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Int J Appl Earth Obs Geoinformation 84 (2020) 101958

Contents lists available at ScienceDirect

Int J Appl Earth Obs Geoinformation

journal homepage: www.elsevier.com/locate/jag

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ARTICLE INFO

Keywords:
Deforestation
Forest degradation
Vietnam
Ecological vulnerability
Landscape approach

ABSTRACT

Forest conservation in human-dominated tropical landscapes ensures provision of major ecosystem services. However, conservation goals are threatened by growing demands for agricultural products. As the expansion of agricultural frontiers continues to exert increasing pressure on forest cover, it is crucial to provide indicators on forest vulnerability to improve our understanding of forest dynamics and prioritize management actions by local decision-makers. The purpose of this study is to develop a rigorous methodological framework to assess forest ecological vulnerability. We aim at evaluating the potential of remote sensing to characterize forest landscape dynamics in spatial and temporal dimensions. We present an innovative method that spatially integrates current landscape mosaic mapping with 45 years of landscape trajectories using Sentinel-2 and Landsat imagery. We derive indicators of exposure to cropland expansion, sensitivity linked with forest degradation and fragmentation, and forest capacity to respond based on forest landscape composition in Di Linh district in the Central Highlands of Vietnam. We map current forest-agricultural mosaics with high accuracy to assess landscape intensification (kappa index = 0.78). We also map the expansion of the agricultural frontier and highlighted heterogeneous agricultural encroachment on forested areas (kappa index = 0.72-0.93). Finally, we identify degradation and fragmentation trajectories that affect forest cover at different rates and intensity. Combined, these indicators pinpoint hotspots of forest vulnerability. This study provides tailored management responses and levers for action by local decision makers. The accessibility of multi-dimensional remote sensing data and the developed landscape approach open promising perspectives for continuously monitoring agricultural frontiers.

1. Introduction

The conservation of forest cover is a key to ensuring sustainable provision of multiple ecosystem services in ecological, climate, biogeochemical and biodiversity processes (Thompson et al., 2009). In human-modified landscapes, forest conservation must also be reconciled with agricultural productivity, food security actions and must support the livelihoods of human populations (Chazdon et al., 2009). Decentralized forest management and policies play a major role in balancing conservation and production, and in controlling the effective use and management of the forest, notably through the transfer of ownership and responsibilities to local forest decision makers (Persha et al., 2011; Phelps et al., 2010; Agrawal et al., 2008).

However, human-modified landscapes are often negatively impacted by the expansion and consolidation of agricultural frontiers, where forests are threatened by land use competition resulting in complex degradation and major habitat fragmentation (Foley, 2005; Lambin et al., 2001). These effects are spatially interconnected and evolve rapidly over time. While deforestation refers to rapid conversion from forest to non-forest areas, degradation implies changes in forest structure following selective logging and fire disturbances, which also characterize progressive encroachment by agricultural activities (Putz and Redford, 2010). Furthermore, deforestation and degradation lead to a feedback loop of fragmentation dynamics that facilitates access to

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https://doi.org/10.1016/j.jag.2019.101958
Received 5 July 2019; Received in revised form 22 August 2019; Accepted 28 August 2019
Available online 05 September 2019
1569-8432/

forest habitats and hence to further disturbances (Broadbent et al., 2008). Historical land/ forest-use-associated drivers (i.e. degradation, fragmentation and agricultural expansion) determine the heterogeneous status and configuration of current forest landscapes. Future forest landscapes will thus be shaped by both ongoing pressures and management responses (Malhi et al., 2014). A first step to tailor effective management by local decision makers is to identify the forest areas that are most vulnerable to agricultural expansion and to characterize the underlying pressures (Klein et al., 2005).

Vulnerability assessments provide guidance on how to target interventions and to support decision making processes (Adger, 2006). Originally formalized for climate change and the agricultural sector by the Intergovernmental Panel on Climate Change (IPCC), vulnerability frameworks make it possible to assess the key determinants of system responses to external stress and pressures (Marshall et al., 2010; Parker et al., 2019). Adapted from the IPCC definition, vulnerability is the degree to which a forest ecosystem is susceptible to, or unable to cope with, adverse effects of human-triggered impacts (McCarthy et al., 2001). Vulnerability is commonly defined as the combination of three main components where *exposure* relates to the magnitude of stress undergone by a system; *sensitivity* refers to the degree to which the stress may affect the system, and the *adaptive capacity* is the system's ability to respond to the stress (McCarthy et al., 2001). This definition is widely used in the literature to describe human-environment interactions and the resulting pressure and response options in the framework of socio-ecological systems (Thiault et al., 2018; Metzger et al., 2006; Morel et al., 2019). However, the applicability and relevance of this approach for assessing forest ecological vulnerability in human-modified landscapes remains hypothetical. Hence, the implementation of vulnerability using available spatial datasets and the constitution of relevant indicators to model exposure, sensitivity and adaptive capacity remains challenging (Berrouet et al., 2018; Manuel-Navarrete et al., 2007).

Until now, agricultural frontier landscapes have never been analyzed through the vulnerability lens using spatio-temporal landscape indicators. In this paper, we propose an innovative method to assess the ecological vulnerability of forest cover at landscape scale. This methodology makes use of free and open source remote sensing images and combines temporal and spatial dimensions to capture the complexity of land use mosaics in human-modified landscapes. To characterize these complex landscape mosaics, we used a landscape approach, defined as an integrated framework to analyze competing land uses and involving local stakeholders to solve social and environmental issues (Oszwald et al., 2011; Reed et al., 2016). This framework is already well referenced and some authors have already highlighted the robustness of the framework for the analysis of spatial patterns of land use dynamics at the landscape scale and to provide further information on human-environment processes (Wu, 2007; Messerli et al., 2009). Landscape structure metrics based on land use and cover information also enable the description of landscape patterns and variability. Some authors also demonstrated the relevance of indicators for the characterization of agricultural frontiers dominated by fragmentation dynamics (Oszwald et al., 2011; Wang et al., 2014; Hargis et al., 1998). Furthermore, the availability of time series of remote sensing images opens a wide range of perspectives to characterize agricultural frontiers through historical trajectories of landscape change (Lausch and Herzog, 2002; Ernoult et al., 2006).

Given the above background, the objective of this work was to produce spatial indicators at the landscape scale using multi-dimensional remote sensing to assess forest ecological vulnerability. The specific steps were to:(1) characterize current landscape mosaics using land use inventory and mapping; (2) reconstruct historical land cover from Landsat time series; (3) identify trajectories of landscape composition and structure dynamics; and (4) develop indicators of exposure, sensitivity and adaptive capacity that quantifies the expansion of agriculture, degradation and fragmentation dynamics and current landscape intensification.

2. Materials and methods

2.1. Study area

The study was carried out in the district of Di Linh (Lam Dong province) in the Central Highlands region of Vietnam. The area was chosen for two reasons: 1) The district is located in a consolidated deforestation front where remnant forests are exposed to degradation risks linked to the expansion of coffee based-agriculture (Dien et al., 2013; Vogelmann et al., 2017); and 2) It is part of a REDD+ (Reducing Emissions from Deforestation and forest Degradation) pilot project that aim at facilitating forest monitoring with decisions makers such as land use planners and local forest rangers (Thuy, 2013).

The town of Di Linh was founded in 1899 along the road connecting Ho Chi Minh City to Da Lat. The district went through a succession of colonization waves and economic transformations during the 20th century, which marked the continuous development of cash crops until the coffee boom in 1980s (Trædal and Vedeld, 2017; Meyfroidt et al., 2013; Déry, 2000; Ha and Shively, 2008). This large-scale coffee production has been identified as one of the main drivers of deforestation and degradation and as responsible for triggering other environmental problems such as increased drought and soil erosion (Meyfroidt et al., 2013; Grosjean et al., 2016).

2.2. Conceptual framework for assessing forest vulnerability

We developed a framework to assess the ecological vulnerability of forest cover to deforestation and degradation at the landscape scale. Fig. 1 presents the methodology, which is divided into four distinct steps (Fig. 1): **i.** Data preparation involving acquisition and preprocessing of remote sensing images and collection of ground truth data; **ii.** Classification and assessment of the accuracy of 2018 Land-Use Land Cover (LULC) using Sentinel-2 or Landsat-8 and historical LC (simplified typology) using the Landsat archive; **iii.** Analysis of current landscape mosaics and historical trajectories of landscape dynamics in standard unit grids, and **iv.** Extraction of metrics to assess adaptive capacity, sensitivity and exposure components and forest ecological vulnerability (at the unit grid scale). Each step is described in detail in the following subsections.

