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Remote Sensing and GIS resources for TAPE indicators for a case study in Northern Ethiopia

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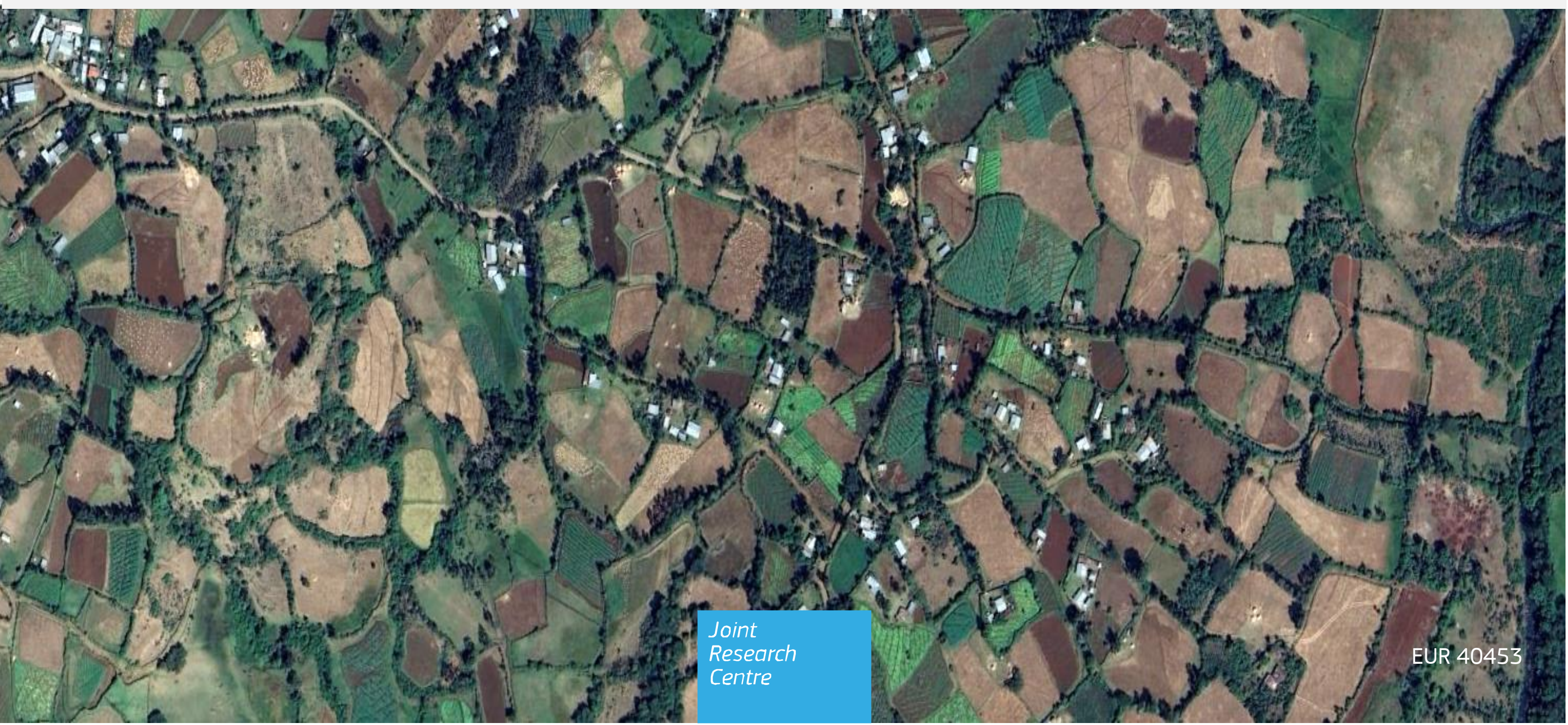

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Contents

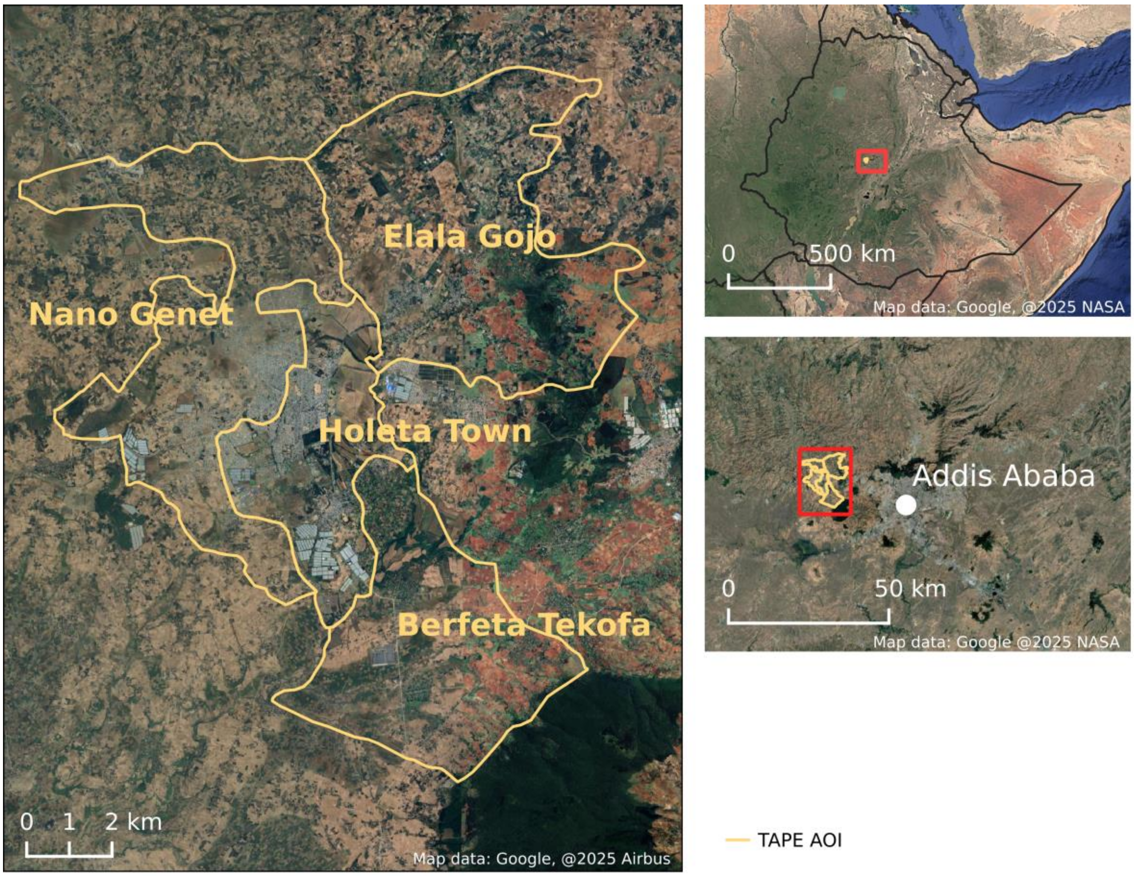
Abstract

This report reviews Remote Sensing (RS) and Geographical Information System (GIS) resources to support the integration of RS-based indicators into the FAO Tool for Agroecology Performance Evaluation (TAPE), currently relying on questionnaire-based data collection. The study focuses on a case study in Northern Ethiopia and provides an overview of existing spatial datasets suitable for supporting TAPE assessments. The report highlights the potential of RS and GIS for evaluating agroecological performance at different scales and identifies areas where further research is needed.

1. Introduction

This document provides a summary of Remote Sensing and GIS-based datasets and tools that can be utilized to retrieve selected TAPE indicators and selected information of TAPE interest. The general aim is to support the application and the upscale of TAPE assessment to new areas, currently limited by the reliance on questionnaire-based data collection, by leveraging Remote Sensing and GIS-based datasets and tools, and to ensure consistency of the indicators across different regions by establishing a standardized procedure for retrieving and calculating them. We provide an overview of existing spatial datasets suitable for supporting TAPE assessments, ranked by their readiness (i.e., if all required data are available, or if they need to be requested, or must be produced ad-hoc) and applicability for TAPE assessments. The selection of the indicators in this document is the result of a collaborative exchange with the TAPE team who provided a list of priority indicators for TAPE assessment on which we focused. These include indicators relevant to context characterization (Step 0), farm-scale assessment (Step 1), and additional indicators which are used in the TAPE assessment, applicable to both scales (Elements of landscape/farm diversity, complexity and connectivity). For each indicator, we provide information on the required data, software for computation, and a practical example of application within a TAPE area of interest. The area of interest, located in Ethiopia, comprises four kebeles (the smallest administrative unit) within the Walmara woreda (the higher administrative subdivision), namely: Holeta Town, Nano Genet, Elala Gojo and Berfeta Tekofa (Figure 1). The area was selected because the TAPE team had already been working in the area and had conducted TAPE assessments on several farms there.

Figure 1. TAPE area of interest used to provide practical examples of remote sensing analysis of agroecology.



Source: JRC

2. Readily available indicators and metrics

In this section we list TAPE indicators and other relevant metrics that can be readily retrieved, given the availability of the datasets needed to calculate or extract them.

