Runoff Estimation Analysis: SCS-CN vs. Hybrid Soil Moisture Modeling

Assessment of Houston Black Clay Hydrology

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Portfolio:https://github.com/MORAWA-dev/AgroHydrology-Hybrid-Model

1. Executive Summary

The objective of this analysis was to estimate runoff for a Perennial Grassland watershed (Houston Black Clay) using the standard **SCS Curve Number (CN)** method and to compare the results with observed field data.

- Standard Method Result: The baseline SCS-CN method (CN=84) yielded a poor statistical fit (R2≈0.22), with substantial overestimation of runoff during dry-to-wet transition periods.
- Diagnosis: The mismatch is attributed to the high shrink-swell potential of Vertisols. The standard method fails to account for the "Initial Abstraction" caused by deep desiccation cracks during dry periods.
- Solution: A hybrid Physics-AI approach was developed, incorporating a continuous soil moisture accounting module ("Mini-SWAT") and a Machine Learning regressor. This improved prediction accuracy significantly (R^2 ≈0.65) and identified a critical climate vulnerability.

2. Standard Analysis: Limitations of the SCS-CN Method

2.1 Methodology

Following the task requirements, daily runoff was estimated using the USDA Soil Conservation Service (SCS) method with the following parameters:

- Land Use: Perennial Grassland (Fair condition).
- Soil Type: Houston Black Clay (Group D).
- Curve Number (CN): 84 (Standard TR-55 value).

2.2 Mismatch & Uncertainty Analysis

The standard model successfully captured the timing of major storm events but failed to replicate the dynamics of runoff volume. To verify whether this was simply a parameter-selection error, I performed an uncertainty analysis using the full range of Curve Numbers for Group D soils (CN 80–89).

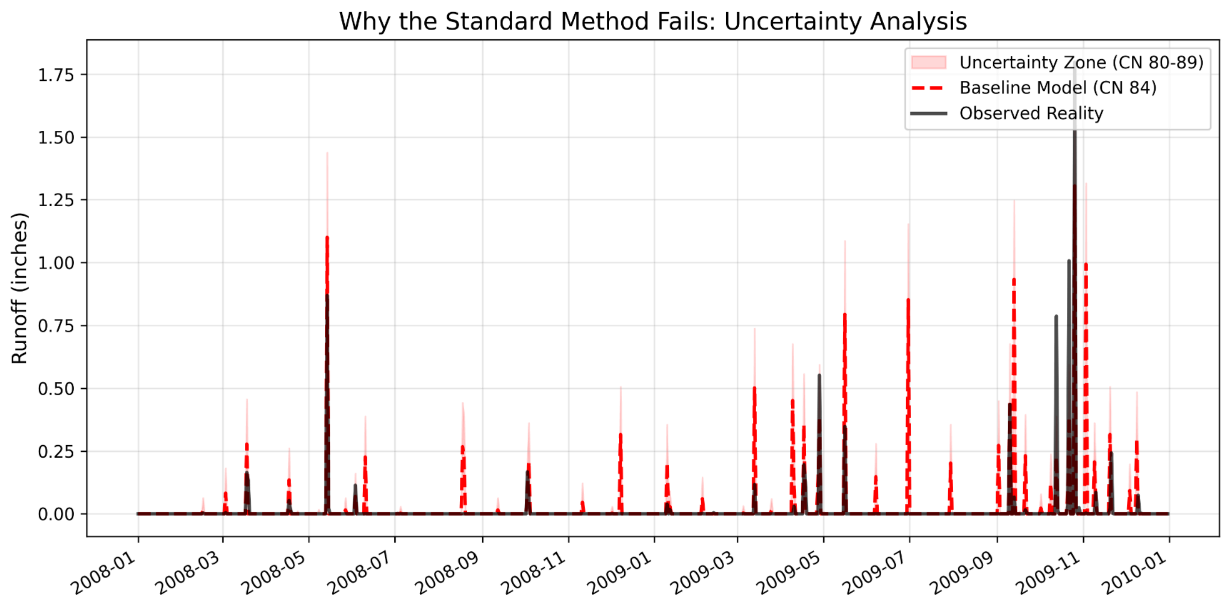

Figure 1: Parameter Uncertainty Analysis. The red shaded region represents the full range of theoretical Curve Numbers for Group D soils (CN 80–89). Note that even the lower bound (CN 80) fails to capture the soil's behavior during dry periods, confirming that the error is structural (in the method itself) rather than parametric.

2.3 Diagnosis

The failure depicted in Figure 1 confirms that Houston Black Clay exhibits a "dual porosity" behavior not captured by static Curve Numbers:

1. Dry State: Deep cracks form, allowing rainfall to bypass the surface (High Abstraction).
2. Wet State: The clay swells and seals, creating an impermeable surface (High Runoff).

