Countrywide mapping of trees outside forests based on remote sensing data in Switzerland

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ABSTRACT

Although trees growing outside forests are less perceived in relation to those inside forests, they are also valuable and serve various functions. The biophysical thresholds of Trees Outside Forests (TOF) were recently defined and standardized by the Global Forest Resources Assessments of the United Nations Food and Agricultural Organization (UNFAO-FRA). With these definitions, standardized mapping of TOF resources became feasible at the national and international level. Here, we aimed to fill the spatial information gap of TOF resources at the national scale with an automated mapping approach based on the UNFAO-FRA definition. The approach was carried out in ArcGIS using adapted UNFAO-FRA biophysical thresholds with routinely acquired countrywide remote sensing data for the whole of Switzerland: a Vegetation Height Model (VHM), a Topographic Landscape Model (TLM Regio) land cover map, and a Forest Mask. Results were validated using stereo-image interpretation data of the Swiss National Forest Inventory (NFI), which verified 95%, 55% and 75% of overall, producer’s and user’s accuracy, respectively. Of the five forest production regions in Switzerland, the highest accuracy was achieved in the Central Plateau and the lowest in the Alps, with accuracy generally decreasing with increasing elevation. Omission and commission errors were highly correlated with the vertical and horizontal accuracy of the VHM, and the applied biophysical thresholds caused both types of error. The final TOF map produced with our approach is at the countrywide scale, is superior to existing TOF information, meets UNFAO-FRA management and reporting needs, and enables the derivation of TOF’s biomass, carbon sequestration potential and species distribution for the whole country.

1. Introduction

Trees Outside Forests (TOF) are limited in their coverage over the landscape, yet they have several important ecosystem functions. For example, they are relevant for ecological (Bofia, 1999; Nair, 2011), recreational (Kienast et al., 2012), social, cultural, economic and protection tasks (Faye et al., 2011). TOF support biodiversity conservation through their green infrastructure and connectivity functions, improve the livelihood of local communities with their many recreational functions, enhance the water holding capacity of the soil, and improve carbon sequestration through their considerable biomass (De Foresta et al., 2013).

TOF include: individual trees on agricultural land, woodlots in the rural landscape, riparian tree corridors, systematically managed agro-forestry systems, and trees in and around human settlements (Klein, 2000). Until recently, TOF have typically been neglected in National Forest Inventories (NFIs), as they are not part of the forest (Schnell et al., 2015). To include TOF in national and international reporting schemes, the United Nations Food and Agriculture Organisation Forest Resources Assessment (UNFAO-FRA) formed the category ‘Other Land’, separate from ‘Forest’, to take the trees and shrubs into account that do not grow inside forests or other wooded land (Global Forest Resources Assessment 2000 Main Report, 2001).

In the last decades, several studies have been conducted to map TOF at various scales using remote sensing data form the whole range of active, passive, airborne and spaceborne sensors (Schnell et al., 2015). Lower spatial resolution typically corresponds with global or regional scale, while studies using data with a higher spatial resolution are focused on city- or district-level TOF assessments. Zomer et al. (2014) used coarse-resolution optical data, the Vegetation Continuous Field Dataset (VCF) product (250 m spatial resolution) from MODIS, to assess TOF resources on agricultural land at a global scale. They aggregated the
pixels from 250 m to 1 km, masked out all the non-agricultural areas, and stratified the tree canopy cover from 0 to 100%. Several studies on the assessment of TOF in human settlements and agricultural areas have been conducted using medium-spatial resolution data, such as Landsat TM and SPOT HVR imagery. Finding TOF and non-TOF resources in the same pixel (mixed pixel, containing spectral information of different land-use categories), due to the spatial resolution of the images, has been the main constraint in using medium-spatial resolution imagery. To overcome this issue, (Foschi and Smith, 1997) applied artificial intelligence strategies (neural network and machine vision approach) to separate the small features on a sub-pixel scale. Barnsley and Barr (1996) used medium-resolution multispectral SPOT-1 HRV data (20 × 20 m spatial resolution) with traditional pixel-based classification approaches (maximum likelihood) to extract urban trees in Southeast London. Furthermore, different TOF categories such as TOF in settlements (Ouma & Tateishi, 2008; Taubenböck et al., 2010), agricultural land (Liknes et al., 2010; Sheeren et al., 2009; Tansey et al., 2009) and, savannas (Boggs, 2010) mapped using object-based classifications. Rutzinger et al. (2008) used high-density airborne laser scanning (ALS) data to detect urban vegetation in the city of Vienna and obtained accuracies greater than 90%, although the study area of 75 ha was relatively small.