2.2.1. Data preparation and preprocessing

In order to map current mosaics of LULC with high precision, data collection involved acquiring Sentinel-2 (S2) images and field data (Drusch et al., 2012) for 2018. For the analysis of LC change and landscape dynamics throughout the colonization period, we used two Landsat-8 (2014, 2016) and nine Landsat-5 images acquired in 1973, 1989, 1992, 1995, 1998, 2002, 2006, 2009 and 2011. We also used one Landsat-8 image acquired in 2018 to assess the difference between Sentinel-2 based classification and to characterize landscape heterogeneity (section 2.2.3). All the images present less than 10% cloud cover and were taken during the dry season (December to March) (Appendix 1).

The Sen2Cor application developed by the European Space Agency (ESA) was used to transform S2 L1C tiles to surface reflectance L2A level (Main-Knorn et al., 2017). We acquired Landsat (L) surface reflectance data already pre-processed by the algorithm developed by the NASA Goddard Space Flight Center (GSFC). For each sensor, we derived vegetation indices that are related to vegetation photosynthetic activity, burned vegetation, soil brightness and vegetation moisture content (Appendix 2). The vegetation indices and the spectral bands were used as input features for the LULC classification.

Our field inventory allowed us to identify landscape elements. A set of 300 GPS points were recorded during a 2-week field survey conducted in Di Linh in March 2018 (Fig. 2). Each GPS point (Garmin

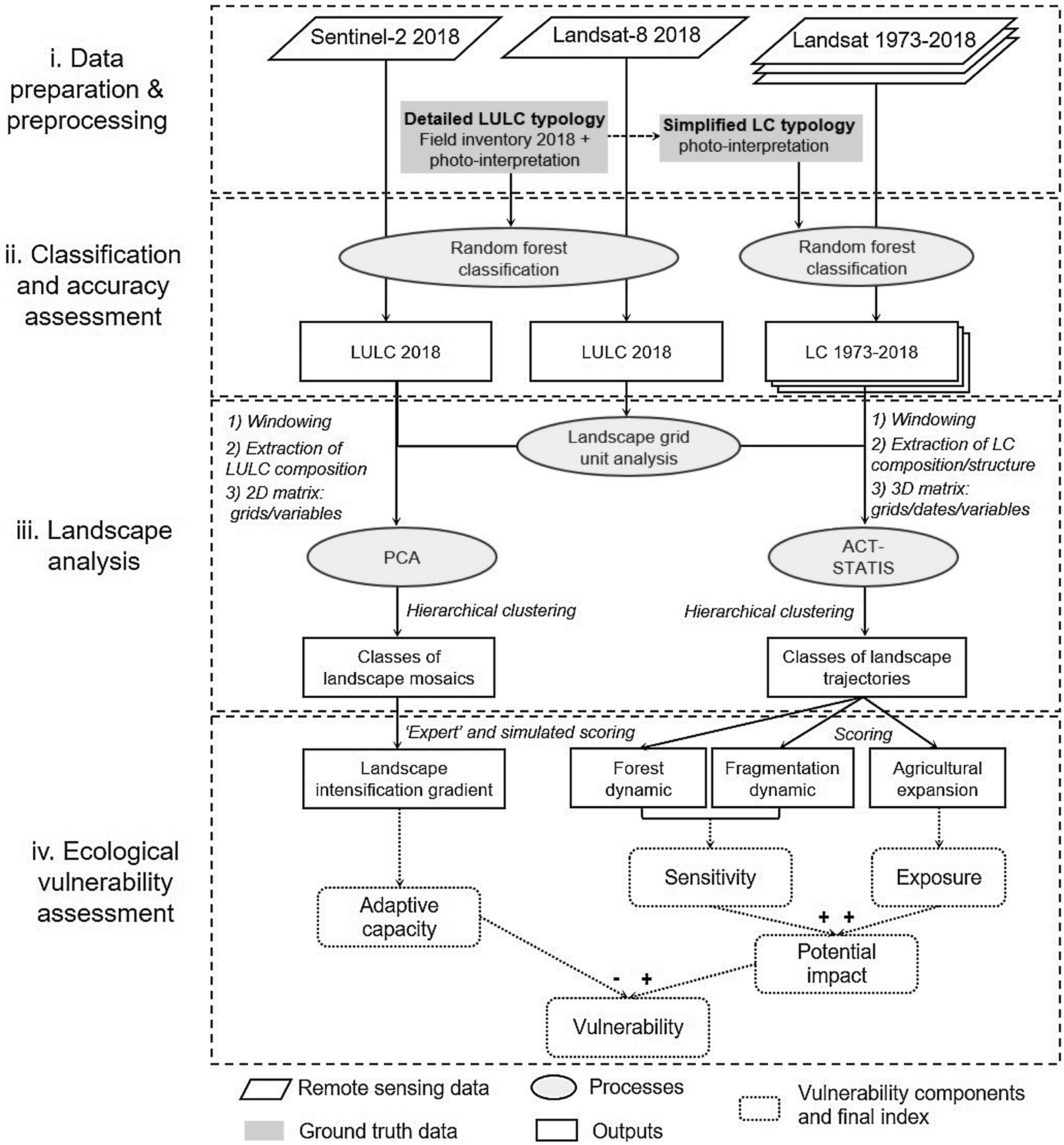

Fig. 1. Methodological framework designed to assess forest ecological vulnerability with its four steps (i–iv).

60CSx, Garmin, Olathe, KS, USA) was associated with a qualitative description of the landscape element identified along with illustrative photos. Sampling (involving transects from agricultural land to natural habitats) was designed to cover agricultural, forested and mosaic landscapes along the main deforestation front (Oszwald et al., 2007). A detailed typology was constructed for the 2018 LULC classification that sums up the major landscape elements identified in the field (Appendix 3). For each class, a score was assigned with reference to a landscape intensification gradient ranging from natural (score close to 0) to anthropogenic (score close to 10). Degraded forest composed of logged or burned evergreen forest, natural or regenerated bamboo forest and bushes were judged to be more natural than pine forests, which are mostly planted for timber (Jong et al., 2016; Hiep et al., 2004). We also identified a simplified 4-class typology, which corresponds to general LC classes, to facilitate the historical classification.

Based on the field data and the detailed LULC typology, we manually discriminated polygons sampled around the GPS points and completed by photo interpretation of Sentinel-2 2018 images. We repeated this process using the simplified typology for each historical Landsat image. We created additional classes for cloud centers, edges and their projected shadows. We also differentiated shadowed and unshadowed evergreen forest due to the difference in reflectance that varied with the slope. For each date of the analysis, the resulting sample data sets were used as inputs for training and validating the classification detailed below.

2.2.2. Classification and accuracy assessment

For each date of the analysis, the classification method uses remotely sensed features (spectral band and vegetation indices) and samples of LULC typology (polygons) as inputs for the Random Forest (RF) classifier (Breiman, 2001). The method is similar to the one developed by Mercier et al. (2019). We randomly generated 50 pairs of