2.1. Step 0

2.1.1. Spatial Heterogeneity

Readiness: High. *Data availability*: The land cover maps can be freely accessed through Google Earth Engine and on other platforms (e.g., https://esa-worldcover.org/en/data-access). *Software requirements*: performed on R free software environment.

Definition

Landscape heterogeneity (LH) refers to the qualitative or quantitative variation of landscape elements (Risser, 1987; Li & Reynolds, 1994, 1995; Pickett & Cadenasso, 1995; Turner et al., 2001; Fahrig et al., 2011). Landscape heterogeneity has two main components: composition and configuration. Specifically, compositional LH is defined as the number and proportions of land cover types, while configurational LH refers to the spatial arrangement of these land cover types (Fahrig et al., 2011).

Furthermore, whether a target species or biological group is considered or not, Landscape heterogeneity can be described from either a structural or a functional perspective. Structural LH focuses on the attributes of a landscape, disregarding the effects of different land-cover types on biotic and abiotic processes. In contrast, functional LH examines how different land-cover types affect a target species or biological group, or their influence on abiotic processes, such as nutrient flow (Li & Reynolds, 1995; Fahrig et al., 2011). Therefore, for assessing functional heterogeneity, a target species or biological group should be identified and information on how different land-cover types influence its demographic and behavioural processes are required.

In this document, we focus on measuring structural and compositional LH. A widely used metric for this purpose is the Shannon diversity index.

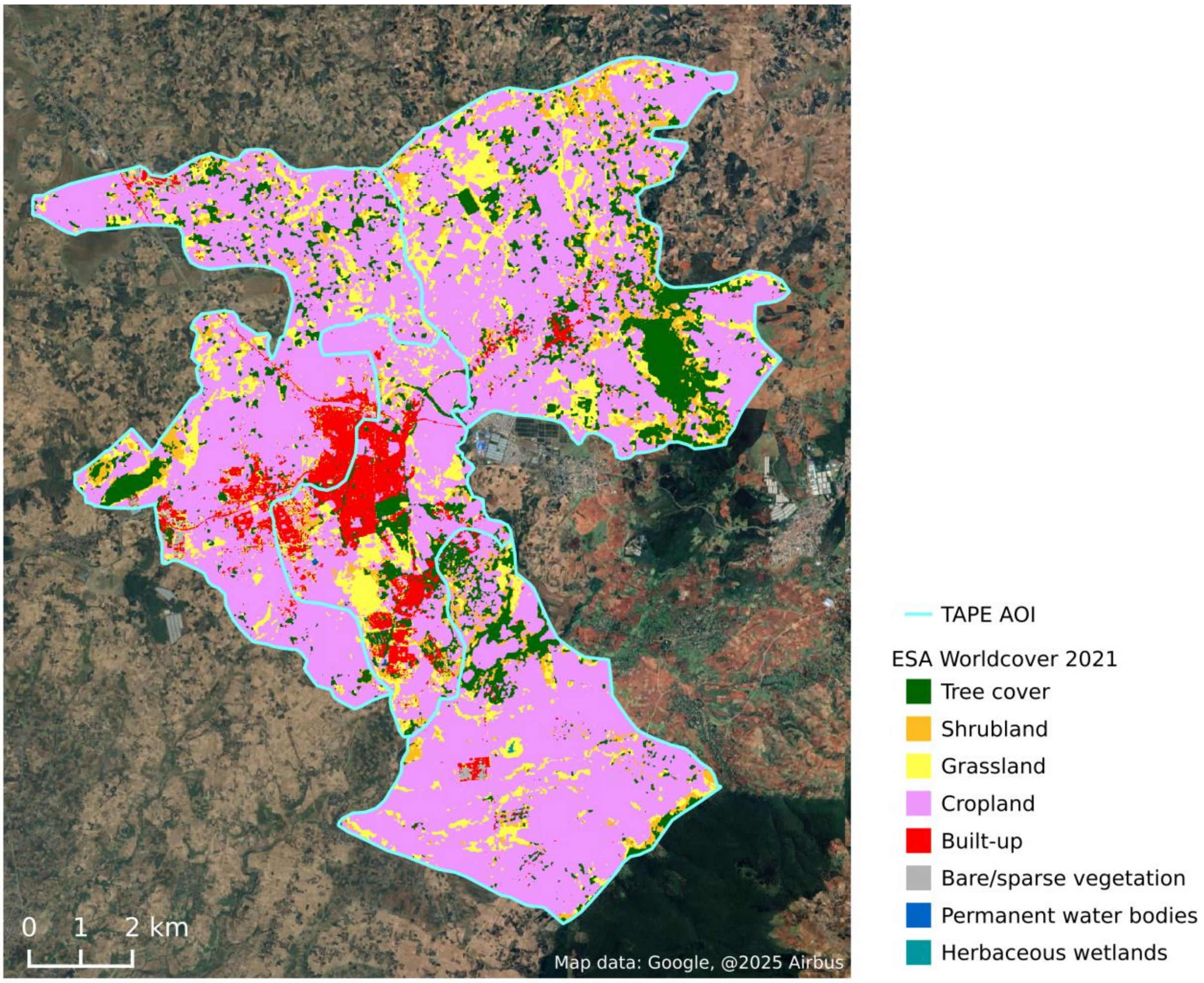
The Shannon index, also known as the Shannon diversity index (Shannon & Weaver, 1949), is a mathematical formula used to measure the diversity or heterogeneity of a system, such as a landscape or a community of organisms. The index is calculated based on the number of different categories or types (e.g., land cover types, species) present in a system and the proportion of each type. The index takes into account both the richness (number of types) and the evenness (relative abundance of individuals among types) of the system.

In the context of landscape ecology, the Shannon index is used to measure the heterogeneity of a landscape, which refers to the mixture of different land cover types, such as forests, grasslands, and urban areas. The Shannon index values range from 0 to infinity, with higher values indicating greater diversity or heterogeneity. A value of 0 indicates a landscape with only one land cover type, while a higher value indicates a more heterogeneous landscape, with a greater variety of land cover types and a more even distribution of those types. The absolute magnitude of Shannon's diversity index is not inherently meaningful, however, it is used as a relative index for comparing different landscapes or the same landscape over time (McGarigal et al., 2012).

Dataset and analysis

To calculate heterogeneity using the Shannon index, a land cover map that characterizes patches of different land cover types is required. We utilized the European Space Agency (ESA) **WorldCover 10m 2021** product, which provides a global land cover map for 2021 at a 10 m resolution.

Figure 2. ESA WorldCover 10m 2021 map over the study area.



Source:JRC

We retained all WorldCover classes and applied the "lsm_l_shdi" function from the Landscapemetrics R package to calculate the Shannon index value for each kebele (Table 1).

Table 1. Shannon index values for the four kebeles in the study area.

	Holeta Town	Nano Genet	Elala Gojo	Berfeta Tekofa
Shannon index value	1.48	1.40	1.40	1.30

Source: JRC

The index provides a measure of the land cover heterogeneity among the kebeles and can be effectively applied wall-to-wall in all TAPE study areas for a first characterization of heterogeneity in tabular form. Note that the choice of the land cover product impacts the results, as factors such as spatial resolution and number of classes influence the outcome. For example, higher-resolution Land Cover maps may lead to a greater number of patches being detected, while a higher number of land cover classes can result in a more nuanced classification, with patches belonging to distinct classes (land cover types) that might not be distinguished in a map with fewer classes. As these factors influence the Shannon index, it is essential to clearly document the characteristics of the chosen Land Cover product and only compare indices retrieved from the same product to ensure consistency.

2.1.2. Connectivity

Readiness: High. *Data availability*: the Global Canopy Height Maps dataset is freely available through Google Earth Engine or it can be downloaded at https://registry.opendata.aws/dataforgood-fb-forests/. *Software requirements*: performed on GuidosToolbox (Vogt et al., 2017) (download at https://forest.jrc.ec.europa.eu/ en/activities/lpa/gtb/#Download)

Definition

Connectivity metrics aim at measuring either structural or functional connectivity. For the purpose of this report, we will focus on the structural connectivity (i.e., how patches are spatially organized) of the natural and semi-natural habitat in the landscape, specifically, forest patches and small woody features. Functional connectivity is species-specific and it explicitly considers the ability of a species to disperse between patches (Crooks and Sanjayan, 2006). The assessment of functional connectivity would therefore require knowing the characteristics and needs of a target species or taxon or functional group.

