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Research Article

# Beyond Averages: A Continental Analysis of Forest Transition Heterogeneity

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**Forest transition (FT) describes a structural land-use change process characterized by a shift from net deforestation to forest recovery. While previous studies have extensively investigated this phenomenon, empirical results regarding the validity of the FT hypothesis remain mixed. Moreover, the specific thresholds triggering widespread reforestation remain obscure. To address these gaps, this study investigates the link between land-use change and development. Utilizing quantile regression and bootstrapping, the relationship between the Human Development Index (HDI) and deforestation rates across 189 countries from 1990 to 2021 is analyzed. The findings reveal that while the FT framework explains land-use dynamics at a macro level, significant continental heterogeneity exists. Specifically, the deforestation phase is notably more protracted and severe in the Americas and Africa. Moreover, current development trajectories in these continents remain well below the critical thresholds required to trigger spontaneous reforestation. These results underscore that relying on passive economic development as a primary mechanism for forest conservation is insufficient and risks critical ecological delays in high-deforestation regions.**

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## 1. Introduction

Forests are indispensable to the health of the planet, serving as vital carbon reservoirs[1] and regulators of regional hydrological cycles[2]. As the primary sanctuaries for global biodiversity[3], their continued degradation poses a severe threat to the essential ecosystem services they provide[4]. Consequently, identifying the mechanisms behind forest depletion and eventual recovery is a critical priority for environmental governance.

The Forest Transition (FT) framework, established by Mather[5], offers a lens through which to view these long-term landscape shifts. The theory predicts a "U-shaped" evolutionary path where an era of heavy clearing is eventually superseded by a phase of net forest expansion[6]. Conceptually, this process moves through four distinct stages: a "pre-transition" state of stability, an "early transition" defined by rapid loss, a "late transition" where clearing decelerates, and a "post-transition" recovery phase where the pace of reforestation exceeds that of depletion[7]. From a mathematical perspective, this nonlinear progression is best represented by a cubic function when modeling the relationship between land-use fluctuations and regional development[8].

Despite its theoretical appeal, empirical support for the FT hypothesis remains mixed. A common finding in the literature is the "partial" transition, typically modeled as a quadratic curve that identifies the peak of forest loss but fails to capture the subsequent recovery. For example, research focused on the turn of the 21st century has observed these patterns in Latin America and Africa, yet findings in Asia continue to be a subject of debate[9][10][11]. Furthermore, investigations utilizing remote sensing data suggest that models based solely on income often fail to capture the full spectrum of the transition curve[12].

The choice of developmental indicators is equally important. While income per capita is traditionally used, there is an increasing shift toward holistic measures like the Human Development Index (HDI), which may more accurately reflect the socioeconomic transformations driving land-use change. This is evidenced in regions like Central America, where HDI has proven to be a superior predictor of forest stabilization compared to purely economic metrics[13].

A major constraint in existing FT scholarship is a restricted geographic and temporal focus, which frequently overlooks the "right tail" of the distribution—the specific juncture where reforestation commences[8]. This study addresses these limitations by analyzing a comprehensive global dataset from 1990 to 2021. The objectives are twofold:

1. To test the applicability of the FT framework across a broader development range.
2. To identify the specific HDI "tipping points" necessary to transition a region from active forest loss into a recovery phase.

The results demonstrate that while the FT model maintains global relevance, the timing and magnitude of these transitions are governed by significant regional variations. The remainder of this paper is organized as follows: Section 2 details the methodology; Section 3 presents the empirical results; Section 4 provides a discussion of the findings; and Section 5 offers concluding remarks.

## 2. Analytical Framework and Data

Figure 1 presents an overview of the methodological analytical framework adopted in this study. The research commenced with data collection and cleaning.

Subsequently, an exploratory data analysis (EDA) was conducted on the resulting dataset. Key findings from the EDA informed the subsequent modeling phase.

