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Research article

Land Use/Land Cover Factor Values and Accuracy Assessment Using a GIS and Remote Sensing in the Case of the Quashay Watershed in Northwestern Ethiopia

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Abstract

Soil erosion by water is a complex process influenced by different factors. Most of these factors are steady over time, but land use/cover and land management practices are gradually altering. Analyzing land use/cover type and C-factor mapping using a Geographic Information System and Remote Sensing is the simplest way to identify vegetation coverage. GIS is a tool that is invaluable for conducting image classification through modeling. The present study was conducted in the Quashay watershed, Burie District, Ethiopia. The objectives of the study were to conduct land use/cover classification, to verify land use/cover factor values derived from LANDSAT images with actual identified types with respect to given values in Ethiopia from the literature. The remote sensing data used was from the LANDSAT 8 Enhanced Thematic Mapper Plus (ETM+) sensor, and were taken in 2017 for land use/cover mapping. Data were gathered through field observation and classification of land use/land cover type into homogenous land units. The inputs for the C-factor values were collected from literature review and in the field. Four land use/cover types were identified. The C-factor value of the study area ranged between 0.01 and 0.17. The overall accuracy of the image classification was 83.72 % and the Kappa coefficient was 0.7823. This means there was 78.23 % agreement for the classified image by chance alone. Therefore, this raster layer can be used as one input for soil loss analysis. It is concluded that analysis of LANDSAT images with accuracy assessment gives due attention for land resource managers to give priority to poor land cover areas with appropriate management plans. We recommend that, before assigning C-factor values to a classified image, accuracy assessment should be carried out and the computed C-factor raster layer of this study can be used as an input for soil loss estimation using GIS and RS.

1. Introduction

Land cover is the biophysical attribute of the earth's land surface, such as the vegetation, water, bare land, etc. or man-made structures such as pit exposures **[1]**, while land use is the economic use placed on the land cover by human activities, such as industrial zones, residential zones, agricultural fields, grazing, forest or logging and mining, among many others **[1]**, **[2]**. According to FAO **[3]**, land cover is the observed biophysical cover on the earth's surface, whereas land use refers to the arrangements, activities and inputs that people undertake on a certain land cover type. It mentions land cover types including crop land, vegetation, grassland, adding that different land cover classes affect soil erosion **[4]**. Each land cover influences soil erosion at different rates, as their potential to protect the soil against how the action of falling rain affects the degree of water infiltration into the soil is quite different **[5]**. Besides vegetation cover, several other land use and management factors affect soil loss, such as type of crop, tillage practice, etc. The influence of land use and management is often parameterized as the cover-management factor (C-factor). The C-factor is among the five factors that are used to estimate the risk of soil erosion within the Universal Soil Loss Equation (USLE) and its revised version, the RUSLE. The C-factor is perhaps the most important factor with regard to planning and land-use decisions, as it represents conditions that can be most easily managed to reduce erosion **[6]**. For example, soil loss rates decrease exponentially as vegetation cover increases **[7]** since it increases the infiltration rate and reduces the speed of surface runoff. Land covers describe how different land cover classes affect soil erosion **[8]**. Based on the above, assessing existing land use/cover is essential for land resource management decision-makers, acting as an input for indicators of vegetation coverage of the area and erosion potential areas. Therefore, land use/land cover classification using the latest technology from satellite images and accuracy assessments is the most effective way to obtain the final output raster layer from inputs of soil loss estimation. The C-factor represents land cover types, such as crop land, vegetation, grassland, bare land or wood land, on a given site and it plays an important role in controlling soil erosion. In the Revised Universal Soil Loss Equation Model, the C-factor is the ratio of soil loss from the existing land cover to the base land **[1]**, **[9]**.