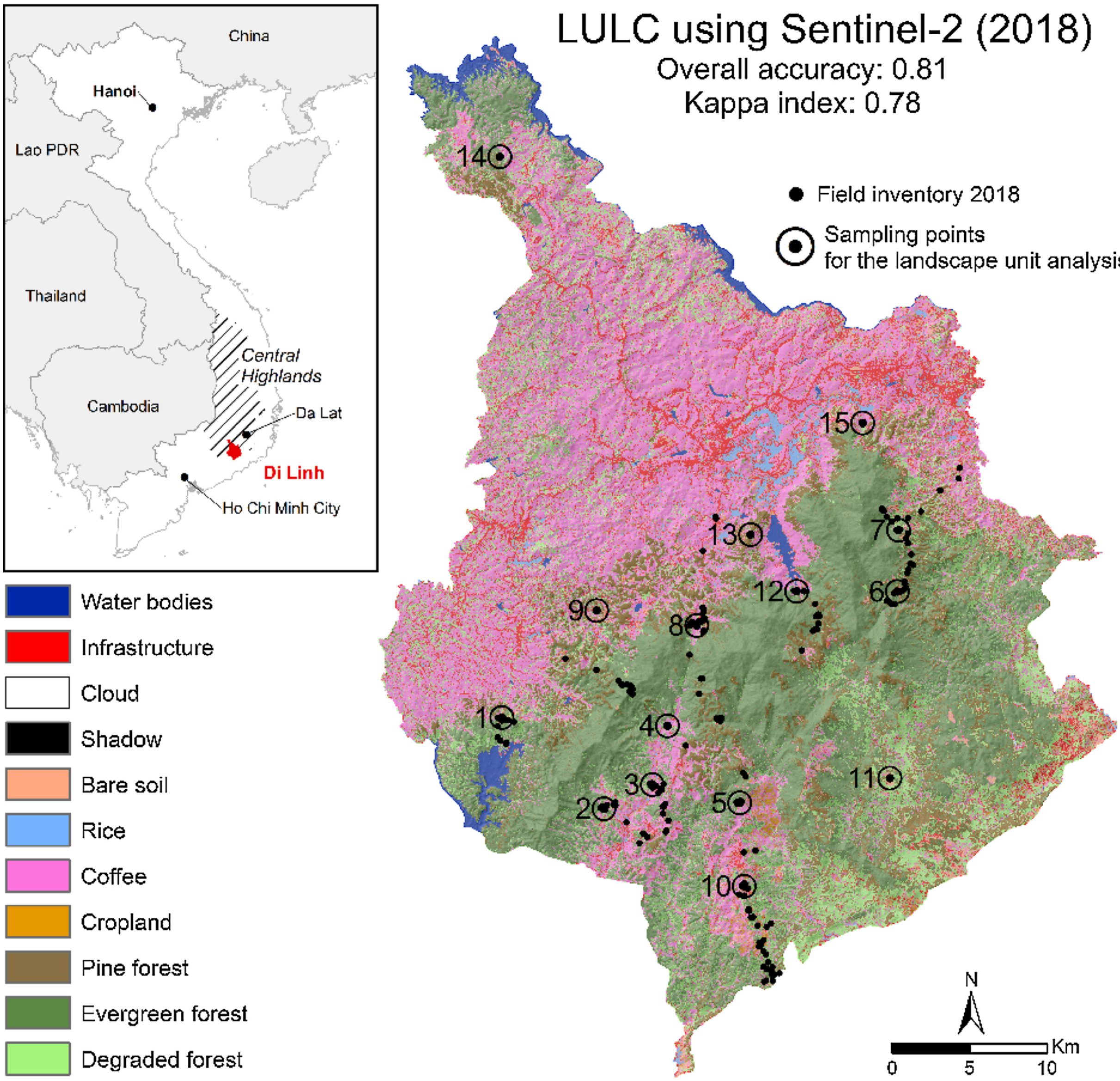

Fig. 2. Location and classification of Di Linh district (Lam Dong province) in the Central Highlands of Vietnam.

training and validation sample subsets from the sample dataset using a 70/30 ratio within which 300 pixels per class were randomly selected. An RF algorithm composed of 100 trees was applied to each selected subsample making it possible to rank the features using the mean decrease Gini (Calle and Urrea, 2011) as well as to identify the optimal number of features using the kappa index (Rosenfield, 1986). Then, we applied RF using the previously defined parameters and one training/validation sample file to generate the LULC classification. We extracted the overall accuracy, kappa index, user and producer accuracy of each class from the confusion matrix (Pontius and Millones, 2011). These two steps were achieved using the RF package in R software. Finally, we applied an 8×8 pixel majority filter to reduce single pixel misclassifications using ArcGIS (Esri, Redlands, CA, USA).

2.2.3. Landscape analysis was conducted using the steps detailed below

- Identifying a landscape unit grid

Based on the classification of Landsat image (simplified typology) in 2018, we calculated the Shannon diversity index (SHDI) in different regions located along the agricultural frontier visited during the field survey (Sampling points in Fig. 2). This metric measures both the richness i.e. number of land cover/use classes (compositional heterogeneity) and regularity i.e. distribution of the surface area of the LULC classes (configurational heterogeneity) in a given area. We calculated the SHDI in buffer zones spanning from 50 to 8000 m surrounding each region of interest. We estimated the plateauing of the average curve based on the resulting profiles of SHDI and recorded the corresponding distance. This distance reflects the optimal unit size to capture the diversity of landscape elements and heterogeneity and was used to define a regular grid of X units covering the study area.

- Classifying landscape mosaics following an intensification gradient

Using the Sentinel-2 detailed classification, we extracted the composition as a percentage of LULC in each unit of the grid. We discarded units containing more than 80% of water bodies from the analysis. The resulting Y number of grid units were systematically compared using principal component analysis (PCA) and grouped in Z number of clusters using hierarchical clustering (Ward's criterion) applied on the first factorial axis of the PCA (Husson et al., 2010). The number Z of clusters is determined by the Huntsberger index that is a function of the number

Table 1
Landscape structure metrics (McGarigal 2012).

Aspect	Metric name	Description
Size, proportion, aggregation	Edge density (ED)	Equals the sum of the lengths (m) of all edge segments in the landscape in relation to the total landscape area (m^2).
	Mean of patch area (MPA)	Mean of all patches in the landscape, describing the patch structure and the overall composition of the landscape.
	Standard deviation of patch area (SPD)	Standard deviation of all patches in the landscape, describing the differences among all patches in the landscape.
	Patch density (PD)	Describes fragmentation (patchiness) but does not necessarily contain information about the configuration or composition of the landscape.
	Aggregation Index (AI)	Equals the number of like adjacencies divided by the theoretical maximum possible number of like adjacencies for that class summed over each class for the entire landscape (He et al., 1999).
Richness	Shannon diversity (SD)	Diversity metric that accounts for both the number of classes and the abundance of each class (Shannon and Weaver, 1949).
	Patch richness density (PRD)	Measures the diversity of landscape composition.
Shape	Evergreen/Pine forest Mean perimeter area ratio (MPARF/MPARP)	Describes patch complexity but not standardized to a particular shape.
	Evergreen/Pine forest Mean Shape Index (MSIF/MSIP)	Describes the ratio between the actual perimeter of the patch and the hypothetical minimum perimeter of the patch if the patch were maximally compact (Patton, 1975).

of units: $Z = 1 + 3.332*\log_{10}(Y)$ (Huntsberger, 1961). The average composition of LULC describing each resulting cluster or landscape mosaic class is weighted by its respective ‘expert based’ land use score (Appendix 3). Each class of landscape mosaic is thus associated with a landscape intensification score.

- Classifying landscape trajectories

For each of the historical classifications, we extracted the land cover composition in the same regular grid. We also calculated 11 structure metrics to quantify size, proportion and aggregation, richness and shape of the landscape (Table 1), and in this way, characterized specific spatial structures of the agricultural frontier following the concepts of heterogeneity, connectivity and fragmentation (Burel and Baudry, 2000). These metrics were computed with the R ‘landscapemetrics’ package (Nowosad and Stepinski, 2018).

The resulting 3D matrix (grid units/12 dates/LC composition and structure metrics) was analyzed using PCA and ACT-STATIS (Lavit et al., 1994; Oszwald et al., 2011). First, we defined the ‘compromise’ or common stationary spatial structures at the different dates using PCA, which provides a global description on the dynamics of overall spatial variability within the study area (Robert and Escoufier, 1976). The second step allows the reproducibility of the compromise to be identified and the structure variability through each grid-variable table to be identified (Blanc et al., 1998). It informs on the variability of spatial dynamics i.e. the trajectory of each unit in the grid. Finally, we grouped these trajectories into Z number of classes using Hierarchical clustering (Ward’s criterion) based on the Huntsberger index, which is similar. Consequently, units of a certain class of landscape trajectory share similar spatial landscape composition and structural dynamics from 1973 to 2018. The statistical analyses were carried out using the ade4 package in R (Thioulouse et al., 1996; Chessel et al., 2004).

2.2.4. Assessment of forest ecological vulnerability at the landscape scale

Ecological vulnerability (V) is constituted by components that include exposure to external stresses (E), sensitivity to perturbation (S) and capacity to cope or adapt (AC). $V = S + E\text{-}AC$ (Fritzsche et al., 2014). Based on the adaptation of different conceptual frameworks, we defined indicators for each component to analyze the vulnerability of socio-ecological systems (Adger, 2006; Gallopín, 2006).