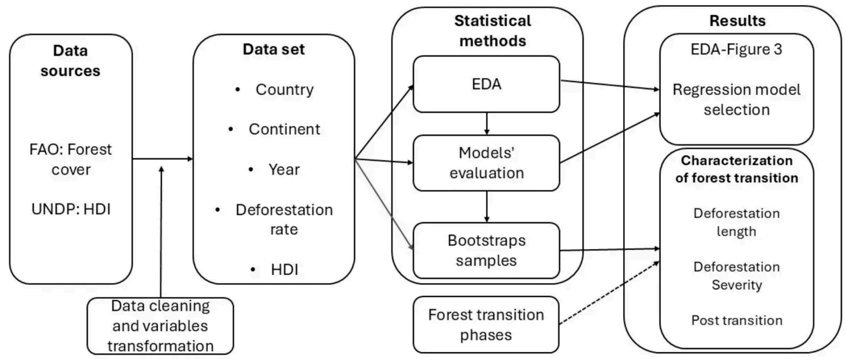


**Figure 1.** Methodology implemented for the study.

A suite of regression models was fitted and tested to identify the most suitable model for the research objectives. Model selection was based on an evaluation of a performance metric.

The optimal regression models were instrumental in delineating distinct stages of forest transition. These identified stages provided a robust framework for quantifying deforestation characteristics across the study regions.

A detailed elaboration of each methodological step is provided in the subsequent sections.

### *2.1. Dataset Composition and Variable Definition*

This study examines the interplay between socioeconomic progress and landscape dynamics using a longitudinal panel of 189 nations from 1990 to 2021. To provide a comprehensive global view, countries are categorized into five continental cohorts: Africa, the Americas, Asia, Europe, and Oceania.

The modeling strategy utilizes two primary indicators:

- **The Human Development Index (HDI):** Sourced from the UNDP Global Data Lab[14], this composite metric serves as the proxy for regional development, integrating health and education outcomes alongside economic output.
- **The Deforestation Rate (**$DR$**)**: Derived from FAOSTAT forest extent data[15], this variable quantifies annual landscape shifts.

Data were available for 189 countries in the period 1990-2021.


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| Variable | Type of variable | Units or categories | Transformation | Source |
|---|---|---|---|---|
| Deforestation rate (dr) | numerical continuous | Percentage | $\%\Delta f_{t-1} = \frac{f_t - f_{t-1}}{f_{t-1}}$ | Our own calculations based on FAOstat data. |
| Human Development Index (hdi) | Numerical | Index | NA | UNDP |
| Continent (con) | Categorical | Africa Americas Asia Europe Oceania | Countrycode function | Our own calculations based on FAOstat data. |

**Table 1.** Variables used in the analysis and their statistical properties.

While alternative land use datasets exist, such as that of Potapov et al.[16], this study prioritized the use of FAO data. This decision was driven by the FAO dataset's longer temporal coverage and the demonstrated high consistency across global and national scales between both data sources[16].

The continent where each country is located was added using the R package countrycode[17]. The supplementary material shows the specific geographical criteria implemented and the list of countries included in the analysis.

## *2.2. Statistical methods*

An exploratory data analysis was initially performed on the dataset, utilizing the `ggplot2` package[18] to visualize deforestation rates against HDI and identify emerging patterns. To formally test these relationships, this research employs quantile regression[19], moving beyond the constraints of Ordinary Least Squares (OLS). While OLS focuses on conditional means, quantile regression allows for modeling the distribution of forest change across specific segments. Specifically, the 50th percentile (median) is evaluated to observe central trends, while the first and third quartiles allow for an examination of extreme dynamics—capturing the behavior of nations experiencing the most rapid forest loss or gain. This methodology is particularly advantageous for global environmental datasets where error terms are frequently non-Gaussian and subject to heteroscedasticity.

To empirically test the trajectory predicted by Forest Transition (FT) theory, annual forest cover fluctuations are assessed as a function of HDI. To identify non-linearities, the analysis examines various specifications, incorporating linear, quadratic, and cubic terms, alongside the inclusion of continental variables. These models were fitted using the `quantreg` package[19] within the R environment[20]. Model selection was guided by the Mean Absolute Error (MAE), a metric robust to the influence of outliers. A lower MAE indicates a superior fit; this was calculated as follows:

$$\text{mae} = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

Where $n$ represents the number of observations and $e_i$ denotes the residuals. The cubic specification consistently outperformed linear and quadratic alternatives across the distribution. For conciseness, the exhaustive comparative results and validation tests are provided in the Supplementary Material.