Automating the TOF mapping process has become an important issue because of growing interest of the countries in monitoring TOF trends. Levin et al. (2009) derived an automated mapping approach for the detection of isolated trees. They used SPOT 5 pan-sharpened imagery for object-based classification in combination with a spectral recognition model and mapped hundreds of thousands of isolated trees. Furthermore Straub et al. (2008) developed an automatic approach to distinguish between forest and non-forest vegetation in Germany. The approach is based on ALS data and consists of two steps: (1) the extraction of vegetation and (2) the classification of vegetation to forest or non-forest. Moreover, Bolyn et al. (2019) used a LiDAR-based Canopy Height Model (CHM) to classify TOF to support their operational management in rural landscapes. They used an automated geometrical classification of single objects, linear objects, and ample objects of TOF on the municipality level, covering three adjacent municipalities in southern Belgium in a study area of 200 km². Furthermore, several studies have been focused on the automation of detecting and counting single tree species. Khan et al. (2018) presented an automated olive tree counting method using high resolution image data from different sensors (IKONOS, QUICKBIRD, aerial cameras) to record crop yield in Spain. Sun et al. (2019) derived an extraction method for sparsely distributed Ulmus pumila using very-high-resolution satellite imagery (Gaofen-2 pansharpened to 1 m resolution) in the Otingdag Sandy Land of China.

Since 1983, the Swiss National Forest Inventory (NFI) has kept track of the Swiss forests' current state, change over time, as well as acquiring information on trees inside the forest and stands (Vidal et al., 2016; Abegg et al. 2020). The Swiss NFI is a two-phase sampling inventory used to assess the state and function of forests periodically, with both aerial image interpretation and terrestrial sample plot surveys. Although assessing TOF resources in the framework of NFIs rarely are a domain of primary interest (Vidal et al. 2016), Switzerland is one of the countries that has conducted TOF-related studies in the past years. For example, Bründli (2010) estimated the canopy cover of trees and shrubs inside and outside the forest using aerial stereo-image interpretation independent of forest stratum during the third Swiss NFI. Ginzler et al. (2011) assessed the nationwide tree information of Switzerland for all trees inside and outside forests using aerial stereo-image interpretation in the framework of the third NFI.

Along with the improved understanding of the importance of TOF resources, countrywide mapping and monitoring of TOF and reporting to international organisations has emerged (Global Forest Resources Assessment 2005). The main goal of our study was to produce a countrywide TOF map for Switzerland, including all land-use categories and every tree species, using an automated approach based on the UNFAO-FRA definition, and countrywide available remote sensing data and products. The entire workflow consisted of several adaptable ge-processing operations. We used a straightforward method in which height information from image-based point clouds was used to map countrywide TOF resources. Moreover, we applied the biophysical thresholds of the UNFAO-FRA TOF definition on a Vegetation Height Model (VHM), and validated TOF and non-TOF classes using 1,978 NFI sub-sampling plots from aerial stereo-image interpretation.