Dataset and analysis

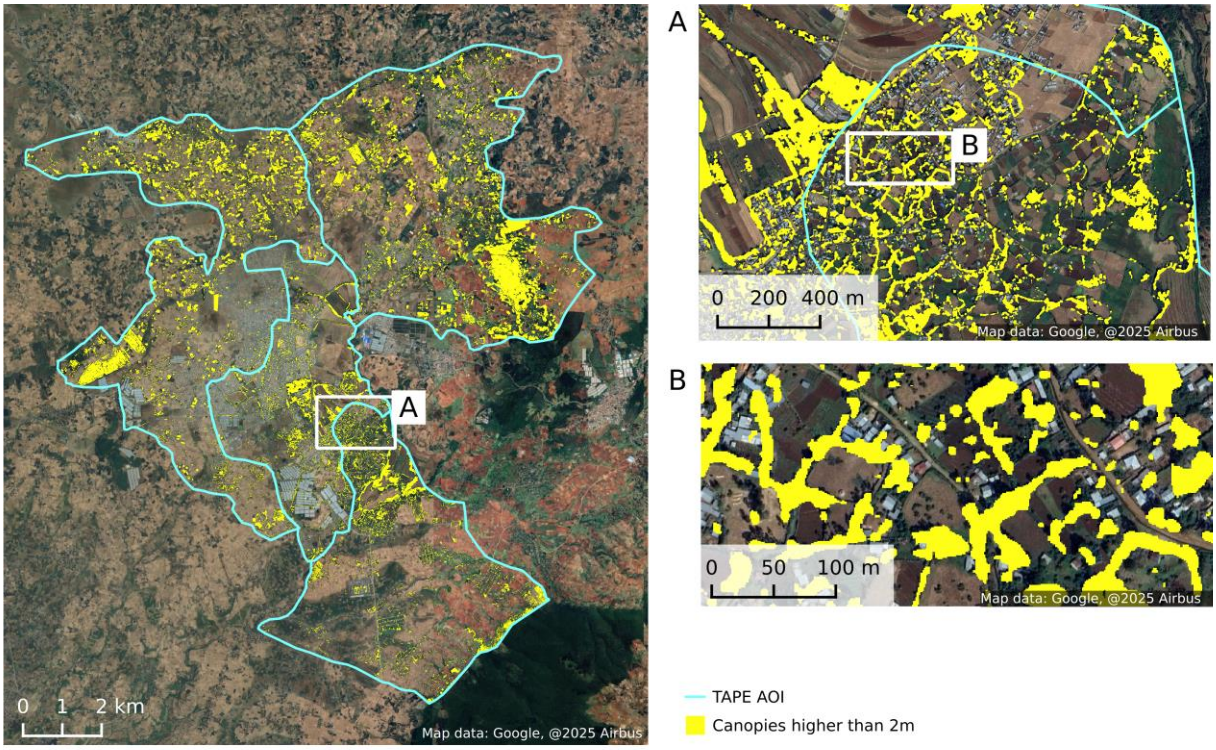
To measure connectivity we drew on the approach used in the identification of green infrastructures (Estreguil et al., 2016; Wickham et al., 2010): we analysed the structural continuity of the forest and small woody features in the study area by identifying networks composed of compact and linear elements, as well as isolated patches (islets). To this aim, we applied a Morphological Spatial Pattern Analysis (MSPA) to identify the morphological shapes within the natural and semi-natural habitat. We then summarized these shapes into three categories (compact shapes, linear shapes and islets) and computed the percentage of the habitat (forest and woody features) that is organized in networks (compact + linear features) and islets.

For this analysis we utilized the **Global Canopy Height maps at a 1-meter resolution** (Tolan et al., 2024). The Global Canopy Height Maps dataset provides detailed information on tree canopy presence and height worldwide. With its spatial resolution of 1 meter, it is the canopy height dataset with the highest spatial resolution available to date. It covers a period from 2009 to 2020, with eighty percent of the data obtained from imagery acquired between 2018 and 2020.

To detect forest and small woody features, we applied a threshold to the canopy height dataset to retain only pixels with a modelled canopy height greater than 2 m (Figure 3). As a result, our binary map for calculating connectivity measures includes woody vegetation taller than 2 m, as "habitat" (or foreground, in the MSPA jargon). All other areas, including agricultural lands, urban areas, water bodies, grasslands, and wetlands, were considered "matrix" (or background). Other threshold values could be adopted based on knowledge of the habitat in focus, for example increasing the threshold value will result in the exclusion of shorter shrubs and trees and therefore in the reduction of the habitat area. If a suitable dataset is available, other land cover (e.g. grassland, wetland) can be incorporated into the habitat category.

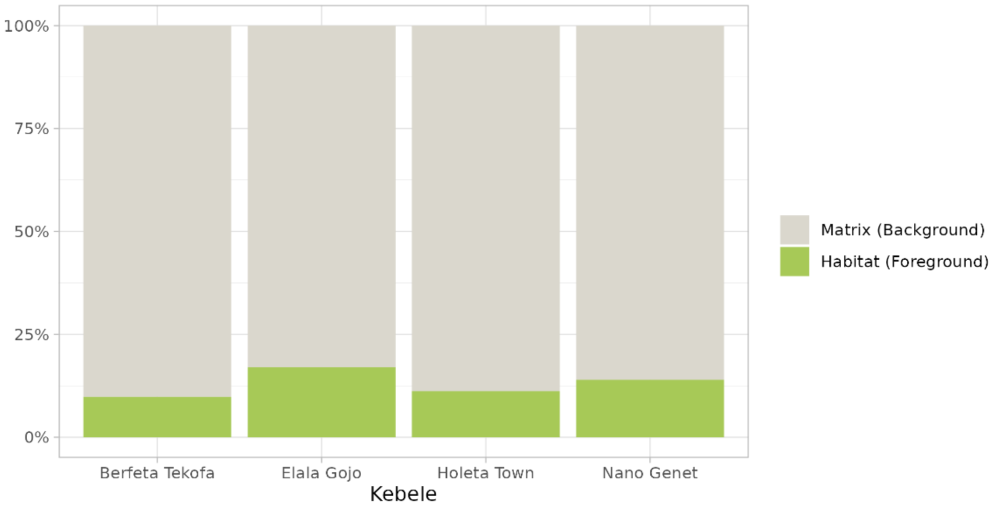
Using the 2 m threshold, the four Kebeles exhibit the following proportions of woody vegetation cover: 11% in Holeta Town, 14% in Nano Genet, 17% in Elala Gojo, and 10% in Berfeta Tekofa (Figure 4).

Figure 3. Binary map showing in yellow vegetation >2 m obtained through thresholding of the Global map of tree canopy height. The layer is overlaid to a Google Earth background for reference and context.



Source: JRC

Figure 4. Percentage of “habitat” (Forest and small woody features) cover in the four kebeles.



Source:JRC

The MSPA is a sequence of mathematical morphological operators targeted at the description of the geometry and connectivity of the image components (Soille et al., 2009). Based on geometric concepts only, this methodology can be applied at any scale and to any type of digital images in any application field. The foreground area of a binary image is divided into seven visually distinguished MSPA classes: Core, Islet, Perforation, Edge, Loop, Bridge, and Branch. The description of these classes is in Table 2. We performed the MSPA analysis with the GuidosToolbox (Graphical User Interface for the Description of image Objects and their Shapes - GTB) (https://forest.jrc.ec.europa.eu/en/activities/lpa/gtb/).

Table 2. Description of the seven classes resulting from the MSPA analysis.

MSPA classes	**Description**	**Example**
Core	The larger patches of habitat in the foreground	A large forest patch
Islet	Small, isolated patches of habitat	A small woodland patch surrounded by agricultural land
Perforation	The boundary between a core patch and an internal non-habitat area	A hole or gap within a larger forest patch
Edge	The boundary between a core patch and the surrounding non-habitat	The margin of a forest patch where it meets a field or road
Loop	A linear feature connected both ends to the same core patch	A narrow strip of vegetation connecting two sides of a gap in a forest patch
Bridge	A corridor connecting two core patches	A linear strip of trees and shrubs bridging two habitat patches separated by agricultural land
Branch	A linear feature connected at only one end to one of the other features	A narrow, elongated strip of vegetation extending from a forest patch

