

An automated method for mapping physical soil and water conservation structures on cultivated land using GIS and remote sensing techniques

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Abstract: An efficient and reliable automated model that can map physical Soil and Water Conservation (SWC) structures on cultivated land was developed using very high spatial resolution imagery obtained from Google Earth and ArcGIS®, ERDAS IMAGINE®, and SDC Morphology Toolbox for MATLAB and statistical techniques. The model was developed using the following procedures: (1) a high-pass spatial filter algorithm was applied to detect linear features, (2) morphological processing was used to remove unwanted linear features, (3) the raster format was vectorized, (4) the vectorized linear features were split per hectare (ha) and each line was then classified according to its compass direction, and (5) the sum of all vector lengths per class of direction per ha was calculated. Finally, the direction class with the greatest length was selected from each ha to predict the physical SWC structures. The model was calibrated and validated on the Ethiopian Highlands. The model correctly mapped 80% of the existing structures. The developed model was then tested at different sites with different topography. The results show that the developed model is feasible for automated mapping of physical SWC structures. Therefore, the model is useful for predicting and mapping physical SWC structures areas across diverse areas.

Keywords: physical SWC structure mapping; automated; mathematical morphology; GIS and remote sensing

1 Introduction

1.1 The need for mapping physical soil and water conservation structures

Identifying and mapping the existing physical SWC technologies is crucial to determine the adoption rate of specific conservation measures and their effectiveness against land degradation and soil erosion. Recognizing the importance of mapping SWC measures, World Overview of Conservation Approaches and Technologies (WOCAT) researchers launched an ini-

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tiative to develop a world map displaying areas where land resources are being used sustainably (Schwilch *et al.*, 2004). Bringing together various experts and land users, WOCAT teams have identified, documented, and mapped SWC technologies and approaches in numerous countries (Liniger *et al.*, 2007). They assessed the spatial extent, effectiveness and impacts of conservation measures using qualitative data (Van Lynden *et al.*, 2012).

In the Ethiopian Highlands, physical SWC structures have been constructed on cultivated land for many years, in an effort to reverse land degradation and improve crop yields. Although physical SWC structures have been used throughout the country since the 1970s, there is no record of where they have been maintained. Having scientific data on the spatial extent of physical SWC structures can be helpful to identify areas where these measures are being effectively used as well as areas where urgent intervention is needed to manage the land resource sustainably. To date, however, the challenges of detecting physical SWC structures over a larger area in an efficient and automated manner have not been addressed in the literature. Nevertheless, recent advances in remote sensing techniques and image analyst software, as well as the need for mapping physical SWC structures over large areas, encouraged us to develop an automated method capable of mapping physical SWC structures on cultivated lands.

1.2 Remote sensing imagery for linear feature mapping

Linear features are geographic elements that can be represented by a line or set of lines, i.e. polylines. Rivers, roads, electric and telecommunication networks, pipelines, field boundaries, trails, physical SWC structures, and ditches are all linear features. Linear features refer to man-made objects, such as field boundaries, stone/soil bunds, ditches, and terraces (Bailly *et al.*, 2008). On satellite imagery, a linear feature is defined as a sequence of points that has a maximum or minimum Digital Number (DN) value not surrounded by pixels of higher gray values in a linear window, or it is manifested as an abrupt change in DN along a certain direction in an image (Gao, 2009).

Although the extraction of large features from coarse imagery is not a difficult task, extraction of small objects or linear features is challenging (Quackenbush, 2004). In moderately high spatial resolution imagery, the pixel size is wider than the dimensions of the linear features, which complicates automated extraction of these features. However, high spatial resolution imagery has very rich and clear information about the target object (Li *et al.*, 2010) and typically has pixels that are smaller than the dimensions of the targeted linear features. Thus, high spatial resolution imagery has become very useful for linear feature extraction and is now used by several researchers for road mapping and other purposes. Very high spatial resolution satellite imagery is necessary for automated linear feature detection (Quackenbush, 2004; Bailly *et al.*, 2008), and has become a determinant for the effectiveness of available linear feature extraction algorithms and techniques (Gao, 2009). Yang and Zhu (2010) have clearly indicated that successful linear feature extraction depends on the spatial resolution of the image.

Several researchers have used different imagery for the extraction of linear features such as roads, ditches, and pipelines. For example, radar data was used for road extraction (Hellwich *et al.*, 2002). Bhakar *et al.*, (2010) used ASTER Digital Elevation Model (DEM), for the extraction of irrigation networks. Bailly *et al.* (2008) used airborne Light Detection and

Ranging (LiDAR) data for ditch network extraction. Yun and Uchimura (2007) extracted road networks efficiently from IKONOS images. Frigato and Silva (2008) used QuickBird satellite imagery for the extraction of roads. Kim and Hong (2012) were able to detect boundaries in areas of diverse land cover using IKONOS data.

Therefore, the very high spatial resolution remote sensing imagery (on the order of meters and centimeters) provided by sensors such as QuickBird (DigitalGlobe, Inc., Longmont, CO), SPOT (Spot Image, Toulouse, France), GeoEye (DigitalGlobe, Inc., Longmont, CO), OrbViewSM (GeoEyeSM Imagery Collection Systems, Inc., Herndon, VA) and IKONOS (DigitalGlobe, Inc., Longmont, CO) is useful for recognizing and detecting small objects and linear features. At present, Google Earth provides such a very high spatial resolution images from airborne and space-borne remote sensing, sufficient for extraction of objects (Guo *et al.*, 2010). Hence, Google Earth has been used by numerous people as a source of high spatial resolution imagery for different applications (Allen, 2009).

1.3 Linear feature mapping techniques

GIS has become extremely useful when detecting small and linear objects on Earth's surface (Gao, 2009; Huang *et al.*, 2010). Similarly, at present various software programmes used to detect and analyse objects from remote sensing images. These include ERDAS IMAGINE® (Intergraph Corporation, Huntsville, AL), ArcGIS®, and SDC Morphology Toolbox for MATLAB, version 1.6. (developed by SDC Information Systems, Naperville, IL).

