Environmental Modelling & Software 72 (2015) 1–9

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

A novel approach to mapping land conversion using Google Earth with an application to East Africa

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ARTICLE INFO

Article history:
Received 5 February 2015
Received in revised form
8 June 2015
Accepted 16 June 2015
Available online xxx

Keywords:
Google Earth
Land conversion
East Africa
Land use land cover
Conservation planning
GE grids

ABSTRACT

Effective conservation planning relies on the accurate identification of anthropogenic land cover. However, accessing localized information can be difficult or impossible in developing countries. Additionally, global medium-resolution land use land cover datasets may be insufficient for conservation planning purposes at the scale of a country or smaller. We thus introduce a new tool, GE Grids, to bridge this gap. This tool creates an interactive user-specified binary grid laid over Google Earth's high-resolution imagery. Using GE Grids, we manually identified anthropogenic land conversion across East Africa and compared this against available land cover datasets. Nearly 30% of East Africa is converted to anthropogenic land cover. The two highest-resolution comparative datasets have the greatest agreement with our own at the regional extent, despite having as low as 44% agreement at the country level. We achieved 83% consistency among users. GE Grids is intended to complement existing remote sensing datasets at local scales.

Software availability

GE: Grids is a web application written in Javascript using the Google Earth application programming interface (API), which is freely available from Google. The program requires a web browser, the Google Earth plug-in and internet connectivity. The codebase is maintained and can be downloaded as a zip file from http://andrewstanish.com/files/GERasterCreator.zip. The zip file contains a.html file, accessory files, and a ReadMe file. Use the ReadMe file for suggestions on program instruction and notes on Google's Terms of Service. GE Grids is free, regulated under the GNU General Public License v3 (http://www.gnu.org/copyleft/gpl.html) and intended for further open-source development. The developer is Andrew Stanish (andybp85@gmail.com).

1. Introduction

Land use land cover (LULC) datasets describe how humans use land (land use) as well as the physical features that cover the earth's surface (land cover). These datasets aid in the identification of the location, intensity, and extent of human activities which is essential to conservation planning (Hansen et al., 2000). In LULC datasets, anthropogenic land cover is typically classified as either cropland or urban extent. However, identification of these land uses is challenging and varies greatly across datasets (Vancutsem et al., 2012; Potere and Schneider, 2007; Fritz et al., 2011). Traditional remote sensing classification approaches require grouping spectral signatures and subsequent accurate discrimination between groups i.e. land cover types (Pfeifer et al., 2012). However, emerging remote sensing techniques, such as object-based classification reduce this

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http://dx.doi.org/10.1016/j.envsoft.2015.06.011
1364-8152/

reliance on unique spectral properties by allowing probabilistic class descriptions (Blaschke, 2010). Classification may be relatively easy where vegetated landscapes are homogenous and extensive e.g. some croplands. However, in heterogeneous landscapes with small, patchy agricultural fields, discriminating cropland from natural land cover using classification algorithms can be difficult (Tchuenté et al., 2011; Vancutsem et al., 2012).

Furthermore, while the financial burdens of obtaining satellite image data are decreasing, generating remote sensing classification products still require specialized, and often expensive, training and software (Stensgaard et al., 2009; Pettorelli et al., 2014). Access to these resources may present particular hurdles to research and conservation programs, particularly those in developing countries. Error in selecting, downloading, processing, and analyzing remote sensing datasets may additionally result in inappropriate recommendations and conclusions (Watson et al., 2015), particularly for ecological applications (Kerr and Ostrovsky, 2003). Inappropriate analyses may result in missed opportunities, or squandered resources (Wilson et al., 2005). There is thus a need for easily created, inexpensive, locally-accurate datasets that can confidently be used in conservation planning (Watson et al., 2015).

One possible solution to problems associated with the cost and difficulty of conducting remote sensing classification analyses and the accuracy of LULC datasets is to use free, easy to access, high-resolution image data (pixel resolution of 10 m or better; moderate resolution data is between 10 and 250 m (Pfeifer et al., 2012)) like that available through Google Earth. Google Earth is a free, easy-to-use program owned by Google Inc. that allows access to sub-meter pixel resolution data for over a quarter of the world's landmass and three-quarters of the global population (Google, 2014).

Google Earth's high-resolution data are useful as a platform for validating datasets (Fritz et al., 2011) used previously with urban extent (Schneider et al., 2009) and land cover (Defourny et al., 2008). While Google Earth has the potential for wider use in scientific literature, particularly in LULC analyses (Potere, 2008), one prominent challenge is that native analysis functions in Google Earth are minimal (Yu and Gong, 2012), limited to drawing points, lines, and polygons. We previously used the polygon drawing feature to identify anthropogenic land use conversion in West Africa (Riggio et al., 2013) and Mozambique (Jacobson et al., 2013). The results were a significant improvement over existing datasets and aided in determining potential habitat. Although the time-consuming nature of these analyses limited further application, the success of the method spurred the creation of a new tool, "GE Grids", to speed land cover class identification. GE Grids is the first free, customizable creator of raster datasets for use with Google Earth. GE Grids creates a user-defined, interactive grid (raster) overlaid on Google Earth image data. This tool circumvents expensive, specialized programs and knowledge, and enables easy use of Google Earth's high-resolution data to create localized datasets. We use GE Grids to document anthropogenic land conversion in East Africa, a region of significant conservation importance (Ray et al., 2005; Myers et al., 2000; Jenkins et al., 2013) experiencing rapid human population growth (UN, 2013).