In RUSLE, the C-factor accounts for how land cover, crops and crop management cause soil loss to vary from those losses occurring in bare fallow areas **[10]**. The bare plot (no vegetation) with till up and down the slope is taken as a reference condition, with a C-factor value of 1. The soil loss from different land-cover types is compared to the loss from the reference plot and the results are given as a ratio. The C-factor value for a particular land-cover type is the weighted average of those soil loss ratios (SLRs), and ranges between 0 and 1. Following the RUSLE handbook **[11]**, the SLRs are computed as a product of five sub-factors: prior land use, canopy cover, surface cover, surface roughness and soil moisture. These sub-factors include variables, such as residue cover, canopy cover, canopy height, below-ground biomass (root mass plus incorporated residue) and time. The SLRs are calculated for several time intervals during a year and multiplied by the corresponding percentage of annual rainfall erosivity to estimate the C-factor. This approach is feasible on plot to field scales. Simplified approaches are adopted for larger spatial scales: (i) assigning uniform C-factor values found in the literature to a land cover map **[2], [12], [13]** and (ii) mapping vegetation parameters using techniques such as image classification **[14]** and normalized difference vegetation index (NDVI). NDVI was not considered in the present study as it has been proved to correlate poorly with vegetation attributes due to the effect of soil reflectance and vitality of vegetation **[15]**, **[5]**. In the present study, assigning C-factor values found in the literature was conducted after accuracy assessment of the classified image. Cover crops reduce soil loss by improving soil structure and increasing infiltration, protecting the soil surface, scattering raindrop energy and reducing the velocity of the movement of water over the soil surface **[16]**. In the study area, land use/cover type was not identified and analyzed, and there was no well-documented information. Therefore, conducting the accuracy assessment of the classified land use/cover is a reasonable and scientific approach based on the ground truth data for land resource assessment rather than detecting the existing land use/cover condition of a particular area. Therefore, the present study aimed to classify the LANDSAT image using ArcGIS10.2 as an alternative image analysis software for land use/cover (LULC) classification and accuracy assessment **[17]**. The study asks what the existing land use/cover type is and how GIS and RS are used as image analysis software. It analyzes the state of land use/cover type and the C-factor from each land unit based on assigned C-factor values in Ethiopia. The study explores how the land use/cover factor raster could be used as an input for soil loss estimation after conducting accuracy assessment and how this may influence the improvement of land cover in local or regional land resource assessment and management. The main objective of the study is to estimate the cover management factor (C-factor) based on the best available data, in combination with a literature review and conducting accuracy assessment of land use land cover classified images in the Quashay Watershed, Northwestern Ethiopia.

2. Material and Methods

2.1 Description of the study area

The study was conducted in the Quashay watershed, which is found between Burie, the West Gojjam Zone and the Guagusa Shikudad District in the Awi Zone of the Amhara National Regional State, Northwest Ethiopia. The study area covers 327 hectares and lies between 10°45′0″ to 10°46′0″ N and 37°3′0″ to 37°4′0″ E as shown in **Figure 1**.

2.2 Data sources and data collection method

The study was conducted by dividing the watershed into homogeneous land units through field observation for the purpose of collecting accurate land use/cover status information. This was then compared with a literature review of C-factor values. Direct observation was also carried out to identify land cover types, which is crucial for visual interpretation of the Landsat images of the area. A LANDSAT Enhanced Thematic Mapper Plus (ETM+) satellite image acquired in January 2017 from the USGS website was used for land use/cover analysis. Landsat images are provided for free from [18] and have a spatial resolution of 30 m*30 m pixel size, which is appropriate for land cover mapping and also to prepare a C-factor map; this is similar to the work of [18]. ArcGIS10.2 was used for this purpose. Field GPS data were collected in order to verify land use/cover type with the classified image using ArcGIS 10.2. The respective land use/cover factor data were collected from a literature review to reclassify the land use/cover raster to the C-factor values. Land cover classification was carried out with respective percentage of area coverage.