A wide range of techniques for detecting and extracting linear features from very high spatial resolution imagery have been developed and used by researchers. Most of them were developed to detect and map roads (Quackenbush, 2004). Some of the techniques are automated (e.g. Baumgartner *et al.*, 1999), whereas others are semi-automated (e.g. Yun and Uchimura, 2007). The most popular automated techniques used for linear and non-linear feature detection from high-resolution images are edge detection (e.g. Tamilarasi and Duraiswamy, 2010), mathematical morphology (e.g. Frigato and Silva, 2008; Bhirud and Mangala, 2011), segmentation/classification (e.g. Yang and Wang, 2007; Jin and Feng, 2010), and the Hough transform (e.g. Fitton and Cox, 1998).

Though there are many linear-feature extraction methods and algorithms (e.g. for roads and geological lineaments), no single method is able to detect and map physical SWC structures effectively on its own (Figure 1). Indeed, the approaches used to detect and map linear features such as roads and ditches – can be used in combination with other techniques to map physical SWC structures.

In very high spatial resolution imagery, linear features such as physical SWC structures, roads, rivers, railways, and field and vegetation boundaries are visible and can be extracted manually or automatically. Some researchers argue that a semi-automated approach to this task is ideal because people can identify objects almost perfectly even in a noisy image (Quackenbush, 2004). Yang and Zhu (2010) confirmed that centrelines can be extracted rapidly and accurately from 0.6-m-resolution QuickBird and 1-m-resolution IKONOS satellite images using a semi-automatic method. It should be noted, however, that manual techniques are time-consuming and costly when used exclusively and are not advisable in an era when high-resolution imagery and several powerful image-processing systems are available. On the other hand, the automatic extraction of linear features is doubtless important to the

fast and effective processing of raster imagery and for covering large areas within a short time, depending on the processing capacity of the computer. Thus, automated extraction of linear features from raster imagery has become a very important part of image processing systems, such as ArcGIS and ERDAS IMAGINE®, and has grabbed the attention of several researchers.

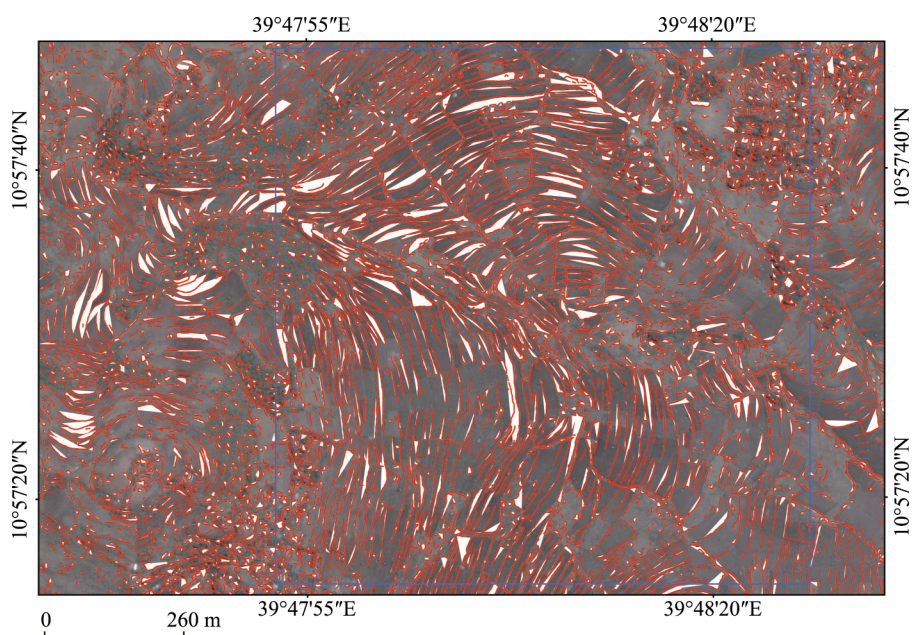


Figure 1 Linear and non-linear features detected after edge detection technique and vectorization

Mapping the spatial distribution of physical SWC structures is important in order to identify the extent of conserved and non-conserved areas on national, regional, and local levels. However, to date no method capable of automatically detecting and mapping such structures on cultivated land has been developed. Realizing these gaps the study aimed at developing automated model that can map existing physical SWC structures on cultivated lands in the Ethiopian Highlands.

1.4 Objective

The objective of this paper was to develop a model capable of mapping physical SWC structures on cultivated lands.

2 Material and Methods

2.1 Materials

The main data used for developing the mapping model was satellite imagery and verified physical SWC structures. The satellite data comprised very high spatial resolution images (pixel size less than or equal to 1 m) available from Google Earth. The Google Earth was chosen as the source of satellite imagery because it provides very high spatial resolution images covering large areas free of charge, and its detailed and comprehensive coverage of Earth's surface. Thus, after identifying the areas for which very high spatial resolution satel-

lite images were available from Google Earth, we downloaded, georeferenced, and mosaicked the images using ERDAS IMAGINE® and ArcGIS®. To process the data image analyst software such as ERDAS IMAGINE®, ArcGIS® and SDC Morphology Toolbox for MATLAB, version 1.6 were used. This is because individual software programmes may be effective in one step but less effective in other steps. For example, ERDAS IMAGINE® is effective for image classification but not for vectorization or morphological operations. By contrast, ArcGIS® and SDC Morphology Toolbox for MATLAB 1.6 are very effective when it comes to vectorization and morphological operations, respectively, but are less effective for image classification. Therefore, software programmes mentioned previously were used to develop a mapping method for physical SWC structures in the present study.

2.2 Methods

2.2.1 Case study area selection

To map the physical SWC structures, the availability of very high spatial resolution satellite imagery (1 meter or better) was critical. Because the edge detection and image classification algorithms used by image analyst software programmes may not properly detect SWC structures in images whose individual pixels are larger than the width of individual structures (Chang *et al.*, 2004).

