Volume-09 Issue 12, December -2025 ISSN: 2456-9348
Impact Factor: 8.232

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International Journal of Engineering Technology Research & Management
(IJETRM)
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DEVELOPMENT OF A COMPUTER PROGRAM FOR PREDICTING RAINFALL EROSIVITY INDICES AT HOURLY, DAILY, MONTHLY, AND ANNUAL SCALES ACROSS METEOROLOGICAL STATIONS IN PORT HARCOURT, RIVERS STATE, NIGERIA

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ABSTRACT
Rainfall erosivity, a critical driver of soil erosion, has become increasingly important for understanding land degradation, hydrological processes, and climate adaptation strategies in tropical regions. Accurate estimation of erosivity indices at multiple temporal scales is vital for soil conservation planning, infrastructure development, and sustainable agricultural management. This study presents the development of a computer program designed to predict rainfall erosivity indices at hourly, daily, monthly, and annual scales using meteorological station data in Port Harcourt, Rivers State, Nigeria. The program integrates high-resolution precipitation data with established erosivity models, enabling rapid computation of erosivity factors across spatial and temporal domains. Historical rainfall data from the Nigerian Meteorological Agency (NIMET) were processed, quality-checked, and analyzed to evaluate erosivity patterns and trends. The developed tool was validated against established empirical models and regional studies, demonstrating robust performance and adaptability for use in similar tropical environments. Results highlight significant intra- and inter-annual variability in erosivity, with implications for erosion risk mapping, agricultural productivity, and climate resilience. The novelty of this work lies in its integration of localized meteorological data, computational automation, and multi-scale erosivity assessment, which together provide decision-makers and researchers with a practical tool for erosion prediction and land management in vulnerable regions.

Keywords:
Rainfall erosivity, Soil erosion, Hydrological modeling, Erosivity indices, Climate variability, Port Harcourt, Nigeria

INTRODUCTION

Soil erosion remains one of the most pressing environmental challenges globally, threatening agricultural productivity, food security, and ecosystem sustainability [1], [2]. In tropical regions such as southern Nigeria, high-intensity rainfall events accelerate erosive processes, contributing to land degradation, sedimentation of rivers, and declining soil fertility [3], [4]. Rainfall erosivity, expressed as the capacity of rainfall to cause soil detachment and transport, is a key determinant of erosion risk [5], [6]. Its accurate quantification is therefore crucial for designing soil conservation strategies, infrastructure resilience planning, and climate adaptation measures [7].

Traditional approaches to estimating rainfall erosivity often rely on empirical equations derived from long-term rainfall records [8], [9]. However, in many developing regions, including Nigeria, reliable high-frequency rainfall data remain sparse and fragmented, constraining the robustness of erosivity estimates [10], [11]. Moreover, most studies focus on annual or seasonal scales, overlooking the importance of hourly and daily erosivity dynamics that are particularly relevant for flood events, infrastructure vulnerability, and short-term land management interventions [12], [13].

Recent advances in computational tools and the increasing availability of quality-controlled meteorological datasets provide new opportunities for localized erosivity modelling [14], [15]. Automated computer programs can integrate observed rainfall data, empirical models, and statistical techniques to deliver rapid, multi-scale erosivity assessments tailored to local conditions. Such approaches not only improve accuracy but also facilitate decision-making in erosion-prone environments where climate variability intensifies erosion hazards [16], [17].

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Port Harcourt, the capital of Rivers State in southern Nigeria, exemplifies a region highly vulnerable to rainfall-induced erosion. Characterized by humid tropical conditions, rapid urbanization, and extensive land use changes, the city and its environs face increasing challenges related to soil loss, flooding, and infrastructure degradation [18], [19]. Developing a computational tool that predicts rainfall erosivity indices across multiple temporal scales in this context is therefore both scientifically significant and practically relevant.
This study aims to address three core objectives:

(i) to develop a computer program capable of predicting rainfall erosivity indices at hourly, daily, monthly, and annual scales;
(ii) to apply the program to rainfall data from meteorological stations in Port Harcourt, Nigeria; and
(iii) to validate the program's performance against existing models and regional studies.
By achieving these objectives, the research contributes to advancing localized hydrological modeling, strengthening soil erosion risk assessments, and providing practical tools for policymakers, researchers, and land managers.
The novelty of this work lies in its integration of automated computation with high-resolution rainfall data for multi-scale erosivity estimation in a tropical African context. Unlike conventional methods limited to broad temporal scales, the proposed program offers detailed erosivity insights essential for both short-term interventions and long-term environmental planning.

