological traits, the presence and distribution of wetlands and vegetation cover, the number of coastal residents, and the density of the coastal population. The study demonstrated how GIS may be used to understand, analyse, and manage complicated environments.

In a study by Faour et al. (2013) [16], the coastal vulnerability index (CVI) and the inundated area under various sea level rise (SLR) scenarios were assessed using a combination of satellite images and topographic maps with the ArcGIS tool. The inundated area was determined based on slope, SLR, and geomorphology. The study discovered that variations in SLR, geomorphology, land use/cover, and population affect how vulnerable the coastal area is to accelerate SLR in different segments. Another study by [17] evaluated multi-coastal vulnerability along the Indian coast between Cuddalore and Villapuram using GIS and RS technologies, taking into account factors including the highest likelihood of storm surges, coastal erosion, and projected sea level rise. The study suggested employing multi-risk vulnerability maps as a planning tool for insurance and the development of new facilities.

The Coastal Andhra Pradesh (CAP) region of India was the subject of a comprehensive analysis of cost risk assessment studies in 2019 by Kantamaneni et al. [18], which concentrated on data sources, risk rates, and mitigation tactics. According to their research, the employment of airborne and LiDAR sensors as well as unmanned aerial vehicles (UAVs) can visit regions that are physically inaccessible and offer more precise data at a lower cost, hence reducing the effects of coastal disasters on the local economy, environment, and population.

The interaction of resources has been impacted by changes in Land Use and Land Cover (LULC), which have raised issues with the government and resulted in socioeconomic disasters that have reduced ecological infrastructure and raised the risk of global warming [19]. The Normalised Difference Vegetation Index (NDVI), which explains agricultural chronology and its relationship to weather and climate, can aid in understanding crop phenology. The NDVI is a metric for assessing the health of vegetation that is calculated using spectral bands in satellite pictures. Healthy vegetation or crops are indicated by the link between NDVI and green biomass. High-resolution satellites like the Landsat series, Sentinel series, and various onboard sensors may estimate NDVI at regional and global scales [20]. NDVI is frequently utilised in environmental and vegetation studies. The link between Land Surface Temperature (LST) and NDVI has been extensively studied. The climate harms the dynamics of the vegetation. By fusing location data with both quantitative and qualitative information about the area, remote sensing and GIS offer a mechanism to visualise, analyse, and report information through maps and charts. Using this technology, we can conduct what-if analyses and visualise the results.

The management of infrastructure assets, natural resources, and other items has been proven to be successful when remote sensing and GIS are used [21]. Using different datasets and methods, remote sensing has been used to map and categorise LULC variations. Thematic Mapper (TM), Enhanced TM Plus (ETM+), and Operational Land Imager (OLI) sensors have been employed with Landsat imagery to examine the LULC changes and NDVI at a greater scale. Since it effectively uses satellite data to reveal changes in vegetation cover and LST, remote sensing has become crucial for observing vegetation changes. Similar tools, such as alterations and conversions of natural vegetation, are provided by Landsat sensors for calculating vegetation deterioration. Additionally, GIS enables the management and analysis of facility and asset data, improving the effectiveness and profitability of design, construction, and maintenance [22].

For millions of people in Pakistan, climate change poses a serious threat to agriculture, rural livelihoods, and food security [23]. Unfortunately, the deterioration of Punjab's ecosystems brought on by climate change is a serious problem that has a detrimental effect on the country's economy [24]. The Sahiwal District's local economy depends heavily on the agricultural industry. However, Punjab's urbanisation, including in Sahiwal District, has led to a decline in major crops in recent years. Increased migration to the Sahiwal District is a result of intensive agricultural activities luring industries. Now as urbanisation is growing to meet demands for human livelihoods, the expanding population is having a significant impact on agriculture [25].

3. Methodology

To develop a Climate Model, the following methods are employed, as illustrated in Figure 1.