Sensitivity is defined by Gallopín (2006) as the degree to which the system is potentially modified or affected by a disturbance over time. We estimated sensitivity based on the combination of evergreen forest (EF) and fragmentation dynamics that provide information on the level of degradation that may affect a forest landscape over time (Shapiro et al., 2016; Vieilledent et al., 2018). These dynamics were calculated using the averaged values of the proportion of evergreen forest and edged density metrics composing each class of the landscape trajectory from 1998 to 2018 (Oszwald et al., 2011). This period makes it possible to capture recent trends that may impact the current landscape.

To capture EF dynamics, we extracted the rate of change (equation 1) and rescaled the values (equation 2) in order to compare EF trajectories with no change or increasing gradient (values close to 0) to decreasing gradient (values close to 10):

1) Rate of change: $EF_{2018} – EF_{1998}$, where EF_{2018} is the proportion of EF in 2018.
2) $X_{rescaled} = 10*(X - X_{min})/(X_{max} – X_{min})$ where X is the value of rate of change based on the change in EF for a given class of landscape trajectory, X_{min} and X_{max} are the minimum and maximum observed values of rate of change based on the changes in the EF in all landscape trajectory classes.

Finally, we multiplied the rescaled rate of change values by the average value of EF from 1998 to 2018 to yield a general score of EF dynamics that combines information on the rate and intensity of EF changes.

To calculate fragmentation dynamics based on the edge density metric, we followed the same procedure as that described above. The rate of change was rescaled to compare increasing gradient (values close to 10) to no change or decreasing gradient (values close to 0).

Sensitivity was obtained by combining (summing and rescaling) EF and fragmentation dynamic scores.

Exposure refers to the length of time the forest has been subjected to external stress or perturbation (Turner et al., 2003; Adger, 2006). In our case, the stress is caused by encroaching cropland linked to the agricultural expansion of coffee. We applied the same procedure as that described above to assess agricultural dynamics through the changes in the proportion of agricultural land for each class of landscape trajectory. The exposure score is thus influenced by the average proportion and rate of increase in the crop cover.

Adaptive or coping capacity refers to the ability of the system to respond to a perturbation (Smit and Wandel, 2006). This potential is linked with the current level of intensification of a forest landscape (Messerli et al., 2009). We assessed adaptive capacity as the additive inverse of landscape intensification scores defined in section 2.2.3. Here we assume that high landscape intensification scores (i.e. fragmented coffee and degraded forest dominated landscape) correspond to low adaptive capacity. As the landscape intensification score is based on ‘expert’ scoring, we simulated different land use scores (LUS) for degraded and pine forest classes such that:

“LUS EF = 0 < LUS degraded forest < LUS pine forest < LUS agricultural elements = 9."

The 28 possible combinations of LUS for both landscape elements generated 28 possible landscape intensification scores and thus adaptive capacity scores related to the forest landscape mosaics we identified. Finally we analyzed the influence of scoring on vulnerability assessment by calculating and mapping the agreement, overestimation and underestimation of simulation and 'expert' ecological vulnerability classifications.

3. Results

3.1. Mapping LULC in 2018

Using Sentinel-2 images, LULC classification in 2018 revealed high overall accuracy and kappa indexes (e.g. OA = 0.81 and kappa = 0.78). Similar results were found for Landsat-8 classifications (Appendix 4). Clouds, water, projected shadow, infrastructure, irrigated rice and pine forest were the classes with the highest user and producer accuracy in both classifications (> 0.8). Degraded forest class included omission errors (producer accuracy of 0.49) due to confusion between coffee and evergreen forest classes. Rainfed rice represents sparse vegetation cover in the dry season and can therefore be confused with the bare soil and infrastructure classes. Evergreen forest was correctly classified with little confusion between shadowed and unshadowed forest cover and degraded forest. Cropland was the least well classified class with 0.27 producer accuracy notably due to confusion with coffee and bare soil and the limited number of training samples (Appendix 5). Lowlands are dominated by irrigated rice, coffee and infrastructure. In the southern part of the district, LULC is driven by topography where rainfed rice is cultivated in the valley bottoms, coffee on the slopes, degraded forest at the edges and evergreen forest grows on higher terrain. Pine forest is often located at the interface between coffee and evergreen forest (Fig. 2).

3.2. Defining landscape mosaics from LULC classification

The inflexion point of the average curve summarizing 15 Shannon diversity profiles is reached at 0.85, which corresponds to a distance of 360 m (Appendix 6). This value defines the size of the landscape matrix grid applied to Di Linh district i.e. 12,259 units of 360 m. Similar inflexion points were found using Sentinel-2 based LULC classification (detailed and simplified typology).

The two first factorial axes of the PCA accounted for 40.2% of the total variability of the landscape elements composing each unit (Fig. 3a). The first PCA axis shows an anthropogenic gradient between forest (evergreen and pine) and agricultural land (cropland, bare soil, coffee and infrastructure) (Fig. 3b). The second axis of the PCA opposes degraded forest and the other landscape elements. Degraded forests are mostly found at the interface between natural and mainly agricultural landscapes.

Using the first seven axes of the PCA (83.4% of the total PCA variance) as inputs for hierarchical clustering and Huntsberger index, we obtained 15 classes of landscape mosaics (Fig. 3c). We defined forest mosaics as those with between 10 and 96% evergreen forest cover and varying proportions of the other landscape elements. L4 landscape mosaics were mainly composed of degraded forest (71% on average) which corresponds to natural shrubland areas and was therefore excluded from the forest mosaic. Agricultural mosaics were characterized by a landscape intensification score higher than 6 in which the proportion of forest cover was very low (< 0.07% on average). L9 landscape mosaics were dominated by water and consequently excluded from the analysis. Mapping the landscape intensification score highlights the spatial distribution of forest mosaic gradients from core evergreen forest landscapes (dark green) to complex landscape mosaics of fragmented elements made up of forest, coffee, degraded forest and pine (light green) (Fig. 3d).

3.3. Mapping historical land cover using the Landsat 1973–2018 archive

LC historical classification from 1973 to 2018 highlights the expansion of cropland, i.e. of infrastructure, coffee, rice and other crops at the expense of evergreen forest. Kappa and overall accuracy indexes ranged from 0.95 for 2018 classification to 0.72 in 1973 (Appendix 7). Over the last 45 years, the evergreen forest cover was reduced from 100 M ha to 60 M ha to the direct benefit of cropland. Pine forests remained stable over the period with a slight decrease starting in 2008 (Fig. 4). In 1973, 62% of the district was covered by evergreen forest and croplands were located along the main roads crossing the district from east to west. Some agricultural regions were found in the south west but remained limited to the valley bottoms, typically rice fields. In 1989, some large patches of forest were deforested, mainly around Di Linh city. This trend continued until 2002 with deforestation reaching a peak in 1992. Starting in 2006, the cropland expansion started decreasing and became consolidated in the northern part of the district but continued in two main poles in the south that were previously inactive. In 2014, the agricultural frontier appears to have stopped advancing. Pine forest was largely reduced in the northern parts of the district. Along the current agricultural frontier, pine forest was conserved and was even still being planted at the interface between cropland and evergreen forest starting in 2009. The pine forest that was originally located in the central region of the district (low elevation, low slope) was rapidly converted into cropland.

3.4. Deriving classes of landscape trajectories

ACT-STATIS and clustering methods generated 15 classes of landscape trajectories within which we analyzed the average composition (evergreen forest, pine forest and cropland) and structure (the Shannon diversity index and edge density) metrics over time. Class T1 groups forest-dominated units were characterized by a slow decrease in EF cover from 1998 on associated with a gradual increase in cropland and a steep increase in edge density (Fig. 5). Class T2 groups units in which evergreen and pine forest decreased starting in 1973, with a shift in 2006 when cropland started to become the dominating class. Since then, deforestation and fragmentation processes have decreased and stabilized. With a similar configuration to Class T1 in 1973, class T3 differed by a sharp decrease in EF cover (reduced by half) with an increase in edge density and cropland. This class underwent the biggest increase in edge density of all the classes. Classes T1, T2 and T3 are located along the current agricultural frontier. Classes T4 to T8 group units dominated by forest that have remained constant over the last 45 years with the exception of T4 in which EF is gradually increasing and T7, which is marked by a fluctuating EF cover and edge density. Classes T9 and T10 group units that were always dominated by croplands and remained unchanged throughout the study period. Typically, Di Linh city and its surrounding region belong to these groups. Classes T11 to T15 group units showing chronological stages of deforestation:T11 (light grey), which is located close to Di Linh city, shows a deforestation process that started before 1973, while T15 (dark grey), which is mainly located in the northern part of the district groups units that were completely deforestated in 2006.