2. Methodology

2.1. GE grids program design and workflow

GE Grids is a browser-based application that provides a customized interface to map land cover using satellite and aerial data available in Google Earth. The application relies on the free Google Earth plug-in (GEP) and Google's public application programming interface (API) as well as a plugin called "filesaver.js" written by Eli Grey and available on GitHub. The program is written in JavaScript and tested in the Google Chrome and Mozilla Firefox web browsers.

The GE Grids program consists of two main objects: "dataset" and "filesys". "dataset" has two functions: to store internal data displayed on the GEP, and to handle the functionalities related to creating, rendering, and updating the ASCII data. "filesys" controls the download and upload of data. The download functionality makes use of filesaver.js for cross-browser compatibility. The upload function handles data uploading and rendering ASCII raster files. It sets the GEP grid parameters to what it reads from the file, triggers the GEP to draw the grid, and creates an array with the IDs of each grid cell lined up in the same order as on the grid. The upload method then reads through the file, value by value, and triggers the dataset object to change the color of the grid cell and change the value stored for the ASCII output, until it reaches the end of the file.

GE Grids calls a series of four functions. These four functions, in the order they are called, are "initGrid," "genPolygons," "makePolygon," and "clickInit." "initGrid" sets the GEP camera view, calls "genPolygons" to draw the grid in the GEP, triggers the dataset object to create the internal copy and render the ASCII, and finally calls "clickInit" to set up the user interface. "genPolygons" draws and positions the grid using the values specified by the user in the html input. The "makePolygon" subroutine creates the actual grid cell in the GEP. Finally, "clickInit" sets up the user interface for interacting with and changing grid cells.

In summary, program execution begins with page load, and the program initiates the GEP. The user can then change the default grid options and Google Earth preferences via the user interface. When the user clicks the "Draw" button, the grid parameters are read into an object, and "initGrid" is called. Once the GEP grid and ASCII raster are set up, the user can click on a grid cell. When this happens, the dataset "object" changes the color of the grid cell, updates its internal store of the values, and re-renders the values in the ASCII output. There is no internal save functionality, but the user can download a copy of the ASCII raster and re-upload it to continue.

The user interface of GE Grids is a combination of generic controls provided by Google Earth and input parameters for creating a grid. Controls allow the user to navigate around the Google Earth imagery and to enter the information necessary to specify or "draw" a grid (Fig. 1). Options include: the latitude and longitude of the upper right-hand corner coordinates of the grid, the size of each cell (in Degrees – a function of Google Earth's use of the WGS 1984 lat/long coordinate system), and the number of cells on each axis. Each cell can be visually divided into 9 minor grids (3×3) using the "Grid Guides" function to ease the classification of heterogeneous cells. Although the study was done using square grids, the program supports any number of cells per side.

The overall workflow is summarized in Fig. 2. Once the user creates a grid using the "Draw" feature, they can interact with the grid by clicking on the grid edges to change their color from white to red. This corresponds with a data value change from 0 to 1; or if the No Data function is clicked on, to -999 (or any other value chosen by the user). The result can be downloaded as a text file in ASCII raster format for import into GIS software or as a KML file to upload into Google Earth. The ASCII file can also be re-uploaded into GE Grids for editing and error checking.

This tool meets the legal requirements of the Google Earth API Terms of Service. GE Grids is free to all users, does not alter or blur imagery from Google Earth, and allows attribution of the image data to remain visible. In using this tool, users are also agreeing to abide by Google's Terms of Service. Importantly, the image data itself and the output from GE Grids should not be used for