2. Materials and methods

2.1. Study area

Switzerland is a central European country on the Alpine arc, located between 5°57′ and 10°29′ E and 45°49′ and 47°48′ N. It has an area of 41,285 km², with an elevation range between 418 and 4636 m a.s.l. According to the Swiss NFI, Switzerland covers five forest production regions that depend on their different conditions of growth and wood production: Jura (J), Central Plateau (CP), Pre-Alps (PA), Alps (A), and Southern Alps (SA). The climate varies from glacier conditions in the Alps to a Mediterranean climate in the Southern part of the country. The main land-use categories found in each production region are classified according to the federal land-use statistics as settlement and urban areas (8% of the surface area), agricultural areas (36%), wooded areas (31%) and other areas (lakes, rivers, unproductive vegetation, rocks, glaciers and perpetual snow; 25%).

There are almost 500 million trees in Switzerland’s forest and the tree cover in the country is 28.5%, including trees both inside and outside forests (Cioldi et al., 2020) that vary between land-use categories and production regions (Ginzler et al., 2011).

2.2. UNFAO-FRA TOF definition

According to the UNFAO-FRA, all trees and shrubs growing in ‘Other Land’ count as TOF. Other Land is divided into the mutually exclusive sub-categories ‘Other Land with TOF’ (OLwTOF) and ‘Other Land with no TOF’ (OLwNoTOF). Other Land with no TOF corresponds to land with trees and shrubs below the defined biophysical thresholds of OLwTOF or to land with no tree and/or shrub cover (De Foresta et al. 2013). There are three classes defined under the OLwTOF and OLwNoTOF categories: Set-1 Agricultural Areas, Set-2 Settlements, and Set-3 Non-Agricultural Areas/ Settlements (Non-A/S). To make the definition operational for data processing in our study, minimum and maximum values of biophysical thresholds were set for patch area, height and crown coverage. An overview of the biophysical TOF thresholds are given in Fig. 1.

For the tree category in OLwTOF Set-1, we set the minimum patch area at 0.05 ha, the minimum tree height at 5 m and the minimum crown coverage at 5% for the shrub and tree category in the same set, we fixed the minimum patch area at 0.05 ha, the plant height at 2.5–5 m and the minimum crown coverage at 10%. According to the FAO, shrubs are perennial woody plants with a height of 0.5–5 m and an indefinite crown (De Foresta et al., 2013). In Set-1, however, some agricultural crops, i.e. corn and sunflowers, can be taller than 2 m and mixed with shrubs and trees. Therefore, the minimum height threshold for the tree and shrub category in this set was fixed at 2.5 m to exclude these agricultural fields. For both Set-2 and Set-3, we followed the FAO definition for shrubs and kept 0.5 m as the minimum height threshold. The thresholds for the OLwNoTOF comprised patch area size < 0.05 ha, and minimum crown coverage 5% for the tree category and 10% for the tree and shrub category. Hence, all the trees and shrubs that were below the biophysical thresholds of OLwTOF were classified as OLwNOToF.
2.3. Remote sensing data

Three data sets were used in this study for geoprocessing: a Vegetation Height Model (VHM), a Topographic Landscape Model (TLM Regio), and a Forest Mask.

2.3.1. Vegetation height Model

The VHM provides height information of vegetation (including grassland, shrubs and crops) for the whole of Switzerland, with a 1 m spatial resolution. Since 2007 the Swiss Federal Office of Topography (swisstopo) has been acquiring repeated (six-year cycle) countrywide RGBI (RGB and Near-Infrared) digital aerial stereo-images with a spatial resolution of 0.5 m (in the Alps) and 0.25 m (in all other parts) using Leica Airborne Digital Sensors (ADS). For more details see (Ginzler & Hobi, 2015). Image-based point clouds from stereo-image strips of the ADS sensors were used to derive a digital surface model (DSM) with a 1 m spatial resolution. By subtracting the LiDAR-based digital terrain model (DTM) provided by swisstopo, a normalised digital surface model (nDSM) was calculated. To produce the VHM, buildings were masked out from the nDSM using the spectral information of the images and the building footprints from the Topographic Landscape Model (TLM) by swisstopo.