3.5. Assessment of forest ecological vulnerability

Forest adaptive capacity is the lowest along the agricultural frontier, which corresponds to fragmented landscapes with mixtures of different land uses including evergreen forest, degraded forest and coffee plantations (Fig. 6). These regions are mainly located along the main deforestation front and in the south of the district where complex forest mosaics were mapped. Forest adaptive capacity had the highest score in core forest regions isolated from agricultural frontiers, infrastructure networks or other forms of human activities; or in mixed evergreen and pine forest landscapes. Concerning sensitivity, a number of regions

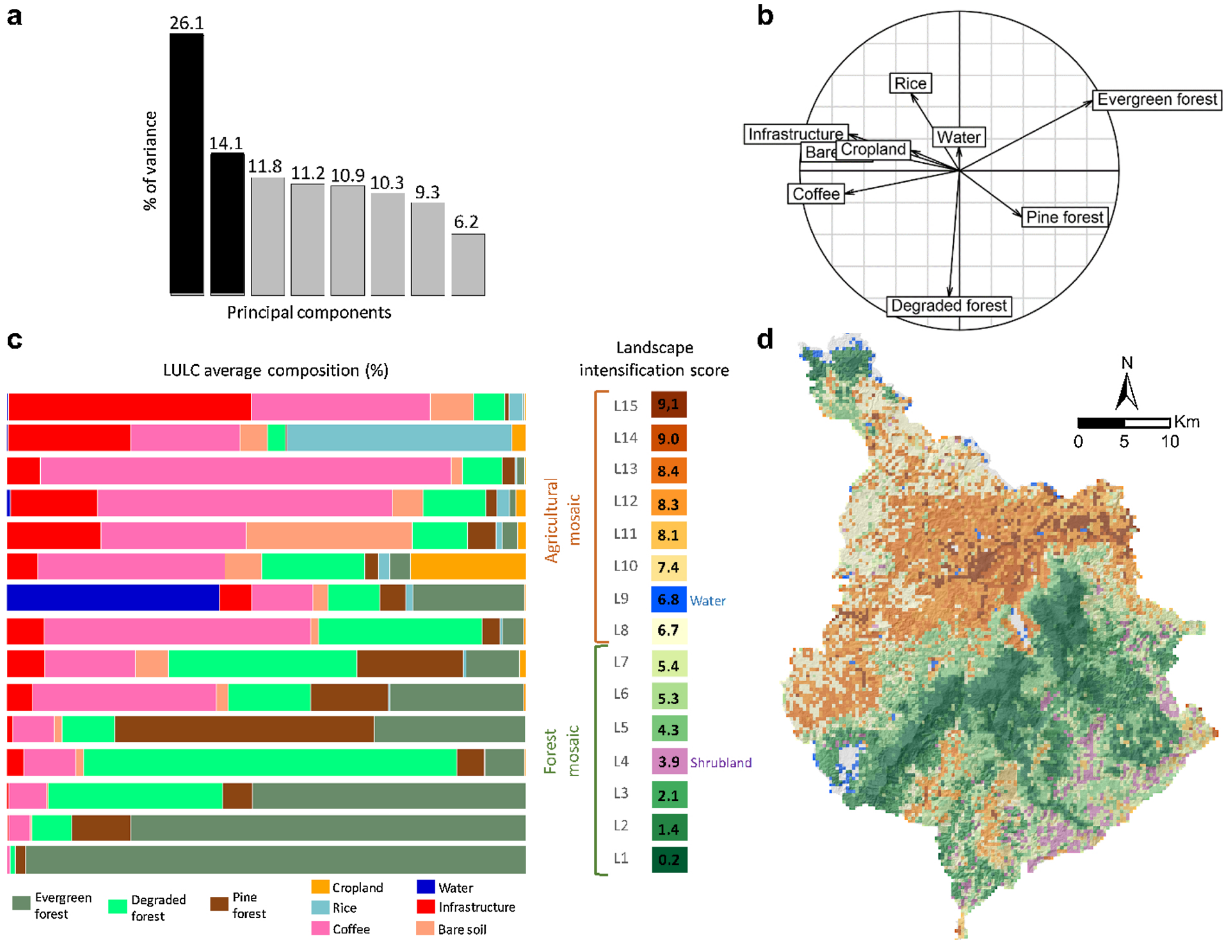

Fig. 3. Transformation of land use/cover patches into landscape mosaics using a regular 360 m x 360 m grid and Sentinel-2 based classification at 10 m resolution (2018). a) Histogram of eigenvalues expressed as % of total variance. b) Correlation circle of the first two PCA components. c) Classes of landscape mosaics (L1 to L15) according to hierarchical clustering based on the first seven PCA components: Average composition of land cover/land use and landscape intensification score attributed to each landscape mosaic class. d) Landscape mosaics distinguished according to the landscape intensification gradient (see the legend to Fig. 3c).

experienced a rapid decrease in forest cover over the last 20 years and an increase in fragmentation (high values). Exposure was highest in the eastern part of the agricultural frontier due to the recent rapid expansion of cropland (Appendix 8 and 9 for more details about the calculations).

All negative vulnerability scores (highest AC, lowest sensitivity and exposure) were reclassified as lowest vulnerability. All positive values were grouped in three classes (labelled low, medium and high) using Jenks Natural Break classification in ArcGIS. Overall vulnerability revealed heterogeneous distribution of values along agricultural frontiers. Frontiers A and B (Fig. 6) are among the most vulnerable due to different combinations of sensitivity, exposure and adaptive capacity. Region A is vulnerable mostly because of low adaptive capacity and high sensitivity. Region B includes scattered highly vulnerable areas and overall low adaptive capacity. However, we also identified high sensitivity hotspots in the western part and a high exposure hotspot in the eastern part of the region.

4. Discussion

4.1. Potential of vulnerability assessment for land use planning and targeted conservation actions

There is a growing consensus that integrating production and conservation is an efficient strategy to achieve conservation goals in human dominated landscapes (Griscom and Goodman, 2015). However, agricultural expansion in forested areas achieved through degradation, deforestation and indirectly through fragmentation can jeopardize conservation goals and land use planning (Tilman, 1999).

In this study, we proposed an innovative adaptation of the vulnerability framework defined by the Intergovernmental Panel on Climate Change (IPCC) to forest ecosystems on the only basis of remote sensing and statistical analysis. We provided indicators of forest vulnerability at landscape level to improve our understanding of forest and agricultural dynamics. Combined, these indicators allowed targeting regions that are most vulnerable to agricultural frontier expansion. We also provided tailored management responses and levers for action by decision makers depending on the importance of forest adaptive capacity, sensitivity and exposure. Consequently, our approach pinpointed where decision makers should prioritize management actions and conservation to prevent future forest degradation and deforestation. Global forest cover monitoring systems usually rely on moderate resolution remote sensing imageries. However, improved resolution and frequency of image acquisition are needed in key areas such as active deforestation fronts. Our work allowed targeting these areas and thus orientating where higher resolution is needed for improving the efficiency of near-real time monitoring systems (Reymondin et al., 2012). Finally, the forest ecological vulnerability approach can be coupled with forest ecosystem modelling such as soil erosion, water availability, biodiversity or forest carbon mapping to provide even more comprehensive and informed data, making it all the more constructive when applied in decision making (Le Clec'h et al., 2017; Grimaldi et al., 2014).

