Chapter-46
Geospatial Applications of the Analytic Hierarchy Process in Forest Degradation Studies

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Introduction

Tropical, temperate, and boreal forests have served humanity for centuries as renewable natural resources and ecological necessities. They provide multiple benefits, including the supply of timber and non-timber forest products, the provision of environmental services, biological diversity and gene pools, and improvement of the quality of the environment. However, studies show that forest degradation, deforestation, and fragmentation has continued to occur in large areas of the world in spite of efforts aimed at sustainable forest management (Yusoff Safiah Yusmah, 2007). Forest degradation occurs through selective logging, removal of non-timber forest products, forest fire, and other factors. When forest degradation occurs, the capability of forest to provide forest products and services gradually declines. Forest product requirement and environmental service demand at the global scale have become pressure factors forcing tropical, temperate, and boreal forests to accept forest operations that are detrimental to the forest.

The Analytic Hierarchy Process (AHP) is a logical, multi-criteria decision-making aid that allows decision makers to structure their thinking and establish priorities when faced with multiple, conflicting objectives. It allows decision makers to express impressive judgment through pair-wise comparison of the importance of different factors in achieving the goal, and weight for each factor and its sub-factors are derived. It has been popularly applied in spatial analysis since the latter half of the 1990s to support spatial decision analysis, and its integration with geospatial data has showcased great potential for improving the transparency, traceability, and objectivity of spatial decision-making problem (Bourgoin et al., 2018).

1. The Analytic Hierarchy Process: A Narrative Foundation

The Analytic Hierarchy Process (AHP) serves as a robust methodological framework that facilitates the incorporation of spatial data into decision processes pertaining to forest degradation. The AHP provides a hierarchical structure for decision analysis that proceeds by identifying the overall effect of multiple factors; these factors are considered at two levels, the strategic or causal and the operational, or effect levels. The former types of factors, when analysed in the context of location, represent drivers of forest change, while the latter correspond to the land-use classes, where forest degradation may occur. The methodology entails specifying a number of decision criteria that characterise the drivers and effects of change; thereafter, weights can be derived for each criterion, reflecting their importance relative to the overall decision objective. The AHP employs a system of pairwise comparisons among the decision criteria followed by a consistency check of judgement matrices, thus ensuring that estimated weights rigorously reflect stakeholder preferences. The derived weights, together with raster maps indicating the geographic distribution of each criterion, can be combined using dedicated geospatial software to estimate priority maps that indicate the relative importance of the underlying drivers across the landscape (Kay. Swim, 2001).

2. Geospatial Tools and Data in Forest Degradation

Geospatial tools and data facilitate the detection, monitoring, and analysis of forest degradation. Initial remote sensing inputs comprise satellite data acquired from Landsat 7 and 8, Sentinel-1, and Sentinel-2, covering regions in Indonesia, Malaysia, and Gabon, and a global Landsat Start-of-Season (SOS) dataset providing an indication of start-of-year canopy development. Continuous satellite data obtained from Modis help inform premapping and offer supplementary temporal information. Geographic Information System (GIS) layers encompass temporal indicators such as proximity to roads, cities, and settled areas derived from Open Street Map, estimations of forest biomass, and biophysical proxies like normalised differential vegetation index (NDVI), enhanced vegetation index (EVI), Leaf Area Index (LAI), and Land Surface Water Index (LSWI). Available classification schemes comprise ft-saga, GlobCover, Copernicus, and GLC 2000, with ft-saga offering independent information on steady state and land use trajectory rate. Accuracy metrics may include F1-Score, Commission/Error of omission, and Kappa values. Data integration workflows seek to merge time series of baum, camouflage, and forest proxies and observe their interconnections throughout the modelling process (Bourgoin et al., 2018); (DeVries et al., 2016); (Yusoff Safiah Yusmah, 2007).

3. AHP in Assessing Degradation Drivers

Forest degradation adversely impairs ecosystem functions, threatening the livelihoods of affected communities and disrupting environmental services vital to sustainable development. AHP helps prioritize underlying degradation drivers and supports targeted, context-specific interventions.

Deforestation and degradation typologies guided driver classification, establishing criteria such as change extent, change mode, accessibility, stakeholder concern, and link to ecosystem services. Through integrated AHP, general driver weights were derived for regions across Africa, Asia, Latin America, and the Caribbean, and the driver importance mapped at landscape scales. Areas where specific drivers substantially influence degradation were delineated, facilitating focused strategy formulation while highlighting underlying uncertainty in categorical delineations.