Source: JRC

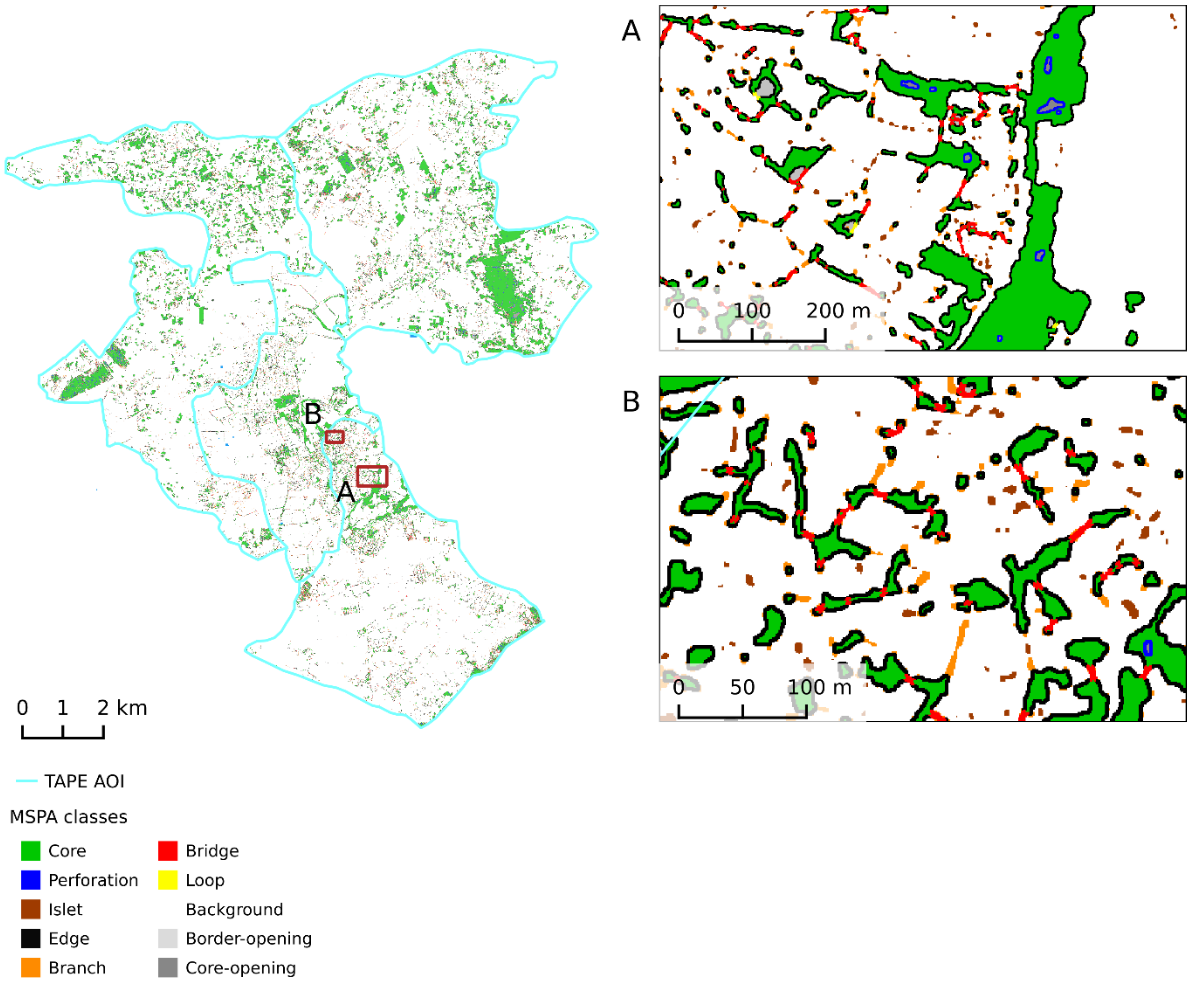
We performed the MSPA analysis using the default parameters, except for EdgeWidth, which we adjusted to suit our dataset. The EdgeWidth parameter controls the thickness in pixels of all classes except Core: higher values of the EdgeWidth parameters result in fewer pixels classified as core. Changing this parameter therefore changes the classes proportion (Figure 5). Given that our dataset has a 1-meter resolution, we set the EdgeWidth to 3 pixels, resulting in a 3-meter thick edge around patches. Knowledge of the ecological characteristics of the habitat can help better tuning the EdgeWidth parameter.

Figure 5. Sensitivity of MSPA results for different settings of edge width: comparison of results with EdgeWidth of 3m (left) and 5m (right).

Source: JRC

The result of the MSPA analysis for the whole study area is shown in Figure 6.

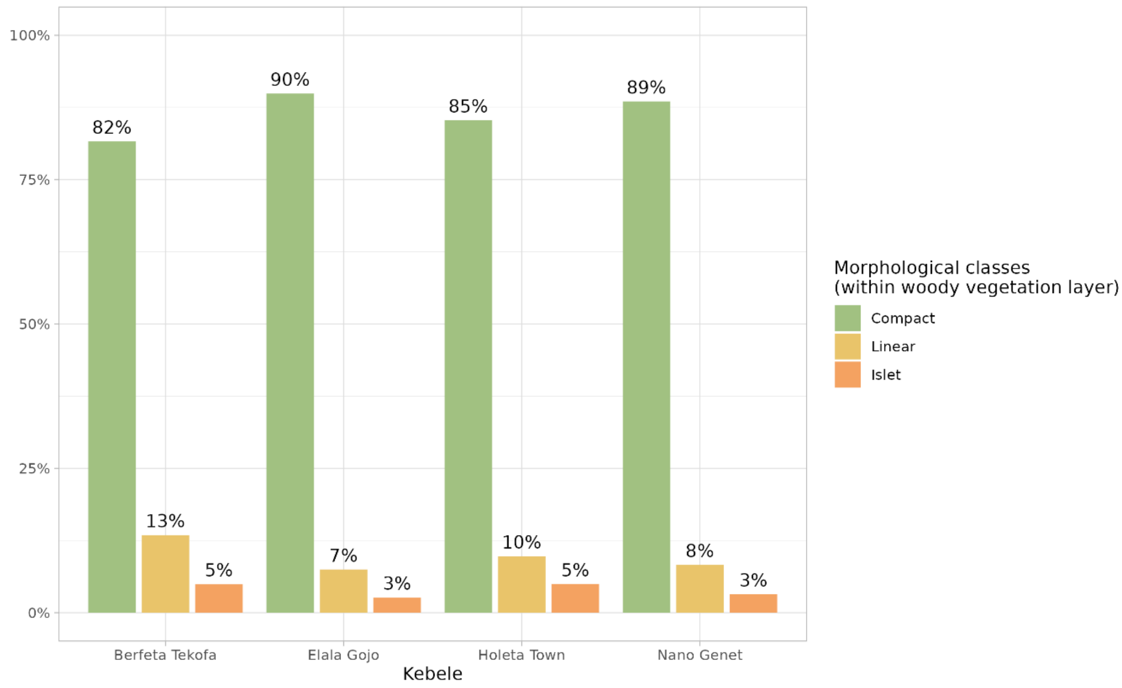
Figure 6. Result of the MSPA analysis in GuidosToolbox.



Source: JRC

We then simplified the classes resulting from the MSPA analysis into three main morphological shapes: *compact* (comprising the classes Core, Edges and Perforations), *linear* (Branches, Bridges and Loops), and *islets*. Figure 7 shows the proportion of these three shape types per each kebele.

Figure 7. Share of the compact, linear and morphological classes within the "habitat" (Forest and small woody cover layer) for each kebele.



Source: JRC

Finally, we grouped compact and linear shapes into *networks*. The fact that a high proportion of the habitat is organized in such networks reveal that the connectivity of the natural and semi-natural habitat (forest and small woody features) is high (Table 3).

Table 3. Shares of networks and isolated patches of woody vegetation per kebele.

	Holeta Town	**Nano Genet**	**Elala Gojo**	**Berfeta Tekofa**
Networks (compact + linear)	95%	96 %	97%	95%
Islets	5%	3%	3%	5%

Source: JRC

The method here presented provides an efficient framework for evaluating the structural connectivity of natural and semi-natural habitats that can be readily applied for TAPE assessment.

2.1.3. Forest type and forest dynamic characterization

Readiness: High. *Data availability*: The Tropical Moist Forest products (TMF) are freely available and can be accessed through Google Earth Engine or downloaded at https://forobs.jrc.ec.europa.eu/TMF/data# downloads. *Software requirements*: we extracted the data using Google Earth Engine code editor.