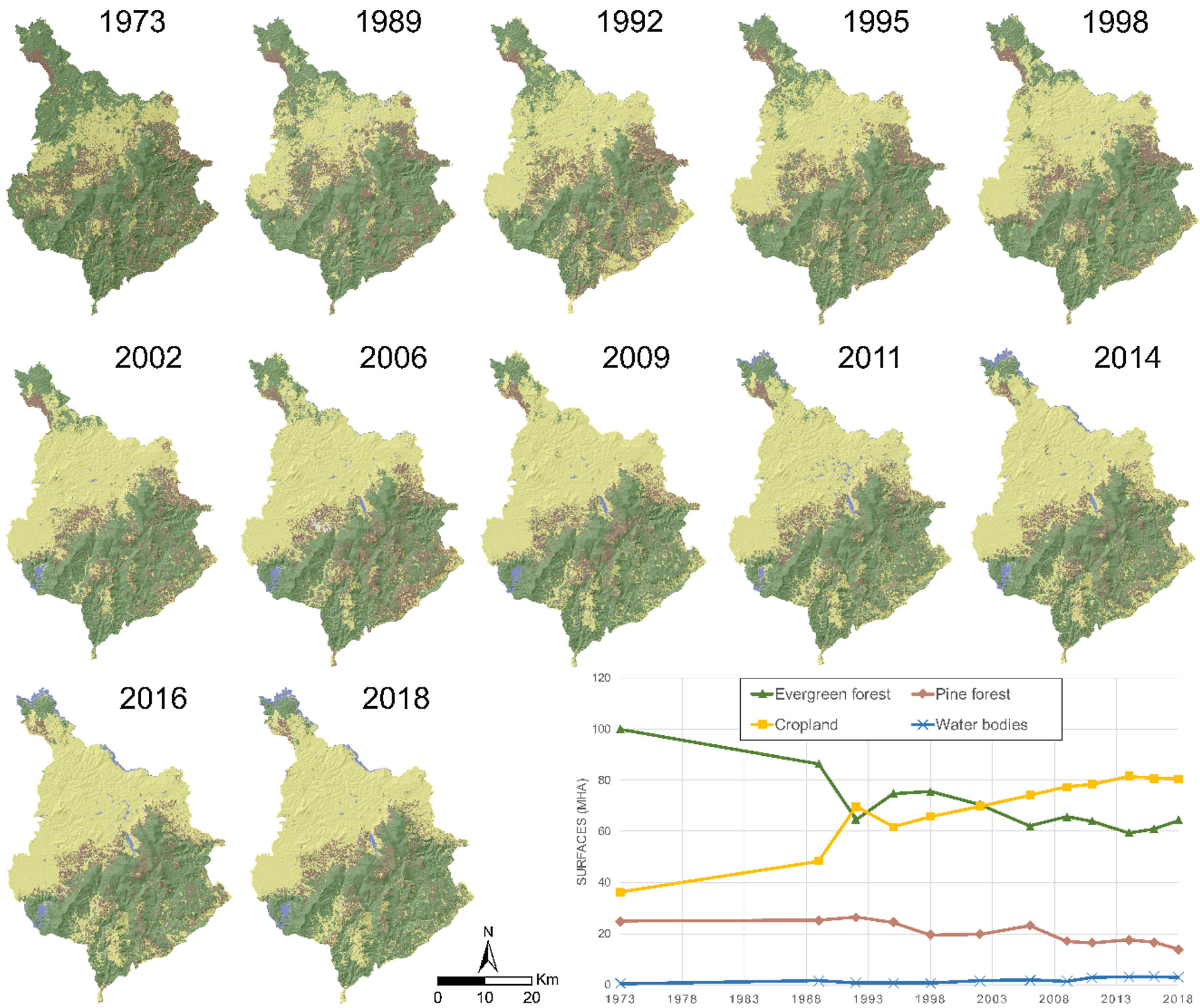

Fig. 4. Maps showing 45 years of evergreen forest, pine forest, cropland and water cover using Landsat archives and random forest classification.

The results of this study pinpoint hotspots of vulnerability along the agricultural frontier. Most areas along the agricultural frontier displayed low adaptive capacity corresponding to fragmented forest mosaics dominated by coffee plantations, degraded forests and infrastructure. Improving the connectivity of forest habitat could increase the adaptive capacity of these landscapes (Ribeiro et al., 2009). One example in Di Linh district is the association of evergreen forest with pine forest (central and western part of the district) to stabilize and protect the agricultural frontier and increase forest surface area (Dien et al., 2013). Sensitivity and exposure indicators revealed localized patterns of forest degradation and agricultural expansion, respectively. The southern part of the district was identified as an active agricultural front recently marked by encroachment of forest cover amplified by fragmentation of the forest edge (trajectory T3) due to an increasing importance of cash crop agriculture (e.g. coffee, maize and banana plantations). The eastern region is experiencing different dynamics with notable opening of the forest cover in the forest habitat. Although driven by different factors, these two regions should both be high on the list of priorities for intervention. We demonstrate the need to adapt conservation and management actions, for example, slower rates of reduction in forest cover were detected (trajectory T1) but they were still characterized by a closed forest habitat, leading to a lower vulnerability index and consequently lower priority for intervention.

It is important to stress that the ecological vulnerability index is not a measurable phenomenon but rather an aggregation of complex and interacting indicators (Fritzsche et al., 2014). Current landscape intensification scores and historical degradation trajectories are indicators that are assumed to affect the ecological vulnerability of forest cover to agricultural expansion, because vulnerability cannot be measured directly (Adger, 2006). These indicators reflect human decisions through changes in land use and in land cover and hence indirectly provide information on social systems. Further research into social vulnerability and their related indicators at the household level is necessary to provide a complete picture of overall socio-ecosystem vulnerability as defined by Thiault et al. (2018). Our ecological vulnerability approach is therefore a first attempt to capture complex realities of forest cover vulnerability using only indicators based on free and open source data.

4.2. Methodological robustness and future outlook

The adaptive capacity indicator reflects a gradient of landscape intensification, which is based on the land use composition of each class of forest landscape and expert scoring. We evaluated the impact of this method of scoring on the vulnerability classification by simulating all possible intensification scores, adaptive capacity indexes and vulnerability scores. Fig. 7 shows that most of the forest landscapes were classified as belonging to the same class of vulnerability when we compared expert based and simulation results. The areas of low agreement are mostly related to overestimation (i.e. the simulations yielded a higher class of vulnerability than the expert result). Vulnerability was rarely underestimated and did not concern any of the

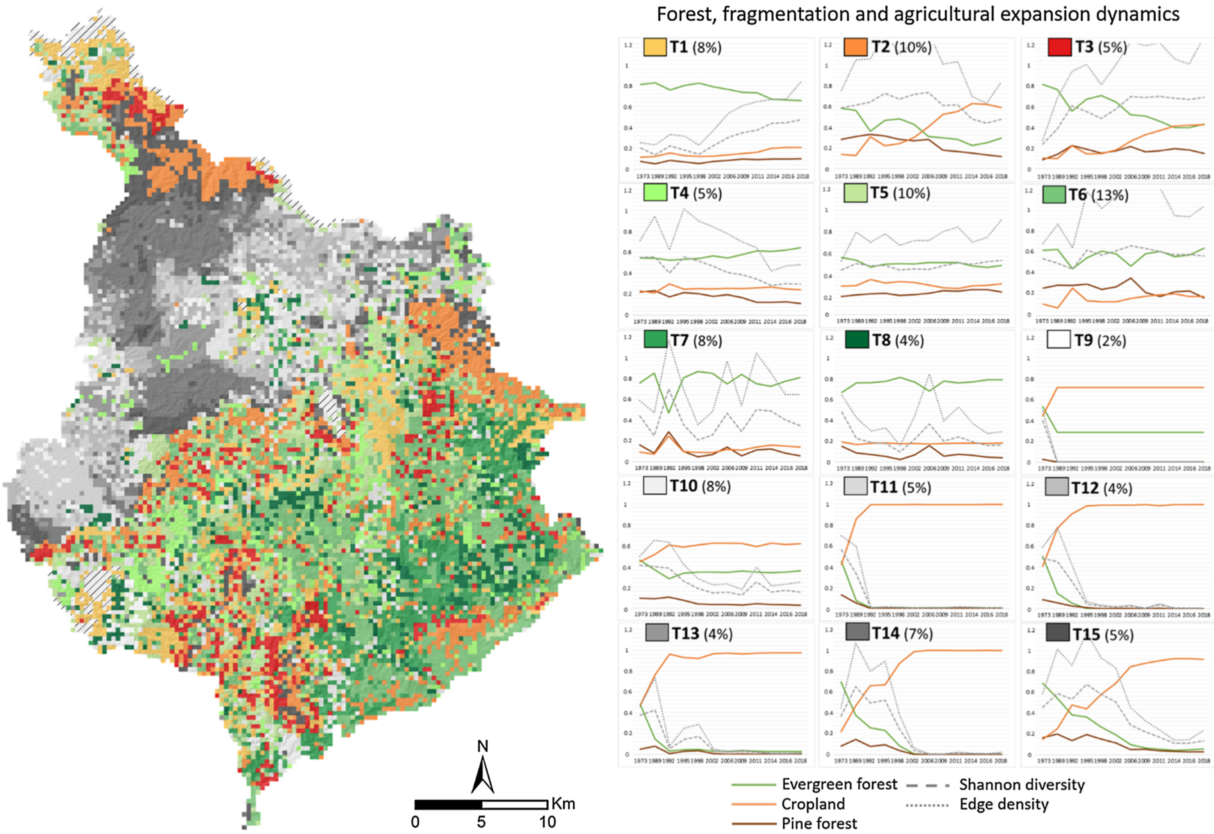

Fig. 5. Classes of landscape trajectories (T1 to T15) based on land cover composition and structure dynamics from 1973 to 2018 obtained using ACT-STATIS and clustering methods. Hatched areas represent water bodies in 2018 (2%).

previously identified and characterized hotspots of vulnerability. This means that 'expert' qualitative inputs had no negative impacts on the ecological vulnerability assessment of forest cover and that the method can be used at other sites. The consequences of scoring are generally not assessed in studies (Lavelle et al., 2016).