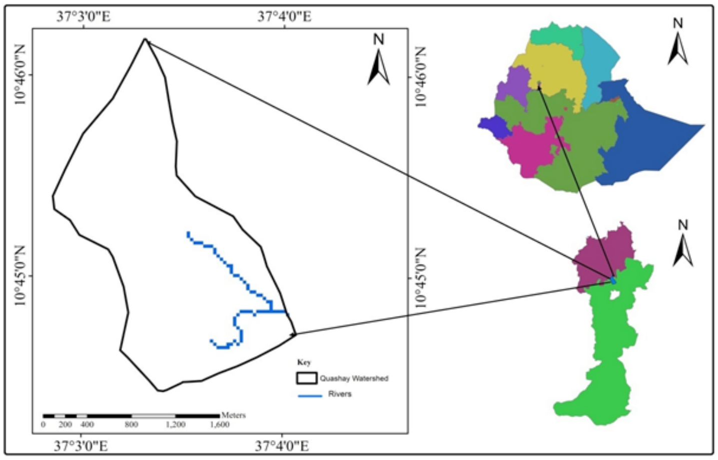

Figure 1: Location map of the Quashay Watershed

2.3 Software and tools used

The following software and tools were used for collecting, processing and/or analysis of data/images. (1) ArcGIS 10.2: Preparation of location of the project area, image analysis, database generation; (2) Google Earth version 1.3.31.5 for creating Keyhole Markup Language (KML) files which is a file format used to display geographic data in an Earth browser such as Google Earth and to verify randomly generated points; and (3) Garmin 72H which is a Global Positioning System to collect accurate ground points.

2.4 Methods of data analysis

The study area was classified into different land use/cover classes using supervised image classification. For this purpose a total of 131 ground control points were collected from grazing land (48 points), settlement (30 points), cultivated land (38 points) and forest (25 points) using a hand-held GPS. By taking more ground control points the accuracy of the land use/cover classification could be higher. As the number of GCPs increases the analysis becomes more correct, so the high number of GCPs was not a problem in this regard. Approximately 30 to 50 ground control points are needed for each land use/cover class in order to compare the accuracy value [19]. This data was used for supervised image classification with the help of a very high resolution image. Similarly, 387 test pixels were taken from the LANDSAT image from 2017 by creating training sample sites and digital image classification, and a Google earth image was used for image to image classification and comparison. Supervised image classification with the maximum likelihood method was used by generating training signatures per pixel; this is in agreement with [19], [20]. The researchers train the computer to recognize patterns in the data by selecting pixels that represent the same patterns or land cover features that can be recognized. The signature files thus created were used in the classification process, where each pixel was categorized into the land cover class it mostly resembled.

2.4.1 Accuracy assessment

After image classification, accuracy assessment was measured using a matrix with user classification and reference images. Individual accuracy was also measured using Equation 1 and overall accuracy was done using Equation 2. An image analysis should identify the sources of error and their magnitude. To conduct this accuracy assessment ground verification was used by the researchers using (1) a global positioning system and (2) comparison of the classified image to an image from Google Earth which is assumed to be correct for validation of the result. The data was summarized and quantified using a frequency table, error matrix, user and producer classification accuracy and the Kappa coefficient method to measure agreement between the model predictions and reality, as done by [19], or to determine the values contained in an error matrix representing a result significantly better than random [21].

$$\text{Individual accuracy} = \frac{\text{reference Value}}{row\ total} \quad (1)$$

$$\text{Overall accuracy} = \frac{Corrected\ prediction}{Total\ prediction} * 100 \quad (2)$$

The Kappa coefficient was used as a measure of agreement between the model predictions and reality [19] or to determine if the values contained in an error matrix represent a result significantly better than random [21], [22]. The Kappa coefficient was computed using Equation 3.

$$\text{Kappa coefficient} = \frac{[total*sum\ of\ correct - sum\ of\ all(row\ total*column\ total)]}{total\ squared - [sum\ of all\ (row\ total*column\ total)]} \quad (3)$$

After the accuracy analysis, the corresponding C values were assigned to each land use/cover class using the reclass and reclassify tools in ArcGIS 10.2. In the case of cultivated fields, the (C) value varies annually where the cover of the fields varies. However, the dominant crops in the study area, teff (*Eragrostis teff*), maize, potato (*Solanum tuberosum*), wheat, and pulses, remain the same year after year, as substitutes to one another through crop rotation. Therefore, a C value of 0.17 was used for all cultivated fields. The C-factor raster layer of the study area was created by assigning adapted C values for each land use/cover class as shown in **Table 1**. The frequency table and error matrix were summarized and used to test whether the classified image was predicted correctly or not, as shown in **Table 2**. The land use/land covers factors represent the ratio of soil loss under a given cover type to that of the base soil [23]. The land use map (**Figure 2**) was used to analyze the C-factor value. After changing the coverage to a grid, a corresponding C-value was assigned to each land use class using the reclass tool in ArcGIS10.2, as given by [2], [22], [24]. To acquire this information, a field survey was conducted to collect ground characteristics at sample points using a comprehensive sampling method. Nevertheless, no well-established rule exists on how many data points are needed for the validation. One rule of thumb is that 30 to 50 points are needed for each land use/cover class **[19]**, **[25]**. Accuracy assessment and validation of land uses are important to assure the credibility of land use/cover estimates.