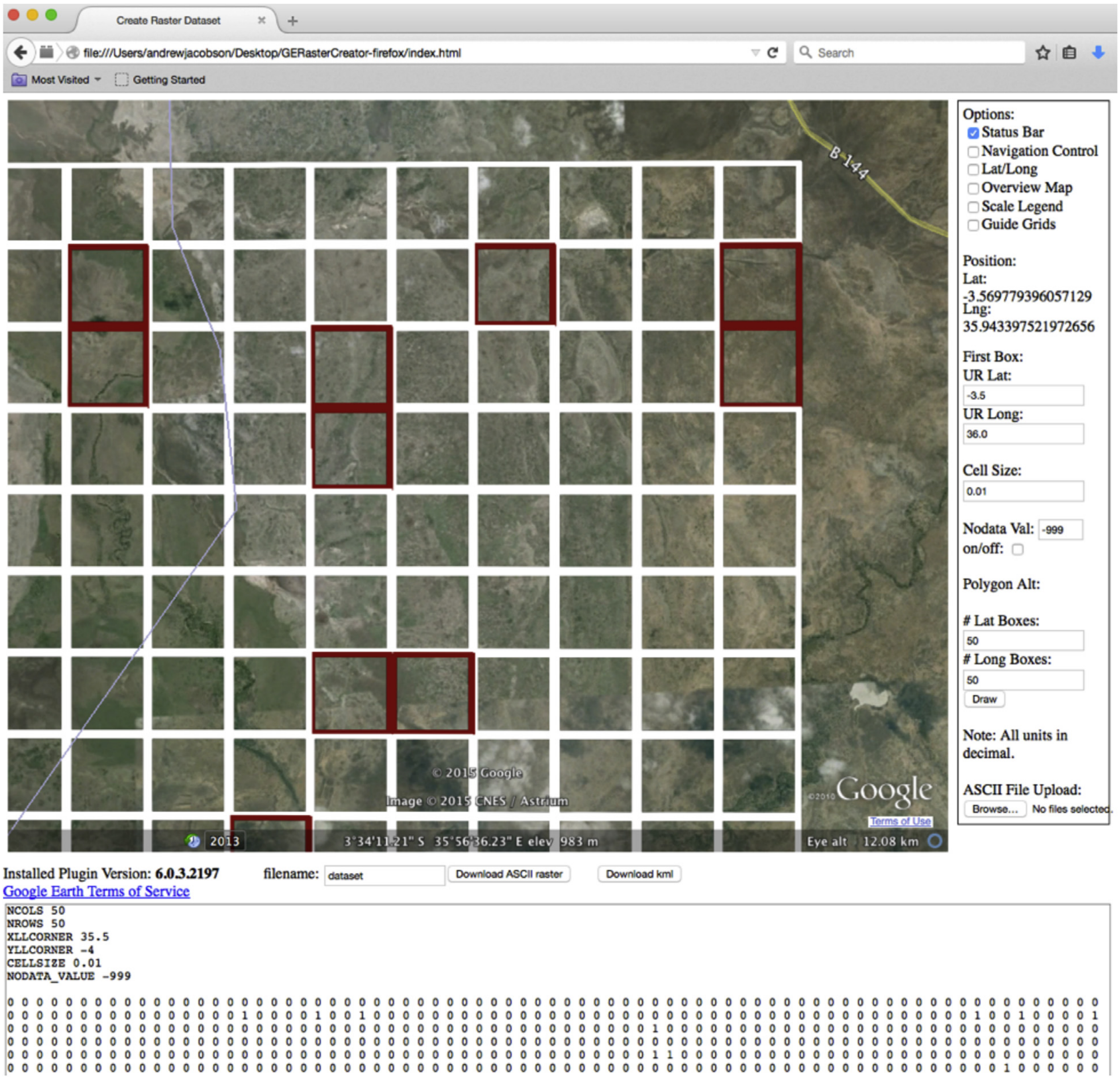

Fig. 1. Screenshot of the GE Grids program interface showing the control options, a portion of the interactive grid, and the layout of the ASCII text file.

commercial purposes without further consent from Google. More information can be found in the ReadMe file, included in the zip file download of this tool.

2.2. Application of GE grids to East Africa

We used GE Grids to document anthropogenic land conversion throughout East Africa at a resolution of 0.01° (~1 km at the equator). Each run of GE Grids covered a 50 × 50 grid cell square (0.5° × 0.5°; ~2500 km^2). Each grid cell was visually evaluated for the presence of anthropogenic land cover (Fig. 3). A cell was classified as 'converted' if 50% or more of the land was converted to human land cover (including agriculture, urban development, industry, mines, roads, and housing units such as bomas). Cells were classified as No Data where identification of land cover was impaired, primarily due to moderate resolution imagery (e.g. Landsat imagery) or cloud cover. We did not consider deforested, degraded or grazed lands as converted. Grid cells partially covered by water were evaluated on the basis of the terrestrial land cover.

After evaluating all cells in a 50 × 50 grid, the resulting file was downloaded in ASCII text format. Each text file was then imported into ArcGIS 10.2.1 (ESRI, 2014) and converted to a raster. The individual files were mosaicked together on a per-country basis. No Data cells were filled using WorldPop, a human population density dataset with 1 km resolution (Linard et al., 2012). We examined correlations between WorldPop and anthropogenic land conversion at five people per km^2 increments with the highest correlation used as a threshold level; any No Data cells with population density above the threshold were classified as "converted" (Table S1). Each country was then merged and clipped to remove islands in the Indian Ocean (Fig. S1). Finally, the "lakes" class from the Global Lakes and Wetlands (GLWD v3; Lehner and Döll, 2004) was overlaid to give context. The resulting dataset is a binary land classification layer of anthropogenic land conversion versus natural habitat.

To illustrate the repeatability of a land cover classification using GE Grids we compared the results of the classification of a grid of

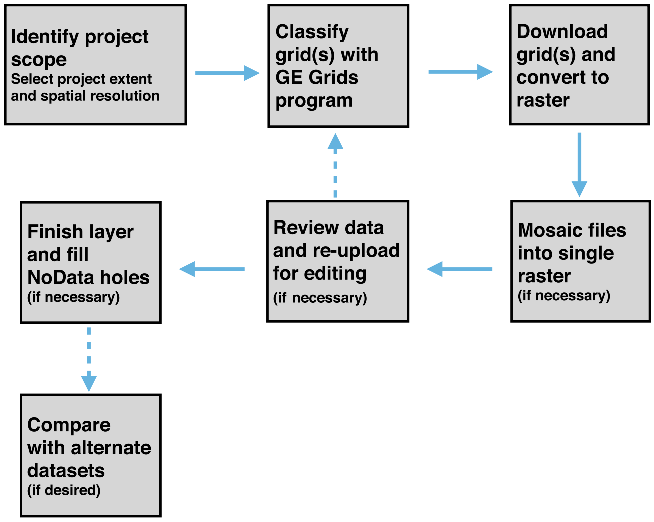

Fig. 2. User interaction diagram depicting the workflow using GE Grids.