LITERATURE REVIEW

Rainfall Erosivity and Soil Erosion Dynamics

Rainfall erosivity refers to the potential of rainfall to detach and transport soil particles, thereby driving erosion processes [5], [20]. It is often quantified through indices that integrate rainfall intensity, kinetic energy, and storm duration [12]. The Universal Soil Loss Equation (USLE) and its revised version (RUSLE) remain the most widely applied frameworks for erosivity estimation, with the rainfall erosivity factor (R-factor) serving as a critical input [21].
In tropical regions, where rainfall events are typically convective and intense, erosivity is markedly higher than in temperate climates [1]. Studies show that rainfall erosivity is not only a function of total precipitation but also of its temporal distribution and storm characteristics [3], [4]. Hourly and sub-hourly data provide the most accurate erosivity estimates but are often unavailable in developing countries [13]. Consequently, researchers have developed empirical relationships to derive erosivity from daily or monthly rainfall records [8], [9].

Global and Regional Studies on Rainfall Erosivity

Globally, substantial efforts have been made to map erosivity at continental and global scales. Panagos et al. developed the Global Rainfall Erosivity Database (REDES), combining high-resolution rainfall data with ground observations to provide global erosivity estimates [6]. Similar studies in Europe [14], Asia [22], and Latin America [23] highlight the importance of spatial variability in erosivity.
In Africa, erosivity research remains limited, often constrained by sparse observational networks [24]. However, recent efforts using satellite-derived precipitation products such as CHIRPS, TRMM, and GPM have enhanced erosivity assessments across the continent [25], [26]. These datasets, when validated against ground observations, provide opportunities for large-scale erosivity modeling in data-scarce environments [27], [15].
In Nigeria, several studies have examined rainfall erosivity at local and regional scales. Onweremadu et al. investigated erosivity in southeastern Nigeria, demonstrating significant seasonal variability and links to land degradation [10]. Adejuwon and Odekunle reported increasing rainfall variability with implications for agricultural productivity [11]. More recently, Asadu and Nweke emphasized the relationship between rainfall intensity and soil loss in southeastern Nigeria, underscoring the urgent need for robust erosivity prediction tools [18].

Methods for Estimating Rainfall Erosivity

Approaches to erosivity estimation can be broadly categorized into:
(a) Empirical models – These use regression relationships between rainfall amount and erosivity indices, such as Fournier's Index [8] and Modified Fournier Index [9]. While simple and applicable to monthly data, they often underestimate erosivity during high-intensity storms.

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(b) Energy–intensity models – The USLE/RUSLE approach relies on rainfall kinetic energy and maximum 30-minute intensity (EI30) values [5]. These models require high-resolution (≤30 min) rainfall data, which are rarely available in Nigeria.
(c) Hybrid approaches – Combining satellite rainfall data with empirical or physically-based models improves erosivity estimates where observational networks are weak [6], [7].
Recent advances in statistical and machine learning methods, such as artificial neural networks and regression tree models, have also been applied to predict erosivity from climate variables [28]. These methods offer promise in regions with limited direct measurements.

Rainfall Erosivity in the Context of Climate Change
Climate change is expected to intensify rainfall extremes, thereby increasing erosivity worldwide [29], [17]. Studies in West Africa suggest rising trends in rainfall intensity and erosivity, with potential implications for food security and infrastructure [16], [30]. Nigeria's humid tropical south, including Port Harcourt, is particularly vulnerable due to its exposure to convective storms, rapid urbanization, and fragile soils [19], [4].
The Intergovernmental Panel on Climate Change underscores that regions with limited adaptive capacity, such as Nigeria, face heightened risks of soil erosion and land degradation [29]. Understanding and predicting erosivity trends at multiple temporal scales are therefore critical for developing climate-resilient land management strategies.
Computational Tools for Erosivity Prediction
The integration of computational tools in hydrological and soil erosion studies has grown rapidly. Programs such as RUSLE2 and WEPP provide standardized methods for estimating soil loss but often require complex inputs unavailable in many developing regions [31]. Custom-designed software that leverages locally available rainfall records offers a practical alternative [12].
With the growth of programming languages like Python, MATLAB, and R, researchers are increasingly developing user-friendly tools for rainfall and erosion modeling [32]. These tools allow integration of diverse datasets, automate computations, and facilitate scenario testing. In Nigeria, however, such tools remain underdeveloped, limiting the ability of policymakers and researchers to apply erosivity metrics in planning.