Google Earth provides very high spatial resolution satellite imagery for large areas of Ethiopia and other countries. When the present study was launched, suitable Google Earth imagery was available on two strips (Figure 2). Because of this, the two strips were selected to develop the physical SWC structure mapping model. Then each strip was divided into small grids (1 km by 1 km). After this, the cultivated lands with dense physical SWC structures were assessed grid by grid using Google Earth. Based on the availability of physical

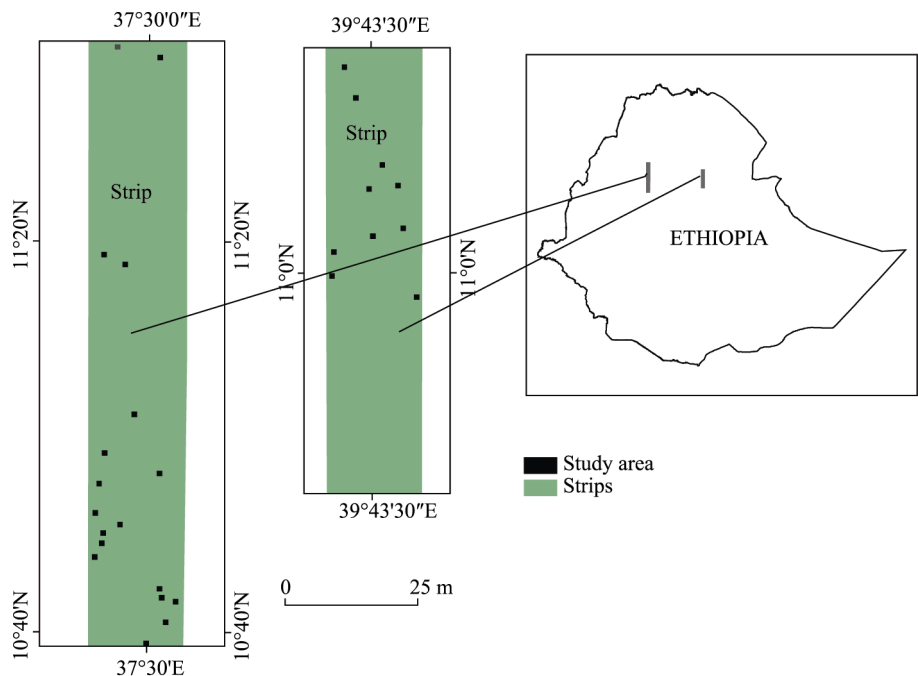


Figure 2 Location map of the study area

SWC structures, a total of 28 grids were selected randomly for the case study areas (18 from one strip and 10 from the other strip).

2.2.2 Ground truthing

Ground truthing is necessary for checking the accuracy and quality of an object being mapped remotely. This is usually done based on ground references, obtained by observing the object and collecting its geographical coordinates (Gao, 2009). Therefore, after the physical SWC structures and other linear features were mapped in analogue format, the following steps were used to verify the accuracy and quality of the map. First, the case study areas were identified on the ground using the prepared map and a handheld Global Positioning System (GPS) – specifically GPSMAP[®] 60CSx (Garmin Ltd., Southampton, United Kingdom) – with an accuracy of ± 3 m. Second, linear features mapped as physical SWC structures were verified by travelling to each plot. To accommodate cases where physical SWC structures had been demolished or had been shifted on cultivated land but still existed on the map, the landowners and the local development agents were asked to pinpoint where structures had been constructed. Linear features mapped as trails and rivers were verified following the same procedure.

2.2.3 Image processing

On the very high spatial resolution input images, objects (with differences in shape, tone, and texture) on the targeted surface are clearly visible (Figure 3). However, extracting specific objects is difficult because the imagery contains numerous features including physical SWC structures, trails, rivers, field boundaries, grazing land, houses, and trees.

Figure 3 clearly shows that within the cultivated lands of the Ethiopian Highlands where physical SWC structures have been built, different land uses including grazing, vegetation, and housing were found. Therefore, to detect and map physical SWC structures from such image the following image processing procedures were used.

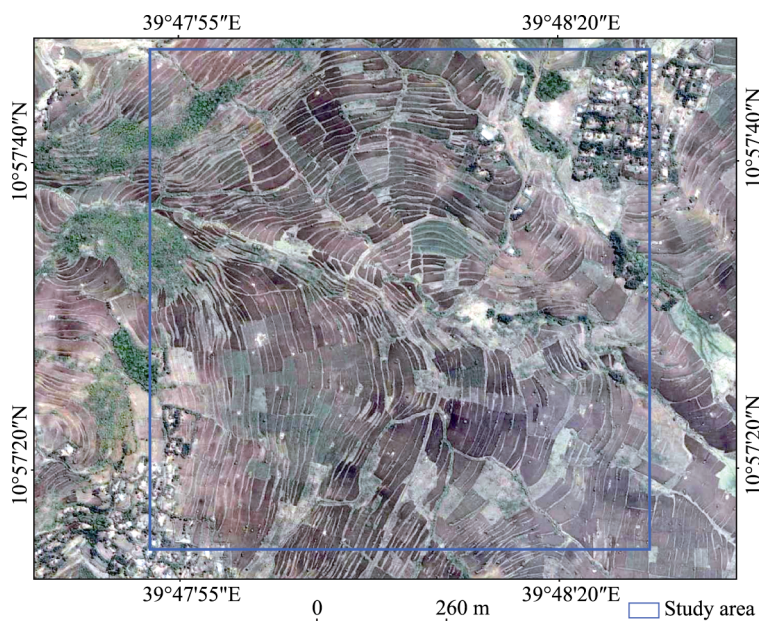


Figure 3 Map showing an input image obtained from Google Earth

(1) Edge detection

Edge detection is a technique or algorithm that is used to detect and extract edges from an input image based on discontinuities in DN values (Tamilarasi and Duraiswamy, 2010). Similarly, Rowe and Grewe (2001) found that edge detection is effective in detecting linear features in high spatial resolution images. Thus it is an important step in finding changes in the intensity value of pixels as well as in the structure of objects found in an input image (Roushdy, 2006). A spatial filter is required to determine whether a certain pixel belongs to an edge set or not (Singh and Singh, 2012). Structural features were extracted using the Laplacian filter (Aksoy *et al.*, 2012). Pirasteh *et al.*, (2011) found that the high-pass filter is more reliable for the detection of geo-structural lineaments than the low-pass, Laplacian, and directional filtering techniques.

In this study, different spatial enhancement functions, such as high-pass spatial filtering, Laplacian edge detection, and non-directional edge filters (e.g. the Sobel and Prewitt operators), were tested to enhance the linear features. As can be seen in Figure 4a, the high spatial filter algorithm can effectively detect physical SWC structures and other linear features than other techniques. Therefore, different linear features on the cultivated lands were enhanced and identified using a high-pass spatial filter available in ERDAS IMAGINE® software.