Table 1: Land use/cover type and its C- factor values taken from different studies

Sn.	Land use/cover type	C- factor value	References
1	Grassland	0.01	[2]
2	Settlement	0.14	[15]
3	Cereals or pulse	0.17	[12]
4	Forest	0.02	[12]

3. Results and Discussion

Based on the analysis shown in **Table 2**, the frequency test pixels resulted in 80 test pixels generated from ground control values from the classified Landsat image, of which 79 pixels were classified correctly as land use/cover class 1 (crop land) but 1 pixel was predicted as class 4 (forest). From 84 test pixel reference points, 61 were correctly classified as class 1 (settlement) but 17 pixels were incorrectly predicted as class 3 (grazing), while 4 test pixels were incorrectly predicted as forest. From 112 ground control points 38 pixels were incorrectly predicted as class 2 (settlement) while 74 pixels were correctly predicted as class 3 (grazing). Finally, out of 114 test ground control points, 4 pixels were incorrectly predicted as class 2 (settlement), 2 points were predicted as class 2 (crop land) while the remaining 180 pixels were correctly predicted as class 4 (forest), including homestead plantation trees and farm forestry. It was a major challenge to identify the latter two types from the landsat image, but they were identified during field observation. Based on this, ArcGIS 10.2 is a possible alternative for land use/land cover (LULC) classification and accuracy assessment **[18]**.

Table 2: Frequency output as input for pivot mattrix using the frequency table

FID	Frequency	Class name * /Truth	Predicted (classified)
1	79	1	1
2	2	1	4
3	63	2	2
4	17	2	3
5	4	2	4
6	38	3	2
7	74	3	3
8	1	4	1
9	1	4	2
10	108	4	4

* *1=crop land, 2=settlment, 3=grazing land and 4=forest land*

As the error matrix result indicates, there were 80 ground pixels for cropland and out of this 79 pixels were correctly predicted while 1 pixel was incorrectly predicted as forest (**Table 3**). The overall accuracy of the land use/cover classification was 83.72 %. This indicates the classification was more realistic than classified by chance alone. Based on satellite image analysis and observation of the existing ground situation in the study area, four major land use/cover types were identified. The total number of predictions was 387 for all land use/cover classes. The total ground control points predicted was 324 (**Table 3**). Predictions along the diagonal are correctly predicted for each land use/cover and each class whereas the other pixel values were incorrectly predicted to the other class. For cropland, out of 80 grounds points 79 pixels were correctly predicted while one pixel was predicted as forest and the classification accuracy of this land use/cover was 97.53 %, which was highly accurate. For settlements, the total number of control points was 84 and out of this 63 pixels were predicted correctly, 21 pixels were incorrectly predicted (17 pixels as grazing land and 4 pixels as vegetation), meaning the accuracy of this land cover was 75 %. For grazing land, 112 ground points were used for prediction, out of this 74 ground pixels were correctly predicted while 38 pixels are classified as settlement, meaning the accuracy of this land cover classification was 66.07 %. For forest land use/cover, the total number of ground control points was 110 and out of this 108 pixels were correctly predicted with an accuracy of 98.18 %. This was the most accurately class in the study area even though, 2 pixels were incorrectly predicted as cropland and settlement, respectively. The Kappa coefficient of this study was 0.7823. This means there was 78.23 % agreement than the classified image by chance alone. The result of this study falls within the ranges and the findings of **[1]**, which was conducted in Gish Abbay Sekela, West Gojjam, Amhara, Ethiopia Kappa accuracy was more than 75 % and another study in Tigray region, Norternh Ethiopia within the overall accuracy of 82 and Kappa accuracy of 77.02 % with Kappa coefficient of 0.7702 **[19]**, **[26]**-**[29]**. Therefore, the result of this study in both accuracy assessment methods (frequency table and error matrix) using ArcGIS 10.2 was the same, but the error matrix table is the best and its results are summarized in **Table 3**. Therefore, this study is acceptable in accuracy as compared with others finding. Google ground control points were generated from Google earth images for accuracy assessment.