2500 cells (50 × 50). We chose a grid containing a mixture of conversion and natural lands, along with a combination of high and medium resolution imagery. For intra-user consistency, the lead author classified this same grid a total of five times. For inter-user consistency, all co-authors, except the programmer (A.S.), classified this grid. Grids were compared in ArcGIS.

2.3. Dataset comparisons

Five datasets, one regional and four global, were spatially compared with the GE Grids classification: Africover (Alinovi et al., 2000), GlobeLand 30 (National Geomatics Center of China, (2014)), GLC-SHARE Beta Release 1.0 (Latham et al., 2014), Globcover v2.3 (Bontemps et al., 2011), and MODIS land cover MCD12Q1 (Friedl et al., 2010, Table 1).

For comparison purposes, all products were standardized to raster datasets at 0.01° resolution, then clipped and aligned to identical geographic extents. Each dataset was re-sampled according to the majority land cover within the 0.01° cell. An important component of previous land cover comparisons was the standardization of classes before comparison as products used different land cover categories and definitions (e.g. the

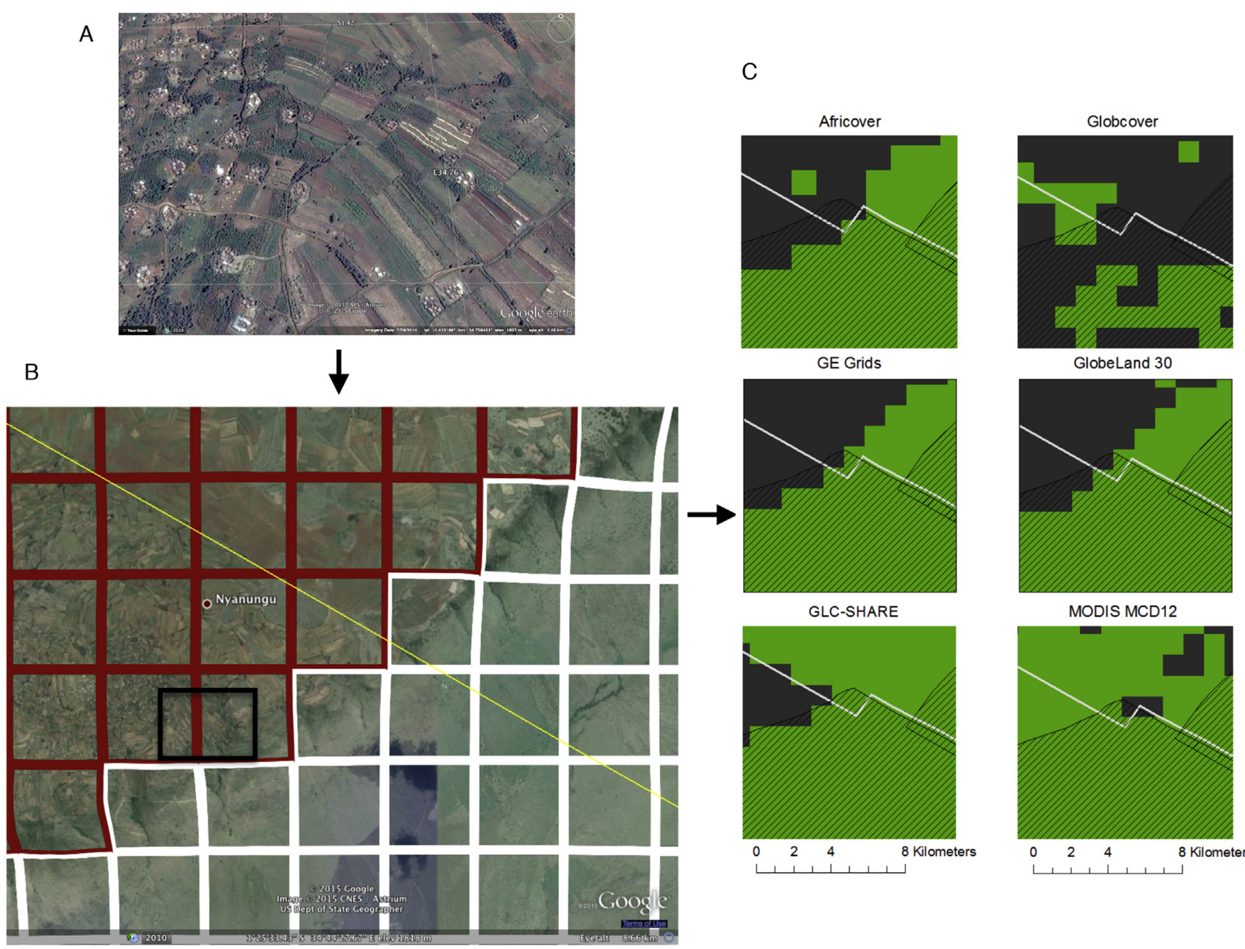

Fig. 3. The upper left image (A) is a screen capture from Google Earth near the western edge where Masai Mara National Reserve (Kenya) and Serengeti National Park (Tanzania) intersect. Fields and houses are clearly visible. Image B is the classification of this area in the GE Grids program, with a black box depicting the area of screen capture. Towns and fields occupy the land on top of the Great Rift Valley escarpment while natural vegetation lies below the escarpment. The clustered six images in C all show an identical area corresponding to the extent shown in B. These illustrate the differences among various dataset's depictions of anthropogenic land conversion. Dark gray is anthropogenic land conversion, green represents natural vegetation, the light grey line is the country border, and hashed regions are protected areas. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of comparative land cover datasets.