Although physical SWC structures were enhanced, other features with similar DN values also appeared over the cultivated land. In addition, certain linear structures that appeared continuous in the input image ended up looking segmented in the enhanced image. However, the edge enhancement process successfully distinguished most of the necessary features and unwanted edges. To minimize the distribution of unwanted edges, an image classification method was used.

(2) Image segmentation using the ISODATA algorithm

In different sites we observed that physical SWC structures generally have good contrast from adjacent cultivated lands, except when the cultivated land is covered by mature crops or the straw of barley, maize, teff, wheat, and sorghum. However, field boundaries, grazing lands, trails, ditches, and threshing plots have spectral characteristics similar to those of the physical SWC structures. This indicates that the DN values of physical SWC structures are within a certain range. Therefore, after high-pass spatial filtering was performed, image segmentation using the ISODATA algorithm was applied to divide the images into two classes (i.e. smooth and sharp). Similarly, Yang and Wang (2007) and Jin and Feng (2010) used automatic segmentation to detect various roads. Pixels with a more or less similar DN value were divided into the same classes. This made it possible to preserve physical SWC structures while filtering out the majority of unwanted small objects. However, unwanted features such as small isolated objects, branches, and linear and nonlinear elements exist on the target image because their pixel spectral characteristics are similar to those of nearby physical SWC structures.

(3) Morphological processing

Linear features can be properly detected from binarized images based on its geometric structures (Tamililakkiya *et al.*, 2011). Therefore, to facilitate detection and extraction of physical SWC structures on the basis of their shape and structure and the removal of unwanted linear features, the imagery was binarized for further processing. After this SDC Morphology Toolbox for MATLAB 1.6 (an image processing and analysis system based on the geometric structure within an image) and the programme Mathematical

Morphology Toolbox contained in MATLAB® 2010a (Math-Works®, Inc., Natick, MA) software was used to detect and extract physical SWC structures. Then, dilation and erosion morphological operations such as opening, closing, thinning and skeletonization were applied (Figure 5). The dilation operator has expanding and filling effects, i.e. it adds pixels to the target object. By contrast, the erosion operator has eliminating and shrinking effects, i.e. it removes pixels from the target object based on the defined structure element (Quackenbush, 2004).

2.2.4 Vectorization

The skeletonized raster data obtained using mathematical morphology was exported to ArcGIS. Then the raster data was converted to vector features using the centreline vectorization algorithm, which generated vector features along the centre of the raster linear elements. The majority of physical SWC structures and other unwanted linear features were extracted (Figure 6).

2.2.5 Application of statistical techniques for removal of unwanted linear features

In GIS, features are described according to their spatial information and attributes (Shahin, 1997). For physical SWC structures, the spatial information includes an object’s shape (structure) and geographical coordinates, whereas the important attributes are compass direction and length.

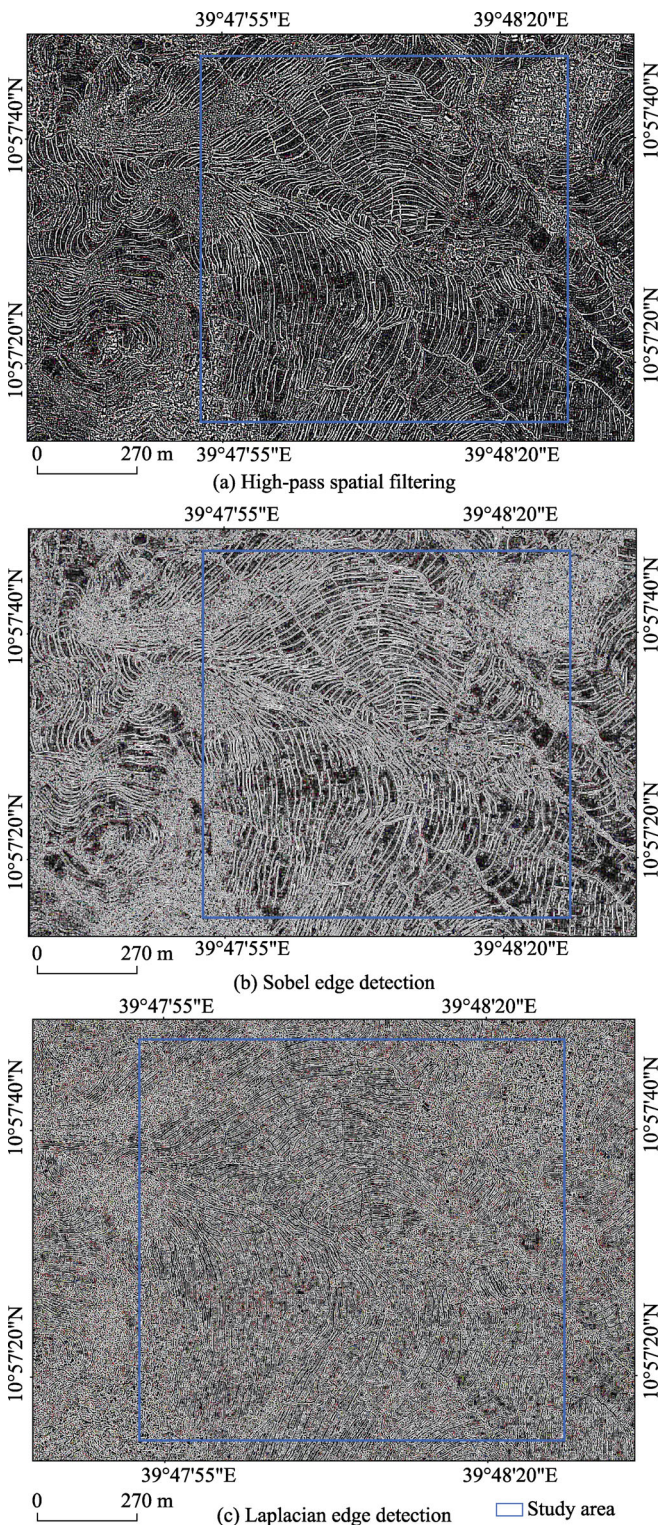


Figure 4 Map showing different linear features after applying High-pass spatial filtering (a), Sobel edge detection (b), and Laplacian edge detection (c)

Figure 6 shows that most extracted polylines represent physical SWC structures, and they have similar directions in a given land unit. However, in the case study area (1 km²) where the aspect is quite heterogeneous, it is difficult to ascertain the major direction of the extracted polylines. To get a land unit in which most of the polylines have a similar direction the case study area was divided into land units: 30 m by 30 m, 50 m by 50 m and 100 m by 100 m. In rugged topography, the 50 m by 50 m unit gives better result. However, in flat lands the 100 m by 100 m units give better result. In both landscapes, the 100 m by 100 m gives better result (Figure 7). Therefore, to get a land unit in which most of the polylines have a similar direction, each case study area was divided into 100-ha units, 100 m by 100 m each. Here, the assumption was that use of length and compass direction classes made it possible to preserve physical SWC structures and also remove unwanted linear features because the physical structures represent the primary direction on any cultivated land where the structures are maintained.

