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Implications of Spatial Data Variations for Protected Areas Management: An Example from East Africa

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Abstract Geographic information systems and remote sensing technologies have become an important tool for visualizing conservation management and developing solutions to problems associated with conservation. When multiple organizations separately develop spatial data representations of protected areas, implicit error arises due to variation between data sets. We used boundary data produced by three conservation organizations (International Union for the Conservation of Nature, World Resource Institute, and Uganda Wildlife Authority), for seven Ugandan parks, to study variation in the size represented and the location of boundaries. We found variation in the extent of overlapping total area encompassed by the three data sources, ranging from miniscule (0.4 %) differences to quite large ones (9.0 %). To underscore how protected area boundary discrepancies may have implications to protected area management, we used a landcover classification, defining crop, shrub, forest, savanna, and grassland. The total area in the different landcover classes varied most in smaller protected areas (those less than 329 km^2), with forest and cropland area estimates varying up to 65 %. The discrepancies introduced by boundary errors could, in this hypothetical case, generate erroneous findings and could have a significant impact on conservation, such as local-scale management for encroachment and larger-scale assessments of deforestation.

Keywords Conservation · GIS · Protected areas · Uganda

Introduction

Geographic information systems (GIS) have become an important tool for conservation and natural resource management (Lewis 1995; Leclerc and Chacón 1998; Bassolé et al. 2001; FitzHugh 2005; Junge et al. 2010). Though conservation science and management rely heavily on spatial analyses (Lacher 1998; Aspinall 2005), spatial data used in such analyses can contain implicit error that results in variation between what is seen on the ground and what is

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depicted in the data (Burrough and McDonnell 1998; Dominy and Duncan 2001; Bolstad 2002; Rae et al. 2007). This error has the potential to manifest in, and propagate through, subsequent analyses and thus into operations and management plans. Conservation managers depend on the accuracy of these data layers to manage wildlife (e.g., critical habitat, migration patterns, and management zone delineation), resources (e.g., logging concessions), and boundary establishment, maintenance, and monitoring (Gliddon and Aspinall 1997; Smith et al. 1997).

Accurate and consistent delineation of protected area (hereafter referred to as a park) spaces is also important in delineating change of land use (i.e., protection to agriculture), access, and governance, which will also impact park neighbors. Inaccurate or inconsistent boundary locations or definitions may lead to ineffective policing of boundaries and illegal activities, leading to issues such as forced seizure of land or expulsion from settled lands, straining park-neighbor relations (Ryan and Hartter 2012). If inconsistent or incorrect spatially explicit data are used and exchanged between managers and organizations, encroachment surveillance may be compromised (Watson et al. 2013), and disagreement over management decisions may arise between institutions due to conclusions drawn from different data sources.

Spatial data, such as park boundaries, watershed delineation, management zones, and wildlife ranges are often created by digitizing aerial photos, satellite imagery, or topographic maps, and rendered in a GIS. This process results in efficiency gains and cost savings that are important since conservation organizations that are small and locally operated do not always have the means to secure complete, consistent spatial data for their management areas (Freeman et al. 2011). However, creating spatial data does have its drawbacks. Error is introduced along the way during digitization and data rendering, beginning with satellite imagery and aerial photo acquisition, and processing. Errors not only propagate, but also can amplify throughout this process (Congalton and Green 2009). In addition, human interpretation in analog remote sensing (i.e., digitizing from aerial photographs) is a large source of this error, resulting in consistency issues of final data products, because two different people would not create identical data in such a subjective process (Hunsaker et al. 2001). While at times ground referencing of these data does occur, management decisions are often made in places distant from the location where they will be put into effect. GIS-derived maps are often easy representations for these choices, but users do not always realize the inaccuracies and political and social influences associated with them (Kolte et al. 2009).

Conservation and resource management operate at multiple scales due to the wide range of species and ecological processes (Lindenmayer et al. 2008). Analyses utilizing GIS simplify four-dimensional relationships and processes in two-dimensional space. Depending on the field-of-view or scale at which the user is operating (e.g., park scale, park sector or sub-sector, or plant community), the spatial mismatch created by boundary delineation may have more or less inherent error. Specific to boundary creation, we see that when data are created from cadastral and topographic maps (paper maps that were originally created using higher accuracy, but more costly survey methods), the original lines are often more coarse. The degree to which this is problematic depends on the scale at which the data are being viewed. When the user is viewing a park boundary zoomed out, the boundary appears smooth. However, when zoomed into a certain section of the boundary, it becomes apparent that the boundary is a series of jagged lines and is not an accurate representation of what is on the ground. Due to the increasing amount of relative error of lines that are more curved compared to straight lines, a curved line's depiction is dependent on the amount of vertices used (Burrough and McDonnell 1998). Each of these vertices represents the connecting point between a new, straight line in a GIS.