Finally, to ensure coefficient reliability and account for variability across the 189 nations, a bootstrapping procedure with 1,000 iterations was applied[21] using the `rsample` package[22]. This resampling method provides robust standard errors and confidence intervals, permitting a precise comparison of forest transition stages across different continental contexts.

### *2.3. Forest transition phases*

Figure 2 illustrates the identification strategy employed in this study. The roots of the estimated cubic function, as well as its minimum point, were analyzed to delineate the stages of forest transition. The roots of a function are the points at which the graph intersects the horizontal axis (e.g., $x = 0$). In the case of a cubic function, there are typically three roots. The minimum of the function represents the point at which the graph reaches its lowest value on the vertical axis.

For the purposes of this research, the lowest root (i.e., the first marked point from left to right in Figure 2) is identified as the onset of the early transition stage. The minimum corresponds to the beginning of the late transition stage, while the middle root marks the start of the post-transition stage. The highest root indicates the conclusion of the forest transition process.

The severity of deforestation during the forest transition is captured by the peak estimated deforestation rate, which marks the commencement of the late transition stage. Likewise, the HDI level required for the post-transition horizon was calculated to approximate the onset of the reforestation phase.

It should be noted that in some instances, the roots contained imaginary components (i.e., non-real roots) or were located outside the HDI range (i.e., 0-1), and were therefore excluded from the analysis. Likewise, unusual minima were identified and filtered out using the interquartile range method[23]. Positive minima, indicative of net reforestation, were also excluded from the final analysis. Rather than mere data loss, the continental distribution and mathematical convergence behavior of these excluded iterations represent critical structural findings regarding global forest transition heterogeneity, which are explicitly detailed and interpreted in the Results section.


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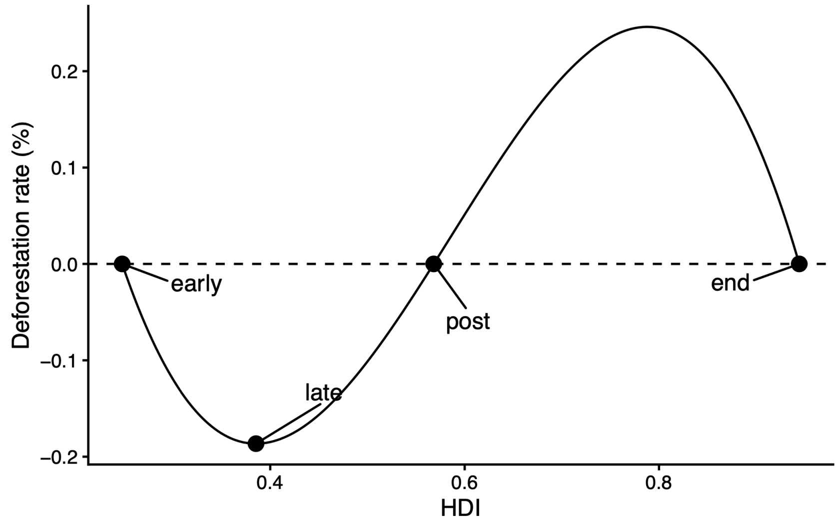


**Figure 2.** Identification of forest transition phases based on a possible model fit.

## 3. Results

In the following sections, the results of the exploratory data analysis, model selection, and characteristics of forest transition (i.e., deforestation length, deforestation severity, and post-transition) are presented.

### *3.1. Exploratory Data Analysis*

Analysis of Figure 3 reveals a stark geographic divergence in how land-use trajectories respond to development (see also Table 2). While Oceania displays a relatively stable and compressed range of forest change, the data for Africa and the Americas reflect significantly higher volatility. Although a broad global correlation exists—linking lower HDI scores with forest loss and higher scores with expansion—the specific “turning points” are non-uniform.