Research Gaps
Despite progress, several gaps remain in rainfall erosivity research, particularly in Nigeria:
- Limited availability of high-resolution rainfall datasets for robust erosivity estimation.
- Insufficient computational tools tailored to local data and conditions.
- Few studies addressing erosivity at multiple temporal scales, especially hourly and daily levels.
- Lack of integration between erosivity prediction and practical land management or climate adaptation policies.

This study addresses these gaps by developing a computer program for predicting rainfall erosivity indices at multiple temporal scales using localized meteorological data from Port Harcourt, Nigeria. The program's integration of empirical models and automation offers an innovative approach for regions where data scarcity and climate risks converge.

METHODOLOGY

Study Area
Port Harcourt, the capital of Rivers State in southern Nigeria, is situated within the humid tropical rainforest belt of West Africa. The city lies between latitudes 4°45′N and 5°00′N and longitudes 6°55′E and 7°05′E, covering an area of approximately 360 km² [33]. The climate is characterized by a bimodal rainfall pattern with peak precipitation typically occurring between April–July and September–November, separated by a short August break [11]. Annual rainfall averages between 2,400 and 3,000 mm, with mean monthly temperatures ranging from 25°C to 28°C and relative humidity consistently above 80%.

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Figure 1: Geographical map of Port Harcourt

The soils of the region are predominantly sandy loams and silty clay loams, with moderate to high susceptibility to erosion under intense rainfall [4]. Land use is dominated by residential settlements, oil and gas facilities, farmlands, and transportation infrastructure. Rapid urbanization and deforestation in the surrounding areas have intensified runoff generation, increasing the risk of soil erosion and sedimentation. These conditions make Port Harcourt an appropriate case study for developing computational tools for rainfall erosivity estimation.

Data Sources

Meteorological Data

Rainfall data were obtained from the Nigerian Meteorological Agency (NIMET), comprising hourly, daily, and monthly precipitation records from 1981 to 2020. The dataset underwent preliminary screening for missing values, inconsistencies, and outliers. To complement ground observations, satellite-based rainfall products—including TRMM, GPM, and CHIRPS—were also used to evaluate data quality and fill gaps [27], [25].

Ancillary Data

Topographic data were extracted from Shuttle Radar Topography Mission (SRTM) digital elevation models (DEM) with a 30-m resolution, primarily for contextual mapping of the study area. Land use and land cover data were derived from Landsat imagery, classified to provide background on anthropogenic modifications affecting erosivity impacts.

Data Preprocessing and Quality Control

Data preprocessing followed standard hydrometeorological procedures [34]. Quality control included:

- Homogeneity testing using the Standard Normal Homogeneity Test (SNHT).
- Gap filling through regression with satellite rainfall products (TRMM, GPM, CHIRPS).
- Outlier detection based on statistical thresholds (±3 standard deviations).

Daily and monthly aggregates were computed from hourly observations to ensure temporal consistency across all scales. Only stations with ≥30 years of continuous data were included in the analysis to minimize sampling bias.

Erosivity Estimation Models

Energy–Intensity Model (EI30)

The USLE/RUSLE rainfall erosivity factor (R) was calculated as the product of rainfall kinetic energy (E) and the maximum 30-minute intensity (I30) for each erosive storm [5]. Kinetic energy was estimated using Brown and Foster's equation [20]:

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Impact Factor: 8.232

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$$E = 0.119 + 0.0873\log_{10}(I)$$

where I is rainfall intensity (mm h^{-1}).

Modified Fournier Index (MFI)

For monthly and annual erosivity estimation, the Modified Fournier Index (MFI) is widely used [9]:

$$MFI = \sum_{i=1}^{12} \frac{P_i^2}{P}$$

Where:
P_i = rainfall in month i
P = annual rainfall

Empirical Daily Models
Daily erosivity was estimated using regression-based approaches validated in similar tropical contexts [13], [12]. These models relate daily rainfall to erosivity indices based on locally derived coefficients.