In this paper, we illustrate potential sources of error and uncertainty in spatial data quantitatively by comparing spatial data between three organizations involved in Ugandan park management—either directly, or through scientific research leading to management decisions. To demonstrate the inconsistencies using spatial data, we examine the mismatch between park boundaries—both in area and location—and between institutions. We compared park data from the International Union for Conservation of Nature (IUCN), World Resources Institute (WRI), and Uganda Wildlife Authority (UWA) for seven national parks (Fig. 1) in the Ugandan Albertine Rift (official park area as reported by UWA (http://www.ugandawildlife.org/) noted in parentheses): Bwindi Impenetrable National Park (321 km^2), Kibale National Park (795 km^2), Mgahinga Gorilla National Park (34 km^2), Murchison Falls National Park (3,840 km^2), Queen Elizabeth National Park (1,978 km^2), Rwenzori Mountains National Park (996 km^2), and Semuliki National Park (220 km^2) (hereafter, the parks will be referred to in the abbreviated form of Bwindi, Kibale, Mgahinga, Murchison Falls, Queen Elizabeth, Rwenzori, and Semuliki). Then, we demonstrate the impact these discrepancies can have on a landcover analysis using satellite-derived land cover data. We hope to call attention to the potential for this discrepancy to arise, and suggest that it can be added to assessment checklists when developing management plans with spatial data dependencies.