Table 3: Pivot table output or error matrix table

	Reference data (Ground control)					Percent (%)	
Classification	Crop	Settlement	Grazing	Forest	Google Truth	UA*	CA*
Crop	**79**	0	0	1	80	98.75	1.25
Settlement	0	**63**	38	1	102	61.76	38.23
Grazing land	0	17	**74**	0	91	78.02	18.68
Forest	2	4	0	**108**	114	94.47	5.26
Total	81	84	112	110	**387**	**OA*=83.72**	
OE*	2.46	25.00	33.92	1.82		**Kappa=78.23**	
PA*	97.53	75.00	66.07	98.18			

* *OE=omission/exclusion, CA=commission accuracy/inclusion, PA=producer accuracy, UA=user accuracy and OA = overall accuracy*

3.1. Cropping and land-cover factor (C)

The C-factor is used to corroborate the virtual efficiency of soil and crop management methods in terms of preventing or reducing soil loss. A C value is a ratio of the soil eroded under a specific crop and management system contrasted to continuous fallow conditions **[27]**, **[30]**. It represents the ratio of soil loss under a given crop to that of the base soil **[30]**. It also reflects the effect of cropping and management practices on the soil erosion rate **[11]**. As shown in **Figure 2**, four land-use and land-cover classes were recognized in the watershed, predominantly agricultural land (27 %) and vegetation coverage (35 %). These include built-up areas, cultivated land, forest land, and grass land. Crop management C-factor values for the study watershed ranged from 0.01 to 0.17; this is similar to the study of **[25]**. According to a field survey, four land use types and 16 patches were identified. As shown in **Table 4** there were four major land use/cover types, as identified in the field and defined based on **[19]**, **[22]** and adapted and modified from **[23]**.

Table 4: Identified land use/cover classes in the study area

Land use/ cover classes	Description
Agricultural land	Land used primarily for production of food, crop land agriculture (cropland harvested, including bush fruits; cultivated summer fallow; land on which crop failure occurs; cropland in soil- improvement grasses and legumes, pasture on land more or less permanently used for that purpose) and other agricultural land (include farmsteads).
Settlement	Land used for residential purposes (housing) settled by the construction of houses as rural settlement areas. Residential land uses range from high density, represented by the multiple-unit structures of urban cores, to low density (including the study area), where houses are on lots of more than an acre or 0.4046 ha and areas of sparse residential land use, such as farmsteads.
Grassland	This land cover includes short term flooded flatlands that are usually used for intensive grazing. Areas of natural/semi-natural grassland with other grazing-like plants and non-grazing-like plants.
Forest /vegetation	Forest lands have a tree crown aerial density (crown closure percentage) of 10 % or more, are stocked with trees capable of producing wood products and exert an influence on the climate or water regime. They also include farm forests, plantation forests, boundary plantation trees and homestead scattered trees.

Land use/cover types with area coverage were forests, cultivated land, grazing land and settlements, covering 35 %, 27 %, 23 % and 13 % (**Table 5**), respectively. Based on field observation, the final forest land use/cover figure includes farm forests, since natural forest covers only 11 % of the study area, with the remaining 14 % covered by other vegetation types including wood lots, boundary and homestead plantations.

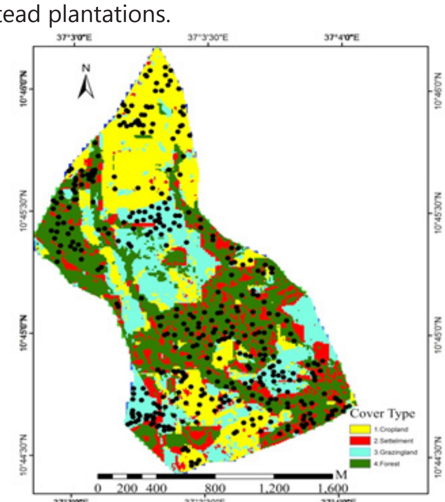

Figure 2: Land use/cover classification map and GPS points

Table 5: Land use/cover area coverage

Sn.	Land use/cover type	Area coverage (%)
1	Cultivated	27.00
2	Settelment	13.00
3	Grazing	23.00
4	Forest (plantation and wood lot)	35.00
Total		**100**

