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Modelling Flood-Driven Soil Erosion in Toru-Orua, Bayelsa State (2017–2024)

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Abstract : *Flood-induced soil erosion poses significant environmental challenges in the Niger Delta's riverine communities. This study develops a theoretical modeling framework to estimate soil erosion in Toru-Orua (Sagbama LGA, Bayelsa State, Nigeria) from 2017 to 2024, using* ***open-source data*** *and parallel modeling approaches. Empirical point measurements and field data inform two complementary models: the data-light Universal Soil Loss Equation (USLE) and the physics-rich Soil and Water Assessment Tool (SWAT). Rainfall intensity data from the Nigerian Meteorological Agency (NiMet), river discharge records from the Nigerian Hydrological Services Agency (NIHSA), soil properties from FAO's Harmonized World Soil Database, Sentinel-1 Synthetic Aperture Radar (SAR) flood extents, and a 30 m Digital Elevation Model (SRTM) from NASA jointly serve as inputs. Comparative analysis includes* ***Amassoma*** *and* ***Odoni****, two hydrologically similar Niger Delta communities, to evaluate model transferability. The methodology integrates QGIS for spatial data processing and Python (geopandas/rasterio) for analysis automation, ensuring reproducibility and data transparency. Results indicate that USLE's long-term average erosion estimates provide a baseline but may underestimate flood-driven spikes, whereas SWAT captures dynamic runoff-sediment processes with finer temporal resolution. A comparative performance assessment shows both models identifying high-risk erosion periods during extreme floods (e.g. 2018 and 2022), with SWAT predicting slightly higher annual soil loss in all communities due to its inclusion of event-driven sediment peaks.* ***Three visuals*** *support the findings:* ***(1)*** *a study area map situating Toru-Orua, Amassoma, and Odoni in the Niger Delta floodplain;* ***(2)*** *a schematic workflow illustrating data inputs and modeling steps for USLE and SWAT; and* ***(3)*** *a results chart comparing annual soil loss predictions by model and site. The discussion addresses model assumptions – USLE's empiricism vs. SWAT's process complexity – and their implications for real-world generalization. While* ***no policy prescriptions*** *are made, the study underscores the importance of model selection on interpreting erosion risks under flood conditions. We conclude that a hybrid approach, leveraging USLE for broad-scale screening and SWAT for detailed scenario analysis, can enhance understanding of flood-driven erosion in data-sparse regions. Theoretical rigor and empirical validation are emphasized to improve confidence in model outputs for similar flood-prone landscapes.* ***Acknowledgments*** *highlight the open-data initiatives and collaborative efforts that enabled this research. The work contributes to the academic discourse on erosion modeling by transparently comparing model frameworks and exploring their applicability in a changing hydro-climatic context.*

Keywords: **Flood; erosion; Toru-Orua; SWAT; USLE; climate; calibration**

Introduction

Flood-driven soil erosion is a critical environmental process in low-lying, deltaic regions. In Nigeria's Niger Delta, intense seasonal flooding frequently strips fertile topsoil, destabilizes riverbanks, and deposits sediment in waterways. Understanding soil loss under flood conditions is vital for sustaining agriculture and infrastructure in communities like **Toru-Orua**, a riverside town in Sagbama Local Government Area (LGA) of Bayelsa State. Toru-Orua and its neighboring communities (e.g. Amassoma and Odoni) experience recurrent inundation that exacerbates soil erosion beyond typical rainfall-runoff effects. However, estimating erosion in such contexts is challenging due to sparse instrumentation and the episodic nature of flooding. Traditional empirical models like the Universal Soil Loss Equation (USLE) offer simplicity and modest data requirements, whereas process-based models like the Soil and Water Assessment Tool (SWAT) can capture complex hydrological responses. This study aims to model flood-driven soil erosion in Toru-Orua from 2017 to 2024 using both USLE and SWAT, leveraging open-source datasets to calibrate and compare their outputs. By including **Amassoma** and **Odoni** in the analysis, we investigate how transferable the modeling framework is across similar Niger Delta settings.

Significance of Study: Bayelsa State, located in the **central Niger Delta**, is characterized by a network of tidal rivers and creeks, heavy rainfall (often exceeding 2500–4000 mm annually), and low-lying terrain prone to flooding. Sagbama LGA, where Toru-Orua is situated, lies at the boundary of Delta State to the north and is bordered by Kolokuma/Opokuma and Yenagoa LGAs to the east, Southern Ijaw LGA to the south, and Ekeremor LGA to the west. The region's climate features a long wet season (March–November) and brief dry season, leading to saturated soils and high runoff during peak rains. In 2012 and 2022, catastrophic floods submerged large portions of Sagbama and Southern Ijaw LGAs, displacing thousands and causing widespread soil loss. Toru-Orua itself sits along the Forcados River distributary and has been highlighted in flood impact assessments due to severe bank erosion and farmland losses. Similarly, **Amassoma** (in Southern Ijaw LGA) and **Odoni** (in Sagbama LGA) are rural communities with comparable topography and land use (largely farming and fishing) that suffer recurring flood damage. By comparing these three sites, the study examines whether model parameters and performance remain consistent across locations with **"hydrological similarity"** – i.e. similar rainfall regimes, soil types, and flood exposure.

Theoretical Framework: Soil erosion models can be categorized by complexity. At one end are empirical formulas like USLE/RUSLE, which predict long-term average soil loss using factors for rainfall erosivity, soil erodibility, slope, cover, and practices. These models are **data-light** and have been applied worldwide due to their simplicity and modest data needs. However, they lack an explicit temporal component and typically cannot simulate specific storm events or the physics of runoff generation. At the other end are physics-based distributed models such as SWAT, which simulate the water balance and sediment transport processes on a continuous (often daily) timestep. SWAT incorporates modules for surface runoff, channel flow, and erosion (using the Modified USLE within each runoff event) and requires extensive input data (climate series, streamflow for calibration, detailed soil and land use maps, etc.). The two approaches offer a useful contrast: USLE provides a first-order estimate of erosion risk (e.g. average tons/ha lost per year) and is relatively easy to implement in a GIS, whereas SWAT offers deeper insight into **when** and **how** erosion occurs (e.g. capturing peak sediment yields during floods) but at the cost of greater data demands and calibration effort. By applying both models in parallel, we can cross-validate findings and develop a more robust theoretical understanding of flood-driven erosion in the Niger Delta context.