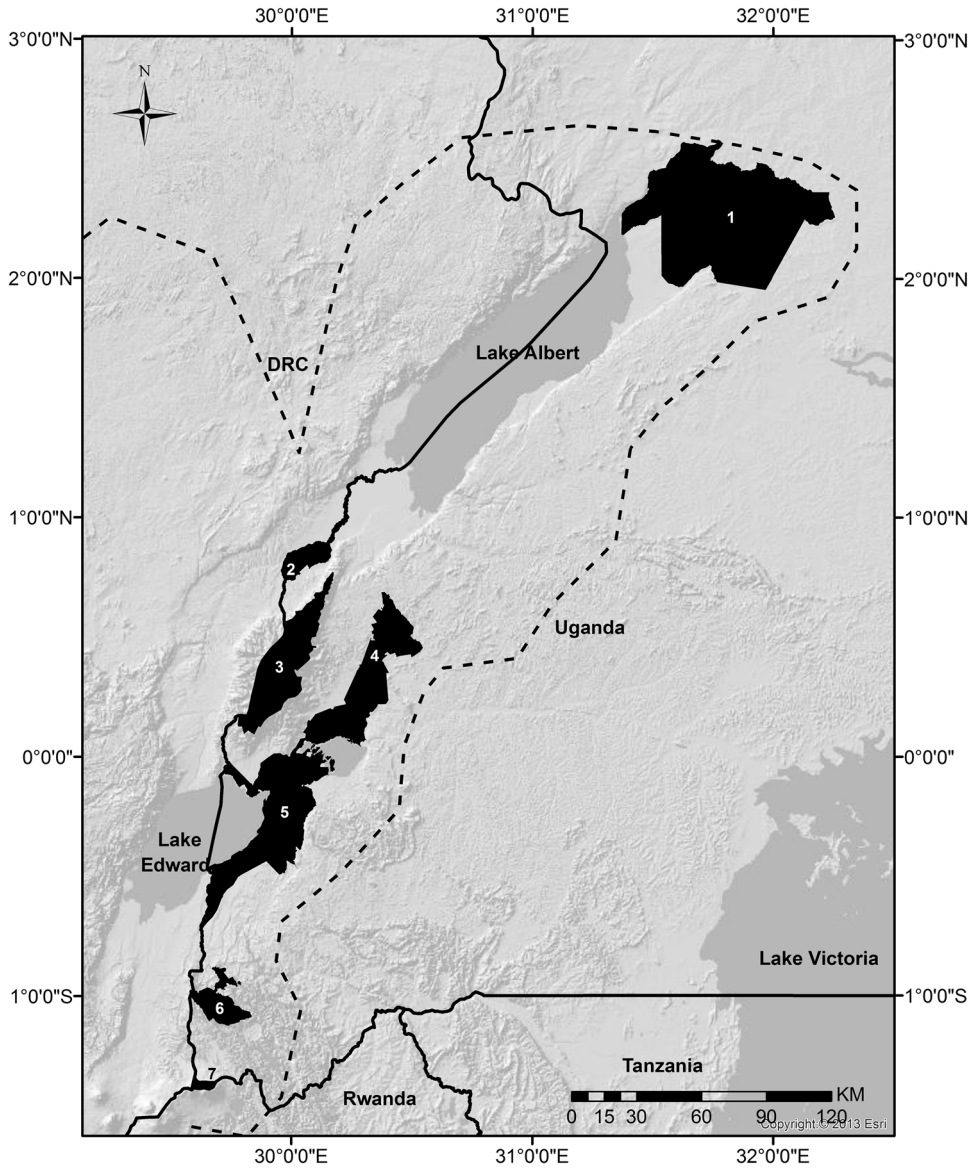

Fig. 1 Seven national parks located in the Albertine Rift (*dashed-line*). *1* Murchison Falls National Park, *2* Semuliki National Park, *3* Rwenzori Mountains National Park, *4* Kibale National Park, *5* Queen Elizabeth National Park, *6* Bwindi Impenetrable National Park, and *7* Mgahinga Gorilla National Park

Methods

The Albertine Rift region in East Africa is one of the world's hotspots for biodiversity (Plumptre 2002; Plumptre et al. 2003, 2007; Cordeiro et al. 2007). High rates of habitat loss and conversion, largely due to intensive smallholder agriculture and land and resource pressures, make this one of the most threatened and high priority areas for conservation (Ryan and Hartter 2012). We focus on a subset of seven Albertine Rift parks within Uganda, where we have access to sufficient data to address our study (Fig. 1). Park boundary polygons were obtained as shapefiles from the WRI (dataset last updated in 2007, with no metadata regarding scale), IUCN (dataset created in 1999, with no metadata regarding scale) websites and from UWA officials (no date specified, with a scale of 1:50,000). Boundary polygons were projected into each park's respective UTM zone within the WGS 1984 datum. We then merged all three boundary layers for each park together into one boundary file using ArcGIS 10.1 to find the areas of overlap and discrepancy between all three datasets.

To provide an example of the type and magnitude of errors that these boundary discrepancies may give rise to, we quantified the area assigned to different landcover classes within each boundary set. Using an independent, pixel-based classification dataset, we can truly illustrate these differences. We used the University of Maryland classification moderate resolution imaging spectroradiometer (MODIS) MOD12Q1 data layer to establish our different landcover classes. The MODIS MOD12Q1 contains 500 m gridded world landcover data. To cover the study area, four images from January 1, 2012 were mosaicked

together in Erdas Imagine 2013. We recoded the classification by combining the various pre-defined classes of forest (Evergreen Needleleaf, Evergreen Broadleaf, Deciduous Needleleaf, Deciduous Broadleaf, and Mixed), shrubland (closed and open), and savanna (woody and regular) into more generalized classes. This resulted in landcover totals within each park boundary for five mutually exclusive classes: (1) forest, (2) shrubland, (3) savanna, (4) grassland, and (5) cropland. Since we are only comparing spatial differences in the landcover of one image and not temporal changes, MODIS landcover products are appropriate for our analysis, and allow us to extend the landcover test to all seven parks. We recognize possible errors associated with the accuracy of this product, but they will not affect our results since the purpose of our analysis is to demonstrate a real-world implication of data discrepancies.