Landscape metrics, the trajectory classes obtained using the ACT-STATIS method and the resulting indicators of vulnerability depend on the validity and accuracy of LULC classifications. This remote sensing field of research is improving significantly thanks to the development of novel classification algortihms and the accessibility of near-real time and high resolution imagery (Bégué et al., 2018). The 2018 land cover and land use maps were produced with a high degree of accuracy and required only a short processing time. Minor misclassification were detected between the land cover and land use classes along the agricultural frontier as these elements are highly contrasted and clearly seperated in the landscape. Transition classes, which often cause misclassification, proved difficult to map (Mercier et al., 2019; Hett et al., 2012). In our case, they were grouped in the degraded forest class, which refers to different land uses with the same vegetation structure. Further work is necessary to be able to distinguish degraded forest due to logging and fire from shrubland and fallow. Spectral unmixing indicators assess the proportion of active photosynthetic vegetation, dead vegetation and bare soil within a pixel and could significantly improve the identification and classification of forest edges subject to degradation risks (Asner et al., 2009). Time series optical images could also provide useful information to help improve the classification of degraded forest. In continental Asia, annual dfferences in the normalized burn ratio revealed highly accurate patterns of canopy disturbances linked with encroachment and logging (Langner et al., 2018). Cropland and rice classes showed misclassification errors due to confusion with bare soil because mapping was based on images acquired in the dry season. High temporal resolution of optical and radar imagery could help describe and account for the phenology of vegetation to map forest-agriculture mosaics (Mercier et al., 2019). Furthermore, small agricultural systems can be mapped using combined pixel and object-based approaches and promising results have already been obtained with the characterization of fine cropland uses (Lebourgeois et al., 2017).

4.3. Landscape approaches that incorporate both spatial and temporal information are keys to characterizing complex agricultural frontiers

Major pressures and conflicts opposing human and natural elements are concentrated along agricultural pioneer fronts (Lambin et al., 2001). Today, remote sensing offers unique opportunities to map and characterize these regions using land cover classification and its contextual transformation into land use information, which is often used to describe landscape mosaics (Mercier et al., 2019). The landscape approach has been shown to be appropriate for studying agricultural frontiers as its scale encompasses spatial patterns that reveal the underlying social, environmental and ecological processes and hence human-environmental interactions (Wu, 2007). The landscape approach is particularly useful when degradation and deforestation are the main drivers that shape the landscape through complex fragmentation patterns integrating agriculture and forest systems (Shapiro et al., 2016). Pixel-based approaches would provide limited information on the consequences of degradation and on their underlying drivers linked with agricultural frontier expansion (Oszwald et al., 2012). The landscape approach has proved to be particularly effective in complex mosaic landscapes marked by high heterogeneity, fragmentation and disconnection between the different landscape elements. The transformation of land use into landscape mosaic has been applied to different human-dominated landscapes such as Northern Laos where complex swidden systems have been successfully mapped and characterized

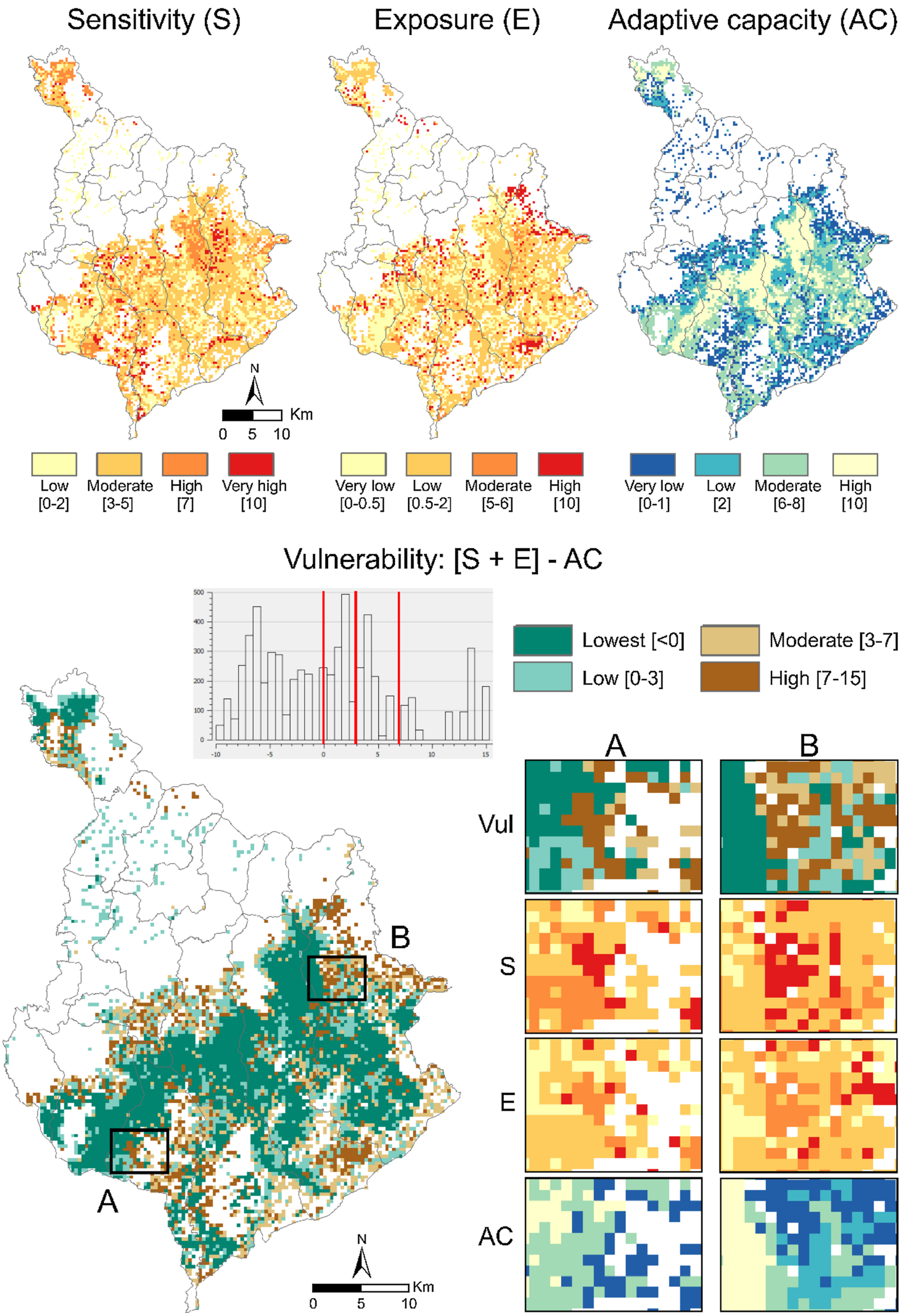

Fig. 6. Forest ecological vulnerability to deforestation and degradation (agricultural landscapes are in white, communes are delimited in grey).

using human-environment data (Hett et al., 2012; Messerli et al., 2009). In the case of Amazonian agricultural frontiers, Oszwald et al. (2011) demonstrated that the combination of composition and structure metrics at both spatial and temporal dimensions are key indicators for characterizing landscape and for reflecting human-induced drivers of landscape change. Indeed, two landscape mosaics sharing similar