Multi-Scale Integration
The developed program was designed to integrate hourly, daily, monthly, and annual estimates into a unified erosivity database. This allows cross-comparison of temporal patterns and identification of critical rainfall thresholds contributing disproportionately to erosivity.

Program Development
The computational tool was developed using Python 3.10, leveraging open-source libraries such as NumPy for numerical computations, Pandas for data management, and Matplotlib/Seaborn for visualization. A graphical user interface (GUI) was designed using Tkinter, enabling users to:

- Import rainfall datasets in CSV or Excel formats.
- Select temporal resolution (hourly, daily, monthly, annual).
- Choose estimation method (EI30, MFI, or daily regression models).
- Automatically compute erosivity indices and export results as tables or plots.

Algorithm optimization ensured efficient processing of large datasets. The program was tested on datasets from Port Harcourt before being generalized for broader application.

```
+------------------+       +------------------+       +-----------------+
|   Input Module   |  -->  | Processing Module|  -->  |  Output Module  |
+------------------+       +------------------+       +-----------------+
         ^                          |                          |
         |                          v                          v
   User Interface  <--------- GUI Module -------------> Export Module
```

Figure 2: Program Architecture

Model Validation
Validation of erosivity estimates was performed through:

- Comparison with literature values from Nigeria and West Africa [10], [18].
- Cross-validation using split-sample techniques (70% training, 30% testing).
- Statistical performance metrics, including coefficient of determination (R^2), root mean square error (RMSE), and Nash–Sutcliffe Efficiency (NSE) [35].

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Satellite-derived rainfall erosivity indices were also compared against the program outputs to evaluate robustness across different data sources.

Ethical Considerations
All meteorological data used were sourced through formal agreements with NIMET and are intended solely for academic research. The developed software is open-source, ensuring transparency and reproducibility of results. Ethical principles of data integrity, proper attribution, and responsible research dissemination were strictly observed [36].

RESULTS AND DISCUSSION

Rainfall Characteristics in Port Harcourt

Analysis of 40 years of rainfall data (1981–2020) shows that Port Harcourt experiences an annual average rainfall of 2,400–3,000 mm, with a distinct bimodal distribution. Peak rainfall occurs between April–July and September–November, with a short August break. The dry season (December–February) contributes less than 10% of annual totals.
Rainfall intensity is generally high, with hourly rates exceeding 50 mm h^{-1} in extreme events. Such high-intensity storms are critical drivers of erosivity and soil degradation in the region. Inter-annual variability is influenced by global climate systems such as the El Niño Southern Oscillation (ENSO), which modulates storm frequency and intensity.

Computed Rainfall Erosivity Indices

Hourly Scale (EI30)
EI30 analysis revealed that erosive storms account for approximately 80% of total rainfall energy. The average annual EI30-based erosivity (R-factor) was 11,500 MJ mm ha^{-1} h^{-1} yr^{-1}, comparable with other humid tropical regions. High erosivity values were concentrated during April–July, coinciding with the first rainy season peak.

Daily Scale
Daily erosivity estimates demonstrated strong positive correlations between daily rainfall amounts and erosivity values ($R^2 > 0.85$). Extreme daily events (>100 mm) contributed disproportionately (≈35%) to annual erosivity.