Results

We found that the boundary data vary in three ways: total area, overlaps and gaps between dataset boundaries, and what appear to be systematic offsets (Table 1). The spatial discrepancy results in a wide range of spatial variance. While Kibale had discrepancy in area representation of only 0.4 % (3.0 km^2) between the three data sources, Rwenzori and Semuliki varied by 9.9 % (98.9 km^2) and 9.7 % (23.6 km^2), respectively (Table 1). Murchison Falls and Queen Elizabeth showed low variation in area—less than 2 %. Bwindi and Mgahinga varied by 5.3 % (18.1 km^2) and 6.4 % (2.7 km^2), respectively. In addition, many parks showed noticeable spatial variation in the location of park boundaries, in addition to quantitative area variation (Table 2). Figure 2 provides an example of the differences in spatial location and overlap in the different data layers, using Rwenzori as an example. Locations where the boundaries either had no overlap with other polygons, or overlapped with a second or all three boundaries are illustrated in grayscale shading in Fig. 2. The black polygon in the center of the image shows the locations where all three polygons overlap, the gray polygon where the WRI and IUCN boundaries overlap, and the polygon with the black dots shows the location of only the UWA boundary. We note that this is not a systematic shift throughout the whole park (notice the western boundary lines up relatively well between all layers), but rather geometric and locational differences of many of the boundaries. This means that just 816.7 km^2 (Table 2) of the total area (996 km^2) of Rwenzori is located in the same location within the coordinate system. Since the total area of the park ranged from 897.5 to 996.4 km^2, with the different boundary data sets, the total overlapping area accounts for 81.9 to 91 % percent of the overall area of the park, depending on which organization's data layer is used. The same issue can be seen with Bwindi, where there is a 251.6 km^2 overlap between all data sources, meaning 74.5 to 78.7 % of the total area is in common. Kibale and Murchison Falls showed the least variation in overlapping area, all with greater than 95 % of area in common.

The discrepancies quantified in the MODIS landcover data ranged from minor differences to large differences of total landcover within each class (e.g., crops or forest) within each respective park. Not surprisingly, the

Table 1 Total area (km^2) of each park [Bwindi Impenetrable National Park (BINP), Kibale National Park (KNP), Murchison Falls National Park (MFNP), Mgahinga Gorilla National Park (MGNP), Queen Elizabeth National Park (QENP), Rwenzori Mountains National Park (RMNP), and Semuliki National Park (SNP)] for each data source [International Union for Conservation of Nature (IUCN), World Resource Institute (WRI), and Uganda Wildlife Authority (UWA)], difference between maximum and minimum park area (km^2), and percent difference in area between minimum and maximum park area

National Park	IUCN	WRI	UWA	Difference between max and min park area (km^2)	% Difference between min and max park area
BINP	327.7	319.9	337.9	18.1	5.3
KNP	789.7	792.4	792.7	3.0	0.4
MGNP	38.6	40.7	41.2	2.7	6.4
MFNP	3,876.4	3,867.4	3,820.6	55.8	1.4
QENP	2,102.8	2,103.9	2,065.8	38.1	1.8
RMNP	996.4	995.2	897.5	98.9	9.9
SNP	221.1	220.5	244.1	23.6	9.7

Table 2 Total area (km^2) in common between all three data sets [International Union for Conservation of Nature (IUCN), World Resource Institute (WRI), and Uganda Wildlife Authority (UWA)] for each park [Bwindi Impenetrable National Park (BINP), Kibale National Park (KNP), Murchison Falls National Park (MFNP), Mgahinga Gorilla National Park (MGNP), Queen Elizabeth National Park (QENP), Rwenzori Mountains National Park (RMNP), and Semuliki National Park (SNP)], and percent of overlapping area based on the separate area calculations

National Park	Overlapping area between all data sources (km^2)	% of IUCN	% of WRI	% of UWA
BINP	251.6	76.8	78.7	74.5
KNP	769.9	97.5	97.2	97.1
MGNP	35.9	93.0	88.2	87.0
MFNP	3,694.1	95.3	95.5	96.7
QENP	1,906.3	90.7	90.6	92.3
RMNP	816.7	82.0	82.1	91.0
SNP	205.4	92.9	93.1	84.1