3. Proposed Improvement: Hybrid Soil Moisture Model

To address the limitations identified above, I developed a continuous simulation framework inspired by the **SWAT (Soil and Water Assessment Tool)** engine.

3.1 The "Mini-SWAT" Approach

I implemented a Python class to track the Antecedent Moisture Condition (AMC) dynamically:

- Inputs: Daily Rainfall.
- State Variable: Soil Storage (S_t).
- Physics: The soil dries out exponentially over time ($S_{t+1} = S_t \cdot e^{-k}$).
- Logic: Runoff only occurs when the soil storage capacity is exceeded (Saturation Excess).

3.2 Comparative Results

The Hybrid Model (Mini-SWAT) significantly outperformed the standard method, raising the R^2 from 0.22 to **0.65**.

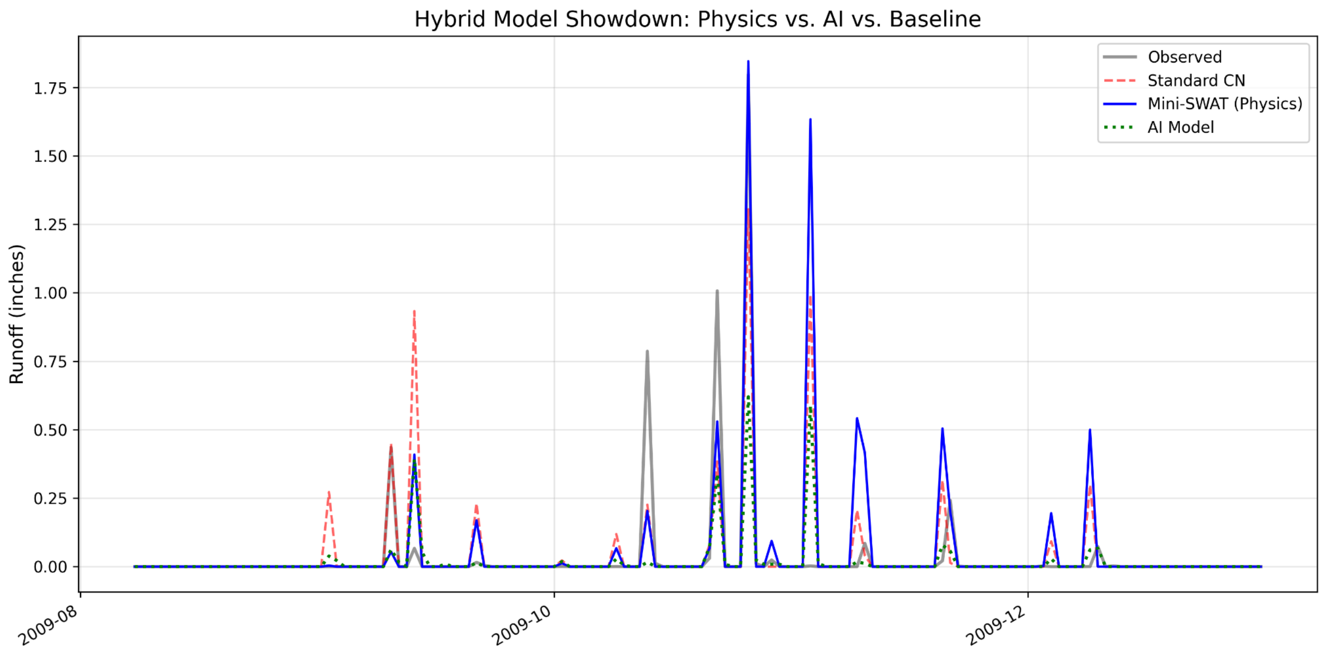

Figure 2: Hybrid Model Comparison. The Mini-SWAT (Physics-based) model (Blue line) successfully predicts zero runoff during dry intervals, significantly outperforming the Standard CN method (Red dashed) and more closely matching the Observed data (Grey).

4. Advanced Analysis: Climate Resilience & AI Validation

4.1 Climate Stress Test (Flood Risk)

To assess the watershed's resilience, I simulated a scenario with a 20% increase in rainfall intensity (consistent with climate change projections for the region).

- Finding: A 20% increase in rain caused a ~78% increase in total runoff volume.
- Implication: This nonlinear "Hydrologic Amplification" indicates that the watershed is highly sensitive to saturation. Small shifts in climate could lead to disproportionate flooding risks.