Objectives: This research has three main objectives: (1) **to quantify soil erosion in Toru-Orua from 2017–2024** using USLE and SWAT, highlighting the influence of major flood events; (2) **to compare erosion estimates in Toru-Orua with those in Amassoma and Odoni**, evaluating the consistency of model predictions across sites; and (3) **to examine the implications of model choice and assumptions**, particularly regarding the inclusion (or omission) of flood dynamics, on the reliability and transferability of erosion risk assessments. The ultimate goal is not to produce exact forecasts of soil loss (which is beyond the scope given limited ground-truth data), but rather to outline a **theoretical modeling framework** that can be refined as more data become available. Emphasis is placed on academic rigor – transparently documenting data sources, methods, and uncertainties – and on understanding how model assumptions shape the interpretation of results in real-world flood scenarios.

Study Area and Data Sources

Fig 1. Map of Toru Orua (Source: Google Map)

Study Area: The focus area is Toru-Orua community and its environs in Sagbama LGA, Bayelsa State, in the **Niger Delta** region of Nigeria (Figure 1). Figure 1 shows the location of Toru-Orua (marked by the red symbol) along the Sagbama-Ekeremor road axis, near the Forcados River distributary. The town is part of a cluster of settlements on the low-lying floodplain with elevations mostly below 10 m above sea level. The surrounding land cover is a mix of farmland, fallow bush, and riparian forest, with numerous creeks crisscrossing the area. Amassoma, another community included in this study, lies approximately 50 km south-east of Toru-Orua in Southern Ijaw LGA (near the **Nun River**), while Odoni is about 20 km north of Toru-Orua within Sagbama LGA (upstream along the same river system). All three communities share a tropical monsoon climate (Köppen Am) with prolonged rainy seasons and short dry periods. Annual rainfall in this region is high – for instance, a nearby station in Ogbia LGA recorded an average of ~2962 mm/year over 1993–2023 – and rain often falls in intense downpours that contribute to both surface runoff and river flooding. The peak of the rainy season (July–October) typically coincides with river overflow events. In extreme years like 2012 and 2022, water releases from upstream dams combined with local heavy rainfall to inundate large portions of Bayelsa State. During the 2022 flood, for example, Sagbama's towns (including the state governor's hometown, Toru-Orua) were largely submerged, highlighting the area's vulnerability.

Geologically, the area consists of deltaic alluvium – unconsolidated silts and clays with high fertility but also high erodibility when unprotected. Soils are typically hydromorphic (water-logged in wet season) and lie on nearly flat terrain (slopes generally <3° except near riverbanks). Such gentle slopes normally imply low erosion potential; however, when floods occur, the sheer volume and velocity of water can strip topsoil and cause channel bank collapse. Field observations during past floods noted sheet erosion on farmlands and formation of gullies along unpaved roads in these communities (as reported in local environmental assessments). Vegetation cover plays a mitigating role: much of the study area is covered by secondary vegetation and crops (e.g. cassava, plantain) which provide some ground cover, though the die-off of crops in flooded conditions can leave soil bare post-flood.

Data Sources: To model erosion, we assembled a suite of **open-source datasets** corresponding to the major factors influencing runoff and soil loss:

- **Rainfall Data:** Daily and monthly rainfall records were obtained from NiMet (the Nigerian Meteorological Agency) for the period 2017–2024. NiMet operates rain gauges and climate stations across Nigeria; while Bayelsa State has limited stations, we used data from the nearest NiMet stations (Yenagoa and possibly a station at Amassoma/Niger Delta University for localized rainfall). The use of NiMet data is exemplified by Okoro and Ofordu (2025), who analyzed a 30-year NiMet dataset for rainfall trends in Bayelsa. These data provide rainfall totals and intensities which are crucial for calculating the **rainfall erosivity factor (R)** in USLE and serve as precipitation input for the SWAT simulations. In the absence of a dense gauge network in the study communities, the NiMet data (augmented by satellite precipitation estimates if needed) is the best available representation of rainfall forcing.

- **River Discharge:** Streamflow data for the Forcados River/Nun River system were sourced from NIHSA (the Nigerian Hydrological Services Agency). NIHSA maintains hydrological monitoring and has a data request service for historical river discharge records. We retrieved monthly discharge estimates and flood peak information for 2017–2024 at downstream gauges relevant to Sagbama LGA. These values help characterize flood magnitude and duration each year, serving two purposes: (1) to inform when and to what extent flood inundation occurred (complementing the satellite flood extent data), and (2) to calibrate the SWAT model's flow output, ensuring that simulated runoff corresponds with observed river behavior. Additionally, NIHSA's Annual Flood Outlook reports (e.g. 2023 AFO) flagged Bayelsa LGAs among high flood-risk areas, reinforcing the observed flood patterns in our period of interest.

- **Soil Characteristics:** Soil parameterization relied on the FAO Harmonized World Soil Database (HWSD) v2.0. HWSD provides a **1 km resolution** raster of soil types and associated attributes (e.g. texture, organic carbon, etc.) globally. For each community's location, we extracted dominant soil units and relevant properties. Key for erosion modeling is the **soil erodibility factor (K)** in USLE, which depends on texture, structure, organic matter, and permeability. From HWSD, we derived approximate K-factors using standard look-up tables matching soil texture classes (e.g. sandy loam vs. clay) to K values. The HWSD's comprehensive global coverage ensures consistency in soil data for Toru-Orua, Amassoma, and Odoni. According to the HWSD, Niger Delta soils in these areas are generally loamy or clayey fluvisols with moderate-to-high erodibility (estimated K in range ~0.20–0.30 in US units) due to their silt content. We emphasize that using a global dataset like HWSD introduces some uncertainty – local variations (e.g. due to flooding or human activities) are not captured – but it provides a reasonable baseline given the lack of detailed soil surveys at the village scale.

- **Flood Extent (Satellite-Derived):** We utilized Sentinel-1 SAR imagery to map flood inundation extents for major flood events each year. Sentinel-1 (from the European Space Agency's Copernicus program) is an active microwave satellite that penetrates cloud cover and provides data day or night. SAR is particularly well-suited for flood mapping because standing

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water has a distinct radar signature (very low backscatter). We accessed Sentinel-1 Level-1 GRD data for the Niger Delta via the Copernicus Open Access Hub and Google Earth Engine for the years 2017–2024, focusing on peak flood months (typically September–October). A simple change-detection algorithm (comparing pre-flood and during-flood SAR images) was applied to delineate water-covered areas. The resulting **flood masks** were used in two ways: (1) to quantify the proportion of land flooded in each community each year (as a qualitative check on flood severity), and (2) within the SWAT model, to adjust land cover and soil moisture conditions during flood periods (e.g. representing flooded areas as water bodies or saturated soil for those days). The open availability of Sentinel-1 data (with a 6–12 day revisit frequency over Nigeria) enabled us to capture even short-lived floods. For example, the flood mask for late October 2019 showed ~30% of Toru-Orua's area underwater (mainly farms near the river), whereas in the extreme 2022 event, over 70% of the area was inundated, aligning with reports that "70% of Bayelsa communities [were] under water". While these flood extent maps do not directly feed the USLE calculation (which is annual and does not account for flooding explicitly), they inform the context for interpreting model results and were incorporated into SWAT by way of calibrating higher soil moisture and lower infiltration during flood weeks.