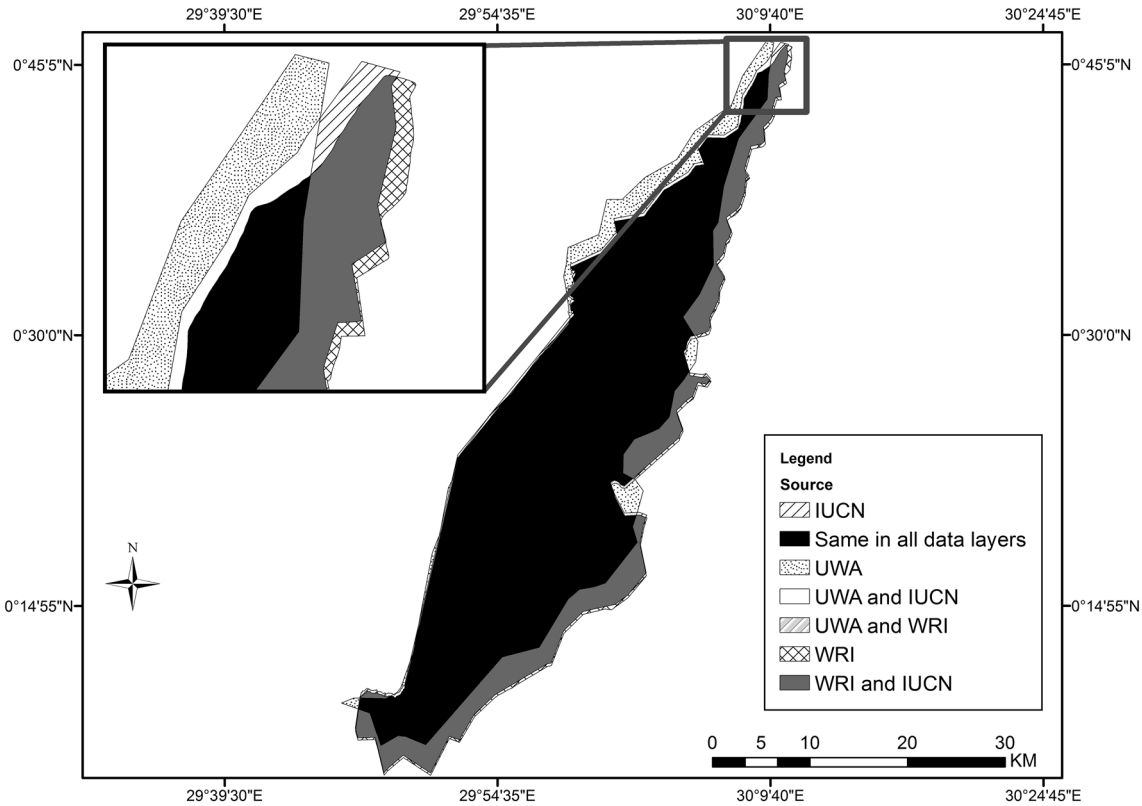

Fig. 2 Spatial inconsistencies of Rwenzori Mountains National Park based on where each data source [International Union for Conservation of Nature (IUCN), World Resource Institute (WRI), and Uganda Wildlife Authority (UWA)] is located

differences varied with the total amount of overlap between the three data sources (Fig. 3; Table 3). For instance, Bwindi had large differences in forest and cropland class area, with differences between 4,650 and 2,475 km^2, respectively. That equates to a 13.1 and 65.6 % difference in forest and crop cover between the largest and smallest estimates. Similar differences can be viewed with Rwenzori, with forest and crop area varying 8.0 and 46.7 % between the largest and smallest landcover estimates, respectively. Kibale, a park that had minimal variation spatially between all three park sources, had variations of only 0.3 and 8.4 %, respectively.

Discussion

There are clear efficiency gains to working in a digital GIS compared to cumbersome paper copies of maps and costly and time intensive field surveys (O'Looney 1997; Obermeyer 2005). However, there are spatial discrepancies (both in extent and location) in data layers, which may in turn alter or lead to misinformed management decisions. These discrepancies are potentially detrimental to conservation policy and management, such as boundary establishment and maintenance, resource extraction, wildlife migration, delineation of management zones, sensitive species monitoring, priority conservation areas, extractive reserve boundaries, and local governance of non-park areas and spaces—the so-called zones of interaction (DeFries et al. 2010).

GIS can be an effective tool for identifying and demarcating the location, quantity, and distribution of resources within a park (Jachmann 2008), but its effectiveness depends on the accuracy of the spatial data. The results of our landcover discrepancy analysis illustrate this point. It is not unreasonable to assume that a scientist or manager could reach different conclusions from landcover studies depending on which boundary layer they use for Bwindi or Rwenzori. For instance, the amount of total forest area circumscribed by the different boundary sources varies considerably, and one could conclude a large difference in an inventory of total forest. One could also reach different conclusions as to the extent of crop encroachment into the park based on the widely different area and boundary location estimates. Importantly though, this discrepancy varies across different parks, and the implications may also be different. Smaller parks within our analysis appeared to be more affected than their larger counterparts.