2.3.2. Topographic landscape Model Regio

The TLM Regio 2019 was provided by swisstopo and gives information on land-use for the identification of Agricultural Areas (Set-1), Settlements (Set-2), and Non-Agricultural Areas/Settlements (Set-3). Set-3 included wetlands, glaciers and rocks. The TLM Regio has artificial and natural landscape features that are mostly manually stereo-interpreted with an updating cycle of 6 years for the whole country. In this study, land-use information was derived from the TLM Regio data instead of from CORINE Land Cover 2006 (CLC2006), as the TLM provides a more detailed representation of land-use information and was recently updated by swisstopo. However, the forest class in the TLM Regio data had a few inconsistencies with the Forest Mask NFI 2016. A visual comparison showed that the Forest Mask NFI is more detailed than the forest class of the TLM Regio. Therefore, the Forest Mask was used to mask out all forest from the TOF map in the last stage of the workflow.

2.3.3. Forest Mask NFI

The Forest Mask is a product from the Swiss NFI with a spatial resolution of 1 m and based on the VHM and TLM land-use information and in line with the Swiss NFI forest definition. The Swiss NFI forest definition is based on minimum tree height (>$3\text{ m}$), minimum crown coverage (\(\geq 20\%\)) and minimum width (\(\geq 25\text{ m}\)) and the land-use category ‘Forest’. All areas in the VHM that meet these biophysical thresholds were masked out of the TOF map using the Forest Mask in the last stage of the workflow.

2.3.4. Reference data

The accuracy assessment of the final TOF map is based on aerial stereo-image interpretation data from the Swiss NFI (Ginzler et al., 2019). The interpretation was based on the same aerial imagery as used for the VHM and was completed for 20,638 plots on a 1.4 km regular grid across the whole of Switzerland (Brändli et al., 2020). For each plot, 25 equally distributed sub-sampling plots were interpreted within a square of $50 \times 50\text{ m}$. See Ginzler et al. (2019) and Waser et al. (2017) for further details.

2.4. Countrywide TOF mapping approach

The TOF mapping approach is based on a series of automated geoprocessing functions. The targeted TOF sets are illustrated using true-colour orthoimages in Fig. 2. Fig. 3 shows the geoprocessing steps applied to classify the VHM based on the UNFAO-FRA TOF biophysical
thresholds.

The following five steps were applied for the automated countrywide TOF mapping:

Step 1 includes the identification of land-use categories. TLM Regio 2019 was used to obtain TOF elements in the ‘Other Land’: Agricultural Areas (Set-1), Settlements (Set-2) and Non-Agricultural Areas/Settlements (Set-3). In total, nine land-use/cover categories from the TLM Regio were included in the present TOF mapping approach to define the required three land-use categories where tree cover exists as TOF: orchards and vineyards were classed as ‘Agricultural Areas’; city centres and settlements were classed as ‘Settlements’, and swamps, reservoirs, lakes, rocks and glaciers were classed as ‘Non-Agricultural Areas/Settlements’ (Table 1). In doing so, we defined the ‘Other Land’ class and used this information to extract the corresponding pixel values of each set from the VHM. Moreover, to keep the TOF elements of the ‘Other Land’, all elements that belong to the forest class – according to the TLM Regio 2019 – were excluded from the geoprocessing. Our intention was to not only keep the TOF elements and exclude the forest class from the further geoprocessing steps, but also to reduce the processing time of the VHM countrywide data set. To avoid any edge effects on very heterogeneously distributed TOF pixels over the landscape, countrywide data sets (VHM) were used without applying any image tiling.

After identification of the land-use categories, these spatial subsets were used for the extraction of the TOF information from the VHM.