- (a) Result obtained after classifying the site into 30 m by 30 m grid
- (b) Result obtained after classifying the site into 50 m by 50 m grid
- (c) Result obtained after classifying the site into 100 m by 100 m grid
- (d) Verified SWC structures

Therefore, physical SWC structures were preserved and mapped (Figure 8) using the following procedures. The extracted polylines were split per ha and the length of each line was calculated. Once this was done, the compass direction of each line was determined and displayed in terms of azimuth angles. After the compass direction of each line (0°-360°) was calculated, it was reduced to 0° to 180° because no direction is given per vector. The 0° to 180° compass directions were divided into four direction classes. Each line was then put into a direction class based on its compass direction and, the sum of all vector lengths per compass direction class per ha was calculated. Finally, the top-length class from each hectare was selected and the remaining direction classes were removed using MySQL Workbench5.2 CE.

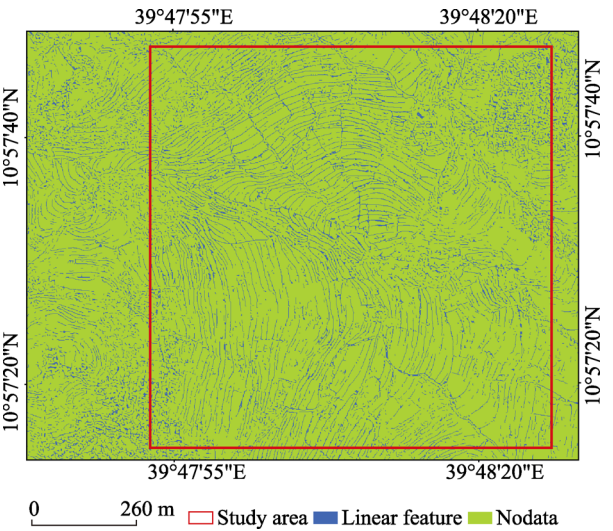


Figure 5 Map showing physical SWC structures and other linear features after skeletonization