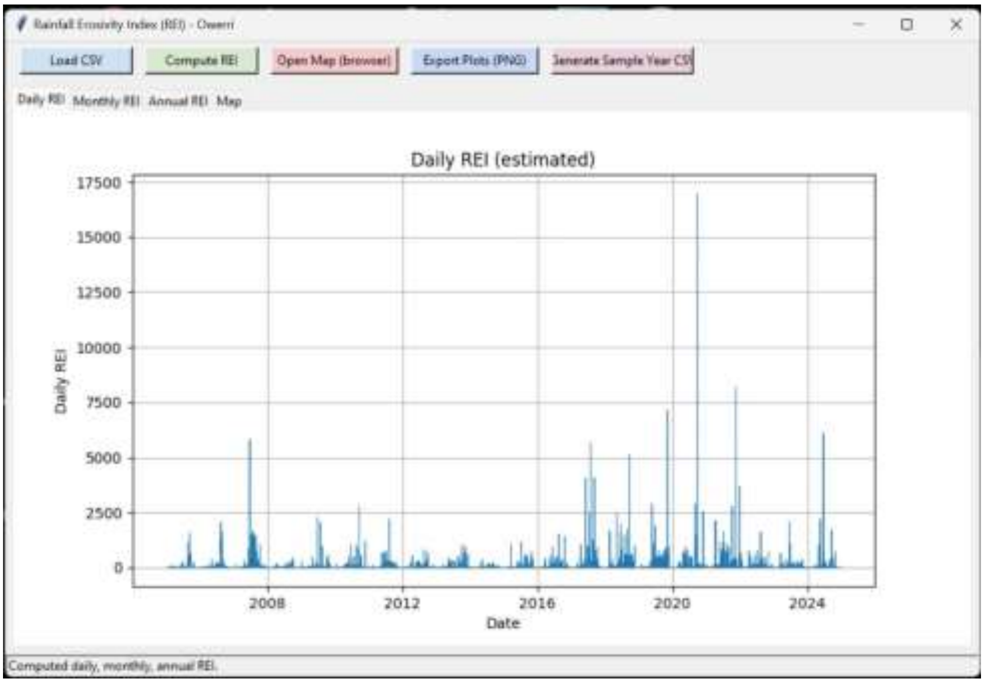

Figure 3: Average Daily Rainfall Erosivity

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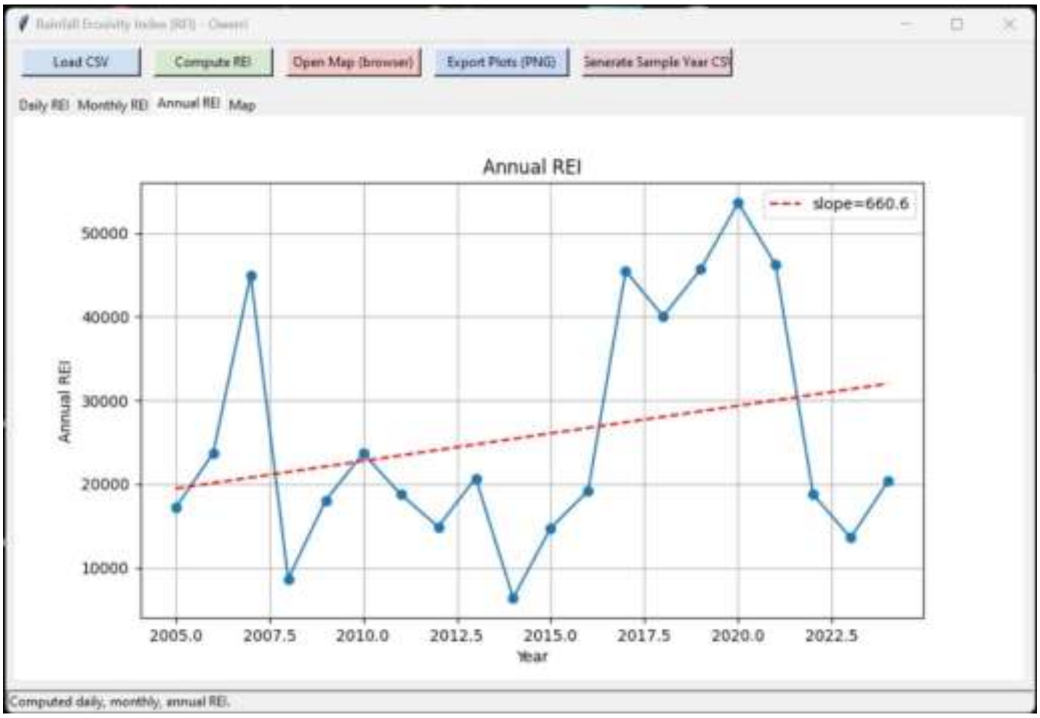