Dataset (website)	Reference	Sensor	Year of data collection	Spatial resolution	Total# of classes (# related to anthro[a])	Accuracy assessment overall[b] (cropland)
Africover (www.glcn.org/activities/africover_en.jsp)	Alinovi et al. 2000	Landsat TM	Burundi 1999, Kenya 1999, Tanzania 1997, Rwanda 1999, Uganda 2000–2001	30 m; spatially aggregated to polygon	Condensed to 6 (2)	NA
GlobeLand 30 2010 (www.globallandcover.com)	National Geomatics Center of China (2014)	30 m multispectral images (e.g. Landsat TM, Landsat ETM+, HJ-1)	2008–2011	30 m	10 (2)	83.5% (83.1%)
GLC-SHARE Beta Release 1.0 (www.glcn.org/databases/lc_glcshare_en.jsp)	Latham et al., 2014	Varied	Burundi, Tanzania, Rwanda, and Uganda 2001; Kenya 2010	30 arc seconds (~1 km)	11 (2)	80%
Globcover v2.3 (due.esrin.esa.int/globcover/)	Bontemps et al., 2011	MERIS FR	2009	300 m	22 (5)	58%
MODIS MCD12 Q1 collection 5; year 2012 (https://lpdaac.usgs.gov/products/modis_products_table/mcd12q1)	Friedl et al., 2010	MODIS, bands 1–7 & EVI	2012	500 m	17 (3)	75% (77%)

[a] Number of classes related to anthropogenic land conversion.
[b] As specified in their dataset descriptions.

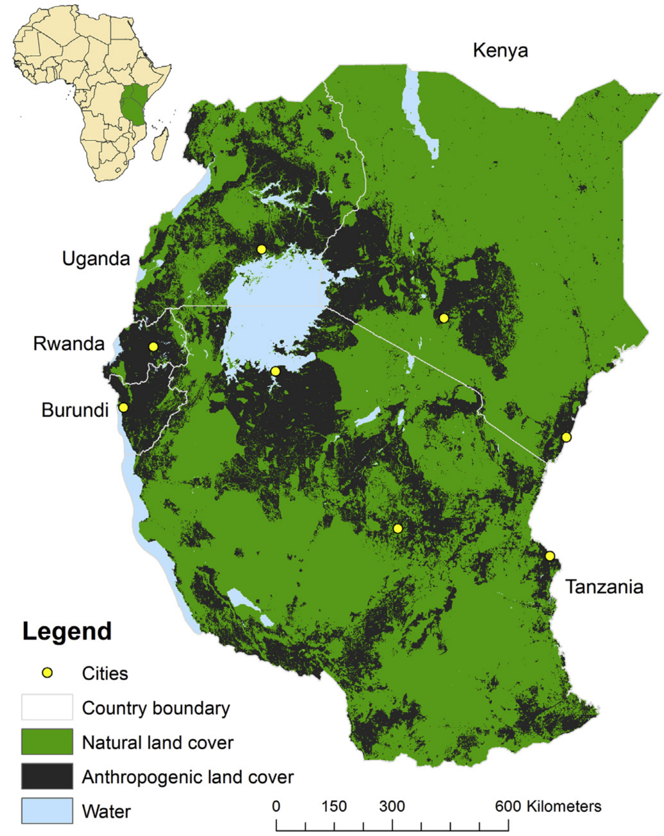

Fig. 4. GE Grids land cover classification map of East Africa. Cities displayed are either country capitals or have populations exceeding 500,000.

International Geosphere Biosphere Project, IGBP, and the Land Cover Classification System, LCCS; McCallum et al., 2006). This is trivial here as all and only anthropogenic classes were of interest. However, both GlobCover and MODIS MCD12 did have a class representing a mosaic of both natural and anthropogenic land covers. Therefore we compared these datasets with and without these mosaic layers.

3. Results

Using GE Grids, we classified 1,479,121 cells for East Africa as either predominately natural or converted to anthropogenic land cover (Fig. 4). Nearly 30% (29.77%) of the region has been converted to anthropogenic land cover although this varies greatly by country (Table 2). Burundi and Rwanda have the highest proportions of anthropogenic land cover at 85.99% and 82.27% respectively. Kenya contains the greatest percentage of land still in a natural state (82.65%), mostly within the nation's arid north. Only 3.74% of cells were No Data and filled via human population density on a country-by-country basis.

Table 2
Percent terrestrial land cover classified as natural or anthropogenic by country after filling no data holes.

Country	% Natural	% Anthropogenic	% No Data
Burundi	14.01	85.99	1.92
Kenya	82.65	17.35	1.37
Rwanda	17.73	82.27	0.13
Tanzania	68.44	31.56	5.12
Uganda	56.54	43.46	3.74
East Africa	70.23	29.77	3.74

Table 3
The percent agreement between the GE Grids land cover classification of East Africa and those from comparative datasets. GlobCover and MODIS MCD12 both have an additional class of mosaic cropland/native vegetation that is added in the (+) comparison and absent in the (−). (Note. All figures and tables are only with the + version of these datasets due to their higher agreement.)