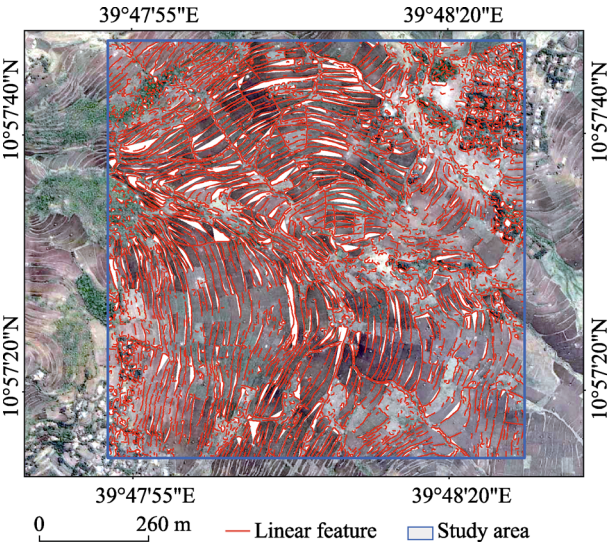


Figure 6 Map showing the extracted linear features

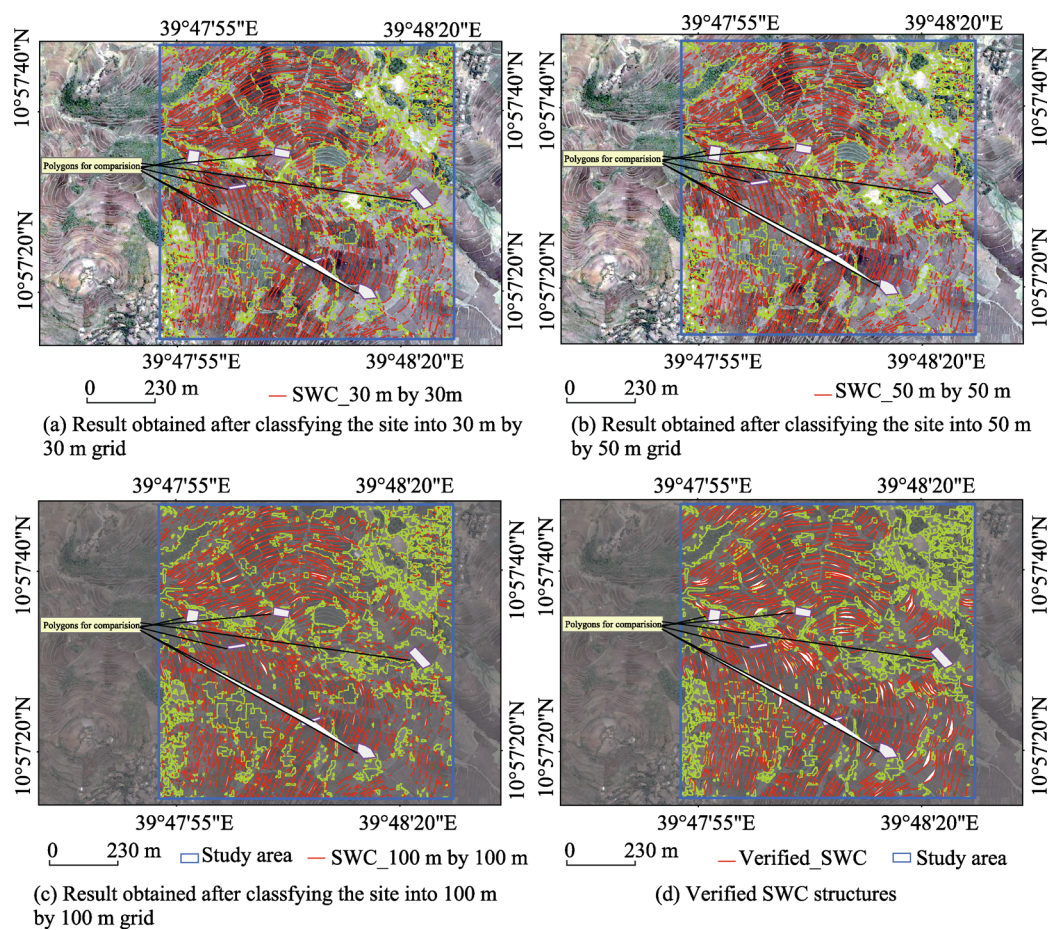


Figure 7 Maps showing SWC structure obtained in different land units: 30 m by 30 m (a), 50 m by 50 m (b), 100 m by 100 m (c) and verified SWC structure (d)

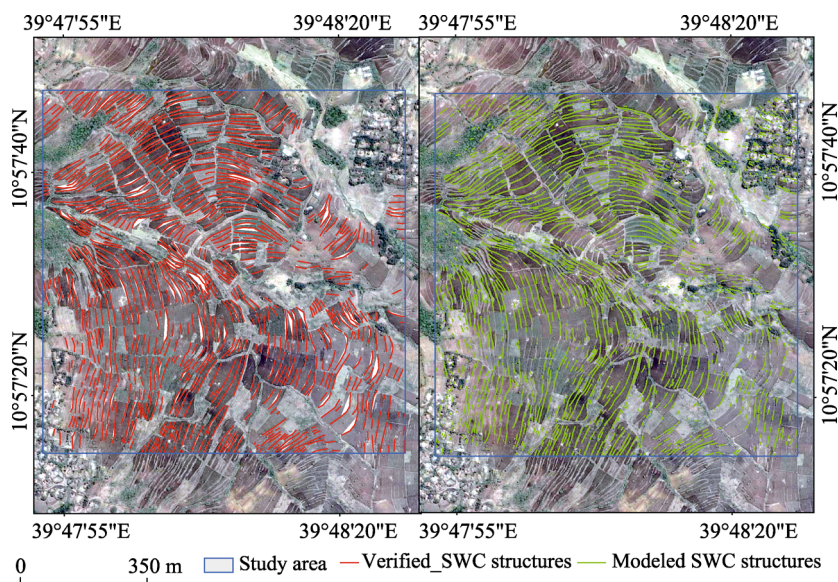


Figure 8 Map showing the verified (left) and automatically mapped (right) physical SWC structures in one site

3 Calibration and validation of the model

The developed model was calibrated in the Ethiopian Highlands to check its accuracy. For this purpose 26 sites (1 km² each) were randomly selected from areas where very high spatial resolution satellite images were available on Google Earth and the physical SWC structures in each area were mapped in the field using the procedure described in section 2.2.2. In addition, the physical SWC structures were mapped automatically using the developed model. After this, each site was split into 100-ha units. Then the total length of the mapped and predicted physical SWC structures was calculated. Finally, the length of the mapped physical SWC structures was correlated with the length of the modelled structures. The result shows that there was a strong positive correlation between the lengths of the verified and predicted physical SWC structures. In addition, there is a significant relationship between the two variables (Figure 9a), $r^2 = .90$, $n = 26$, $p < 0.001$. The result also shows that the model could correctly map nearly 80% of the physical SWC structures, missing about 20% of the necessary structures. Therefore, it can be concluded that the proposed model performed well when mapping physical SWC structures from high spatial resolution satellite imagery.

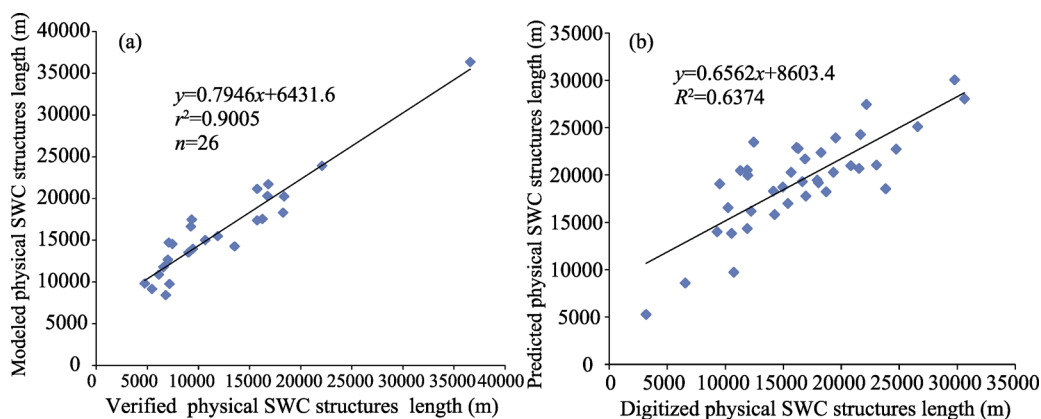


Figure 9 Graph showing the relationship between verified and predicted physical SWC structures (calibration samples sites: $n = 26$) (a), and the relationship between digitized and predicted physical SWC structures (validation samples sites: $n = 39$) (b)

The developed model was validated in the Ethiopian Highlands to check its applicability. For this, 39 sample sites (1 km² each) were randomly selected from five strips (Figure 10). In each site, the physical SWC structures were digitized from the imagery, and each site was split into 100-ha units. The total length of the digitized physical SWC structures was then calculated. In the same site, the physical SWC structures were predicted using the developed model. Following this, the total length of the modelled physical SWC structures was calculated. Finally, the length of the digitized physical SWC structures was correlated with the length of the modelled structures (Figure 9b).

There was a positive correlation between the digitized and predicted physical SWC structures, $r^2 = .64$, $n = 39$, $p < 0.001$. As shown in the graph (Figure 9b), a moderate relationship between the digitized and predicted terrace lengths was found in some sites. This moderate relationship occurred in sample sites where most of the land is non-cultivated and covered mainly by vegetation and also in areas where the images were taken during the har-

vest season. However, this discrepancy did not significantly affect the validation of the model. Overall, there was a positive correlation between the digitized and predicted terraces. This result indicates that the developed model effectively predicted the physical SWC structures from high spatial resolution satellite imagery of the sample sites and thus can be applied to other areas. The model has also been applied in different areas of the Ethiopian Highlands with varied ground cover and with high spatial resolution images taken in dry season. The model was able to properly map the physical SWC structures from different images and areas (Figure 11), demonstrating its versatility.