According to **[22]**, **[27]**, **[30]** land cover plays a significant role in reducing rain drop impact on soil particles. Dense vegetation cover means less erosion and subsequently a low soil loss rate. By reducing runoff velocity, long horizontal movement and potential energy are reduced. The estimated C-factor represents the percentage ground cover for each land cover type, as well as the presence of plant residue. Based on the analysis, the C-factor value of the study area is between 0.01 and 0.17. Most of the lower and middle catchment of the watershed is covered by cropland (millet and maize), and thus, this part of the watershed has the highest C-factor value (0.17). This is because annual crops like millet and maize do not reduce the direct impact of rainfall on soil resources, unlike forest land, for example. The higher C-value indicates that the specified land use/cover is highly vulnerable to soil erosion and the lower value in forest land indicates that it is the least vulnerable land cover type in the study area; this is similar to **[9]**. The C-factor raster map value was high in the northern part of the study area, as this area is used for crop cultivation with poor land cover conditions. The lowest value was in mostly grazing land and forest land in the central part, northeast and southwest of the study area. The C-factor values with respective land use/cover type were 0.01, 0.14, 0.17, and 0.02 in grazing, settlement, cultivated (cereals or pulse) and forest land, respectively, as shown in **Figure 3**b. Cultivated land is more exposed to erosion than other land use/cover types, which is why its C-factor value is high.

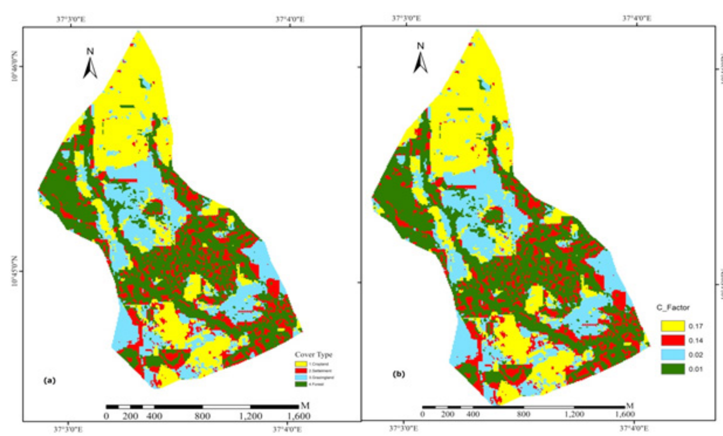

Figure 3: Land use/cover class (a) and C- factor map (b)

4. Conclusions

Based on these results, four land use/cover types were identified. The C-factor value of the study area is ranged between 0.01 and 0.17. The overall accuracy of image classification was 83.72 % and the Kappa coefficient was 0.7823. Areas characterized by the maximum C-factor value should be given special priority for improvements to vegetation coverage. The study demonstrates that ground truth data, very high spatial resolution images from Google Earth, together with GIS and RS provide major advantages for deriving C-factor values and conducting the subsequent accuracy assessment. The parameter values of the land cover factor are site specific and checked by the accuracy assessment. They need to be standardized for the specific area to enable reasonable prediction of the land use factor (C). Similar research needs to be implemented to identify the accuracy of land use/cover type on the ground and the derived Cover factor value in different parts of the country based on land units before using the raster layer of the land use/cover map as an input for soil loss estimation by comparing the result with the standard value. Therefore, we conclude that GIS and RS provide an immense advantage when examining land use/cover data spatially and quantitatively within this specific site. The evaluation of land use/cover (C-factor value) in the watershed and the accuracy value of the classified image using GIS is also in the ranges of other studies and above the standard value. Therefore, GIS not only provides accurate results but also cost and time efficient ways of spatial data analysis.

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Author Contributions

Habtamu Tadele conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, wrote the paper, prepared figures and/or tables, reviewed drafts of the paper. Asnake Mekuriaw conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, wrote the paper, reviewed drafts of the paper. Yihenew G. Selassie contributed reagents/materials/analysis tools, wrote the paper, reviewed drafts of the paper. Lewoye Tsegaye contributed reagents/materials/analysis tools, wrote the paper, reviewed drafts of the paper.

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