Step 2 consists of the application of the biophysical thresholds and extracting the pixels from the VHM. To have a continuous set of pixels, single or group pixel gaps were filled with the majority filter tool using the parameters ‘8’ (kernel of the filter) and ‘half’ (half of the cells must have the same value and be contiguous). This process filled the gap pixels, assigned them to a certain value, and smoothed the edges of the neighbouring pixels resulting in continuous vegetation elements. After that, to calculate the patch area, neighbouring pixels were grouped using a region group operation that creates individual zones of contiguous sets of pixels under the condition of connectivity through eight nearest neighbours (both orthogonal and diagonal). The size of the individual groups was calculated with a zonal geometry function that determines the specified geometric measurement (patch area in ha) for each group of pixels. The patch area threshold applied for an individual pixel group depended on whether it was in the OLwTOF (0.05 < x < 0.5 ha) or OLwNoTOF class (x < 0.05 ha). Once the size of each pixel group met the required thresholds, the height information of each pixel was extracted from the VHM. To separate the category ‘trees’ from the category ‘shrubs and trees’, the height information of each pixel was extracted and minimum and/or maximum height thresholds were applied. Then, the threshold for the crown coverage was applied to the pixels that met the previously applied thresholds. Crown coverage was calculated using a moving window approach, with a rectangle of 11 × 11 m to correspond to the size of the interpretation plot of the Swiss NFI. For each centre pixel, the proportion of vegetation that met the height threshold inside the window was calculated and the defined crown coverage threshold of 5–10% was applied. Since the moving window approach resulted in an overestimation at the borders of TOF, morphological operations were used to remove the overestimation. The number of pixels to be shrunk was calculated by multiplying the interpretation area by the minimum crown coverage threshold, as described below (Wasser et al., 2015), i.e. number of pixels to shrink = window size × (0.5 – threshold of crown coverage). To apply the UNFAO-FRA TOF definition, the window size was taken as 11 × (0.5–0.05) (threshold crown coverage = 4.95 pixels (rounded to 5)).

Step 3 includes the application of the Forest Mask from the final output to avoid any inconsistencies between the Forest Mask and the TLM Forest class. The total TOF area was determined by calculating the area of the ‘trees’ and ‘shrubs and trees’ classes from the final output (step 4).

Step 5 includes the accuracy assessment of the TOF map with independent aerial stereo-image interpretation data from the Swiss NFI. The accuracy of the TOF map was assessed through comparison with the aerial stereo-image interpretation at each sub-sampling plot. For this, the aerial stereo-image interpretation data were filtered as follows: First, the forests and buildings were masked out, as already applied to the TOF map and the VHM. To reduce edge effects, both masks were buffered by 10 m. Second, only samples interpreted on imagery from the same year were used without applying any image tiling. To have a continuous set of pixels, single or group pixel gaps were filled with the majority filter tool using the parameters ‘8’ (kernel of the filter) and ‘half’ (half of the cells must have the same value and be contiguous). This process filled the gap pixels, assigned them to a certain value, and smoothed the edges of the neighbouring pixels resulting in continuous vegetation elements. After that, to calculate the patch area, neighbouring pixels were grouped using a region group operation that creates individual zones of contiguous sets of pixels under the condition of connectivity through eight nearest neighbours (both orthogonal and diagonal). The size of the individual groups was calculated with a zonal geometry function that determines the specified geometric measurement (patch area in ha) for each group of pixels. The patch area threshold applied for an individual pixel group depended on whether it was in the OLwTOF (0.05 < x < 0.5 ha) or OLwNoTOF class (x < 0.05 ha). Once the size of each pixel group met the required thresholds, the height information of each pixel was extracted from the VHM. To separate the category ‘trees’ from the category ‘shrubs and trees’, the height information of each pixel was extracted and minimum and/or maximum height thresholds were applied. Then, the threshold for the crown coverage was applied to the pixels that met the previously applied thresholds. Crown coverage was calculated using a moving window approach, with a rectangle of 11 × 11 m to correspond to the size of the interpretation plot of the Swiss NFI. For each centre pixel, the proportion of vegetation that met the height threshold inside the window was calculated and the defined crown coverage threshold of 5–10% was applied. Since the moving window approach resulted in an overestimation at the borders of TOF, morphological operations were used to remove the overestimation. The number of pixels to be shrunk was calculated by multiplying the interpretation area by the minimum crown coverage threshold, as described below (Wasser et al., 2015), i.e. number of pixels to shrink = window size × (0.5 – threshold of crown coverage). To apply the UNFAO-FRA TOF definition, the window size was taken as 11 × (0.5–0.05) (threshold crown coverage = 4.95 pixels (rounded to 5)).