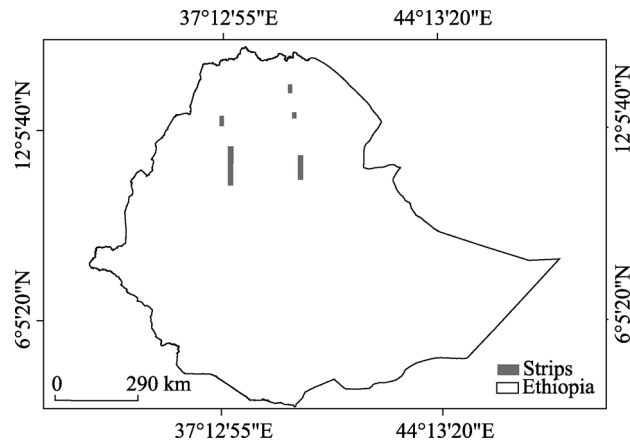


Figure 10 Map showing the strips where the model was validated

4 Discussion

The developed model is very efficient for mapping the physical SWC structures on cultivated land in circumstances where very high spatial resolution imagery is available. It was observed that in areas where the cultivated land was covered by the straw of crops or in areas where the images were taken during crop growing season, it is very difficult to separate the physical SWC structures from other features.

Figure 12 presented an example of the verified and modelled physical SWC structures. The red and green lines indicate the verified and modelled physical SWC structures, respectively. The results show that the model has efficiently mapped the physical SWC structures on the cultivated lands. However, linear features that have similar intensity and geometric shapes as the terraces (e.g. field boundaries, ditches, streams, and trails) were also mapped, and both types are clearly visible on the superimposed maps.

4.1 Strengths of the model

(1) Automated. Remote sensing provides very high spatial resolution imagery for many applications. From such image, nearly all natural and man-made objects with dimensions at least equal to the pixel size can be derived. This process can be done automatically and/or manually. Digital mapping of physical SWC structures is required to assess and update their spatial distribution and sustainability. Although the physical SWC structures can be manually identified and mapped on high-spatial resolution imagery with ease, manual extraction is time-consuming and costly. Available satellite imagery and image analysis software

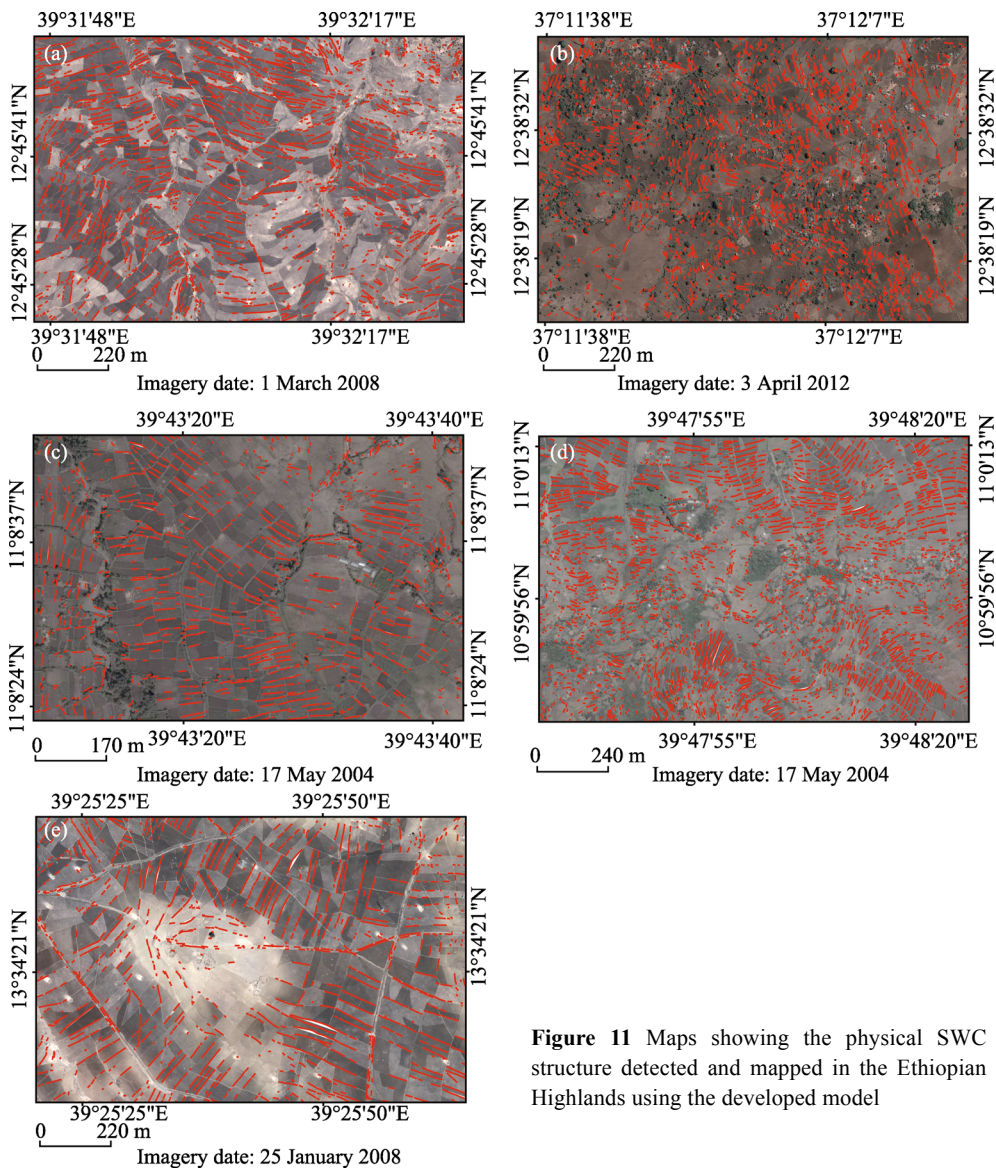


Figure 11 Maps showing the physical SWC structure detected and mapped in the Ethiopian Highlands using the developed model

provide opportunities to overcome these temporal and cost barriers. However, automated extraction of the physical SWC structures from satellite images is still a difficult task. Therefore, the researcher developed an automated model capable of mapping these structures with improved speed and accuracy, irrespective of the size of the area.