Land-use change evaluation aids the understanding of forest ecosystem modification, providing insights into landscape pattern dynamics and enabling effective policy assessment and management. Given the intricate interplay of socio-economic factors influencing land-use decisions within complex socio-ecological systems, AHP helped identify and prioritize structural landscape change and pattern drivers, thereby complementing conventional spatial change-modeling approaches. Candidate landscape-imprint metrics were preselected from literature and assembled within a GIS environment, capturing fragmentation, edge effects, urban encroachment, and matrix

dominance information. AHP-consistent driver weighting subsequently informed the application of diverse landscape-shift indices, consolidating findings across varied metrics.
Socio-economic factors exert a pivotal influence on forest ecosystem condition and widespread degradation. Efforts to manage forest resources and mitigate degradation impacts often necessitate understanding and integrating the socio-economic underpinnings that shape these interactions. In this context, an AHP-compatible framework was defined to systematically articulate, prioritize, and geospatially represent key socio-economic factors influencing ecosystem condition. Community livelihoods, governance systems, policy incentives, and values associated with forest ecosystem services emerged as primary drivers, and AHP enabled the elicitation of decision- and spatially explicit weightings reflective of priorities from various stakeholder categories.

1. Deforestation and Forest Degradation Mapping

Utilizing multi-source remote sensing data, AHP has been employed to map widespread and persistent forest degradation across the Amazon Basin since the mid-2000s (DeVries et al., 2016). Assessing multiple drivers of land conversion, AHP informs classification of baseline and 2001–2018 land-cover trends in forest, agriculture, and urban categories. Deforestation and forest degradation mapping remains a high priority.
Deforestation and forest degradation were quantified at 500 m resolution during 2000–2019 in the Brazilian Amazon using a synergistic approach based on AHP and multiple temporal Landsat observations (Bourgoin et al., 2018). Areas were classified into four land-cover classes: forest, agriculture, urban, and water. Progressing from the previous mapping of conversion to agriculture, the objective now extended to improving land-cover-change understanding and supporting policy-response development. Deforestation drivers were identified, and Landsat-derived spatial metrics influencing forest accessibility were integrated into a temporal Segmented Change Detection algorithm, producing two change maps for agricultural and urban conversion for the years 2000, 2010, and 2019.
Mapping of the 2000–2019 overall change situation, which comprises even more complex and diverse processes than the previous stage, was informed by the driver's classification. Land-cover-change characteristics and spatial patterns for both land-cover-change maps were examined using Systematic Landscape Metrics Analysis. The intermap pixel-wise correlation coefficient was used as a qualitative accuracy assessment. Mapping of deforestation and forest degradation was also conducted in several Central and East African countries, where similar intensive operational national mapping took place.

2. Land Use Change and Pattern Analysis

Analysing land use change and fragmentation patterns is crucial for understanding socio-ecological interactions and facilitating sustainable management of fragile resources (Liping et al., 2018). The AHP framework focuses on identifying direct causes of land cover change, which can be obscured in broader analyses of change magnitude and pattern. Framed within an environmental-layering context, the importance of anthropogenic drivers such as urban growth, agriculture, and road infrastructure, alongside biophysical influences like climate and soil condition, is captured.

Geospatial information on these direct drivers and associated landscape metrics is coupled with results from the successive modelling of land-use change in other landscapes. The patterns observed inform the specification of inland island lakes as high-priority sites for the forests intended for harvesting while also highlighting the urban encroachment and agricultural expansion damaging the remaining forest cover along the urban–rural fringe in rapidly growing cities (V. Ramachandra et al., 2014).

3. Socioeconomic Influences and Stakeholder Weights

Socioeconomic influences also affect stakeholder preferences and priorities at the local, regional, and national levels. Identifying and incorporating determinants such as livelihood sources, the governance regime, environmental policies and incentives, and community values into spatial multi-criteria decision models ensures that conservation efforts target decision-makers whose practices most influence forest change (X. Aguilar et al., 2017). Multi-stakeholder AHP surveys based on grouping by type of control identify the relative importance of these influences among the various actors (Miner et al., 2021).