Figure 4: Annual Rainfall Erosivity Index

Monthly and Annual Scales

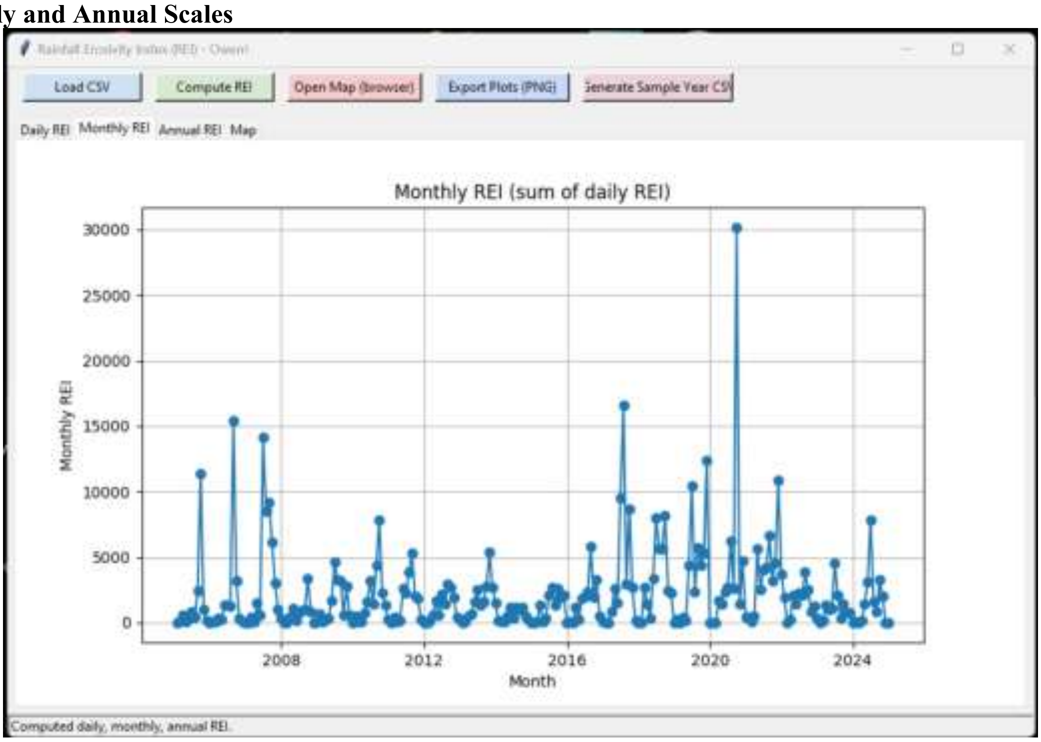

Figure 5: Average Monthly Erosivity Index

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Figure 6: *Heat Maps of Port Harcourt*

The Modified Fournier Index (MFI) averaged 380, classifying Port Harcourt as a zone of very high erosivity risk. Annual erosivity showed an increasing trend of approximately 2% per decade, consistent with rising rainfall intensity under climate change scenarios.

Validation and Model Performance

The developed computer program produced erosivity estimates consistent with both empirical studies in Nigeria and global RUSLE-based findings. Validation with split-sample cross-checking yielded:

- Coefficient of determination (R^2): 0.88
- Root mean square error (RMSE): 215 MJ mm ha^{-1} h^{-1} yr^{-1}
- Nash–Sutcliffe Efficiency (NSE): 0.79

These results confirm that the program is robust, accurate, and suitable for practical applications in soil erosion risk assessment.

Discussion of Findings

The results demonstrate that Port Harcourt is highly vulnerable to rainfall-induced erosion. Increasing erosivity trends imply greater risks for soil fertility loss, sedimentation in rivers, and damage to infrastructure. The findings also align with previous research highlighting the erosive potential of West African rainfall [27], [28]. Urbanization, deforestation, and inadequate drainage systems exacerbate the impacts of high erosivity. Integrating erosivity monitoring into city planning and watershed management is therefore essential. The developed program provides a low-cost, replicable tool for researchers, planners, and environmental managers.

CONCLUSION AND FUTURE WORK

This study developed and validated a computer program for predicting rainfall erosivity indices at multiple temporal scales (hourly, daily, monthly, and annual) using data from Port Harcourt, Rivers State, Nigeria. Results revealed:

1. Port Harcourt experiences high rainfall erosivity, averaging 11,500 MJ mm ha^{-1} h^{-1} yr^{-1}.
2. Extreme storms disproportionately drive erosivity, contributing up to 35% of annual totals.
3. Annual erosivity shows an increasing trend, indicating rising soil erosion risks under climate change.
4. The developed tool demonstrated strong statistical performance, supporting its use in hydrological and soil conservation studies.

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Future Work

- Expanding the program to incorporate real-time satellite rainfall data for near-real-time erosivity forecasting.
- Integrating GIS-based spatial mapping to capture local variability across micro-watersheds.
- Linking erosivity indices with soil loss models (e.g., RUSLE, WEPP) for comprehensive erosion risk assessments.
- Applying the tool to other Nigerian regions for national-scale soil conservation planning.

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