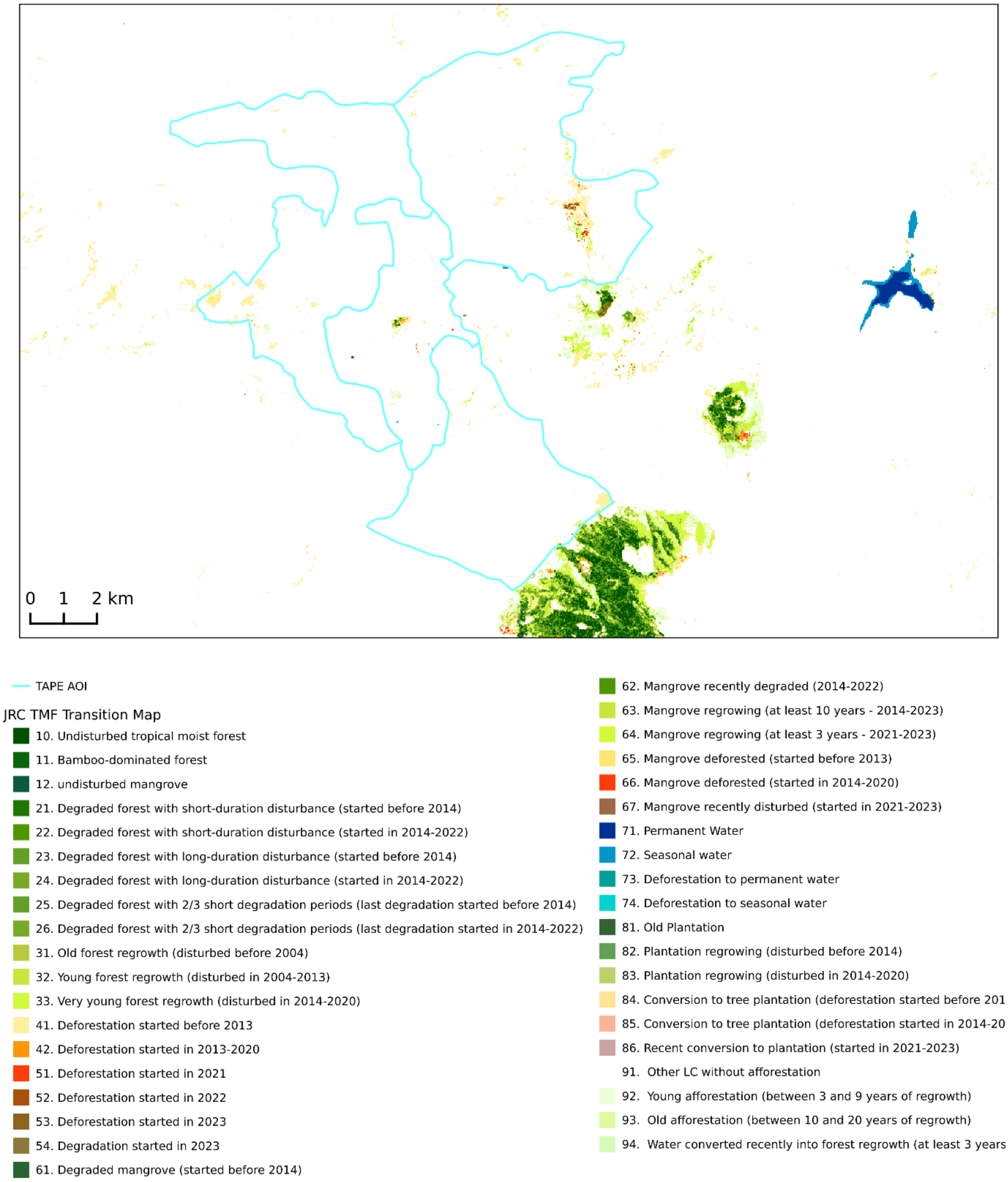
Dataset and analysis

JRC developed the **JRC's Tropical moist forest maps (TMF)** (resolution: 30 meters, latest year: 2024; Vancutsem et al., 2021). The maps depict the tropical moist forest extent and the related disturbances (deforestation and degradation), post-deforestation recovery and forest regrowth through two complementary thematic layers: a transition map and an annual change collection over the period 1990-2024.

This dataset is rich in information and can be used to retrieve information on deforestation, afforestation, expansion of forest and more. The TMF maps can also be used for the characterization of forest types, as it encompasses classes such as Forest Regrowth, Tree Plantations, and Degraded Forest, with additional subclasses providing further details on the type and period of change (e.g., "Young forest regrowth (disturbed in 2004-2013)"; "Deforestation started in 2022"; "Mangrove regrowing (at least 3 years - 2022-2024)"). More detailed information and user guides are available at the website https://forobs.jrc.ec.europa.eu/TMF

Figure 8 shows the TMF map for the study area, with the boundaries of the kebeles overlaid. From this map, the area of each TMF class per kebele can be extracted and presented in a summary table (Table 3), offering a detailed overview of the forest type and dynamics within each kebele.

Figure 8. TMF maps for the study area and surroundings, in blue the boundaries of the four kebeles of interest.



Source: JRC

Table 4. Area of TMF classes per kebele

Subtype code	Subtype name	Area TMF class per kebele (ha)			
		Holeta Town	Nano Genet	Elala Gojo	Berfeta Tekofa
10	Undisturbed Tropical Moist Forest (TMF)	0.7	0.0	0.0	0.3
21	Degraded forest with short-duration disturbance (started before 2014)	0.8	0.0	0.0	0.1
23	Degraded forest with long-duration disturbance (started before 2014)	0.2	0.0	0.0	0.0
25	Degraded forest with 2/3 degradation periods (last degradation started before 2014)	0.3	0.0	0.6	0.0
26	Degraded forest with 2/3 degradation periods (last degradation started in 2014-2022)	1.0	0.0	0.8	0.8
31	Old forest regrowth (disturbed before 2004)	0.3	0.0	0.0	0.0
32	Young forest regrowth (disturbed in 2004-2013)	0.2	0.1	0.9	0.1
33	Very young forest regrowth (disturbed in 2014-2020)	2.3	1.1	8.6	3.5
41	Deforestation started before 2013	12.1	47.5	98.7	27.3
42	Deforestation started in 2013-2020	1.9	0.0	0.1	0.2
51	Deforestation* started in 2021	0.6	0.1	1.0	0.1
52	Deforestation* started in 2022	0.3	0.1	9.4	0.0
71	Permanent water (Pekel et al. 2016 & updates for years 2015-2021)	0.4	0.0	0.0	0.0
72	Seasonal water (Pekel et al. 2016 & updates for years 2015-2021)	0.4	0.0	0.0	0.0
91	Other land cover without afforestation	1752.5	3410.6	3644.1	2520.7
92	Young afforestation (between 3 and 9 years of regrowth)	9.7	8.7	14.4	7.6
93	Old afforestation (between 10 and 20 years of regrowth)	2.0	1.2	2.8	0.3

Source: JRC

Overall, the results of the analysis indicate that in our study area, the forest covers a relatively small area and has been subject to significant human impact or degradation, as illustrated by the prevalence of the classes “Deforestation started before 2013” and “Very young forest regrowth (disturbed in 2014-2020)”. It is important to note that TMF is a global product, and it can thus provide a useful indication to describe forests in regions where tropical moist forest is present. However, it may not be accurate at the local level, and it is therefore recommended to visually check the classes to ensure accuracy. For applications requiring higher resolution, a 10m resolution TMF Hybrid Transition map is available (https://forobs.jrc.ec.europa.eu/TMF/data), although it is currently limited to the period 1990-2022. For regions outside the tropical belt or for non-moist tropical forests, the Global Forest Cover dataset for 2020 (GFC 2020) can be used to retrieve forest data relative to that year.

2.2. Step 1

2.2.1. Connectivity

Note: connectivity is described in section 2.1.2 with reference to Step 0. It is recalled here because the same approach can be used to inform on connectivity aspects related to TAPE Step 1.

Readiness: High, see paragraph 2.1.2.

In the context of the TAPE assessment, this indicator of step 1 aims at assessing and quantifying the presence of the semi-natural environments and the potential zones of ecological compensation within and around the productive system. The dataset and procedure outlined in paragraph 2.1.2 can be applied at the farm level to assess the presence and connectedness of natural and semi-natural habitats within farm boundaries.

2.3. Elements of landscape/farm diversity, complexity and connectivity

2.3.1. Small woody features

Readiness: High. *Data availability*: the Global Canopy Height Maps dataset is freely available through Google Earth Engine or downloaded at https://registry.opendata.aws/dataforgood-fb-forests/. *Software requirements*: we performed them on Google Earth Engine, but R or any GIS software are viable options.

Definition

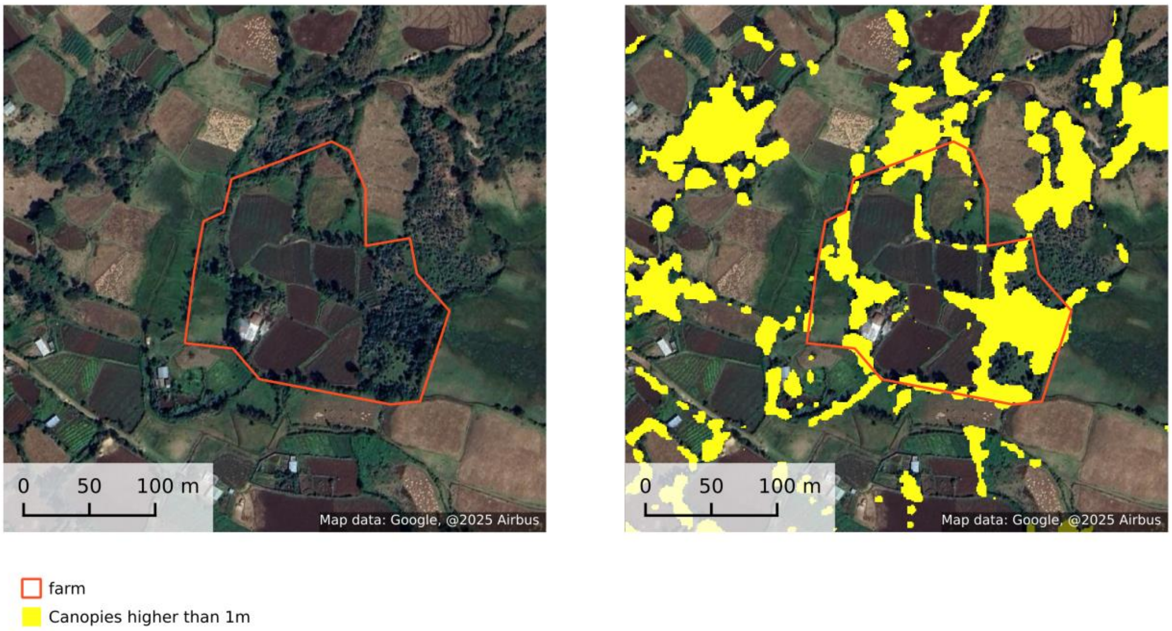
Small woody features include features like hedgerows, field margins, shrubs, isolated trees and small patches of vegetation (< 0.5 ha) with shrubs and trees (d’Andrimont et al., 2024).