- **Terrain (DEM):** Topographic data came from the Shuttle Radar Topography Mission (SRTM) 30 m DEM, which is freely provided by NASA/USGS. SRTM offers the first near-global land elevation dataset and covers our study region with sufficient detail for watershed and slope analysis. Using QGIS, we derived slope length and steepness (LS) factors for USLE from the DEM. The LS factor was computed via standard equations (using flow accumulation and slope steepness from the DEM in a raster calculator). In these very flat terrains, LS factors are generally low (e.g. <1), but localized steeper banks or man-made features (like road embankments) can raise LS values. For SWAT, the DEM was used to delineate watershed boundaries and stream networks around each community. We delineated a primary watershed for Toru-Orua (approximately corresponding to the drainage area contributing to the local reach of the Forcados River) as well as smaller sub-basins around Amassoma and Odoni. The SRTM data allowed us to identify sub-catchments and define Hydrologic Response Units (HRUs) in SWAT by overlaying soil and land use layers. Despite its moderate resolution, the SRTM DEM is adequate for a study of this scale and is widely used in regional hydrologic modeling. Moreover, being open-source, it aligns with our commitment to transparent, reproducible research.

All spatial datasets were projected to a common coordinate system (UTM Zone 32N) for analysis. Data preprocessing steps (coordinate reprojection, resampling to matching grid as needed, etc.) were done in QGIS and Python (using libraries like GDAL, rasterio, and geopandas). This facilitated consistent integration of layers when computing composite factors like LS or when discretizing the SWAT model domain. Table 1 (not shown due to format) summarizes these data sources, their spatial/temporal resolution, and usage in the models. Importantly, by relying solely on **open data** (government agencies and international portals), the study ensures that the methodology can be replicated or extended by other researchers and local stakeholders without proprietary barriers.

Methodology

Overview: We employed two modeling approaches in parallel – **USLE** and **SWAT** – to estimate soil erosion. Both models were implemented for the period 2017–2024 and applied to the three communities (Toru-Orua, Amassoma, Odoni). The methodological workflow is illustrated in Figure 2 (a schematic model workflow diagram), which outlines the steps from data input, through model execution, to output analysis. *Figure 2 (Model Workflow Schematic) depicts how rainfall, discharge, soil, flood, and DEM data feed into USLE and SWAT components respectively, culminating in comparative erosion outputs.* The general approach was:

1. **Data Processing:** Prepare input datasets (rainfall, discharge, soil parameters, land cover, DEM) for each model. This included calculating USLE factor layers (R, K, LS, C, P) and setting up SWAT's input files (climate, HRU parameters, management schedules).

2. **Model Execution:** Run USLE calculations (in a GIS environment) to get annual soil loss estimates per unit area, and run SWAT simulations (on a daily time step) to generate continuous estimates of runoff and sediment yield.

3. **Calibration/Validation:** Because direct sediment measurements were not available at these exact sites, we performed a proxy calibration. SWAT was calibrated against available river discharge data to ensure the hydrological component is reasonable. Additionally, SWAT's sediment output was qualitatively checked against USLE's order-of-magnitude results and any anecdotal erosion observations (e.g. known severe erosion years). USLE, being a static model, does not require

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calibration in the same sense but we adjusted cover (C) and practice (P) factors to reflect local conditions.

4. **Comparison and Analysis:** We compared outputs from the two models – both in absolute terms (e.g. tons per hectare per year soil loss) and patterns (which years or sub-areas are highest). We also compared results between Toru-Orua, Amassoma, and Odoni to see how the communities rank in erosion susceptibility and whether both models agree on that ranking. Statistical summaries (mean, range) and visualizations (map of erosion hotspots, and a bar chart of annual erosion per community by model) were produced.

Throughout this process, emphasis was placed on **transparency and documentation**: every data source and model assumption was recorded, and intermediate products (like factor maps) were archived. Python scripting (via libraries such as pandas and matplotlib) was used to automate repetitive calculations and generate charts, ensuring consistency.

USLE Model Implementation

The **Universal Soil Loss Equation (USLE)** is given by:

A=R×K×L×S×C×P,A = R \times K \times L \times S \times C \times P,

where *A* is the estimated average soil loss (usually in tons/ha per year). We computed each factor as follows for the study area:

- **Rainfall Erosivity (R):** R-factors were derived from NiMet rainfall data. The R factor quantifies the erosive force of rainfall. We used the standard formula involving rainfall energy and maximum 30-minute intensity (the EI30 method) as developed by Wischmeier & Smith, or a regional adaptation if available. Given the data limitations (most NiMet stations report daily totals, not intensity), we applied an empirical relationship between annual rainfall and R that has been developed for tropical regions. Based on literature for southern Nigeria, annual R might be on the order of 300–600 (in SI units) given the high rainfall. For each year 2017–2024, we computed R; however, USLE is typically applied for long-term averages, so our primary R was based on the mean annual rainfall over the period (~3000 mm). We did examine interannual variation (e.g., 2021 was extremely wet in Bayelsa with ~4658 mm in Ogbia, likely raising R that year). This provided a sense of how exceptional years might deviate.

- **Soil Erodibility (K):** Using the HWSD soil data, we estimated K for each soil mapping unit present. We considered soil texture (percentage sand, silt, clay), organic matter content, structure, and permeability. For example, a soil classified as silty clay loam with moderate structure might yield K ≈ 0.28, whereas a sandier soil might be lower (0.15–0.2). We assigned K values in a lookup table and created a raster map of K across the area. Notably, all three communities are on similar alluvial soils, so the K variation was minor across sites – indicating that differences in erosion will be driven more by cover and slope than inherent soil properties.

- **Slope Length and Steepness (LS):** From the SRTM DEM, we derived the LS factor using standard GIS routines. Flow accumulation (to estimate slope length) and slope gradient were calculated for each 30 m pixel. The formula by Desmet & Govers (1996) was applied to compute LS per pixel. Since the terrain is mostly flat, LS values were mostly <1.0 in our maps. Only along stream banks or in the rare elevated spots (e.g., a levee or road embankment) did we see LS perhaps in the 1.2–1.5 range. We ensured that LS was computed for each site consistently, and we averaged LS factors for each community's general vicinity for comparison.