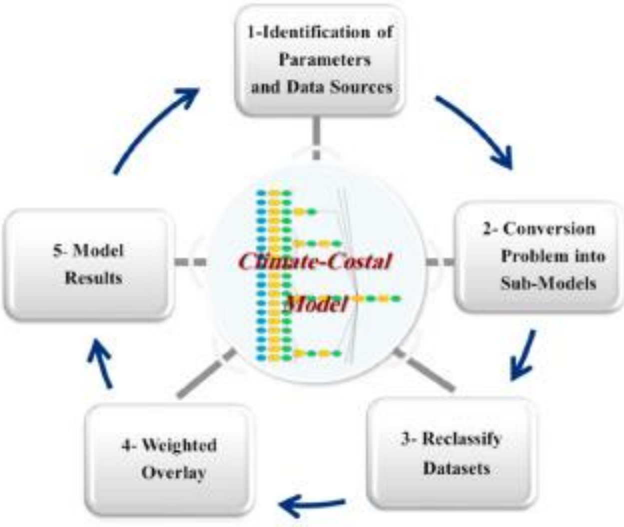

Fig. 1. Steps for Developing a climate model

2.1. Parameters and data sources are identified

The extracted satellite images are examined to determine the classification of the land cover and to create vector layers for the shoreline and water layers. There are three processes in the analysis of each image.

2.1.1. Parameters and Data Acquired via Remote Sensing Techniques: Different types of satellite imagery and ENVI 5.1 tool processing is used in the creation of earth images. The 30-year study period, which is divided into equal segments of five years each, runs from 1988 to 2018. This method enables the tracking and forecasting of long-term climate changes. Consequently, this paper makes use of a variety of satellite The Advanced Spaceborne Thermal and Reflection Radiometer (ASTER) data, which has a spatial resolution of 30 m, is used to generate the Digital Elevation Model (DEM).

2.1.2 Meteorological data and parameters: Seven satellite pictures from EarthExplorer - USGS, spanning the years 1988 to 2018, were extracted for the research region to create coastline maps. Using the ENVI 5.1 software, many steps are taken during the preprocessing of the satellite remote sensing (RS) data, including atmospheric correction, radiometric calibration, and dark removal. To use surface reflectance for certain applications, such as classifying land cover, atmospheric effects must be eliminated. Incoming radiance variations from sensors and optics, as well as additive noise, are both targets of radiometric correction. The dark subtraction technique subtracts a backdrop signature pixel value from each band to remove atmospheric scattering effects from the image.

2.1.3. Data and parameters related to engineering geology: Using ArcGIS 10.4.1, the geologic map is used to derive the compositions of earth components.

2.2. Problem with sub-model conversion

The study parameters and their local criteria are broken down into sub-models to improve organisation, clarity, and the main objective's effectiveness. Ten multi-criteria evaluation sub-models based on four parameter sets—meteorological parameters, topographical structure parameters (Earth Shape), engineering geology parameters, and shoreline characteristics—make up the proposed Climate-Coastal Model. Table 1 lists the sub-models and parameter sets in detail.

TABLE I. CLIMATE CHANGE INDICATORS.

Parameters	Sub-models	Source of data	Units
Meteorological Data	Surface Temperature Precipitation Sea Level Pressure (SLP) Dew Point Wind Speed Wind Direction	National Climatic Data Center (NCDC) at National Center of Environmental Information (NOAA) eNOAA's NCDC NASA's open data portal	Celsius (C) Mm mm of mercury (mmHg) Celsius (C) m/sec from 0_ to 360_
Topographical Structure (Earth Shape)	Coastal Slope Coastal Regional Elevation	Digital Elevation Model (DEM)	Degrees for the inclination of a slope m
Engineering Geology	Composition of Earth Materials	Geologic Map	Type
Shoreline	Erosion Accretion	Land Cover Classification (Satellite Imagery)	Km2 Km2

2.3. Reclassify datasets

To create a comprehensive model, the values obtained from each sub-model must be standardized by grouping them into a common number of intervals. The variety and variability of the parameters employed make this necessary. Each dataset is then divided into five intervals and given a value between 1 and 5. The most important qualities are given higher values, and the least dangerous ones are given lower values.