For example, the developmental threshold for forest depletion varies; in Africa, the process is often observable at HDI levels below 0.4, whereas the Asian cohort typically requires surpassing this 0.4 mark before significant loss trends emerge. Regional context further influences the recovery phase; while European nations generally shift toward net forest gain around an HDI of 0.6, the graph shows that African and American nations continue to endure substantial forest depletion at that same developmental stage. These disparities indicate that the forest transition is not a singular phenomenon but a process contingent on regional factors. These initial observations directly informed the nonlinear regression specifications explored in the following sections.


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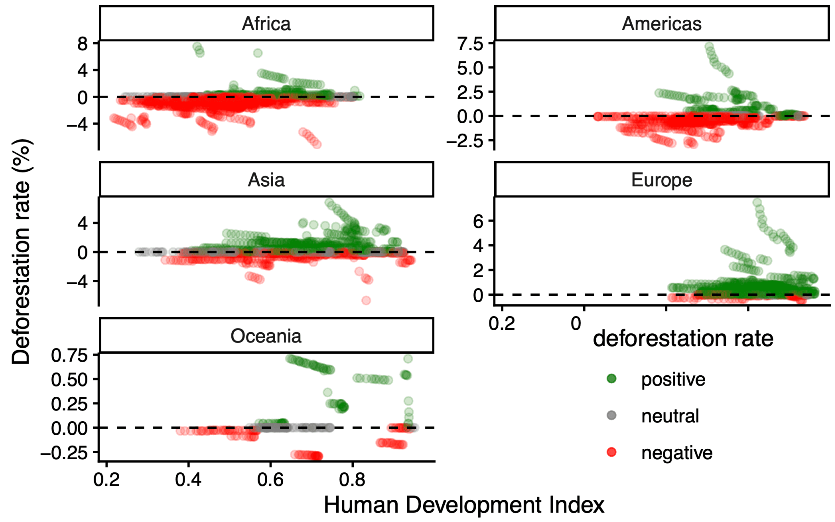


**Figure 3.** Deforestation rate vs. HDI per continent for the period 1991–2021.

| continent | min | q1 | median | mean | q3 | max |
|---|---|---|---|---|---|---|
| **Africa** | -7.10 | -0.87 | -0.41 | -0.52 | 0.00 | 8.84 |
| **Americas** | -2.93 | -0.48 | -0.17 | -0.13 | 0.00 | 7.16 |
| **Asia** | -15.15 | -0.14 | 0.00 | 0.22 | 0.43 | 6.82 |
| **Europe** | -0.47 | 0.00 | 0.16 | 0.41 | 0.51 | 10.53 |
| **Oceania** | -0.30 | -0.03 | 0.00 | 0.07 | 0.04 | 0.71 |

**Table 2.** Descriptive statistics of deforestation rate per continent.

### *3.2. Model Evaluation*

Across all quartiles, cubic specifications demonstrated superior performance relative to linear and quadratic alternatives. Furthermore, the systematic underperformance of regression models omitting the continent variable underscores its statistical significance and explanatory power within the analysis. Comprehensive metrics regarding model evaluation are available in the supplementary material.

For the first and second quartiles, the optimal model specification was the following:

$$dr = \beta_0 + \beta_1 hdi + \beta_2 hdi^2 + \beta_3 hdi^3 + \beta_4 continent + \beta_5 (hdi \times continent) + \epsilon$$

For the third quartile, the optimal model was:

$$dr = \beta_0 + \beta_1 hdi + \beta_2 hdi^2 + \beta_3 hdi^3 + \beta_4 continent + \beta_5 (hdi^3 \times continent) + \epsilon$$

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### 3.3. Characterization of forest transition

The analysis delved deeper into the characteristics of forest transition by examining the length and intensity of deforestation periods. Furthermore, it investigated the development level, measured by the HDI, necessary to initiate forest recovery. This comprehensive analysis provides a holistic understanding of the dynamics of forest transition at a continental scale. Subsequent sections present and further analyze the mentioned characteristics of forest transition.