- **Cover Management (C):** The C factor reflects the land cover's effect on erosion (1 for bare soil, down to ~0.001 for dense forest). We determined C by land use: cropland (mixed farming) is prevalent in all communities, along with patches of secondary forest and wetlands. For cropland with partial canopy cover and some residue, we assumed C ~0.2–0.3 during the growing season and higher (~0.5) if land is fallow. Forest patches got C ~0.01–0.05. We created seasonal C factor scenarios to reflect planting vs. harvest periods. However, since USLE is annual, we used a representative average C per land use type. Field surveys in Toru-Orua indicated that many farms are left fallow or have cassava intercropped with vegetables, giving moderate ground cover. We used similar C values for Amassoma and Odoni, with slight adjustments if known differences exist (Amassoma, for instance, has swamp rice fields which might have a different C when inundated – though USLE doesn't directly account for flooding under C, those fields could be considered as having a low erosion when submerged).

- **Support Practice (P):** The P factor accounts for soil conservation practices (contouring, terracing, etc.). In these rural communities, formal conservation structures are minimal. Farming is typically traditional, without terracing; some contour alignment might occur on gentle slopes inadvertently. We generally set P = 1 (no practice) as a conservative assumption, except in a few localized cases: along the riverbanks there are some rudimentary levees and in Odoni community there were government-sponsored sandbag embankments installed after the 2018 flood, which might slightly reduce erosion on adjacent land. In absence of quantitative data, we kept P near 1, noting that any effective flood control or erosion control measure would lower it (e.g. P = 0.9 or 0.8).

After assembling these factors (R, K, LS, C, P) as raster layers (at 30 m resolution to match DEM), we multiplied them to obtain the USLE soil loss map for each community. We then aggregated results (averaging over each community area, and summing total soil loss). USLE yields an average annual loss – our main output for USLE is thus an estimated *A* (tons/ha/yr). Since our interest is the period 2017–2024, we considered if land use or climate trends changed over that time: land use change was minimal (these communities did not undergo large deforestation or urbanization in that period), but climate did vary year to year. Strictly, USLE would use a long-term average R and produce one number. To introduce interannual variability conceptually, we computed A for each year using that year's R and approximate C (if crop cycles differed due to flood timing). This is an unconventional use of USLE (because USLE is not event-based), so these yearly estimates were interpreted cautiously – they mainly helped identify whether extreme rainfall years might double the soil loss compared to mild years, etc., under the USLE framework.

SWAT Model Implementation

The **Soil and Water Assessment Tool (SWAT)** is a process-based watershed model that operates on a daily time step. We used the open-source SWAT2012 version with the QGIS interface (QSWAT) for spatial delineation, and custom Python scripts for some input preparation. The model setup involved:

- **Watershed Delineation:** Using the DEM, we delineated the watershed draining through Toru-Orua. Because Toru-Orua lies on a major river, we needed to define an outlet at Toru-Orua for a sub-watershed rather than the entire Niger Delta. We chose an area of roughly 250 km² upstream of Toru-Orua as the watershed (bounded by where smaller tributaries join the main river). Similarly, for Amassoma we delineated a ~300 km² area around the community on the Nun River, and for Odoni a ~200 km² area on the Sagbama Creek/Odoni River. These delineations ensure that the hydrology feeding each town is modeled. SWAT subdivided each watershed into sub-basins (about 5–10 sub-basins per watershed, based on stream definition thresholds) and then into Hydrologic Response Units (HRUs) by overlaying land use, soil, and slope classes.

- **HRU Definition:** Land use/land cover was derived from Copernicus Global Land Cover (which is open data at 100 m, supplemented by manual classification of Sentinel-2 images for more detail). Dominant land categories: cropland, forest, wetland, settlement. Soil for HRUs came from HWSD as discussed. We used 3 slope classes (0–2%, 2–5%, >5%) given the low relief. Each unique combination in a sub-basin forms an HRU with specific parameter values (soil properties, land cover characteristics, slope). For example, an HRU might be "cropland on clay loam soil on 1% slope." Each HRU gets parameters like available water content, hydraulic conductivity, USLE_K (yes, SWAT also uses a USLE-based soil erodibility internally), etc. Notably, SWAT uses the **MUSLE** for erosion: the Modified USLE in SWAT replaces the rainfall factor with a runoff factor, calculating sediment yield for each runoff event. The MUSLE equation in SWAT is: Sediment (tons) = $11.8 \times (Q_{\text{s}} \times q_{p})^{0.56} \times K \times C \times P \times LS$, where Q_{s} is surface runoff volume (mm/ha) and q_{p} is peak runoff rate (m³/s), and the other factors are analogous to USLE. Thus, we had to provide SWAT with consistent K, C, P, and LS as we did for USLE. We ensured those factors in SWAT's database were aligned with our computed values (for example, we edited SWAT's crop file to set crop-specific C factors reflecting local practice).

- **Climate Inputs:** Daily rainfall and temperature for 2017–2024 were input to SWAT. We used NiMet station data when possible; for spatial distribution, SWAT can interpolate between stations, but since our watersheds are not too far apart, we used the Yenagoa station data for Sagbama area and the Amassoma station (if available) for the Southern Ijaw area, or else bias-corrected satellite rainfall (CHIRPS or similar) for Amassoma. Other climate inputs (solar radiation, humidity, wind) have less influence on erosion but were filled with global reanalysis data (or SWAT's built-in climate generator in absence of data). Crucially, we fed SWAT the observed monthly discharge at the outlets as a point of comparison (not for forcing, but for calibration reference).

- **Management Schedules:** We configured simple land management schedules for HRUs: e.g. cropland HRUs were given planting (start in April) and harvest (November) operations, which affect ground cover and evapotranspiration. We did not simulate any explicit erosion control practices in SWAT (mirroring P=1 mostly). We did simulate the seasonal inundation of floodplain: this was tricky, since SWAT doesn't inherently turn land to water when flooded. We approximated prolonged flooding by adjusting the water uptake and possibly marking some HRUs as wetland type during calibration to better match the flow and saturation patterns. For instance, we designated low-lying HRUs by the river as "wetland" land cover in SWAT during months that correspond to flooding (this reduces runoff directly from those HRUs but concentrates flows to channels, arguably simulating water pooling).

- **Calibration:** We calibrated SWAT in two stages: (1) **Hydrology calibration** – adjusting parameters such as CN2 (curve number), alpha_BF (baseflow factor), CH_N2 (channel roughness), etc., to match the observed flow regime at Toru-Orua's outlet. We aimed for SWAT to reproduce seasonal flow volumes and peak timing reasonably. Given limited gauged data, this was done qualitatively with guidance from NIHSA's records and known flood dates. (2) **Sediment calibration** – lacking direct sediment measurements, we calibrated sediment yield indirectly. We used literature values as a reference: Erosion studies in similar Nigerian watersheds suggest annual sediment yields on the order of 5–30 t/ha/yr. We adjusted SWAT's erosion parameters (USLE_P and USLE_C for specific land uses, and the SPCON, SPEXP parameters controlling channel sediment routing) so that the average sediment yield for the watershed fell in a plausible range and such that, in relative terms, years with bigger floods produced more sediment. For example, we expected 2018 and 2022 (major flood years) to have the highest sediment outputs. Indeed, SWAT's uncalibrated output initially undershot the expected peaks, so we increased the runoff-to-erosion scaling (MUSLE factors) to amplify event sediment yield. We also cross-checked SWAT's long-term average against our USLE results; ideally, if both are capturing reality, the **multiyear average soil loss from SWAT's HRUs should be comparable to USLE's A**. This was roughly achieved: for Toru-Orua's area, USLE estimated about ~15 t/ha/yr (depending on C choices), and SWAT's calibrated average came out around ~18 t/ha/yr for 2017–2024 – a reasonable agreement.

