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Understanding the Relationship Between Environmental Energy Availability and Bird Species Richness in Kenya Using Remote Sensing and Ancillary Data

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Abstract: The energy hypothesis predicts that, in regions of roughly equal area, energy flux per unit of area should be the prime determinant of species richness. In the case of plants, primary production represents realized energy capture. Potential evapotranspiration is a measure of community energy use and it is related to terrestrial primary productivity. The best correlate of the latter on regional scale is the Advanced Very High Resolution Radiometer (AVHRR) derived Normalized Difference Vegetation Index (NDVI). I examined the relationship between bird species richness and measures of available environmental energy (interannual maximum average NDVI and mean annual potential evapotranspiration) at a quarter degree scale (55 x 55 km). Statistical analyses revealed higher interannual maximum average NDVI results in higher bird species richness, whereas mean annual potential evapotranspiration correlated negatively with species richness. Understanding these relationships can help in estimating changes in bird species richness in response to global climatic change.

INTRODUCTION

The most striking feature of the Earth is the existence of life, and the most striking feature of life is its diversity. This biological diversity has long been a source of wonderment and scientific curiosity, but is increasingly a source of concern. Humankind domination of Earth's ecosystems is markedly reducing the diversity of species within many habitats worldwide, and is accelerating extinction [1]. One factor thought to be important in modulating any effect on the physical structure of the Earth in determining species diversity is the relationship between the number of species in an area and ambient available ('usable') environmental energy. This energy is usually estimated from models or indirectly from other variables and often used interchangeably with 'net primary productivity' [2]. The form and cause of diversity-productivity relations are hotly debated in the study of patterns of species diversity, with many fundamental issues as yet unresolved. Much of the discussion centers on the influence of spatial scale on diversity-productivity relationship [2]. At a relatively local scale, there is a marked tendency for general hump-shaped relationship between species richness and productivity, with species richness increasing from low to moderate levels of productivity and then declining again towards high levels of productivity when a sufficient range of productivity values is sampled [3, 4]. By contrast, at geographical scales diversity generally increases with productivity [5, 6].

Net primary productivity (NPP) is a difficult variable to measure directly, especially at regional scales. Consequently, in regional biodiversity studies, NPP is typically derived from climatic data collected at scattered (and often biased) sampling points—these points are extrapolated in order to characterize productivity over a large region [5, 7]. Such climate-based models assume that the vegetation cover is 'natural', and *ipso facto* is under the control of climate [8]. However, at regional scales, vegetation productivity is also influenced by non-climatic factors including soil nutrient and structure, topography, disturbance and land use. Thus, the Advanced Very High Resolution Radiometer (AVHRR)-Normalized Difference Vegetation Index (NDVI) provides a more accurate index of net primary productivity compared with climate-based models, by virtue of being spatially explicit [4, 8]. Another factor that has been established to influence species diversity at geographical scales is potential evapotranspiration [6, 9]. It may be interpreted as a measure of integrated, crude, ambient energy. Potential evapotranspiration is estimated from air temperature and solar radiation, and represents the maximum amount of water that would be lost by evaporation from surfaces and transpiration of plant leaves when evapotranspiration is not limited by water availability [10]. It is highly correlated with terrestrial primary productivity and is thus a measure of community energy use [5].

This study investigated the relationship between bird species richness and measures of available environmental energy (mean annual potential evapotranspiration and interannual maximum average NDVI) at regional scale. The study was performed at a quarter degree scale (55 × 55 km) that matches the scale of the distribution maps in the Bird's Atlas of Kenya [11].

MATERIAL AND METHODS

The Study Area

Kenya is situated between latitudes 5° 40' north and 4° 4' south and between longitudes 33° 50' and 41° 45' east. Altitude exerts the greatest influence on temperature in Kenya. There is a wide range between the maximum and minimum temperatures from below freezing point on the snow-capped Mount Kenya to over 40°C in some parts of the north and

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northeastern parts of the country. Generally, the low-lying northern plains are the hottest areas with maximum temperatures commonly exceeding 35°C. Annual rainfall follows strong seasonal variations, which are most pronounced in the dry lowlands and the north as well as east, but weakest in the humid highlands of the Central and Rift areas. There are three main regions of heavy rainfall: a relatively wet belt extending along the Indian Ocean coast; western Kenya just east of Lake Victoria and main mountain ranges. The wide range of habitats in Kenya is a reflection of the great altitudinal range and distinct regional patterns of rainfall. The diverse community assemblages range from montane forest habitats in the central west to semi-arid scrub in the north and mangrove forests in the southeast. Consequently, most bird species have well-defined distributions [11]. The Kenyan avifauna is one of the richest in Africa [12]. The importance of conserving Kenyan birds is emphasized by the fact that bird watching is an important component of African tourism [13].