Dataset and analysis

The **Global Canopy Height Maps dataset** at a 1-meter resolution (Tolan et al., 2024) described in section 2.1.2 is very well suited for identifying small woody feature, given its fine resolution (1 m). Differently from section 2.1.2, here we threshold it at 1 m to include lower shrubs that are likely to be part of hedgerows. However, as noted above, best is to base the choice of the threshold on knowledge of the vegetation of the system in study. By adjusting the upper and lower bounds of the threshold, it is possible to selectively include or exclude specific vegetation height strata, allowing for the targeted study of particular vegetation types.

One approach to quantifying the presence of small woody features at the farm level is to calculate their area as a percentage of the total farm area. To illustrate this, we created a mock farm polygon in the Berfeta Tekofa kebele (Figure 9, orange boundary). We first vectorized the overlapping patches of woody vegetation to verify that all patches were less than 0.5 ha, conforming to the definition of small woody features. Since all patches are below the 0.5 ha threshold, all woody vegetation within the farm boundaries qualifies as small woody features. For this mock farm, the total area covered by small woody features is 0.8 ha, accounting for approximately 30% of the farm's total area (2.6 ha).

Figure 9. Left, mock farm boundaries overlaid on a Google Earth background. Right, a layer representing small woody features (in yellow) derived from the Global Canopy Height dataset, by thresholding it to retain values above 1m.



Source: JRC

2.3.2. Ponds, rivers, and other water bodies

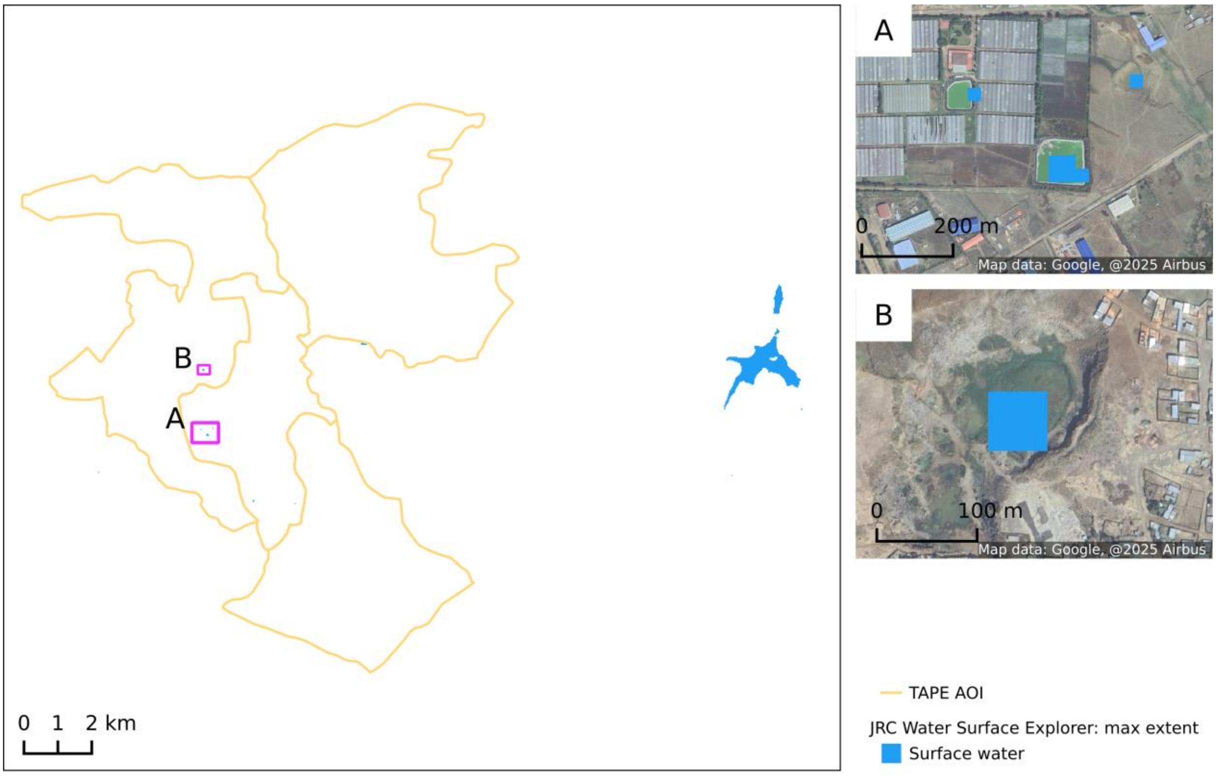
Readiness: High. *Data availability*: the Global Surface Water dataset is freely available and can be accessed through Earth Engine or downloaded at https://global-surface-water.appspot.com/download. The dataset is integrated into the TMF maps, and can be therefore extracted with the TMF data as well (see Table 1). *Software requirements*: Google Earth Engine, or any GIS software.

Dataset and analysis

The dataset **JRC Global Surface Water Dataset** (Resolution: 30 meters, latest year: 2021) provides maps of surface water presence and temporal distribution from 1984 to 2021, accompanied by statistics on the extent and change of water surfaces over time. For more information see the associated journal article (Pekel et al., 2016) and the online Data Users Guide. Note that the dataset's 30m resolution may not be sufficient to capture smaller water bodies, such as small ponds and narrow rivers, which may not be accurately represented. There is ongoing work to update this dataset at an annual time step.

Figure 10 shows the "max extent" band of the dataset for the study area and surroundings. Within the study area, the dataset reveals very few small water bodies. Although the dataset does not provide information on their origin, a visual inspection of the Google Earth basemap suggests that these are likely artificial basins. In cases where ponds are found in proximity to farms and are relevant to the TAPE assessment, a potential approach to summarize them in a tabular format is to vectorize the water bodies from the map and calculate their individual areas.

Figure 10. Global Surface Water Max extent layer for the study area and its surroundings.



Source: JRC

2.3.3. Ecological corridors

Ecological corridors are species-specific and should be assessed for a species or taxon as the focus, taking into account the specific habitat requirements and movement patterns of the target species. The MSPA analysis outlined in section 2.2 provides a classification of "bridges" that can serve as a proxy for potential corridors, this can be adopted after calibrating the "habitat" definition and EdgeWidth parameter settings to reflect the specific needs and characteristics of the target species, when species-specific data are available.

3. Indicators that require ad-hoc analysis and/or Very High Resolution imagery acquisition

In this section we list indicators that cannot be readily retrieved using existing datasets and require the availability or development of specific dataset (e.g. crop type maps), the acquisition and analysis of very high resolution (VHR) images, or the application of emerging methods that are still being refined.

3.1. Step 0

3.1.1. The presence of agroforestry, tree orchards, palms

Readiness: Low

If detailed Land Cover maps with classes such as agroforestry or tree orchards are not available, an ad-hoc classification should be performed. However, while classifying monospecific tree orchards or palm monocultures is relatively straightforward, identifying and mapping agroforestry systems where crops are planted under dense shade trees, remains challenging and is an active area of research.