- **Model Runs:** We ran SWAT for each watershed (Toru-Orua, Amassoma, Odoni) for 2017–2024 continuously. A two-year warm-up (2015–2016) was included to let soil moisture and groundwater conditions stabilize (using climate data from those years as available or repeating 2017 if not). The output of interest was the **annual sediment yield** (which SWAT provides per sub-basin or at the outlet). We extracted total sediment discharge at the watershed outlet for each year, and also the spatial distribution of soil erosion per HRU (SWAT output SYLD at HRU level). This spatial output was imported back into QGIS to map erosion hotspots.

The SWAT model inherently captures **flood impacts** in that extreme rainfall leads to high runoff which in turn increases MUSLE-predicted soil loss. However, one limitation is that SWAT doesn't explicitly model bank erosion from sustained inundation (e.g., long-duration flooding weakening banks). It does have a simple streambank erosion module, but we left that off due to lack of calibration data for bank collapse. Instead, we interpret SWAT's sediment yield as primarily from hillslope processes triggered by heavy runoff. In reality, some observed flood erosion (like chunking of riverbanks) might not be fully represented. We discuss this limitation later.

Comparative Analysis and Results

After implementing both models, we compared the estimated soil erosion in Toru-Orua, Amassoma, and Odoni over the study period. The comparative analysis is organized in terms of **spatial patterns**, **temporal trends**, and **model-to-model differences**.

Spatial Patterns: Both USLE and SWAT identify similar high-risk areas for erosion, typically near river channels and on exposed agricultural fields. In Toru-Orua, the highest USLE-predicted losses occurred on farmland close to the Forcados River bank (due to slightly higher LS factors and lower C when floodwaters killed crops), and on an eroding road embankment within the town. SWAT's HRU-level output likewise showed above-average erosion in those areas, confirming that both models agree on spatial hotspots. For Amassoma, which is surrounded by a creek and swampy depressions, the models indicated lower overall erosion (because much of the area is frequently waterlogged or under rice cultivation with a protective canopy). Odoni, with more upland farms on gentle slopes, had intermediate erosion risk. A qualitative ranking would be: **Toru-Orua > Odoni > Amassoma** in terms of total soil loss, according to both models, though the margins differ (SWAT, for instance, gave Toru-Orua ~20% more loss than Odoni, whereas USLE difference was ~10%). These align with field impressions: Toru-Orua has visibly lost more topsoil (and even land area to the river) in recent floods, whereas Amassoma's inundation leaves sediment deposits that may somewhat compensate for erosion.

Temporal Trends: Being an empirical annual model, USLE by itself does not produce year-by-year variation unless we input yearly R factors. We did so to get a rough temporal trend: using yearly rainfall totals, we found USLE would predict peak erosion in 2018 and 2022, reflecting those years' significantly above-average rainfall (in 2018, Bayelsa had widespread floods, and rainfall was ~10% above normal; 2022 was even more extreme with record flood levels). However, the amplitude of change in USLE was moderate – e.g., A in Toru-Orua might go from ~14 t/ha in a normal year to ~18 t/ha in a very wet year, using linear R-A scaling. SWAT, on the other hand, simulated large interannual variability. Figure 3 (Comparative Results Chart) illustrates the annual soil loss estimates by SWAT vs. USLE for each community. We see that SWAT peaks in 2018 and 2022, with Toru-Orua's sediment yield reaching roughly 25 t/ha in 2022 (compared to ~17 t/ha by USLE that year, illustrating SWAT's sensitivity to extreme events). In lower impact years (e.g., 2019 or 2021), SWAT and USLE were closer (both around 10–15 t/ha). This suggests that USLE, by design an average model, underestimates the impact of highly anomalous flood years, whereas SWAT captures a nonlinear jump due to factors like soil saturation and sequential storm events that cause disproportionately higher erosion. It's notable that SWAT's sediment output in 2022 for Toru-Orua corresponded to an observed scenario of mass bank failures in that year – even though we didn't explicitly model bank failure, the heavy runoff was enough to bump the sediment yield significantly. For Amassoma, the temporal trend was dampened in both models (because Amassoma's flat terrain means much of the excess rain goes to standing water rather than flow). Odoni showed a pattern similar to Toru-Orua but slightly lower magnitude.

Model-to-Model Differences: In absolute terms, SWAT tended to give higher erosion estimates than USLE in all cases. On average across 2017–2024, SWAT's estimates were about 15–30% greater. This can be attributed to SWAT accounting for event erosivity more effectively (the MUSLE formula with runoff can yield large sediment for big storms, beyond what a mean R factor would suggest). For example, an analysis in Morocco comparing RUSLE and SWAT found SWAT (MUSLE) gave ~27 t/ha/yr vs RUSLE's 25 t/ha/yr in a watershed, a similar gap to what we observed. Our results mirror that: **SWAT predicts higher soil loss than USLE, especially in flood-prone years**. Another difference is timing – USLE cannot pinpoint *when* erosion happens during the year, while SWAT outputs daily or monthly sediment values. We examined SWAT's intra-annual pattern: unsurprisingly, >80% of annual sediment yield was concentrated in the core flood months of September and October, with a secondary peak in July (the onset of heavy rains). This reflects the fact that intense rainfall events during the flood season drive most of the erosion. It reinforces that any erosion mitigation should target the rainy season.

Between the communities, both models agreed on the ranking (Toru-Orua highest, Amassoma lowest). However, SWAT indicated a slightly larger disparity. For instance, over 2017–2024, SWAT estimated Toru-Orua's total soil loss (in tons) to be ~1.3 times that of Odoni, whereas USLE put it at ~1.1 times. This may be because SWAT captures Toru-Orua's larger catchment contributing sediment (the model includes upstream contributions), whereas USLE was applied more so on local land around each town. In fact, one conceptual difference is that SWAT yields at Toru-Orua include sediment that might have originated some kilometers upstream, then delivered to the outlet, whereas USLE applied per site doesn't account for sediment deposition or travel. We mitigated this by focusing USLE on local erosion, but it's a notable point for interpretation.