GE grids v. Dataset	Africover	GlobeLand 30	GLC-SHARE	GlobCover (+)	GlobCover (−)	MCD12 (+)	MCD12 (−)
Natural–Natural	64.67	69.84	70.57	58.63	69.01	67.80	71.25
Converted–Converted	22.96	17.05	12.38	15.12	3.79	8.08	1.20
Natural-Converted	7.28	2.11	1.38	13.32	2.94	4.15	0.70
Converted-Natural	5.09	11.00	15.67	12.93	24.26	19.97	26.85
Total % Agreement	**87.63**	**86.88**	**82.95**	**73.75**	**72.79**	**75.88**	**72.45**
Unweighted Kappa Statistic	**0.734**	**0.692**	**0.585**	**0.444**	**0.304**	**0.408**	**0.255**

The consistency of a single classified grid (50×50 cells) from all co-authors was 82.76%. Agreement between the five replications by the first author was higher, at 94.6%.

Africover has the highest overall agreement (87.63%) with the GE Grids dataset (Table 3). Africover classifies the least amount of land as natural that we find converted. GLC-Share classifies the least amount of land as converted that we find natural. Both GlobCover and MODIS MCD12 have higher agreement with GE Grids when mosaic cropland/natural vegetation land cover classes are combined with anthropogenic land cover classes (Fig. S2).

A spatial comparison between the GE Grids' classification and comparative products suggests that all global datasets had difficulty identifying development in southeastern Burundi and coastal regions of Kenya and Tanzania (Fig. 5, Fig. S3). On a per country basis, Burundi had the lowest rate of agreement from all comparative products with GE Grids, while Kenya had the highest (Table S2).

The software design and approach satisfied our goals in this case study of East African land cover. GE Grids enabled the evaluation of reasonably sized grids (50×50) using high-resolution satellite data. Since this is a manual process much larger grids would become burdensome. In all, we had to complete roughly 600 individual runs of the program given the size of the study area. However, the ASCII text files were readily converted into raster grids and, despite the large number of grids, were easily mosaicked using ArcGIS without slivers or gaps.

4. Discussion

4.1. Review of results

We introduce a new tool, GE Grids, and with it create a binary classification layer of anthropogenic land conversion versus natural habitat in East Africa. Although East Africa is a region of conservation significance (Jenkins et al., 2013), there is substantial disagreement over the extent of anthropogenic land cover among existing datasets (Fritz et al., 2011, 2010; Hannerz and Lotsch, 2008; Vancutsem et al., 2012). Accurately identifying this extent provides a useful metric for previous or future change analyses. Unsurprisingly, Burundi and Rwanda have the highest rates of land conversion, as these countries also have the highest human population densities. Kenya and Tanzania have the lowest rates of land conversion and population densities.

The reliability of this tool is important to consider as GE Grids relies on manual classification of image data. Using a test grid, we show that this process is highly repeatable (83% overlap between co-authors) and even higher for a single user (95%). This suggests that multiple contributors following strict rules can produce output consistent enough to be merged together, although output by a single user will be more consistent.

Comparison of GE Grids with existing datasets reveals several trends. Although Africover is the oldest, it has the highest percentage agreement with our dataset. This is likely due to the regional nature of the dataset and its comparatively high-resolution input data (30 m). GlobeLand 30, the only other comparative dataset with 30 m resolution, has the second best overlap with our layer. GlobeLand 30 has nearly the same overall agreement as Africover, yet on a country-by-country basis, its agreement is highly variable whereas Africover's is not (Table S2). GlobeLand 30 has both the lowest (Burundi is only 44%) and the highest countrywide agreement (Kenya at 95%) of any comparative dataset. This inconsistency strengthens the recommendation by Fritz et al. (2011) to review any dataset for your area and application before use.

4.2. Classification challenges

The use of GE Grids to visually classify anthropogenic land conversion does present some new challenges. One issue is image data of moderate resolution or otherwise obscured land cover (commonly due to clouds). However, these regions can first be classified as No Data and later modified using ancillary data layers where available. We chose to use WorldPop, a human population density dataset (Linard et al., 2012), as we were evaluating land cover datasets, otherwise land cover datasets would be the natural choice. The high level of agreement between WorldPop and our own (between 81 and 93% at the country level) validate their use.

Other issues with using GE Grids for identifying anthropogenic land conversion are inherent to Google Earth. These include positional error in data, variability in image date and resolution, and methodological variation among data providers and sensors. The positional accuracy of Google Earth data is debated, but errors are likely sufficiently small to allow for the evaluation of moderate-resolution remote sensing products across the globe (Yu and Gong, 2012; Potere, 2008). A significant drawback is the temporal variation of Google Earth data. Dates for high-resolution imagery from a random sample of 100 points throughout the study area range from August 10, 2001 to June 27, 2014. This variation makes it impossible to give a definitive reference date for this product. However, roughly 90% of sample points are from the 2010s. Unfortunately, the spatial coverage of various imagery dates cannot be easily estimated. Naturally, uses at smaller extents would have less temporal variation and represent a more precise period of time. Another challenge is that the imagery displayed in Google Earth is not easily integrated with GIS software, and is updated regularly, thus reducing the replicability of GE Grids' output over long durations.