3.2. Step 1

3.2.1. Crop diversity

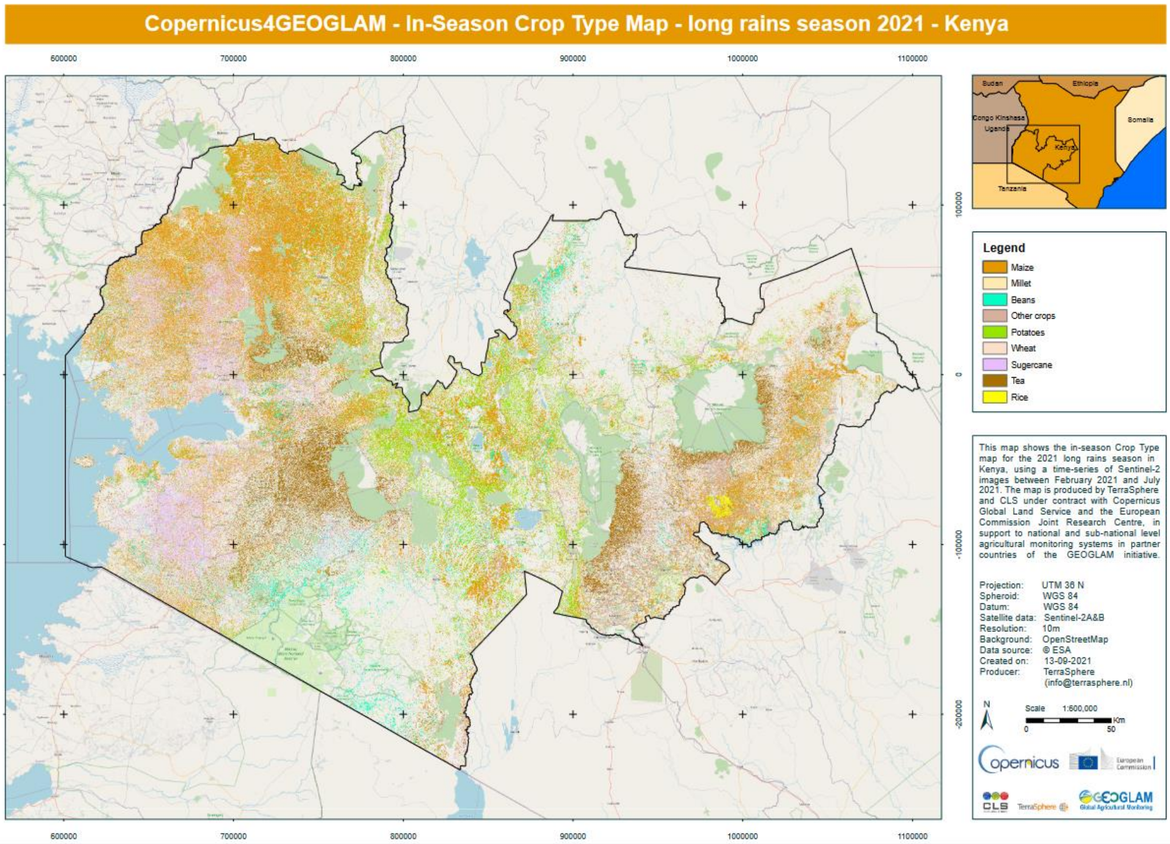
Readiness: Medium. *Data availability*: Crop type maps are necessary for this analysis. Such maps are available for the European Union but not globally. The Copernicus service Copernicus4Geoglam provides crop type maps for Uganda (2021), Kenya (2021-2023), Tanzania (2021-2023) and soon Mozambique and Moldova. In addition to these efforts, other initiatives are also underway to produce crop type maps. For instance, the Food and Agriculture Organization's (FAO) Earth Observation for Statistics (EOSTAT) project is supporting crop mapping activities in Senegal, Afghanistan, and Lesotho (https://www.fao.org/in-action/eostat/en). Furthermore, the European Space Agency's (ESA) WorldCereal project (https://esa-worldcereal.org/en) has developed a dynamic system to generate cereal and maize crop type maps at 10-meter spatial resolution. The project also released global maps of temporary crops and crop type (maize, winter cereals and spring cereals) for the year 2021. *Software requirements*: performed in QGIS and python.

Dataset and analysis

Where a crop type map is available, crop diversity can be assessed following the method of Machefer et al. (2024). The Shannon diversity index described in section 2.1 can be applied also to assess crop diversity at different spatial and temporal scales. The Shannon index gives a better understanding of crop diversity than just the number of crop types (crop richness) because together with their number it also accounts for their relative abundance, providing a more comprehensive measure of species evenness and overall diversity. Species evenness refers to the degree to which individuals are distributed among the different species in a community, with high evenness indicating that each species has a similar number of individuals, and low evenness indicating that one or a few species dominate the community. We compute the γ-diversity which corresponds to crop diversity computed at a regional scale. We adopted a reference scale at 5 km resolution to compute γ -diversity.

The γ-diversity is computed for Kenya for the year 2021 (Figure 11), using data obtained from the Copernicus4GEOGLAM In-Season crop type map (https://jeodpp.jrc.ec.europa.eu/ftp/jrc-opendata/Copernicus4GEOGLAM/Kenya/Crop_Maps&Area_estimates/Long_Rains2021/D3_InSeasonMapping/D3.5_cartographic_product/Kenya_CropType_InSeason_LongRains_2021_V1.pdf).

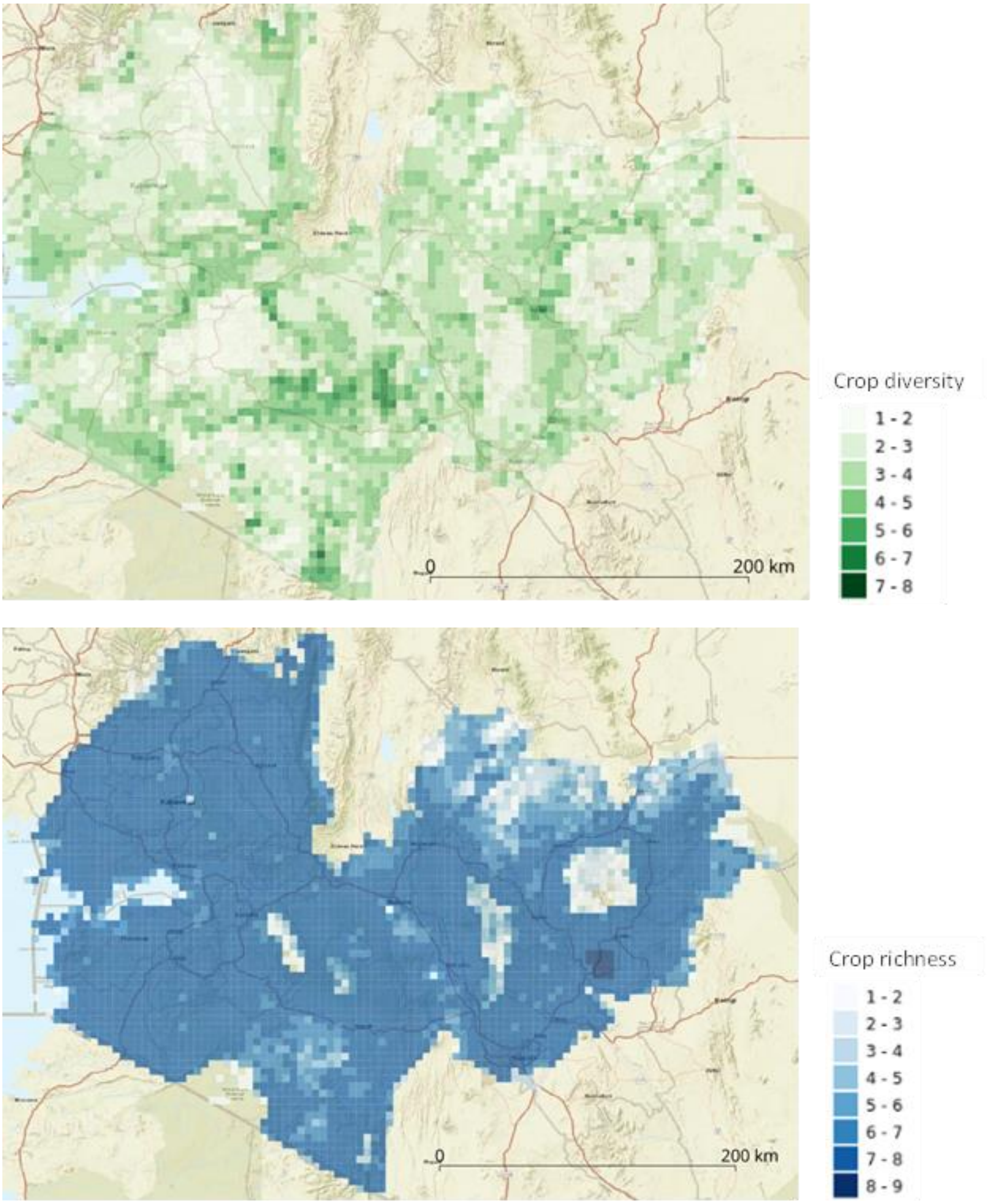
Figure 11. Copernicus4GEOGLAM In-Season crop type map for Kenya for the year 2021.



Source: JRC

Figure 12 shows the crop diversity (shades of green) and the crop richness (shades of blue) computed at 5km scale for the area covered by the Copernicus4GEOGLAM crop type map.

Figure 12. Crop diversity in shades of green (top) and crop richness in shades of blue (bottom) for the area covered by the Copernicus4GEOGLAM crop type map, overlaying the ESRI basemap.



Source: JRC

For TAPE purposes, the above diversity indicators can be converted to tabular form using zonal statistics.

3.2.2. Tree diversity

Readiness: Low

This indicator seeks to quantify the number and diversity of tree species present on the farm. Tree number quantification using remote sensing is an active area of research, with the most promising results being achieved with images at a resolution of 3m or higher (see section 3.5). Tree diversity can be assessed using remote sensing techniques, exploiting the spectral and phenological differences between tree species. However, for analysis at the farm scale, the resolution of freely available satellite images is often too coarse, and commercial very high-resolution (VHR) imagery would be required to obtain reliable results. Currently, to our knowledge, no available dataset is suitable for assessing tree diversity at the farm scale, and acquiring VHR imagery would be necessary for an ad-hoc analysis.

3.2.3. Integration of trees

Readiness: Low

This indicator aims at quantifying whether trees and other perennials provide products or services within the farm. Although remote sensing can detect the presence or absence of trees in a farm area, to determine whether these trees are being utilized for products or services cannot be easily inferred from remotely sensed data. Information on the tree species, management practices, and harvesting activities could be used as proxies, however these information require analysis on VHR at multiple time steps.