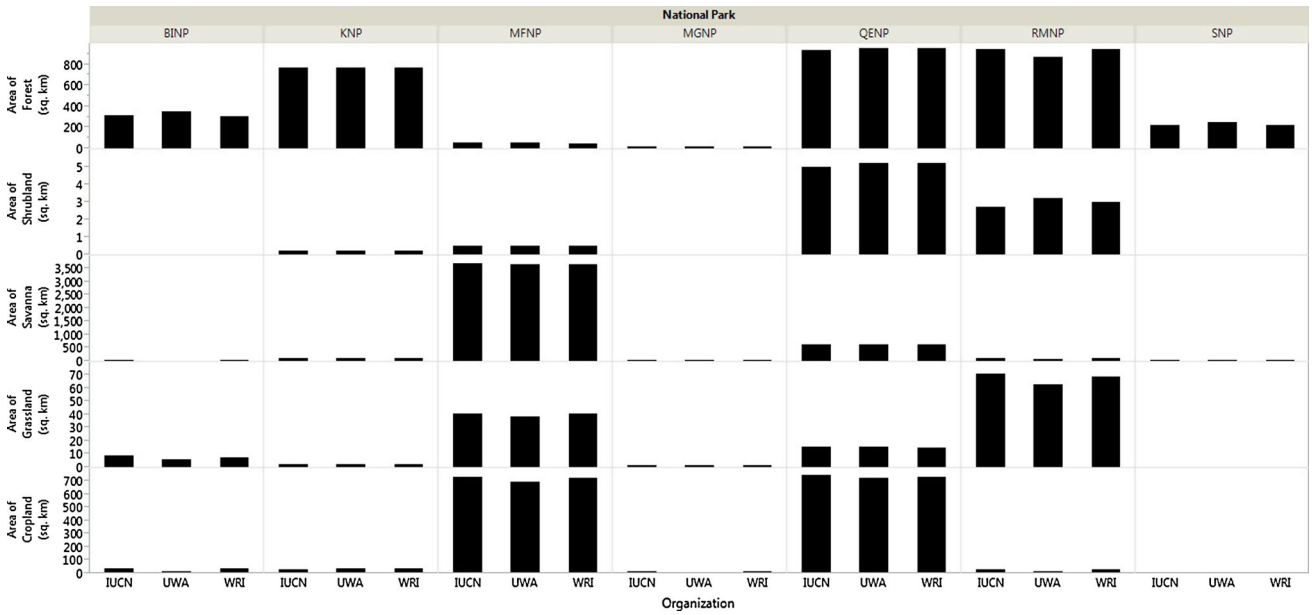

Fig. 3 Difference in total area (km^2) of each landcover class (forest, shrubland, savanna, grassland, and cropland) between all three data sets [International Union for Conservation of Nature (IUCN), World Resource Institute (WRI), and Uganda Wildlife Authority (UWA)] for each park [Bwindi Impenetrable National Park (BINP), Kibale National Park (KNP), Murchison Falls National Park (MFNP), Mgahinga Gorilla National Park (MGNP), Queen Elizabeth National Park (QENP), Rwenzori Mountains National Park (RMNP), and Semuliki National Park (SNP)]

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National Park	BINP			KNP			MFNP			MGNP		
Organization	IUCN	UWA	WRI	IUCN	UWA	WRI	IUCN	UWA	WRI	IUCN	UWA	WRI
Forest	314.0	356.3	309.8	767.5	770.0	767.5	52.3	55.0	49.8	14.0	15.5	14.3
Shrubland	0.0	0.0	0.0	0.3	0.3	0.3	0.5	0.5	0.5	0.0	0.0	0.0
Savanna	23.3	16.5	20.0	111.8	115.0	113.0	3,687.0	3,652.3	3,679.8	19.3	21.8	19.8
Grassland	9.0	6.0	7.8	2.3	2.3	2.3	40.8	38.5	40.8	1.5	1.5	1.5
Cropland	36.5	13.0	37.8	32.8	35.8	34.8	737.0	698.8	728.3	12.0	10.3	12.0

National Park	QENP			RMNP			SNP		
Organization	IUCN	UWA	WRI	IUCN	UWA	WRI	IUCN	UWA	WRI
Forest	932.8	952.8	956.5	945.3	869.3	940.5	225.3	247.5	223.3
Shrubland	5.0	5.3	5.3	2.8	3.3	3.0	0.0	0.0	0.0
Savanna	623.5	613.0	619.5	112.3	92.0	113.0	27.0	28.8	28.3
Grassland	15.3	15.5	14.5	70.8	62.8	69.3	0.0	0.0	0.0
Cropland	751.5	724.8	734.8	26.3	14.5	26.8	5.8	7.0	5.5

This is largely due to the potential for a greater proportion of a small park to be affected with even a small discrepancy between layers.