(2) Applicability. The physical SWC structure mapping model has been used with high spatial resolution images obtained from different sensors including IKONOS, WorldView, QuickBird, GeoEye, and SPOT, and taken in dry season. The model has also been applied in different areas of the Ethiopian Highlands with varied ground cover. With calibration, the model was able to properly map physical SWC structures from different images and areas.

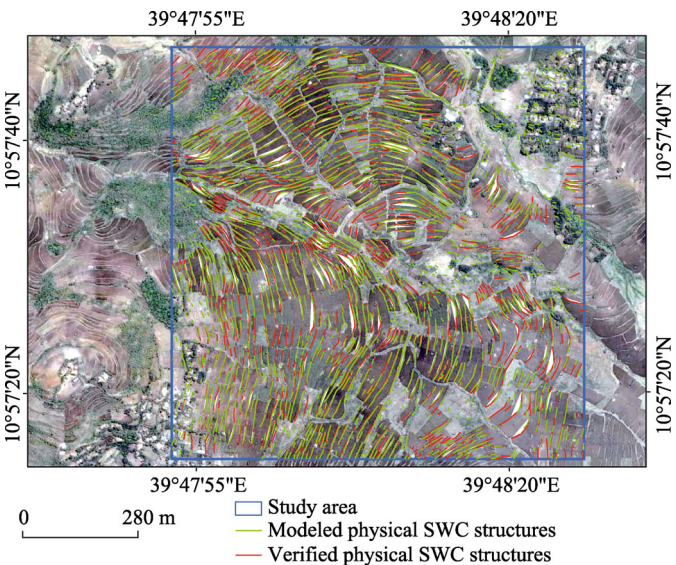
(3) Data availability. The model works on images available on Google Earth. Google Earth imagery is relatively detailed and comprehensive, and acquisition is fast and flexible. Above all, it provides very high spatial-resolution images for different applications freely.

4.2 Conditions of the model

The developed physical SWC structure mapping model was very effective on cultivated land where very high spatial resolution satellite imagery was available. However, the effectiveness of the model depends on the following conditions:

(1) Date of imagery. The model was not effective in areas where the imagery was taken during crop growing season. It is found that on images taken prior to the harvest season, where the cultivated land was covered by mature crops (e.g. maize and sorghum), visualization of physical SWC structures in a raster image was almost impossible. Likewise, in areas where the cultivated land was covered by the straw of crops, separation of physical SWC structures from other linear features was difficult. Consequently, the model mapped many linear features with brightness values and geometric structures similar to those of the physical SWC structures. The season when the imagery was taken thus had a substantial impact on the quality of the interpretation. This problem can be solved by applying the model on imagery taken before crop growing season and after harvest season.

(2) Land cover. The model has the ability to map any linear features from all land use types. Therefore, processing the whole land use types affects the quality of the mapped physical SWC structures. Given this situation, although detailed land use/land cover classification over such a large area represented another difficult task, it was noted that application of the model after masking of the non-cultivated lands and non-grass lands will give accurate results (Figure 13)(3) Presence of non-physical



Figures 12 Maps showing verified (red lines) and automatically mapped (green lines) physical SWC structures

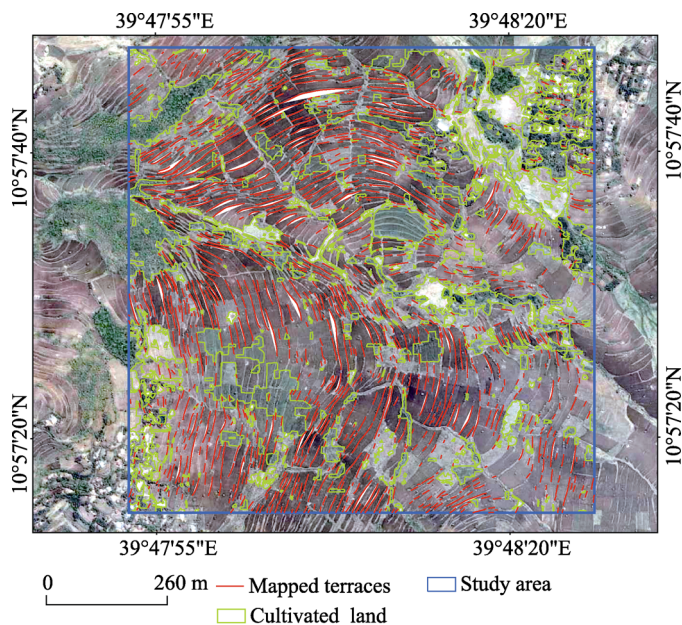


Figure 13 Map showing mapped the physical SWC structures after masking non-cultivated land. The green colour indicates areas classified as non-cultivated land

SWC structures on cultivated lands. Unwanted linear features such as field boundaries and drainage ditches exist in parallel with physical SWC structures. Therefore, in cases where the total length of field boundaries and ditches that are perpendicular to the contour line is longer than the total length of the physical SWC structures in a given hectare, the model would map the unwanted linear features rather than the terraces, which, at some level, affects accuracy. However, these unwanted linear features are completely or nearly perpendicular to the contour lines, whereas the physical SWC structures found along the contour lines. Therefore, this problem can be solved – and thus the accuracy of the model improved – if a very high spatial resolution DEM (better than 3 m) is available. With use of a DEM, contour lines can be generated and linear features that are completely or nearly perpendicular to them can be removed by determining their angle of deviation from the lines. In Ethiopia, where the model was developed, no high-resolution DEM was available at the time.

5 Conclusions

The developed model is automated, efficient, reliable, and fast, depending on the processor capacity of the computer, and assumes no prior knowledge of the physical SWC structures. In almost all of the images subjected to physical SWC structure mapping, the model performed well. The model proved to be essential for processing a large volume of raster images and thus for mapping of physical SCW structures on cultivated lands. Because the model performs well for mapping and predicting physical SWC structures, with calibration it could be applied to other areas with available high-spatial resolution images.

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