Bird Species Data

The *Bird Atlas of Kenya* [11] mapped the distribution of 871 species in Kenya. However, at the time of publication of this atlas, it was estimated that only 40% of the possible records, which vary considerably depending on the block (quarters of degree squares) had been obtained. Since then, additional records [14] have increased this to about 42% [15]. The atlas maps [11] use symbols to indicate the nine categories of records. Since it was not possible to get the data for total number of bird species (1065 species) in Kenya [11], only a sample of 871 species recorded in the Bird Atlas of Kenya since 1970 were included in this analysis. Vagrant species and those represented only by anecdotal records were excluded. The distribution maps [11] for 871 of the species of Kenyan birds were photocopied and scanned in 256 gray scales and then saved as Tagged image file format (Tiff). An algorithm was developed for extracting the mapping symbols (Fig. **1**) for the following status of birds from the scanned tiff maps: (1) confirmed breeding after 1/1/1970; (2) present and probable breeding after 1/1/1970; and (3) records after 1/1/1970 (but no confirmation of breeding). The algorithm rectified the images to obtain standard northing by identifying the location of two pixel patterns that appear in all images, and from their positions computed the orientation of the map. Finally, the algorithm translated and rotated the image to obtain a rectified image. For each status, the maps use a specific pattern. After rectification, the position of each block (55 × 55 km) was approximately known. For each block position, the algorithm computed a slightly wider buffer and then tried to find the best match for all three patterns. For some block positions, I found that lake and country boundaries obscured the recognition of patterns. I corrected for this at specific block positions by cross-checking the pattern against the original map in the bird atlas. In addition, I looked at trends in histograms per pattern that helped to identify problems where the algorithm erroneously identified patterns. Thus, all errors caused by translating the analogue database to a digital database were removed by the operator intervention [9, 16].

NDVI Time Series Data

The Normalized Difference Vegetation Index (NDVI) is a measure of vegetation vigor. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation [17]. In general, higher values of NDVI indicate vigor and quantity of vegetation [18]. The NDVI data were obtained from the data collected by the National Oceanic and Atmospheric Administration (NOAA) satellites, and processed by the Global Inventory Monitoring and Modeling Studies (GIMMS) at the National Aeronautics and Space Administration (NASA). The GIMMS group at NASA Goddard Space Flight Center developed the GIMMS NDVI first generation dataset [19].

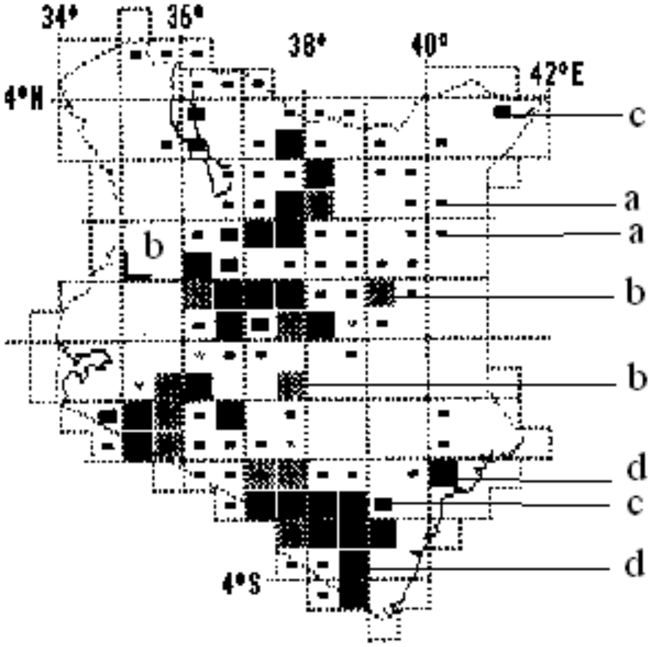

Fig. (1). A sample species distribution map showing the distribution of Ostrich (*Struthio camelus*) in Kenya used in our study. (**a**) Vagrant species and those represented only by anecdotal records, (**b**) Species present and probable breeding after 1/1/1970, (**c**) Records after 1/1/1970 (but no confirmation of species breeding), (**d**) Confirmed species breeding after 1/1/1970.