#### 3.3.1. Deforestation severity

Deforestation severity was characterized across continents and estimated quantiles. The bootstrap estimation of this critical turning point proved to be exceptionally robust for the regions experiencing active, contemporary clearing pressures. Africa and the Americas retained near-absolute parametric stability across the simulation pool, yielding structural rejection rates below 3%. Conversely, Europe exhibited a severe drop in operational convergence, with over half of its bootstrap iterations excluded due to statistical outlier behavior or the manifestation of non-negative values ($dr \geq 0$). This mathematically confirms that while a well-defined, severe deforestation trough is a structural certainty for Africa and the Americas, such a negative depletion phase is no longer representative of contemporary European land-use dynamics, where stable or positive forest cover trajectories dominate. The precise regional frequency distributions and exclusion breakdown for this metric are detailed in the Supplementary Material.

Figure 4 illustrates the estimated deforestation severity for each successful bootstrap repetition, categorized by continent and quantile, alongside the mean severity for each respective category. As the visual evidence dictates, regardless of the specific quantile analyzed, the deepest and most intense deforestation rates were systematically estimated in the Americas and Africa.

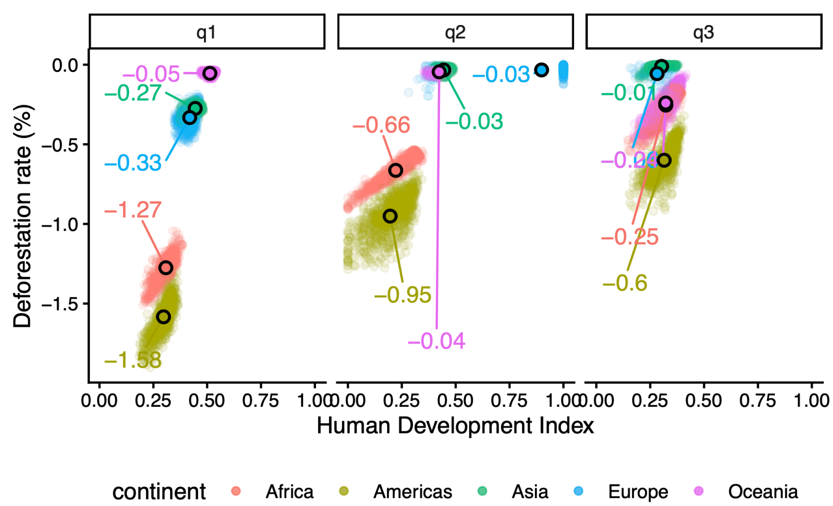


**Figure 4.** Severity of forest transition per quartile. Results based on valid bootstrap iterations (n = 2,929 for Africa, n = 2,914 for Americas, n = 2,514 for Asia, n = 1,369 for Europe, and n = 2,831 for Oceania). Individual dots indicate the estimated coordinate for each bootstrap repetition. The highlighted circle indicates the mean of individual estimations for each continent and quartile.


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As can be observed, regardless of quartile, the highest (and second highest) deforestation rates were estimated in the Americas and Africa. In the first quartile, for instance, the mean of the highest deforestation rate in the Americas is -1.58, while in Africa this figure is -1.27. The same figures in Asia, Europe, and Oceania are -0.27, -0.33, and -0.05, respectively. This indicates an important difference in the highest deforestation rate among the studied continents.

In the lower quartile, for instance, the mean of the peak deforestation rate in the Americas reaches -1.58, while in Africa this figure stands at -1.27. In sharp contrast, the same parameters for Asia, Europe, and Oceania drop significantly to -0.27, -0.33, and -0.05, respectively. This structural gap highlights an immense disparity in the maximum speed and scale of forest depletion among the studied continents. For both the median ($q = 0.50$) and the upper performance segment ($q = 0.75$), a highly consistent geographic hierarchy is maintained, where the average of the maximum deforestation intensity remains greatest in the Americas, closely followed by Africa.

These findings indicate that macro-regional drivers cause deforestation to be significantly more aggressive within the American and African cohorts. However, this continental disparity is not uniform; it systematically diminishes across the conditional distribution of forest change rates. Specifically, the most substantial differences between continental baselines are observed in the first quartile ($q = 0.25$), which captures countries experiencing exceptionally high, unconstrained deforestation rates. Conversely, the least pronounced continental differences are evident in the third quartile ($q = 0.75$), encompassing countries with relatively stabilized, low-deforestation regimes. Notably, matching the behavior observed in the duration analysis, Oceania presents an opposing trend, with deforestation severity increasing across the estimated quantiles.