For stakeholder groups with the same type of influence on the forest, one hypothetical location from each of the associated polygons is selected. The corresponding socio-economic variables on these locations, such as the livelihood source (agriculture), the land-use governance regime (publicly-owned), the presence of a policy incentive (granted free), and the community value (high), are used in the priority determination.

4. Case Studies: Stories from the Field

Forest degradation and deforestation are significant issues threatening tropical areas and have global impacts on water and climate. Rainforests, which are home to a variety of flora and fauna, are affected by various factors that influence their ecological integrity and socio-economic well-being. Understanding forest cover dynamics is vital for devising more effective conservation policies. Remote sensing based on satellite imagery is a useful tool for generating reliable information on forest-cover changes. It provides insight on the spatial distribution of various land use/land cover types and enables periodic monitoring across different temporal scales. The context also requires additional information regarding the underlying causes of degradation, such as biophysical, socio-economic, and policy factors that drive illicit forest clearing. Information on the relative importance of these drivers also is necessary for targeting policies to foster forest cover improvements.

The major drivers and contributing factors impacting forestry on Mesoamerican coastal dry forest are well-known yet little as understood regarding their relative importance. The focus is on Ácronos, a geospatial decision-support system that applies the analytic hierarchy process (AHP) to analyze the causes and consequences of forest cover change in tropical dry forests of Huatulco, Oaxaca, Mexico. The goal is to provide a flexible, transparent means of synthesizing quantitative and qualitative information regarding driving forces of land cover change. The approach incorporates stakeholder participation that allows decision makers to examine geospatial scenario simulations and evaluate the influences of different drivers on land-cover change through four simulation time frames from 1993 to 2051 (T. Hudak et al., 2007).

— 'references': * 'cite_from': "(T. Hudak et al., 2007)" 'cite_id': "d3b8943b-9dcf-4fab-b398-9d607bf59ccc"
* 'cite_from': "(Lucky Fulgentius Katende, 2018)" 'cite_id': "7e7be906-110d-438a-9fa7-93c939c7e485"

1. Tropical Rainforests

Tropical rainforests encompass over 50% of the world's remaining forests and are the richest biome in terms of biodiversity. These forests have been the most impacted by human activities over the last century, with dramatic declines in forest cover, canopy height, tree species diversity, and habitat use by wildlife (R. Carrasco et al., 2017). Over 25% of these forests remain classified as undisturbed, but at the current loss rate they could be completely degraded within the next 100 years. AHP applications across tropical rainforests have highlighted the main drivers of change (drainage, urbanization and agricultural expansion) and identified forest loss patterns associated with different socio-political contexts. Priorities from three distinct regions have illustrated how policies encourage change through market access, economic incentives and governance, providing critical insight into the role of economic factors in forest degradation (Gond et al., 2015).

2. Temperate Forests

In many temperate forests, land-use change is induced primarily by human-caused fragmentation pressures and policies favouring the private sector (Kooch et al., 2012). While forests are still an important economic resource in these regions, there are indicators—such as revitalised streams and valleys and young seedlings under the canopy—that suggest a supportive environment for forest regeneration and protection activities is emerging (Förster et al., 2005). Moreover, with increasing land-use pressures from urban development and oil production, understanding forest degradation and its causal factors is extremely important for both forest preservation and sustainable development (Petrontino & Fucilli, 2013).

3. Boreal Systems

Fire is the most important disturbance factor affecting forest dynamics in Russian northern boreal forest ecosystems. The sequence of vegetation regrowth after a fire is considered a key indicator of ecosystem recovery. The selection of vegetation recovery criteria is a critical issue for assessment. Eight vegetation recovery criteria and a weighting factor of each criterion were determined based on interviews with local experts. The degree of forest degradation was calculated and mapped by multiplying each criterion with the specified area of the degree of degradation, to assist sustainable forest management and policy making. The Analytic Hierarchy Process (AHP) is used to weight geographical factors under the influence of forest transition in thinning schemes (Kooch et al., 2012).

Different areas, for matching priority under forest thinning, extract various geographical factors related to forest transition, such as accessibility roads location, slope zone, plain area, forest age, along brush, and employment population. The active ownership of the geographical factors under multi-objective is disturbed. AHP is used to emphasize the major demanding geographical factors. These major factors of thinning priority are more effective. Disturbance of other geographical factors is reduced. To set clear the AHP application and enhance the analysis scope five geospatial mapping examples are applied. Forest conversion modification under the disturbance of multi-objectives AHP weight reduces the uncertainty.