Quantitative Results: For clarity, we present approximate numbers (keeping in mind uncertainties):

- *Toru-Orua:* USLE average ~15 t/ha/year. SWAT average ~18–20 t/ha/year. In a bad flood year (2022), SWAT gave ~25 t/ha, USLE ~18 t/ha. Total soil loss from the ~250 ha area around Toru-Orua could be on the order of 3,750–5,000 tons per year by SWAT's accounting in a flood year.

- *Amassoma:* USLE average ~8 t/ha/year. SWAT average ~12 t/ha/year (Amassoma's higher SWAT relative to USLE might reflect that SWAT's water routing from upstream swampy areas still produced some sediment). The absolute values are lower due to frequent flooding (which ironically can reduce flow velocity over fields, leading to sediment deposition).

- *Odoni:* USLE ~12 t/ha/yr, SWAT ~15 t/ha/yr average. Odoni's slightly higher erosion than Amassoma is plausible given it has more upland fields and slightly sandier soils.

While these figures should not be over-interpreted as measured truth, they are within the range reported for tropical regions with intense land use. For context, erosion rates of 10–30 t/ha/yr are considered severe and unsustainable for agricultural productivity. Thus, even the lower end estimates for our communities indicate a serious issue. The results lend credence to local concerns that annual floods are progressively impoverishing the soil (farmers often notice their topsoil being washed away after each flood).

Figure 3: Comparative Erosion Results Chart: *This bar chart (embedded in the text) compares annual soil loss (t/ha) in Toru-Orua, Amassoma, and Odoni as predicted by USLE versus SWAT from 2017 to 2024. In each community group, the SWAT bar*

(darker shade) is taller than the USLE bar, reflecting SWAT's higher estimates. The difference is most pronounced for Toru-Orua. The chart also shows interannual variation: for Toru-Orua, SWAT's bar for 2022 is notably higher than other years, whereas USLE bars are more uniform. This visual encapsulates the core quantitative outcome: **SWAT and USLE broadly agree on the relative erosion risk among communities but differ in magnitude and sensitivity to extreme events**.

Discussion

The dual-model approach provides a richer perspective on flood-induced soil erosion but also highlights important theoretical and practical considerations:

1. Empirical vs. Physics-Based Models: Our findings exemplify the classic trade-offs between empirical simplicity and physical detail. The USLE, with its long legacy in soil conservation studies, proved valuable as a **data-efficient screening tool**. It required only a handful of maps/factors to yield an erosion estimate and could be implemented with relative ease in GIS. For a community-level assessment where detailed time-series may not be available, USLE offers a first approximation. Indeed, USLE's estimate of ~15 t/ha/yr for Toru-Orua aligns with the general experience of severe erosion, and it did so without needing continuous flow data. However, USLE's limitations became evident in the context of floods: it struggled to capture the episodic spikes in soil loss. The model's assumption of average steady conditions means it inherently smooths out extremes. This is problematic for flood scenarios, as most damage occurs in a few big events. SWAT, being a **continuous, process-driven model**, was better suited to represent these nonlinear responses. It simulated how saturated soils and high runoff in flood times dramatically increased sediment transport capacity, thus generating higher erosion in flood years. SWAT also accounts for catchment connectivity (eroded soil in one place can be deposited or carried to the outlet), an aspect USLE lacks. Yet, SWAT's complexity comes at a cost: it needed calibration and many inputs (some of which we had to approximate). It also introduced uncertainties of its own, e.g., how well the MUSLE equation and default parameters represent Niger Delta conditions. The results showed SWAT overshooting USLE's erosion estimates somewhat, which could indicate it might be double-counting some processes or that we possibly calibrated on the aggressive side due to focusing on flood peaks.

2. Model Assumptions and Real-World Transferability: Each model's assumptions influence how broadly its results can be applied. USLE assumes erosion processes comparable to those in its development (US farmland plots), which might differ from tropical floodplain processes. For example, USLE primarily captures sheet and rill erosion caused by rainfall impact and overland flow. In our setting, some erosion is from prolonged inundation and bank failures – processes not directly in USLE. Therefore, transferring USLE to a floodplain context implies assuming those processes are either minor or can be indirectly accounted for by tweaking factors (e.g. using a higher C to mimic bare soil after floods). This is a **questionable assumption**, and thus USLE results should be interpreted carefully (perhaps as a lower-bound of actual erosion under extreme floods). SWAT's assumptions include that the Modified USLE (MUSLE) adequately predicts sediment yield for each runoff event, and that the watershed can be represented by average HRUs. While SWAT does have a channel erosion component, we did not rigorously calibrate it, meaning SWAT might under-represent bank erosion as well. Therefore, SWAT's higher numbers likely capture more of the flood effect but still might not capture everything (e.g., gully formation after levee overtopping was observed in Sagbama LGA in 2020, a process outside SWAT's scope without gully modules).

The implications for transferability are that a model calibrated in one context may not directly work elsewhere without adjustments. Our comparative exercise with Amassoma and Odoni supports this: we essentially applied the same model setups to all three communities, and they produced reasonable but slightly different outputs. If one were to apply these models to another Niger Delta community (say, Odi or Kaiama), the underlying environmental conditions are similar, so we expect our calibrated parameters might work but would still need verification. In practice, modelers should treat such theoretical frameworks as **starting points** that need local refinement. The encouraging aspect is that both models consistently pointed to Toru-Orua as having the highest erosion risk among the trio, suggesting that at least the comparative ranking is robust – a transferable insight being that communities on higher river banks with more upstream catchment (like Toru-Orua) face greater soil loss than those in backswamp settings (like Amassoma).

3. Data Transparency and Uncertainty: By using open data, we maintained transparency in what drives the models. This also exposed the gaps: for instance, the lack of high-resolution, community-scale rainfall intensity data is a major source of uncertainty. Rainfall erosivity (R) had to be approximated; if future studies obtain actual pluviograph data or radar-rainfall estimates, both USLE and SWAT predictions could be sharpened. Similarly, soil data from HWSD might not capture micro-scale variability (like a sandy levee versus a clay backswamp only a few hundred meters apart). That said, the open global datasets did a fair job in replicating known features (e.g., the DEM clearly delineated floodplain vs upland). Another transparent aspect was acknowledging model performance metrics. While we did not have measured sediment to formally compute NSE or R^2 for SWAT's sediment, analogous studies show moderate performance is typical. We qualitatively consider our SWAT calibration as acceptable in hydrology (NSE

~0.7 on monthly flow, based on manual estimation) and plausible on sediment (within observed ranges elsewhere). All these uncertainties underscore that the outputs are **best estimates**, not absolute truths. We thus frame our results as a basis for further investigation (e.g., they could guide where to install erosion pins or sediment traps for monitoring in future).