Further challenges to the use of GE Grids for LULC classifications impact traditional remote sensing analyses as well. The potential misclassification of fallow or retired fields, especially in areas with shifting cultivation, can overestimate anthropogenic impact (Vancutsem et al., 2012). Another potential issue is the use of only one image date in classification (Sedano et al., 2005; Watson et al., 2015). The single image may be captured at a time when distinction between croplands and natural vegetation may be difficult; for example following a fire, during dry seasons, or when lands are left fallow. Additionally, a single image precludes historical analysis (Watson et al., 2015).

However, previous research supports the idea that simple, rapid approaches to land cover mapping have benefits. See et al. (2013b) found that crowdsourced data from Google Earth delineating the spatial distribution of cropland in Ethiopia had a higher overall accuracy than global land cover datasets. When analyzing the crowdsourced data itself, See et al. (2013a) found that users

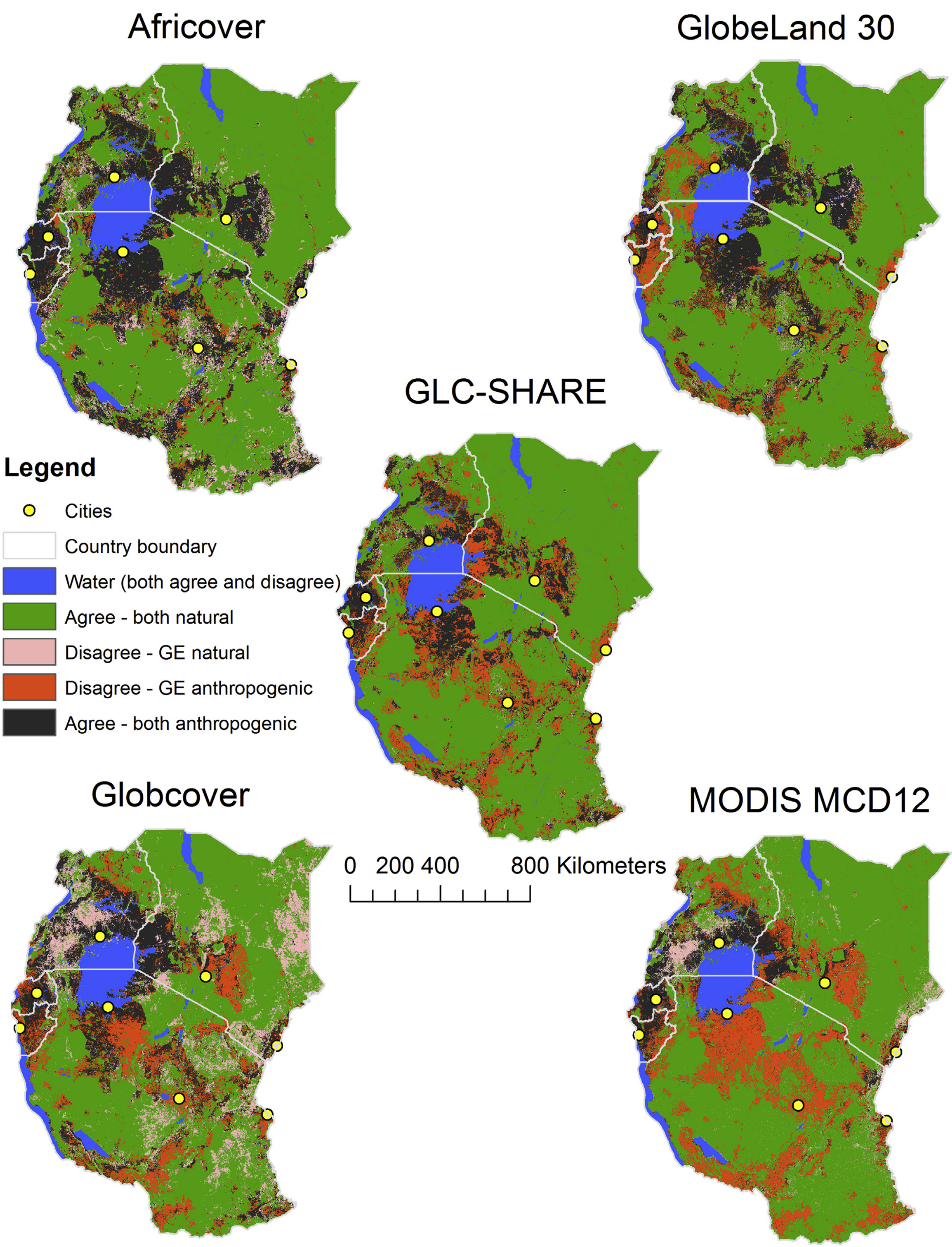

Fig. 5. A spatial comparison of anthropogenic land cover in East Africa between GE Grids and comparative datasets.

underestimate the degree of human impact and there was little difference between experts and non-experts in identifying human impacts. These results suggest that the GE Grids process can produce accurate, conservative estimates of anthropogenic land conversion and be effectively implemented by non-specialists.