### *3.3.2. Post-transition*

This section examines the socioeconomic turning points by analyzing the specific Human Development Index (HDI) levels at which land-use dynamics cross the zero-deforestation threshold, transitioning from net forest loss to active reforestation. The bootstrap estimation for this post-transition threshold —corresponding to the function's second real root—proved to be exceptionally robust across regions experiencing active forest pressures. The interaction models solved for a valid real root within empirical limits ($0 \leq HDI \leq 1$) in the vast majority of simulations for Africa and the Americas, showing high mathematical stability. Anomalies were virtually nonexistent, with negligible instances exceeding the physical upper bound ($HDI > 1.0$), while the remaining exclusions were driven strictly by localized non-convergent imaginary roots. This high mathematical convergence indicates that the developmental stage required to trigger a shift toward forest recovery is a highly predictable, stable, and structurally realistic parameter within the Global South, yielding tightly bound continental thresholds that can be reliably evaluated against contemporary development trajectories. The comprehensive breakdown of these post-transition exclusion frequencies is documented in the Supplementary Material.

Figure 5 displays the empirical distribution of the post-transition phase for each continent across the evaluated quantiles. In addition, the graph highlights the interquartile range of the HDI for the most recent historical year in the dataset as a shaded area. This shaded baseline serves to approximate the current development level in each continent, allowing for direct inferences regarding active land-use dynamics (i.e., active deforestation versus expanding reforestation).

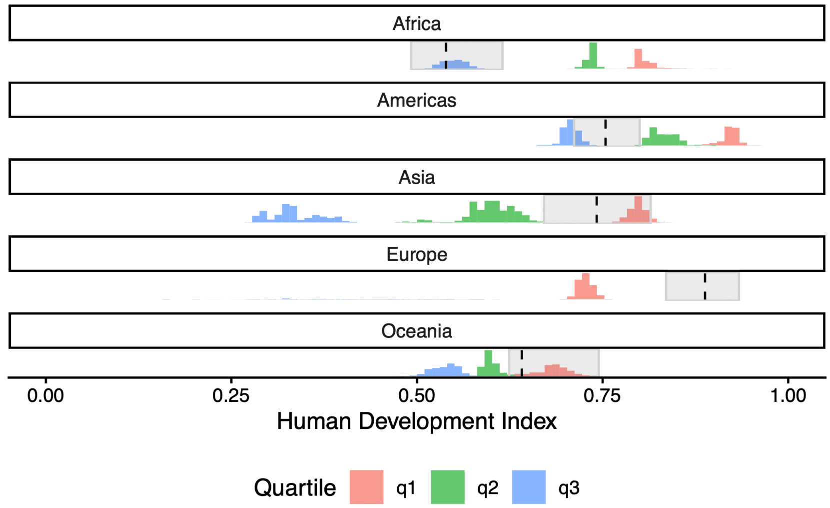


**Figure 5.** Post-transition distribution per continent and quartile and interquartile range of HDI. Results based on valid empirical bootstrap iterations (n = 2,951 for Africa, n = 2,705 for the Americas, n = 2,127 for Asia, n = 1,165 for Europe, and n = 2,995 for Oceania). Extreme outliers exceeding HDI = 1.0 were excluded to preserve scale consistency.

As illustrated in the visual evidence, a significantly higher HDI threshold is required to initiate reforestation efforts in the Americas and Africa compared to other macro-regions. For example, within the median distribution, the Americas necessitate an average HDI of 0.83, whereas Africa demands an HDI of 0.74. In sharp contrast, the required HDI threshold to achieve this structural turnaround is substantially lower in Asia (0.6), Europe (0.5), and Oceania (0.6). This pattern of heightened institutional and socioeconomic requirements for reforestation in the Americas and Africa persists systematically across all conditional quantiles of the distribution.