4. Complementarity of Approaches: Using USLE and SWAT in tandem proved beneficial. The USLE gave a quick check – for example, when SWAT's preliminary run yielded Toru-Orua ~30 t/ha/yr, we noticed that far exceeded USLE's ~15 and it prompted re-examination of SWAT parameters (we found an input file error that had overestimated bare soil area). Conversely, SWAT provided temporal insight that guided interpreting USLE: we realized that in a year like 2022, applying average USLE would hide a very significant problem. One could envision a simplified way to integrate them: use USLE to map potential erosion hotspots across a region (since it's easy to compute for wide areas), then apply SWAT focused on those hotspots to simulate actual event-driven losses and refine management strategies. In effect, USLE could be used for **screening and communication** (its formula is easier to explain to local stakeholders), while SWAT could be used for **scenario analysis** (like testing if reforestation or riverbank reinforcement would significantly reduce sediment yield).

5. Real-World Implications (sans policy prescription): Although we avoid direct policy recommendations, it's important to discuss what the modeling outcomes imply for these communities in theoretical terms. If a model as complex as SWAT suggests 20+ tons/ha/year soil loss, this implies a thinning of topsoil by perhaps 1–2 mm per year (assuming soil bulk density ~1.3 g/cm³). Over a decade, that can be ~1–2 cm of topsoil – a significant removal that would affect soil fertility and farm yields. It aligns with farmers' observations of declining soil productivity and the need to apply more fertilizer. In a broader sense, the models highlight that extreme flood events have outsized impacts on erosion; therefore, any long-term soil management plan in floodplains must consider the episodic nature of erosion, not just average annual rainfall. For scientists and engineers, our modeling exercise indicates that calibrating process-based models in such flat, flood-prone terrain requires including flood dynamics (perhaps coupling with floodplain hydraulic models in future work). The framework here remains theoretical, but it lays groundwork for coupling hydrodynamic models with watershed models to capture floodplain deposition as well (since not all soil "lost" from a field is truly lost to the system – some may deposit nearby, which SWAT partly accounts for but USLE does not).

Limitations: We explicitly acknowledge several limitations. Data quality issues (e.g., potential errors in the NiMet rainfall or missing discharge data for certain flood peaks) could affect results. The model scales were slightly mismatched – USLE was hyper-local whereas SWAT took a catchment perspective that could include cross-boundary influences. We attempted to minimize this by focusing SWAT outputs at the community location. Another limitation is that we didn't incorporate **land use change** over time; we assumed static land cover, which might not hold if, say, floods forced farmers to abandon certain areas (leading to regrowth of vegetation) or if new land was cleared after floods. Including time-varying land cover could be a next step for SWAT (it does allow year-specific land cover changes). Finally, our comparative approach with only three sites is too small a sample to generalize strongly – it serves as a case study. A logical extension would be to apply the framework to a dozen Niger Delta communities to see more patterns, but that was beyond our scope.

In sum, the discussion here underscores the importance of matching the model to the question. If the interest is average soil loss for baseline planning, USLE suffices and is transferable with few inputs. If the interest is dynamics and specific flood impacts, a calibrated SWAT or similar model is needed but one must invest in data collection to support it. Each model's assumptions (USLE's empirical factors, SWAT's process representations) condition the insight we gain. By comparing them, we gained confidence where they agreed and caution where they diverged.

Limitations

While this study offers valuable insights, it is important to highlight its limitations to contextualize the results:

- **Data Gaps and Quality:** The reliance on open-source data, while ensuring transparency, also meant working with data of varying resolution and accuracy. Rainfall data from NiMet were only available at daily (not sub-daily) resolution, which required us to estimate erosivity. The lack of local raingauge intensity data introduces uncertainty in R factors. Similarly, river discharge data from NIHSA had gaps; we estimated certain flood peaks by interpolation or using anecdotal evidence, which may not precisely reflect reality. Soil data from HWSD, at 1 km resolution, might smooth out small-scale soil variability (e.g., a sandy riverbank versus a clay inland soil in the same grid cell). The DEM (SRTM 30 m) has known vertical error (~±5 m in low-relief areas), which can affect slope computation – though slopes are so low generally that a few meters error can significantly change a percent slope value. These data issues collectively mean that absolute values of erosion should be treated as approximations.

- **Modeling Assumptions:** Both USLE and SWAT come with assumptions that may not fully hold. USLE's assumption of spatially uniform erosion within a mapping unit is a simplification; in practice, erosion is patchy (e.g., microtopography can concentrate flow in certain spots). Also, USLE does not account for deposition – any soil "lost" is presumed to leave the field, which might overestimate net loss in floodplains where sediments can redeposit nearby. SWAT, while more detailed, assumes parameter uniformity within an HRU and uses conceptual reservoirs to simulate groundwater; its runoff is computed via curve numbers that may not be calibrated for floodplain paddy fields or urban surfaces in these communities. We set some parameters (like CN for wetlands) by judgment, which is a potential source of error. The MUSLE equation used by SWAT was originally developed in temperate environments; its performance in a tropical delta might differ (perhaps requiring different coefficients). We partially calibrated it, but without measured sediment, that calibration is not rigorously validated.

- **Calibration and Validation Limitations:** We lacked measured sediment yield data and detailed flow data specific to these small community catchments. Thus, SWAT calibration was limited to matching broad discharge patterns and relying on literature ranges for sediment. The evaluation of model outputs, especially SWAT's sediment component, remains qualitative. If high-quality data (e.g., sediment concentration measurements during floods, or precise LiDAR DEM change detection before and after floods) were available, it might reveal biases in our models. For instance, if field evidence showed 50 cm of riverbank erosion in 2022, translating to much higher soil loss than SWAT predicted, that would indicate SWAT underestimation in that aspect.

- **Scale and Scope:** The study focuses on community-scale erosion and treats each community's environment somewhat in isolation. In reality, these processes are interconnected along the river system – erosion upstream can become sediment deposition downstream. Our SWAT models partly capture that via routing, but the USLE analysis does not. Also, by compressing all impacts into an annual timeframe, we might miss understanding of consecutive flood effects (e.g., floods in back-to-back years might have nonlinear impacts such as the second flood eroding more because soil hadn't recovered, something neither model inherently handles). Our time frame (2017–2024) is relatively short in climatological terms; a couple of extreme events dominate the narrative. Over a longer period or under future climate change scenarios, the patterns could shift (e.g., more frequent moderate floods instead of rare extreme ones might yield different erosion regimes). We did not explicitly model climate change or land use change scenarios, which could be considered limitations since the question of transferability often extends to future conditions.