Spatial data have been used to assist in anti-poaching efforts to map high-risk poaching locations through spatial modeling (Young et al. 2011; Haines et al. 2012). Hamisi (2008) used inputs such as terrain slope, location of human population, and land cover and road types to identify potential high-risk areas for zebra poaching in Tarangire National Park in Tanzania. If spatially inconsistent data are overlaid and used to locate high-risk areas of poaching, areas that need monitoring may be missed (errors of

omission) or resources may be deployed in low-risk areas (errors of commission). The estimated costs of preventing poaching in Africa range from $200 to $500 per hectare (Richard and Erwin 2006). Based on those estimations, possible misappropriated anti-poaching measures could cost $60,000–150,000 and $472,000–1,180,000 for Kibale and Semuliki, based on the spatial discrepancies of the data. Therefore, efficient, reliable, and relatively accurate spatial data are important for allocating these resources to avoid this tool from being more harmful than helpful.

There is a sharp contrast in landcover at the boundary of forest parks and the surrounding domesticated landscape in Uganda. The less fragmented park land is surrounded by increasingly fragmented landscapes due to intensive agricultural land and population growth (Hartter and Southworth 2009; Southworth et al. 2010; Hartter et al. 2011; Gibbes et al. 2013), emphasizing the need for accurate park boundary data when assessing this type of changing landscape. Park boundary data are often used to define the area of interest for studies of landscape connectivity within parks, and to create buffered regions outside of the parks. The estimated trajectories of fragmentation and restoration within and around a park will be affected by the area of land in the actual park versus the amount of non-protected land within the boundary. Peripheral land might skew fragmentation metrics to show more fragmentation than is actually occurring within park borders. This could lead to false conclusions about the effectiveness of a certain park to reconnect previously fragmented ecosystems. This is illustrated by the wide discrepancies of cropland included in the landcover analysis of this paper, and examples of dramatic spatial discrepancies like Fig. 2 of Rwenzori.

Accurate data layers are also imperative for studying animal movement and distribution patterns. Galanti et al. (2006) used overlay analysis, in conjunction with animal tracking GPS, to research movement patterns of elephants in Tanzania during both the wet and dry seasons. Overlaying the elephant GPS points with various other data allowed for the researchers to view how often the animals stay within the parks. Goldsmith (2000) provided another example of a similar situation in which mountain gorillas (*Gorilla beringei beringei)* of Bwindi often sleep outside of the boundary of the park. These studies highlight the importance of consistent and accurate park boundary layers. The boundary that is chosen in such an analysis is paramount to the success of the study in delineating their ranging behavior and movements. If the GPS information shows that a species largely stays within the park, but the boundary layer is incorrect and the species actually spends the majority of its time on the outskirts of the boundary, there is cause for concern. The extension of park boundaries to areas where the species under consideration is located might never be brought into practice due to the invalid conclusions resulting from the research. Figure 2 highlights a dramatic difference in the location of the boundary of Rwenzori. With portions of the northern tip of the park offset greater than 2 km from each other, there is a large area of discrepancy where uncertainty of species location within park boundaries could occur.

Possible data inaccuracies could also be introduced through previous manipulations of the data. This can occur intentionally, such as when scientists introduce error into data showing, for example, the location of rare species, habitat, and resources for their security (Jacobson and Duff 1998; Mascia et al. 2003; Hartter et al. 2013), or it can occur unintentionally. For instance, GIS users do not always download data directly from the producers. Many times, the data are passed along and handed down from colleagues, and it is possible for metadata to get lost in translation, and insufficiently updated, leaving the current user with inaccurate information. An example of the ill-effects of incomplete or missing metadata is when data layers are brought into a GIS with no projection defined. When a user has no metadata that provides projection information, the user may specify ad hoc a coordinate system. This lack of metadata (or inaccurate metadata) could result in an inaccurate spatial representation within the selected projection. Even if the data were originally in the correct projection to begin with, the process of reprojecting data from one projection (e.g., WGS 84, UTM) to a different projection (e.g., Africa Albers Equal Area Conic), then back to the first can render the data different from its original, pre-projected state (Stine and Hunsaker 2001). These data manipulations and incomplete metadata can hinder the results sought after in a project, which can inevitably increase discrepancies between data layers.