Furthermore, intersecting these thresholds with current development levels suggests sharply contrasting forest cover dynamics across the globe. Asia, Europe, and Oceania exhibit macroeconomic characteristics indicative of expanding forest cover, whereas Africa and the Americas demonstrate the opposite trend. Notably, irrespective of the specific quantile analyzed, European countries consistently display contemporary development levels that comfortably exceed the estimated post-transition distribution. This empirical observation strongly suggests that European nations are not only characterized by net forest expansion but are also nearing the completion of their historical forest transition cycle. A highly similar structural pattern emerges for Asia and Oceania, with the sole exception of the lower performance quantile (q=0.25), where the median development level marginally falls below the required post-transition threshold.

In contrast, Africa and the Americas exhibit distinct and more challenging developmental patterns. In the lower (q=0.25) and median (q=0.50) quantiles of forest cover change, contemporary development levels in both continents align


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tightly with active deforestation dynamics, mathematically indicating that current HDI values still fall below the macro-regional threshold required to initiate net forest recovery. However, a pivotal shift is observed in the upper performance quantile (q=0.75). In the Americas, contemporary development levels successfully surpass the post-transition distribution, while in Africa, the current baseline directly overlaps with it. This implies that countries within these continents that are characterized by lower relative levels of deforestation are either nearing the conclusion of the depletion process or are already entering the post-transition phase.

## 4. Discussion

The results of this analysis highlight a stark contrast between the land-use trajectories of the Global South and the rest of the world. Specifically, the empirical evidence confirms that forest loss in Africa and the Americas is significantly more entrenched and intense than in Europe, Asia, and Oceania. Rather than acting as a universal baseline, this structural divergence enriches the extensive body of literature analyzing the limitations of orthodox developmental frameworks, such as the Environmental Kuznets Curve (EKC) [24] or generalized Forest Transition assumptions[5]. While contemporary scholarship widely accepts that economic growth does not automatically guarantee environmental recovery[25][26][27][28], the empirical evidence generated here refines this understanding by providing a nonlinear, multidimensional perspective on where and why these models deviate.

The unique convergence behavior of the bootstrap resampling process provides a robust mathematical validation of these regional dynamics. Both the peak rate of net forest loss (*deforestation severity*) and the subsequent recovery threshold (*post-transition horizon*) proved to be exceptionally stable, predictable, and structurally realistic parameters for Africa and the Americas, exhibiting high mathematical convergence across the simulation pool. By moving beyond conditional averages through quantile regression, this study demonstrates that the developmental stage required to trigger a shift toward forest recovery is well-defined, yet relying on passive economic growth remains an insufficient strategy for the Global South. Expecting economic maturity to spontaneously resolve environmental degradation creates a critical delay; in continents where the baseline crisis is highly entrenched and the required turning points demand significantly higher development levels than those currently observed, waiting for countries to naturally cross these thresholds risks causing irreversible ecological collapse long before the predicted recovery phase can ever materialize.

This identified geographic gap aligns with the foundational work of Culas[10], which suggested that while certain Asian economies had crossed the developmental rubicon into reforestation, Latin American and African regions remained trapped in high-deforestation phases. Intersecting the estimated thresholds with contemporary development baselines further reinforces this divide. As demonstrated by the empirical density overlaps, European countries consistently display modern development levels that comfortably exceed the estimated post-transition distribution, suggesting they are nearing the completion of their historical transition cycle. Conversely, the contemporary development baselines for Africa and the Americas remain deeply submerged within active deforestation territories across the lower and median quantiles.


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While FAO[29] data support the findings of this study regarding high loss rates in these areas, the continental-scale model did not detect the specific cropland-driven shifts reported in Asia. This variation suggests that while macro-level trends explain broad regional trajectories, the continental scale of the analysis may mask localized or sub-national drivers, pointing to a vital need for future, more granular country-level research. Furthermore, the massive exclusion of contemporary European iterations due to non-negative or chaotic minima further reinforces this regional divide, mathematically confirming that enforcing a standard cubic transition model is inadequate for regions that have long bypassed active depletion phases.