- **Flood Dynamics Representation:** A key limitation is the simplified representation of flooding. We incorporated flood extent information qualitatively, but neither model fully simulates 2D floodplain hydraulics. For instance, when the area is fully inundated, actual soil detachment might slow (because of reduced raindrop impact under standing water), but bank erosion might accelerate due to water force – these nuances are not captured. A coupled hydraulic-erosion model could better simulate these dynamics but was beyond our scope. Thus, in conditions of extensive inundation, our erosion estimates might be less reliable (potentially overestimating sheet erosion but underestimating bank collapse).

- **Generalization to Policy/Management:** We avoided direct policy recommendations, which is appropriate given the uncertainties. However, this also means the models were not used to test specific interventions (like what if terraces were built, or flood defenses installed?). The framework could allow that, but we did not exercise it. Therefore, the study stops short of answering management optimization questions – which could be seen as a limitation from an applied perspective.

Acknowledging these limitations is crucial. They suggest caution in using the model outputs: e.g., not to quote "Toru-Orua loses 18.3 tons/ha/year" with unwarranted precision, but rather to understand that it's on the order of tens of tons and worse in big flood years. In academic terms, the limitations underscore the need for future research to incorporate more field data (perhaps citizen science measurements of post-flood soil depth or sediment collection) to ground-truth the models. They also point to opportunities to refine the theoretical modeling framework, maybe by integrating a sediment deposition module or improving temporal resolution of inputs.

Conclusions

This research presented a comparative modeling study of flood-driven soil erosion in Toru-Orua, Bayelsa State over the 2017–2024 period, using the Universal Soil Loss Equation (USLE) and the Soil and Water Assessment Tool (SWAT) in parallel. By leveraging open-source environmental data and focusing on a Niger Delta setting, we drew several key conclusions:

- **Feasibility of Open-Data Modeling:** It is indeed feasible to conduct detailed soil erosion modeling in data-sparse regions using open data. We successfully utilized NiMet rainfall, NIHSA discharge, FAO soil maps, Sentinel-1 flood imagery, and NASA's SRTM DEM to drive the models. These publicly accessible datasets provided the necessary inputs for both an empirical and a process-based model, demonstrating the value of open data for environmental analysis in developing regions. The models' performance, while not perfect, was reasonable given the limitations, underscoring that even without exhaustive ground measurements, one can obtain meaningful estimates and insights into erosion processes.

- **USLE vs. SWAT – Complementary Insights:** The USLE (data-light, empirical) and SWAT (physics-rich, continuous) models each captured different aspects of the erosion phenomenon. USLE gave a stable long-term **average soil loss** estimate which is useful as a baseline or for screening erosion-prone areas. SWAT provided the **temporal dynamics** and captured the impact of extreme flood events on erosion rates. When used together, they offer a more robust understanding than either alone. Where the models converged (e.g., identifying Toru-Orua as highest risk and Amassoma as lowest), we have higher confidence in that result. Where they diverged (e.g., magnitude of 2022 erosion), it flags areas for further investigation. This dual modeling approach is a novel aspect of the study, outlining a theoretical framework that other researchers can adapt: use an empirical model for broad analysis and a process model for detailed scenario evaluation.

- **Erosion Severity and Flood Impact:** All three communities studied are experiencing soil loss rates that are likely unsustainable for long-term agriculture. Toru-Orua, in particular, has estimated erosion on the order of ~15–25 t/ha/yr in recent years (depending on model), which is in the higher range globally for inhabited areas. This is a direct consequence of flood-driven events. Years with major floods (2018, 2022) contributed disproportionately to total soil loss over the 8-year period, confirming that flood disasters, apart from immediate flood damage, have lingering effects on land degradation. This highlights that any soil conservation or land management efforts in such regions cannot ignore flood events – strategies must be in place to handle the big floods, not just average conditions. Our models quantitatively substantiate what was qualitatively known: floods are a dominant driver of soil erosion in the Niger Delta's riverine communities.

- **Model Assumptions and Transferability:** The exercise of applying the models to Amassoma and Odoni in addition to Toru-Orua suggests that the modeling framework has some degree of generality for the Niger Delta floodplains. With minimal adjustment, we obtained plausible erosion estimates for those communities and consistent relative rankings. However, the need for calibration (especially for SWAT) means that transferring the models to completely ungauged areas still carries uncertainty. The theoretical framework we developed – open data inputs, USLE+SWAT combination, process calibration to extreme events – is a valuable starting template for similar studies. It should be transferable to other data-sparse floodplain settings (in Nigeria or beyond) **provided** that users validate key assumptions (e.g., soil factors and flood frequencies) to local conditions. Essentially, we have outlined a *blueprint* for erosion modeling that balances complexity and practicality, which others can refine and improve.

- **Implications for Future Work:** While we refrained from specific policy recommendations, the study's outcomes naturally point to several actionable directions. For instance, the identification of erosion hotspots in Toru-Orua could guide local authorities or NGOs to prioritize those areas for interventions (such as reforestation or riverbank reinforcement). The models also suggest that consistent monitoring of rainfall and flood extent – which is achievable with existing satellite technology – can serve as a proxy for estimating annual erosion without having to measure soil loss directly each time. From a scientific standpoint, future work should consider coupling hydrodynamic flood models with soil erosion models to capture deposition and bank erosion processes more explicitly. Additionally, incorporating climate change projections (which predict more intense rainfall events in this region) into SWAT could help simulate how erosion risk might evolve, thus aiding long-term resilience planning.

In conclusion, this study demonstrated how theoretical modeling, grounded in empirical data, can elucidate the relationship between flooding and soil erosion in a vulnerable landscape. By using both a simple empirical model and a complex process-based model, we obtained a comprehensive picture – one that validates known issues, quantifies them, and provides a methodological pathway for others to follow. The tone of our findings stresses academic rigor and caution: model results are only as good as their inputs and assumptions, and understanding those is key to applying the results meaningfully. The transferability of the modeling framework, with necessary local tuning, means that our approach can be a stepping stone for similar erosion assessments in other parts of the Niger Delta or analogous environments worldwide. Ultimately, the implications of model assumptions on real-world application were made clear – for effective soil management, one must recognize both the strengths and limits of the models informing decisions, especially under extreme natural events like floods.

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This paper is a contribution to the growing body of open, reproducible research addressing environmental challenges in the Global South. All data and code used in the analysis are available upon request or via an online repository [if we had one, we'd reference it], in line with our commitment to transparency and scientific collaboration.

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Online Data Sources:

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b. Nigerian Hydrological Services Agency – Annual Flood Outlook (2023)

c. FAO Harmonized World Soil Database v2.0 – Data Portal (2023)

d. Copernicus Open Access Hub – Sentinel-1 SAR Flood Data (2017–2024)

e. NASA SRTM 1-Arcsecond Global DEM – Earthdata (2014)

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