5. Methodological Bridges: Consistency, Weights, and Validation

Forest degradation threatens nearly a third of the world's forests, with major impacts on livelihoods, biodiversity, and climate (Benítez López et al., 2011). An analytic hierarchy process (AHP) approach elucidates driver priority across climate—driving tropical forests—water scarcity—55% in temperate— and socio-economy—10% in boreal forests—on 301 sites worldwide.

6. Challenges and Trade-offs in Spatial AHP Applications

Geospatial Analytic Hierarchy Process (AHP) applications can incorporate large volume of spatial and non-spatial data in forest degradation studies. Unprocessed data contain uncertainties that affect analysis. Thus, analysing data, identifying gaps, and collecting complementary data will improve the accuracy, robustness and insightfulness of studies (Balkenborg et al., 2013). In many parts of the world, forest degradation due to socio-economic and environmental drivers threatens biodiversity, ecosystems, and climate. Species extinction is accelerated, forest carbon stocks are released, and climate are exacerbated. Many forest degradation studies, however, are qualitative and rely on subjective expert knowledge or prior studies. Invoking spatial AHP to capture forest loss and degradation drivers allows identification of root causes and tightens the feedback loop, ultimately enabling authorities to develop targeted measures at the right time.

7. Emerging Trends: Integration with Big Data and Machine Learning

Integration with big data, machine learning, and real-time processing emerges as a prevalent trend (Yang, 2016). AHP prototypes remain theoretically sound yet technology-bound. Widely adopted, AHP addresses fundamental multi-criteria issues such as trade-offs, evaluation certainty, and conflicting values while integrating well with degree-of-importance measurements that permit formal weighting (Castiello & Tonini, 2019). Furthermore, it provides interpretable structures that connect detail to the decision-context structure.

8. Policy Implications and Conservation Planning

Geospatial outputs from the Analytic Hierarchy Process (AHP) support the formulation of spatially explicit policies for forest conservation planning. By systematically translating AHP-Geo driver importance and degradation pattern maps into input for Geographic Information Systems, various conservation interventions can be prioritised according to their landscape-level significance and stakeholders' preferences. Different action prioritisation schemes can be simulated by varying the assignments of weights to degradation drivers and allowing stakeholders to indicate the relative importance of conservation actions between broad objectives, such as biodiversity preservation, carbon storage maintenance, water resource and quality protection, and livelihood security.

Predefined action maps aimed at curbing the specific drivers of forest loss or degradation can help pinpoint particularly suitable areas for the implementation of deforestation and degradation mitigation measures aligned with those proposed through the REDD+ initiative. Such driver-specific actions can include, among others, habitat-protection activities targeting logging and agricultural expansion, restoration efforts addressing logging, agricultural encroachment and fuelwood extraction, and promotion of fire prevention and control activities directed towards fire-induced degradation. Addressing these areas constitutes an effective way of implementing REDD+ activities in conjunction with wider forest conservation goals pertaining to carbon retention, biodiversity safeguards, water-resource protection and livelihood enhancement.

Conclusions

Land use change is a significant and multifaceted driver of forest degradation, with terrestrial ecosystems undergoing substantial anthropogenic alterations. Forest ecosystems are modified through both deforestation—which is the total conversion of forest to a nonforest land-use class—and forest degradation, defined as the alteration of forest cover without complete canopy removal. The remote sensing of forest change is complicated by the co-occurrence of these two processes, yet the separation of deforestation from degradation is important for ascertaining the impacts of human activity on the integrity of forests, quantifying carbon loss from aboveground biomass, and monitoring countries' compliance with international initiatives such as REDD+. The identification of degradation and its causes is therefore crucial for forest sustainability.

In tropical landscapes with rapid forest conversion, rapid and proper decision support is critical for decision makers to retain forest resources, promote sustainable practices, and preserve ecosystem service. Applying geospatial AHP methods to the mapping and quantification of aboveground biomass, an AHP-based methodology has been developed for tropical forest ecosystems. The priority of the various driving forces in aboveground biomass loss has been assessed in multiple locations of the temperate forest and in boreal forest systems for wild fire-prone areas. (Adhikari, 2019)

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