3.3. Elements of landscape/farm diversity, complexity and connectivity

3.3.1. Standalone trees/Trees counting

Readiness: Medium.

Data availability: The Tree Detection Probability layers utilized here are not publicly available but they can be obtained upon request from the author.

Software requirements: analysis performed on QGIS.

Dataset and analysis

Recent research has explored the use of remote sensing to identify individual and standalone trees. A promising line of research comes from Prof. Brandt's laboratory at the University of Copenhagen. Using deep learning models, Brandt and colleagues have successfully mapped individual trees using both very high-resolution (VHR) imagery and coarser images, (i.e PlanetScope at 3m resolution) (Brandt et al., 2020; Mugabowindekwe et al., 2023; Reiner et al., 2023). To assess the applicability of their approach in the context of Walmara, we requested access to their data and conducted a pilot test. Specifically, we utilized their tree detection confidence layer derived from PlanetScope images, described in Reiner et al. (2023). In this layer crown centres appear as local maxima. To map the individual trees, we applied the "Local minima and maxima" function from SAGA GIS, accessed through QGIS.

The result shows that the approach is fairly effective in identifying individual trees if they are isolated. However, its accuracy declines when dealing with clustered trees, such as those found in tree lines along field edges or small tree patches. In these cases, the approach tends to underestimate the number of trees. Since clustered trees are the predominant feature in the study areas, it is challenging to obtain a reliable estimate of the total number of trees using this method.

Figure 13. Tree detection results in a farmland area in the Berfeta Tekofa kebele. On the left, a Google Earth background is overlaid with a tree detection confidence layer (thresholded at 30% confidence for visualization purposes), shown in shades of red. Green points indicate locations identified as trees using the local maxima function. On the right, only the local maxima points are displayed. Note that in areas with clustered trees, such as the tree line indicated by the arrow, the number of green points (representing detected trees) is lower than the actual number of trees present, as revealed by their shades.

Source: JRC

4. Conclusions

We reviewed currently available methods and datasets that could support TAPE assessment and provided a guide with examples for their application. Our review highlights that options for assessing agroecological performance at the fine scale, as it would be for a small farm area, are currently limited, with the most interesting options coming from the new high resolution Global canopy height dataset (Tolan et al., 2024). However, the field is rapidly expanding with new high resolution datasets being produced and made available. For example, the Copernicus Land Monitoring Service (CLMS) has recently launched the first two products from its Land Cover and Forest Monitoring (LCFM) suite, including a Global Land Cover Map (10 m) with annually updated data that will be available from 2020 to 2026 (https://land.copernicus.eu/en/products/global-dynamic-land-cover/land-cover-2020-raster-10-m-global-annual) and a Tree Cover Density 2020 (10 m) pantropical layer annually updated (https://land.copernicus.eu/en/products/global-dynamic-land-cover/tree-cover-density-2020-raster-10-m-pantropical-annual). These datasets can provide valuable insights for the TAPE scope, and the annual availability over the last 5 years offers opportunities for assessing changes and trends. Another newly released map is the Natural Forest of the World 2020 map at 10 m resolution (Neumann et al., 2025) which provides insight into natural forest cover, and allows for distinguishing between natural forest and plantations. This map can provide valuable data for the context characterization (step 0). In parallel, emerging methods may soon provide viable options for finer scale analysis and the retrieval of indicators suitable to assess farm-level adoption of agroecological practices (step 1). An example is the growing body of work by Brandt and colleagues (Brandt et al., 2020, 2024; Mugabowindekwe et al., 2023; Reiner et al., 2023), for the identification and characterization of individual trees. In contrast, we also presented a multitude of datasets that are already available at coarser scales (30m or 10m), which can be readily utilized for performing TAPE assessment in new regions, thanks to their global coverage. In the context of TAPE assessment, these are particularly suitable for the description of context (step 0) across multiple countries and regions. However, it is essential to consider that the quality of the derived indicators is tied to the quality and limitations of the base products. Where available, using local or national datasets, such as national Land Cover maps, to replace global datasets, could provide more accurate and detailed information. Additionally, where resources are available, further ad-hoc analysis can also be used to refine the assessment.

As a final note, we recommend that TAPE operators collect farm polygons during field campaigns, as these are crucial for performing geospatial analysis and retrieving indicators at the farm scale, ultimately enabling to leverage the potential of RS and GIS for TAPE assessments.

References

Brandt, M., Gominski, D., Reiner, F., Kariryaa, A., Guthula, V. B. et al. (2024), 'Severe decline in large farmland trees in India over the past decade', Nature Sustainability, https://doi.org/10.1038/s41893-024-01356-0.

Brandt, M., Tucker, C. J., Kariryaa, A., Rasmussen, K., Abel, C. et al. (2020), 'An unexpectedly large count of trees in the West African Sahara and Sahel', Nature, Vol. 587, Issue 7832, pp. 78–82, https://doi.org/10.1038/s41586-020-2824-5.

d'Andrimont, R., Czucz, B., De Marchi, D., Gallego, J., Iordanov, M. et al. (2024), 'Estimation of the share of Landscape Features in agricultural land based on the LUCAS 2022 survey', JRC Publications Repository website, https://doi.org/10.2760/5923183.

Estreguil, C., Caudullo, G., Rega, C. and Paracchini, M.-L. (2016), Enhancing Connectivity, improving Green Infrastructure. Cost-benefit solutions for forest and agri-environment. A pilot study in Lombardy, Publications Office, LU, https://data.europa.eu/doi/10.2788/774717.

Machefer, M., Zampieri, M., Van Der Velde, M., Dentener, F., Claverie, M. et al. (2024), 'Earth Observation based multi-scale analysis of crop diversity in the European Union: First insights for agro-environmental policies', Agriculture, Ecosystems & Environment, Vol. 374, p. 109143, https://doi.org/10.1016/j.agee.2024.109143.

McGarigal, K., Cushman, S. A. and Ene, E. (2012), 'FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical and Continuous Maps. Computer software program produced by the authors at the University of Massachusetts, Amherst.'

Mugabowindekwe, M., Brandt, M., Chave, J., Reiner, F., Skole, D. L. et al. (2023), 'Nation-wide mapping of tree-level aboveground carbon stocks in Rwanda', Nature Climate Change, Vol. 13, Issue 1, pp. 91–97, https://doi.org/10.1038/s41558-022-01544-w.

Neumann, M., Raichuk, A., Stanimirova, R., Sims, M., Carter, S. et al. (2025), 'Natural forests of the world - a 2020 baseline for deforestation and degradation monitoring', EarthArXiv, https://eartharxiv.org/repository/view/9085/.

Pekel, J. F., Cottam, A., Gorelick, N. and Belward, A. S. (2016), 'High-resolution mapping of global surface water and its long-term changes', Nature, Vol. 540, Issue 7633, Nature Publishing Group, pp. 418–422, https://doi.org/10.1038/nature20584.

Reiner, F., Brandt, M., Tong, X., Skole, D., Kariryaa, A. et al. (2023), 'More than one quarter of Africa's tree cover is found outside areas previously classified as forest', Nature Communications, Vol. 14, Issue 1, p. 2258, https://doi.org/10.1038/s41467-023-37880-4.

Shannon, C. E. and Weaver, W. (1949), The mathematical theory of communication, The mathematical theory of communication, University of Illinois Press, Champaign, IL, US, pp. vi, 117.

Soille, P. and Vogt, P. (2009), 'Morphological segmentation of binary patterns', Pattern Recognition Letters, Vol. 30, Issue 4, pp. 456–459, https://doi.org/10.1016/j.patrec.2008.10.015.

Tolan, J., Yang, H.-I., Nosarzewski, B., Couairon, G., Vo, H. V. et al. (2024), 'Very high resolution canopy height maps from RGB imagery using self-supervised vision transformer and convolutional decoder trained on aerial lidar', Remote Sensing of Environment, Vol. 300, p. 113888, https://doi.org/10.1016/j.rse.2023.113888.

Vancutsem, C., Achard, F., Pekel, J. F., Vieilledent, G., Carboni, S. et al. (2021), 'Long-term (1990–2019) monitoring of forest cover changes in the humid tropics', Science Advances, Vol. 7, Issue 10, pp. 1–22, https://doi.org/10.1126/sciadv.abe1603.

Vogt, P. and Riitters, K. (2017), 'GuidosToolbox: universal digital image object analysis', *European Journal of Remote Sensing*, Vol. 50, Issue 1, Taylor & Francis, pp. 352–361, https://doi.org/10.1080/22797254.2017.1330650.

Wickham, J. D., Riitters, K. H., Wade, T. G. and Vogt, P. (2010), 'A national assessment of green infrastructure and change for the conterminous United States using morphological image processing', Landscape and Urban Planning, Vol. 94, Issue 3–4, pp. 186–195, https://doi.org/10.1016/j.landurbplan.2009.10.003.

List of abbreviations and definitions

Abbreviations	Definitions
EO	Earth Observation
GIS	Geographical Information System
LH	Landscape Heterogeneity
MSPA	Morphological Spatial Pattern Analysis
TAPE	Tool for Agroecology Performance Evaluation
TMF	Tropical Moist Forest

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