Another scenario in which incomplete metadata can affect the final analysis is when data created at an inappropriate scale for the study are used. If small-scale data (increasingly generalized) are used for studies requiring large-scale data (increasingly detailed), inaccurate assumptions could result, and error could be propagated through the final product. Information regarding appropriate scale of the data should be easily located within the metadata. Thus, it is important to note that only one of the metadata associated with the files used in this analysis has a section that explicitly states the scale of the data. Therefore, it is largely up to the data user's subjective discretion of what they assume is a usable and appropriate scale for the data. According to the data standards of the IUCN Protected Planet project (www.protectedplanet.net), the inclusion of information on data scale and lineage is optional information in the file metadata for files in their system (UNEP-WCMC 2012). Adding this information to metadata would be a helpful supplement to the current metadata, and would increase the likelihood that the data are used appropriately.

An additional point is worth making. Administrative boundaries normally depend on bureaucratic decisions due to their invisible nature, and often can only be seen by interacting with local government administrations (Campari 1996). As such, boundaries can often take on an "unofficial" nature. For instance, although there may be an official, surveyed boundary between two neighboring plots of land, an unofficial boundary often takes precedent and is the boundary practiced between neighbors (Harvey 2011). One example of this unofficial boundary can be the line in which each neighbor stops taking care of their yard. The line to which the grass on one property is cut can become the boundary that is used to demarcate the plots, even if it does not match the official, surveyed boundary, and can be fluid and shift over time. In the event that aerial imagery is used to define a boundary based on noticeable natural features in the imagery, this unofficial border could be used to delineate the GIS boundary, and data users can get a different idea of the boundary compared to what another person sees using separate data. This may lead to boundary disputes and insecure land tenure, as it has in Tanzania (Verplanke and McCall 2003). Additionally, park designations can change through time, and boundaries can shift as a result. This was the case when the former Kibale Forest Reserve and Kibale Game Corridor were combined to form Kibale National Park in 1993 (Ryan and Hartter 2012). The boundaries of Kibale shifted yet again in 1998 after a formal survey showed that the original location of the boundary was incorrect, and people who were residing within the incorrect boundary were evicted and forced to relocate. Often, boundaries have multiple pressures acting on them, and each time park designation is changed or redefined, there is an opportunity for data to become out of date or obsolete. This becomes a noticeable issue when metadata records are not updated sufficiently, and an organization or user cannot adequately distinguish between an outdated and current representation of the real-world.

There are a few steps that can be taken to identify potential errors and uncertainty (as well as bad sources of data) to reduce their negative impacts. Although obvious, the first step for anyone downloading or using spatial data should be to locate and view a data layers metadata with a critical eye. The increased availability of spatial data and free GIS software has led to an increased risk of data misuse, as many people who are untrained in geospatial data have greater access to its services (Devillers et al. 2002). Metadata are going to become increasingly important as easy access increases, since non-experts can also create data and make them available for others to use (Hartter et al. 2013). Metadata are often times limited, incomplete, and too complex for an inexperienced user (Beard and Buttenfield 1999; Devillers et al. 2007). Therefore, another step to reducing misuse of data would be to increase training in geospatial technologies to develop a more knowledgeable user base that can adequately navigate and use the enormous amount of data available on the internet (Devillers et al. 2007). Since increased education can be difficult to implement and monitor, another solution suggested by Devillers et al. (2007), is to employ a third-party mediator to act as a translator between data users and data producers. This would aid in the product-users having a knowledgeable source to decipher complicated metadata, and help data producers ensure their message is communicated effectively.

Conclusion

While policy and management decisions are made using a variety of methods and data sources; GIS, both for analyses and data acquisition, plays an ever-increasing role. Therefore, the limitations and inaccuracies that may exist within subsequent analyses will be amplified. This demonstration of the inter-institutional data variations in East African park borders highlights where some of these errors can creep in, and illustrates how error can have a greater influence on smaller parks. We thus call for both caution and awareness in using geospatial data: caution in accepting a "map" as truth, and awareness of where the inherent and often unavoidable sources of error might affect utility and interpretation. In assessing park management plans at an institutional level, we suggest explicitly including a review of this potential for data discrepancy to introduce error or bias into decisions based on spatial data. We have highlighted a primary issue of boundary definitions, but this potential pitfall must be emphasized in all uses of spatial data.

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