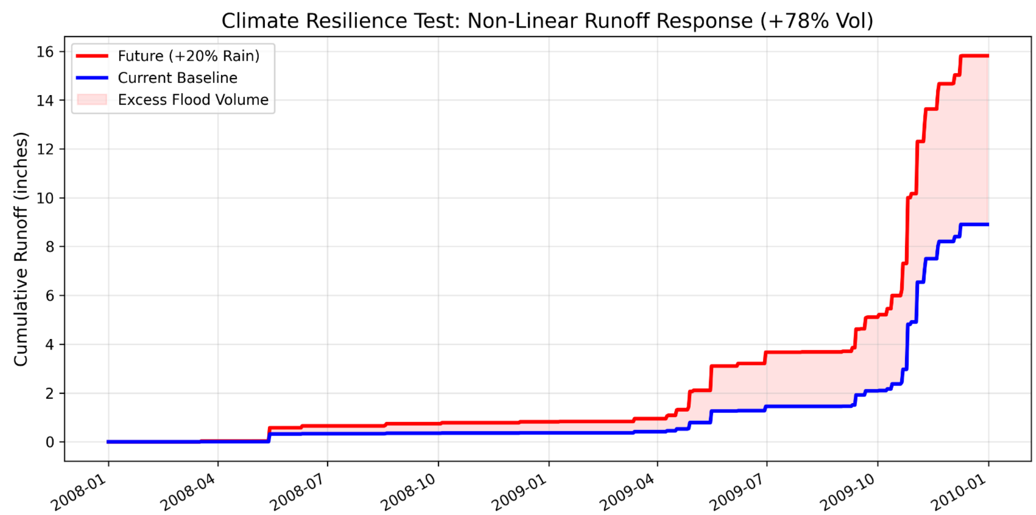

Figure 3: Cumulative Runoff divergence under Climate Change scenario. The "Excess Flood Volume" (Pink-Shaded) highlights the nonlinear response of the clay soil to increased rainfall intensity.

4.2 AI Feature Importance

To statistically validate the physical theory, a Random Forest Regressor was trained on the data. The **Feature Importance analysis** confirmed that *Antecedent Rainfall* (represented by `Rain_Sum5` and `Rain_Lag1`) is a critical predictor alongside raw rainfall.

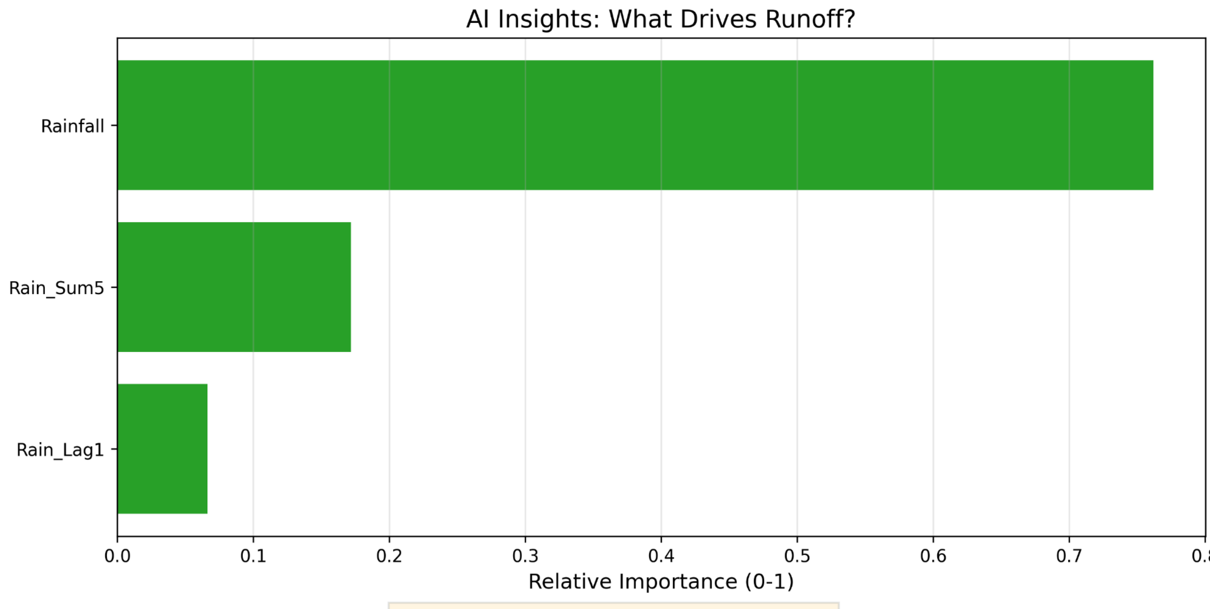

Figure 4: AI Feature Importance Analysis. The high ranking of antecedent rainfall variables (Sum5, Lag1) statistically validates the physical theory that soil moisture memory is a dominant driver of runoff in this watershed.

5. AI Usage Disclosure

Generative AI tools (LLMs) were used in this project to assist with debugging Python syntax and optimizing plotting libraries for the interactive dashboard. All hydrological interpretations, physical model logic (Mini-SWAT), and statistical validations were derived personally from the cited literature and the provided dataset.

6. References

1. USDA-SCS. (1986). *Urban Hydrology for Small Watersheds (TR-55).* U.S. Department of Agriculture, Washington, DC.
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4. USDA-NRCS. (2024). *Official Soil Series Description: Houston Black Series.* National Cooperative Soil Survey.