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Fig. 3. Workflow of the Trees Outside Forests (TOF) map implementing the UNFAO-FRA TOF biophysical thresholds. TLM: Topographic Landscape Model; VHM: Vegetation Height Model.
as used for producing the VHM were chosen. This was done to remove errors due to changes that occurred at the sample locations, such as those resulting from construction and forest management activities. Third, only one of the 25 sub-samples per NFI plot was chosen randomly to mitigate cluster effects, resulting in a total of 1978 sub-samples well distributed in all production regions and elevation ranges. Fourth, the land-use categories interpreted for each sample was modified to match the TOF definition, i.e. by reclassifying ‘coniferous tree’, ‘broadleaved tree’, ‘larch’ and ‘shrub’ to TOF and all the other classes to non-TOF. However, this implementation was not entirely consistent since e.g. dwarf shrubs are classified as ‘herbaceous vegetation’ by the NFI aerial stereo-image interpretation (Ginzler et al., 2019). As a consequence, TOFs such as Juniperus communis, Rhododendron ferrugineum and Vaccinium myrtillus were assigned to the non-TOF class.

The following statistics were used: Overall Accuracy (OA) and Cohen’s kappa (K) for the whole map and the metrics Producer’s Accuracy (PA) and User’s Accuracy (UA) for the TOF class. The PA indicated the percentage of TOF reference points that belonged to the TOF class in the map, while the UA indicated the percentage of correctly classified TOF class pixels. The accuracy assessment comprised the following spatial subsets: (1) all Switzerland, (2) each of the tree TOF sets separately, (3) the five NFI production regions, and (4) the five elevation ranges $<601$, $601–1000$, $1001–1400$, $1401–1800$, and $>1800$ m a.s.l.

3. Results

The countrywide TOF map covers a total TOF area of 1,813.3 km$^2$ with a spatial resolution of 1 m (Fig. 4). TOF’s overall appearance in the settlements and agricultural areas where trees occur as TOF was reasonable, whereas trees inside the forest were completely excluded from the mapping approach. Table 2 lists the area covered by TOF within each of the relevant land-use categories and their percentages (see Fig. 5).

The accuracy assessment of the final TOF map revealed 0.95 OA (Table 3) and 0.6 Kappa. For each of the three TOF sets, the OA was

### Table 1
The distribution (area and percentage) of the three land-use categories according to TLM Regio 2019 data.

| Land Use                  | Total Area (km$^2$) | Percentage |
|---------------------------|---------------------|------------|
| Other                     |                      |            |
| Agricultural Areas        | 17,343              | 42.0%      |
| Settlements              | 3182                | 7.7%       |
| Non-Agricultural Areas/  | 9623                | 23.3%      |
| Settlements              |                      |            |
| Forest                    | 11,137              | 27.0%      |
| Total                     | 41,285              | 100.0%     |

### Table 2
Area per land-use category and the percentage of TOF cover within each category.

| TOF Set              | Area (km$^2$) | TOF (km$^2$) | Percentage |
|----------------------|---------------|--------------|------------|
| Agricultural Areas   | 17,343        | 992          | 5.7%       |
| Settlements          | 3182          | 683          | 21.4%      |
| Non-Agricultural Areas/ Settlements | 9623 | 131 | 1.3% |
| Total                | 30,148        | 1813         | 6.0%       |

Fig. 4. TOF map of Switzerland (shown in green) covering the five forest production regions © swisstopo (JA100118). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
greater than 0.89, which indicated successful classification. The lowest OA was obtained for elevations at 1401–1800 m a.s.l. (0.87) and for the Southern Alps (0.91), while the highest values were obtained for areas at 600–1000 and 1000–1400 m a.s.l. (0.96) and for the Pre-Alps (0.96), Central Plateau (0.95) and Jura (0.95), respectively. For most TOF sets, the UA was higher than the PA, indicating an underestimation of TOF. Specific attention should be given to the low PA (0.54) for Agricultural Areas, which had the highest UA overall (0.86). Moreover, both PA and UA decreased with increasing elevation and were lowest for areas higher than 1800 m a.s.l. This trend was observed in all production regions.