2.4. Overlaying weights

Each sub-models impact on the overall evaluation is quantified by a percentage based on its relative importance. The weights assigned to each sub-model must add up to 100%. However, some sub-models might be more crucial than others, or all sub-models might carry the same amount of weight. Each dataset is classed into five intervals on a scale of 1 to 5, where higher values denote more severe impacts and lower values denote less important impacts, to standardise the weights.

2.5. Model results

The climate-coastal model is then put into action after being built using the four phases mentioned above. To determine the vulnerable zone areas in square kilometres, the output raster of the model is then transformed into a vector layer.

4. Results

Data for all indicators were entered after creating the climate-coastal model, and the model was run using datasets spanning 30 years. Five separate favorability classes, ranging from very low to very high, were created to categorise the influence of each indicator on the four evaluation parameters for the research area. The most impacted regions by climate change are represented by these classes. The next subsections provide a detailed analysis of the findings and a map of them.

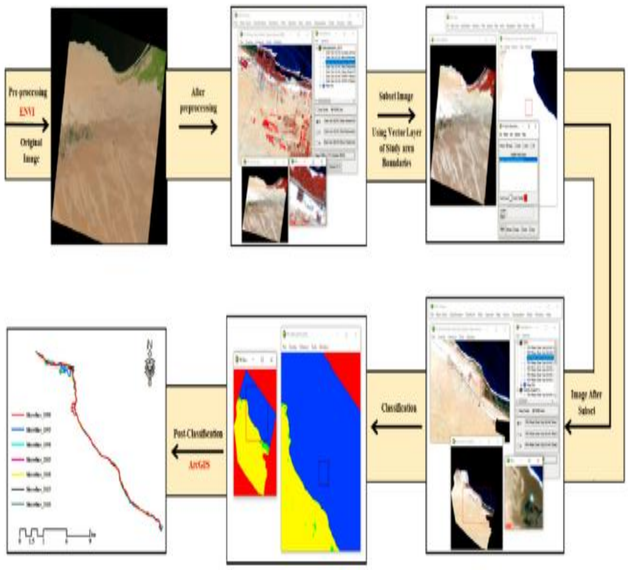

Fig. 2. Analysis of satellite images

TABLE II. VULNERABILITY DEGREE OF AL-ALAMEIN NEW CITY SECTORS.

Sector	Area (Km2)	Vulnerability Degree	Vulnerable Area (Km2)

Al-Alamein City	148.406	Low Medium High	0.00154 0.63772 0.19324
Tel Al-Eis	64.3888	……… Medium High	……… 0.03160 0.016578
Sidi Abd El-Rahman	14.858	……… Medium High	… …. . 0.32478 0.511102

5. Discussion

Increasing agricultural production can improve the economy and lead to social welfare, contributing to the overall progress of the country. Similarly, sustainable land management involves implementing productive and sustainable restoration practices on transformed lands and protecting vegetation cover. This study's assessment of Land Use Land Cover (LULC) changes and their impact on climate change can assist managers and policymakers in basin management and development by providing spatiotemporal analysis. This research can help enhance local governments' capacity to develop sound plans for agriculture at the local level. LULC management can create secondary fragmented forests, increasing their coverage, which is crucial for biodiversity recovery and ecosystem services.

6. Conclusion

The climate model that has been proposed has the potential to support decision-makers in evaluating the susceptibility of coastal regions to the impacts of climate change and prioritize necessary adaptation measures based on a range of parameters and criteria. The combination of remote sensing (RS) and geographic information system (GIS) techniques enables effective mapping, visualization, and management of long-term climate change observations. By implementing this approach, it will be possible to establish a common perspective among government decision-makers and analysts, which can facilitate informed prioritization and selection of sustainable adaptation strategies.

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