4.3. Comparison with existing tools

GE Grids is not the first tool to intersect Google Earth with LULC mapping, nor is it alone in attempting to improve traditional land cover classification procedures. In fact, Google Inc. has developed their own online tool, Google Earth Engine (https://earthengine.google.org/#intro), which allows users free access to a massive public collection of satellite imagery (e.g. Landsat and MODIS) and a large-scale computational facility to perform earth observation data analyses. Importantly, their interactive user interface is designed for LULC image classification with only a moderate learning curve. However, the high-resolution imagery available on Google Earth is not included in the accessible collection, and therefore use of Google Earth Engine will likely result in the same challenges of classification accuracy associated with low- and medium-resolution images. Additionally, user understanding of software is important in ensuring sound results and correct inferences (Ahmed et al., 2015). Indeed, the ease of access may even result in worse classification accuracy because it is a process similar to traditional LULC analysis but Google Earth Engine may not have the functions or users may be without the knowledge to fine-tune the analysis to achieve better results.

Other tools also incorporate Google Earth in LULC analyses. Global Mapper, was developed for mapping global land cover with the aid of Google Earth (Gong et al., 2013); however, the tool is not widely available and could not be tested. VIEW-IT was developed to provide high-quality reference data for training and validation (Clark and Aide, 2011). Bastin et al. (2013) developed an open-source program to track land cover change in Important Bird Areas. Geo-Wiki is another tool that uses Google Earth to assist in the training and validation of land cover products (Fritz et al., 2009). Geo-Wiki goes beyond the other options to create interpolated maps of certain land cover classes, such as cropland in Ethiopia (See et al., 2013b) or a global hybrid land cover map (See et al., 2014). Yet, the fundamental difference between these previous options and GE Grids is that they primarily assist in training or validating existing land cover products and do not allow the user to conduct their own land cover classification.

4.4. Software evaluation

We believe the software performed well in this case study. We successfully evaluated nearly 1,500,000 individual grid cells over the course of 600 runs on the basis of image data provided via Google Earth. Despite multiple users, the program gave reliable results and the data are easily interfaced with ArcGIS.

The software evolved during the case study as we made modifications to improve reliability and focus on essential program elements. A major addition was the ability to upload a previously evaluated grid cell, enabling us to edit individual runs of the program. Manual edits of raster grids are difficult in ArcGIS and much easier to complete in GE Grids. However, there is room for further improvements to evaluating and editing grid cells. We would like to add the ability to include KMZ files (Google Earth files) as an overlay while running the program. For instance, the user could then bring in protected area boundaries and specifically evaluate land cover on either side of the border. Additionally, transforming GE Grids into a crowdsourcing or open-source tool could expand opportunities. Finally, allowing for a greater number of classification categories would be useful in most contexts. However, a greater number of classes can affect accuracy by introducing greater subjectivity and ambiguity of class definition (Powell et al., 2004).

GE Grids is a manual approach, having both benefits and drawbacks. A potential lack of consistency is likely the greatest drawback, although we believe that this will not be the case under proper conditions. A manual approach can also be time-intensive. However, Google Earth and GE Grids are both free, downloadable programs, require little training, do not require download of large satellite images from servers, require essentially no processing time, and hence have significant built-in timesaving. The manual approach of GE Grids is also very transparent and results can be quickly and easily compared to each other and to existing data. This can be an advantage over complex algorithms used in traditional land cover classification procedures. While we recognize that the trend in land cover classification is towards automated data processing, we believe that a diversity of approaches is essential. Not all approaches will work in all situations, and a transparent method like GE Grids can help ensure accuracy from more complex classification methods.

4.5. Conclusions

Habitat loss via anthropogenic land conversion is a primary driver in biodiversity loss (Pimm et al., 2014). Therefore, identification of human-impacted areas is a critical first step in conservation planning and planning for ecological resilience (Baguette et al., 2013). Yet, existing global land cover datasets poorly and variably identify croplands and urban areas (Fritz et al., 2011; Fritz et al., 2010; Vancutsem et al., 2012). Improvements in the identification of these important areas are necessary. GE Grids can aid conservation purposes by pinpointing anthropogenic land cover and providing complementary data for existing LULC layers.

An important difference between traditional LULC mapping and GE Grids is that this tool only produces a binary output as opposed to assigning multiple land cover classes. But when identifying a particular land cover type is very important, such as anthropogenic land cover, GE Grids can be a valuable complement and validation to existing datasets. Traditional remote sensing techniques require specialized knowledge and potentially expensive data and software (although this is changing), (Stensgaard et al., 2009; Pettorelli et al., 2014). Comparatively, GE Grids is a free, simple, transparent process that can quickly confirm results from more complicated analyses.

Acknowledgments

A.J. was supported by a fellowship from National Geographic Society's Big Cats Initiative (grant SP08-11), and the Mohamed bin Zayed Species Conservation Fund (#10251555). We acknowledge Mat Disney, Sarah Durant, Tim Caro, Stuart Pimm and 8 anonymous reviewers for proofreading the manuscript; their comments greatly improved the paper. We also thank Jose Gomez-Dans for downloading and mosaicking MODIS data. Kyle Bennett, Megan Hendrix, Sasha Montero, Arti Sharma, Pulin Shi, Or Sperling and Shani Sperling deserve recognition for assisting in grid classification, and early trial and error with the GE Grids program. Author contributions: A.J. and J.R. designed the research; A.S. wrote the program; A.J., J.D., J.G., H.J., Z.R., H.W. and J.R. conducted the research, A.J. and J.R. analyzed the results; and A.J. and J.R. wrote the paper. We declare no conflict of interest.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2015.06.011.

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