4. Discussion

The most significant contribution of this research is the finding that automated countrywide TOF mapping is feasible if UNFAO-FRA TOF biophysical thresholds are applied to a VHM that is based on routinely acquired aerial stereo-images. In the present study, an overall accuracy of the final TOF of 95% was achieved, which is comparable to accuracies achieved in other studies, as reviewed by Schnell et al., (2015). However, a direct comparison with these studies is difficult because different remote sensing data sets, with different spatial resolutions were used with traditional pixel- and object-based classifications (Zomer et al., 2014; Meneguzzo et al., 2013). Moreover, none of the previous studies included biophysical thresholds. Instead, they used morphological classifications while mapping TOF, such as single, linear, and ample objects (Bolyn et al., 2019) or forest / non-forest classes (Foschi & Smith, 1997). It should also be noted that the study areas used in previous investigations were relatively small, e.g. on the municipality level (Rutzinger et al., 2008; Bolyn et al., 2019).

With this study, we propose a method for countrywide TOF mapping that uses the biophysical thresholds (patch area, plant height, crown coverage) and is in line with or can be adapted to any forest definition of the countries. From this point of view, it is complementary to the NFI forest definitions and is capable of producing countrywide maps including forest areas and trees outside forests based on the required biophysical thresholds for both. From a data set perspective, VHMs derived from image-based point-clouds (Ginzler & Hobi, 2015) are sufficient and enable to obtain the defined biophysical thresholds of TOF. Additionally, the biophysical thresholds used in our study are aligned with the TOF definitions of national (Swiss NFI) and international (UNFAO-FRA) reporting bodies, but still flexible enough to adapt to the definitions of other reporting bodies, such as the State of Europe’s Forest.

4.1. Errors of omission and commission

Errors of omission (OE) refer to NFI sub-sampling plots that were
omitted from the correct class in the final map, specifically it is the complement of PA (OE = 1 − PA). Most of the OE in the final TOF map are related to the settings of biophysical thresholds, explicitly in Agricultural Areas (i.e. corn and sunflower fields). A height threshold of 2.5 m had the consequence that some smaller shrubs (pixels) were removed from the final TOF map (0.54 PA) (Fig. 6).

Errors of commission (CEs) are calculated by reviewing the classified TOF pixels for incorrect classifications and are the complement of UAs (CE = 1 − UA). Some agricultural crops (corn and sunflower) that are taller than 2.5 m were still extracted as the ‘shrubs and trees’ category for the final TOF map (CE) (Fig. 7-1 a, b). The use of time-series data might enable the mapping of agricultural fields and help to exclude the pixels in these areas from the TOF map. Linear TOF elements, e.g. street edges and riparian corridors, were another source of CEs. In cases where the distance between the two sides of a street or river was small (<20 m from the centre of one tree to the centre of another), those TOF elements were tendentially mapped as one single object (CE). For example, if two parallel lines of trees are close together, the area between the lines fulfills the criteria of a minimum crown coverage of 10% and is mapped as TOF. This has two reasons: (1) Pixels can be overestimated because of the moving window approach (Fig. 7-2 a, b, -3 a, b). A data set with information about roads and rivers might enable a separate classification of these elements. (2) Some CEs can be attributed to the fact that dwarf shrubs are part of the non-TOF class in the NFI reference data. As a result, correctly classified TOF in the form of dwarf shrubs would be treated as CEs in the accuracy assessment.