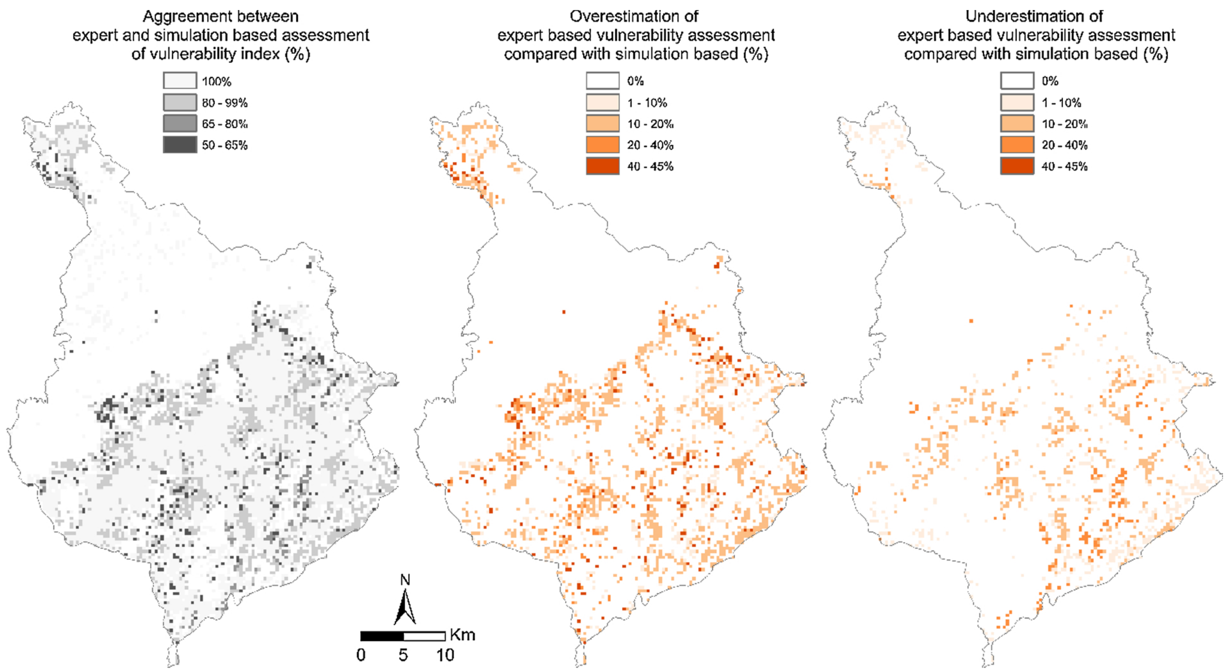

Fig. 7. Agreement, overestimation and underestimation in expert and simulation based ecological vulnerability assessments.

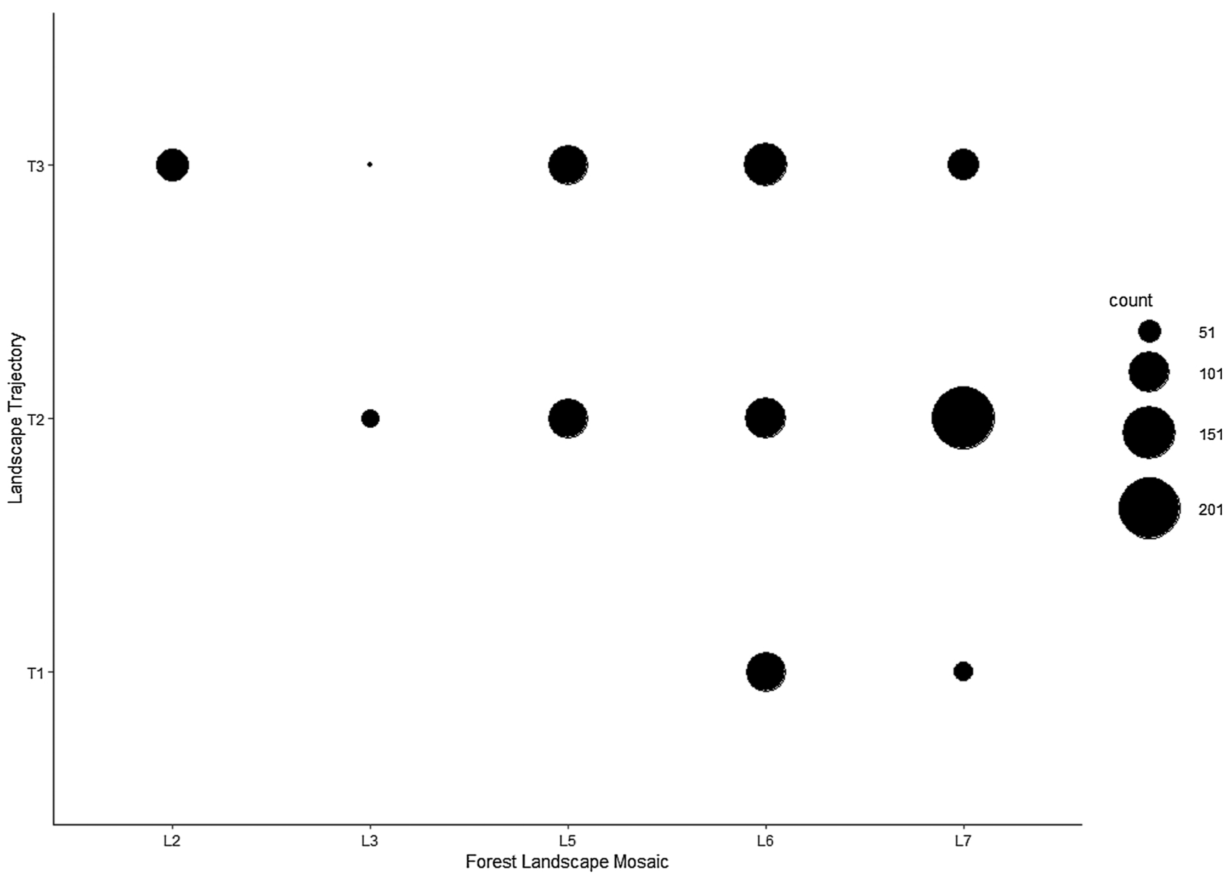

Fig. 8. Number of forest landscape mosaic and landscape trajectory pairs identified in the most vulnerable forest cover areas.

characteristics at a given moment in time may have experienced different historical landscape dynamics. Our analysis demonstrates that the relationship between the spatial and temporal dimensions of landscape analysis is effectively verified, especially in regions that are highly vulnerable to agricultural expansion (Fig. 8). Current mosaics and historical trajectories are complementary, providing dependent and non-redundant information to help understand landscape complexities. Highly vulnerable areas (brown areas in Fig. 6) are five types of current forest landscape mosaics with specific past trajectories and any given landscape can be the result of multiple types of dynamics.

So far, the multiplication of scales in landscape analysis has been applied to the spatial dimension and has made it possible to capture trends at different organizational levels (Ostrom, 2009). In this paper, we emphasize the importance and added value of including the temporal scale in the landscape approach conceptual framework in order to reconstruct landscape dynamics and analyze underlying drivers and pressures that drive agricultural frontiers and other areas where competition between land uses is high (Sayer et al., 2013; Reed et al., 2016). With accessibility, global coverage, temporally rich archives and frequency of acquisition of optical remote sensing images (Landsat and Sentinel), this study paves the way for replicating and scaling out the proposed framework to other agricultural frontiers for more effective management and conservation actions of forest landscapes.

5. Conclusion

A need exists to identify which forest areas are most vulnerable to agricultural expansion and thus require prioritized conservation. In light of this, this paper demonstrates the potential and robustness of the proposed innovative methodology based on multidimensional remote sensing and landscape analysis to assess forest ecological vulnerability. We successfully mapped current land uses using Sentinel-2 and retrospectively reconstructed land cover over a 45-year period using Landsat archive. Landscape structure dynamics revealed heterogeneous trajectories of cropland expansion, degradation and fragmentation while the composition of forest-agricultural mosaics highlighted different landscape intensification levels along the agricultural frontier. Most vulnerable forest areas were experiencing rapid and recent forest cover loss associated with landscape fragmentation, land use competition due to coffee production and forest degradation. Long-term landscape structure analysis coupled with detailed description of land uses opens up prospects for continuously monitoring forests within agricultural frontiers over time and space.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgements

This work was implemented as part of the CGIAR Research Program on Forest Trees and Agroforestry (FTA) and on Climate Change, Agriculture and Food Security (CCAFS), the latter with support from CGIAR Fund Donors and through bilateral funding agreements. For details, please visit https://ccafs.cgiar.org/donors. The views expressed in this document cannot be taken to reflect the official opinions of these organizations.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jag.2019.101958.

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