While development is a powerful predictor of long-term landscape shifts[9][12][27], the sheer variance in the duration (*deforestation length*) and depth (*deforestation severity*) of deforestation observed here implies that human development is a highly relevant but not the sole variable at play. Forest scarcity is one potential catalyst that may force an institutional shift toward recovery earlier than development metrics alone would predict[30]. Furthermore, the efficacy of conservation hinges heavily on the strength of institutional frameworks. Governance and land tenure security may be critical factors in accelerating the arrival of a turning point or mitigating the maximum rate of forest depletion[31]. Future research must look beyond aggregate socioeconomic indicators to quantify how specific institutional contexts can shorten the transition cycle.

Another important aspect to consider in global development policy is agricultural displacement. As affluent nations reach post-transition stages, they might appear to be “greening” simply because they have outsourced their deforestation footprint to less developed regions via international commodity trade[32][33]. This cross-border dynamic suggests that a successful domestic forest transition in the Global North may inadvertently complicate the global goal of forest sustainability. Consequently, transnational environmental policy must evolve to address these transboundary economic drivers rather than focusing solely on isolated national forest cover.

Finally, it is essential to distinguish between the quantity of forest cover and its ecological value. While the model presented here tracks the expansion of forest area, it does not differentiate between primary old-growth forests and young secondary plantations. Mature ecosystems offer vastly superior carbon storage and biodiversity habitats[34][4]. Relying purely on development-driven recovery metrics risks overlooking a “hollow transition” where forest area increases while biodiversity continues to plummet. Therefore, future models should integrate ecological quality indicators to provide a holistic view of forest health[35]. To effectively mitigate global deforestation, interventions in Africa and the Americas must be targeted, multilateral, and multidimensional, bridging the gap between local development needs and transboundary ecological requirements.

## 5. Conclusion

This study has re-examined the Forest Transition Hypothesis by moving past conditional averages to explore the deep structural heterogeneity that characterizes global land-use dynamics. By applying a robust quantile regression framework with bootstrapping to a 31-year panel dataset of 189 nations, this research provides empirical confirmation that the relationship between human


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development and forest cover change is fundamentally non-linear, highly heterogeneous, and region-dependent.

The empirical findings yield two critical conclusions. First, while macro-level trends suggest a global alignment with forest transition trajectories, a stark continental divergence exists: both the peak rate of net forest loss (*deforestation severity*) and the subsequent recovery threshold (*post-transition horizon*) are exceptionally stable and entrenched realities for Africa and the Americas. Second, when intersecting these stable mathematical thresholds with contemporary human development baselines, the current HDI trajectories in these macro-regions remain deeply submerged within active deforestation territories, fundamentally decoupled from the socioeconomic levels required to trigger spontaneous, development-driven reforestation within contemporary limits.

These insights have profound implications for global development policy and environmental governance. They reinforce the consensus that environmental recovery is not an automatic byproduct of economic growth. Relying on passive development strategies as a primary mechanism for forest conservation is an insufficient approach that risks inducing critical, irreversible ecological loss in the Global South long before these estimated developmental thresholds can ever be reached.

Consequently, effective forest preservation requires a paradigm shift from reactive domestic conservation to proactive, integrated, and transnational management frameworks. Given the continental scale of the pressures identified, regional bodies and multilateral development institutions in Africa and the Americas must design synchronized environmental policies that look beyond conventional national borders. Isolated domestic efforts are easily undermined by international commodity trade and cross-border agricultural displacement; therefore, only regional cooperation and targeted international interventions can match the geographic reality of modern deforestation drivers.

Finally, while this study establishes a comprehensive macro-level framework through the lens of conditional quantiles, future academic inquiries should look beyond aggregate socio-economic indicators. Investigating the specific institutional mechanisms, governance structures, and land tenure frameworks that can actively shorten the deforestation phase remains a vital avenue for research. Ultimately, protecting global forests demands a dual commitment: recognizing the heterodox realities of the Global South and implementing immediate, coordinated policy interventions before developmental thresholds arrive too late.

## Statements and Declarations

### *Funding*

No specific funding was received for this work.

### *Potential Competing Interests*

No potential competing interests to declare.

### *Data Availability*

The datasets analyzed during the current study are publicly available from the UNDP Global Data Lab and FAOSTAT. The processed data and analysis code are available from the corresponding author upon reasonable request.

*Author Contributions*

M.L. was the sole author and is responsible for all aspects of the manuscript.

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