The vertical accuracy of the VHM is decreased at higher elevations and in steep slopes, resulting in a lower accuracy for these locations (larger OE and CE) (Ginzler & Hobi, 2015). We conclude that the accuracy of the VHM at high elevations remains a limiting factor, despite its continuous improvement. Further research is needed to improve the mapping of Set-3 (Non-Agricultural Areas/Settlement), which is mostly found at elevations above 1400 m a.s.l. Additionally using NDVI to avoid the over estimation of TOF (i.e. street/riparian trees) would decrease CE. The methodological approach proposed in this study could therefore be used with such a data set. However, this would not exclude the evaluation of satellite imagery as an alternative to digital aerial imagery for TOF mapping.

4.2. Operational use of the TOF map

Principally, our countrywide TOF mapping approach could be applied to any VHM and is therefore appropriate for countrywide mapping. VHMs are reliable data sets that are required to derive the geometric parameters of the biophysical thresholds of the UNFAO-FRA TOF definition: patch area, minimum height and minimum crown coverage. Since these thresholds directly depend on the VHM, they can easily be adapted to the relevant biophysical TOF definitions of other countries. However, full availability of actual and countrywide aerial stereo-imagery or LiDAR data could be a limiting factor for the application in much larger countries than Switzerland. Alternatively, Digital Globe’s multispectral stereo-imagery derived from QuickBird-2, GeoEye-1, and WorldView-2/3/4 could be used to generate VHMs in large-area TOF assessments (Brandt et al., 2020).

The method we present here is also applicable to LiDAR-based VHM data. Moreover, the proposed method could help other countries to create their own data sets on non-forest tree resources as input to energy, environment, forest policy-making, and wood industry decision-making and to contribute to the development of strategies to better cope with the challenges of a changing climate and environment.

We believe that the availability and the application of methods like the one proposed in this paper will stimulate the integration of TOF into forest inventories in general and the Swiss National Forest Inventory specifically. Furthermore, it will help to integrate information on TOF resources into land-cover databases. This will in turn fill a critical spatial TOF information gap in landscape management. Moreover, with the method we present countrywide investigations might become more feasible for the other countries. Hence, it is planned to expand the proposed method to the European Alpine arc. Finally, the TOF map of Switzerland will be a valuable data source to assess the biomass, carbon sequestration potential, and tree species distribution of TOF resources on a countrywide scale.

5. Conclusions

In this study, an automated approach to countrywide TOF mapping for Switzerland (41,285 km²) based on a high-resolution VHM was realised, revealing that 6% of the country is covered with TOF. The proposed method incorporates three different TOF sets found in Agricultural Areas, Settlements and Non-Agricultural Areas/Settlements that match the biophysical definitions of the UNFAO-FRA.

Since a detailed description of the automated and efficient mapping algorithm was given, the proposed method can be repeated for other countries – provided that a VHM is available. The use of a standard definition for TOF allowed our TOF mask to be nationally and internationally functional for reporting purposes.

In the present study, reliable results with high OA (0.95), and moderate PA (0.55) and UA (0.75) were achieved and clearly demonstrates that automated TOF mapping is feasible in a timely and cost-effective manner with the internationally accepted TOF definition. In addition, the results fill an important knowledge gap by providing spatially explicit information on the distribution of TOF for entire Switzerland. This suggests that repeatedly acquired high-resolution

Fig. 6. Error of omissions: 2.5 m height threshold lead to underestimation of some TOF elements (omitted plants between the two green trees) © swisstopo (JA100118). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
remote sensing data have a huge potential to facilitate the mapping and monitoring of countrywide TOF in the long term and to stimulate TOF-related research.

CRediT authorship contribution statement

Eylül Malkoç: Conceptualization, Methodology, Investigation, Visualization. Marius Rüetschi: Validation, Writing - review & editing. Christian Ginzler: Resources, Writing - review & editing. Lars T. Waser: Conceptualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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