The processing chain of the GIMMS mapping system begins with stratification by continent in order to reduce the amount of data that must be processed. Suspect data are eliminated by discarding the 45 outer pixels on either side of a scan to reduce the variation in NDVI as a result of viewing geometry. The threshold of 45 pixels corresponds to a scan angle of approximately 42 degrees off-nadir [20]. In addition, data with a channel 5 brightness temperature below 288 K is assumed to be clouds and are eliminated. This cloud screening technique does not discriminate between warm clouds or partially cloud covered or "mixed" pixels [21]. Digital counts of channels 1 and 2 are then converted to radiances, and then normalized for incoming solar radiation with the preflight calibration coefficient from NOAA [22]. NDVI is computed as the normalized ratio of the difference between near-infrared and red reflectance measurements by their sum [23]:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R}) / (\mathrm{NIR} + \mathrm{R}) \qquad (1)$$

where *NIR* = near-infrared measurements and *R* = visible red measurements. Normalization reduces differences due to overall brightness of sunlight or of surfaces (e.g., shadows) that can strongly influence the image. High positive values of NDVI correspond to dense vegetation cover, whereas negative values are usually associated with bare soil, snow, clouds or non-vegetated surfaces.

Global Area Coverage NDVI data are mapped to the Hammer-Aitoff projection and resampled to 7.638 km in order to display the Africa continent on a 1024 by 1280 screen. In cases where pixels overlap, the value of the pixel with the highest NDVI is used [20]. Geo-registration is accomplished using the orbital parameters provided by NOAA. When a mismatch between features is found, the entire image is shifted over a whole number of pixels, which reduces the registration error to approximately 4 - 8 km [20].

The daily images show large areas of missing data, resulting from gaps between mapped orbits. The effects of clouds, atmosphere, viewing and illumination geometry further reduce the utility of the data.

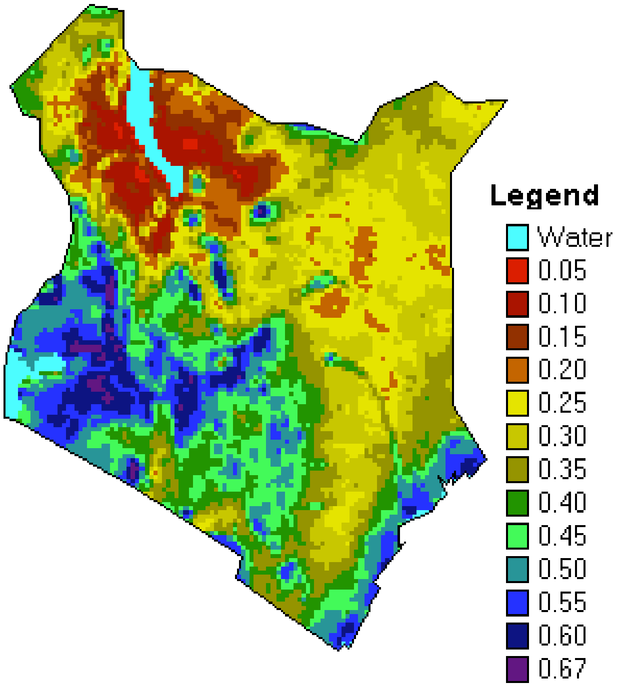

Fig. (2). Spatial distribution of interannually integrated maximum average NDVI in Kenya.

To obtain complete cover of the land surface and to reduce the impact of these effects, a 10-day maximum value composite is obtained from the daily images by selecting the maximum NDVI value for each pixel. The 10-day maximum value composite procedure selects the 'greenest' value, which generally represents the least cloud contaminated pixel for each dekad period [19]. Compositing does not account for changes in NDVI as a result of sensor degradation, solar zenith angle and/or soil background.

Analysis of Data

The calculation of species richness was based on combination of the status of birds recorded since 1970, namely, confirmed breeding after 1/1/1970, present and probable breeding after 1/1/1970 and records after 1/1/1970 (but no confirmation of breeding). In each grid cell (55 × 55 km), the number of species present was counted to give a value for total species richness. The mean annual potential evapotranspiration (mm) was estimated by averaging the means of mean annual potential evapotranspiration recorded within the 55 × 55 km grid cells [9] in the agro-climatic zone map of Kenya 1980 [24].

The study aims at measuring ecological variations within pixels in such a way that regions affected by occasional droughts or erratic changes in the timing and strength of rains, could be separated from those where the impact of such anomalies is slight. This was done by aggregating dekads to their appropriate months, calculating maximum NDVI for each month over the 11 year period, and then averaged maximum NDVI for all 12 monthly NDVI values over the 11 year period. Thus, the variability over an 11-year period (1982 to 1993) of monthly NDVI values represents temporal variation of productivity. The historical image products of Kenya comprising 396 dekads of maximum NDVI were downloaded from the website [18]. These historical NDVI products were statistical summaries (i.e., average or maximum NDVI) for the historical time period (1982-1993) and hence there was no significant influence from cloud contamination. Since dekads span from the 1st to the 10th, the 11th to the 20th, and the 21st to month end, a year has 36 dekads (i.e., 3 dekads multiplied by 12 months). Hence, 396 dekads (i.e., 36 dekads multiplied by 11 years) correspond to an 11-year time period. This implies that each month over an 11-year period has 33 dekads (i.e., 3 dekads multiplied by 11 years). By using Windisp 3.5 time series data processor [25], maximum average NDVI (VI) was computed for each of the 12 months over 11-year period as:

$$\mathrm{VI} = 1/n\Sigma\,(pv) \quad (2)$$

where p is the individual pixel values (i.e., for all 33 dekads maximum NDVI images) and n is the number of dekads. Estimating the average NDVI for all 12 monthly values over 11-year period produced the interannual maximum average NDVI image (Fig. **2**).

The coordinates of the grid cells (55 × 55 km) containing bird species were then conformed to the same geographic coordinate system as the NDVI image as well as mean annual potential evapotranspiration. Since the spatial resolution of the species data was different from NDVI data (7.6 × 7.6 km), the sample points representing species data were overlaid on NDVI image. For every sample unit the mean values of maximum average NDVI were computed. The maximum average NDVI values were extracted using lower left corner coordinates of the grid cell [16]. Thus, each grid cell finally contained independent variables (interannual maximum average NDVI and mean annual potential evapotranspiration) and bird species richness. The Pearson correlation between bird species richness and independent variables were calculated. In addition, regression lines between the dependent variable (bird species richness) and the independent variables (interannual maximum average NDVI and mean annual potential evapotranspiration) were calculated.

RESULTS

The interannual maximum average NDVI, which represents net primary productivity [8, 16] shows readily distinct patterns in Kenya (Fig. **2**). Predictably, the semi- humid to humid zones such as the lake Victoria region, central highlands and the coastal strip have the highest maximum average NDVI (net primary productivity). Since the higher the value of NDVI, the more photosynthetically active the cover type [22], low average NDVI values indicate that these areas have less photosynthetically active cover types. Fig. (**3a**) shows that the net primary productivity estimated by interannual maximum average NDVI has a significant positive relationship with bird species richness, which account for 35 percent (r^2=0.354) of the observed variation in Kenyan bird species richness.

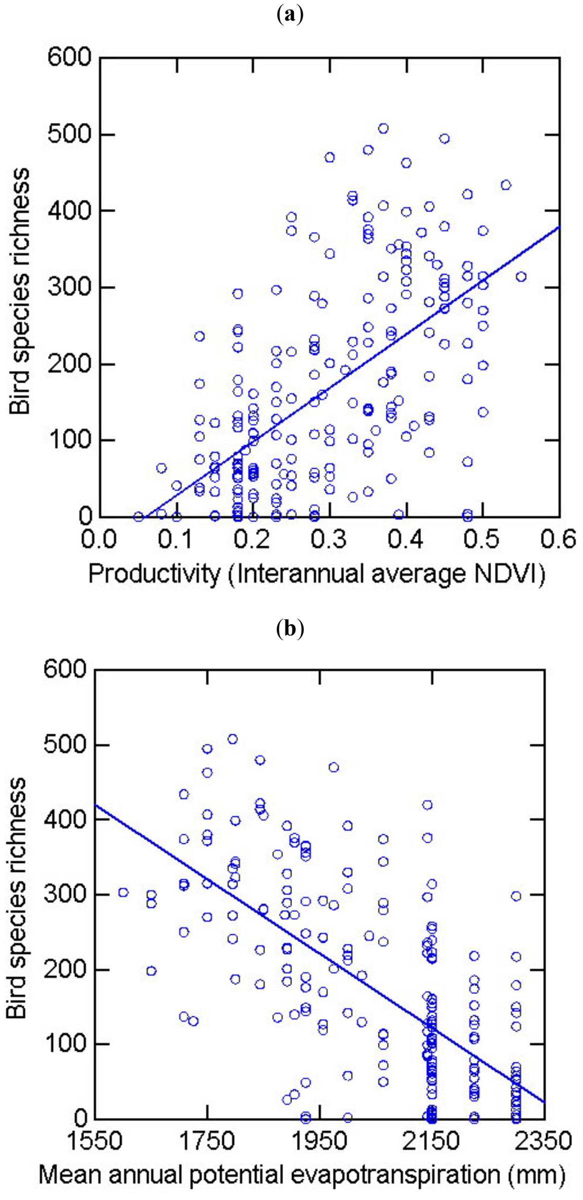

Fig. (3). Scatterplots of bird species richness versus (**a**) productivity (interannual maximum average NDVI), r = 0.595, n = 212 and (**b**) mean annual potential evapotranspiration, r =-0.680, n = 212.

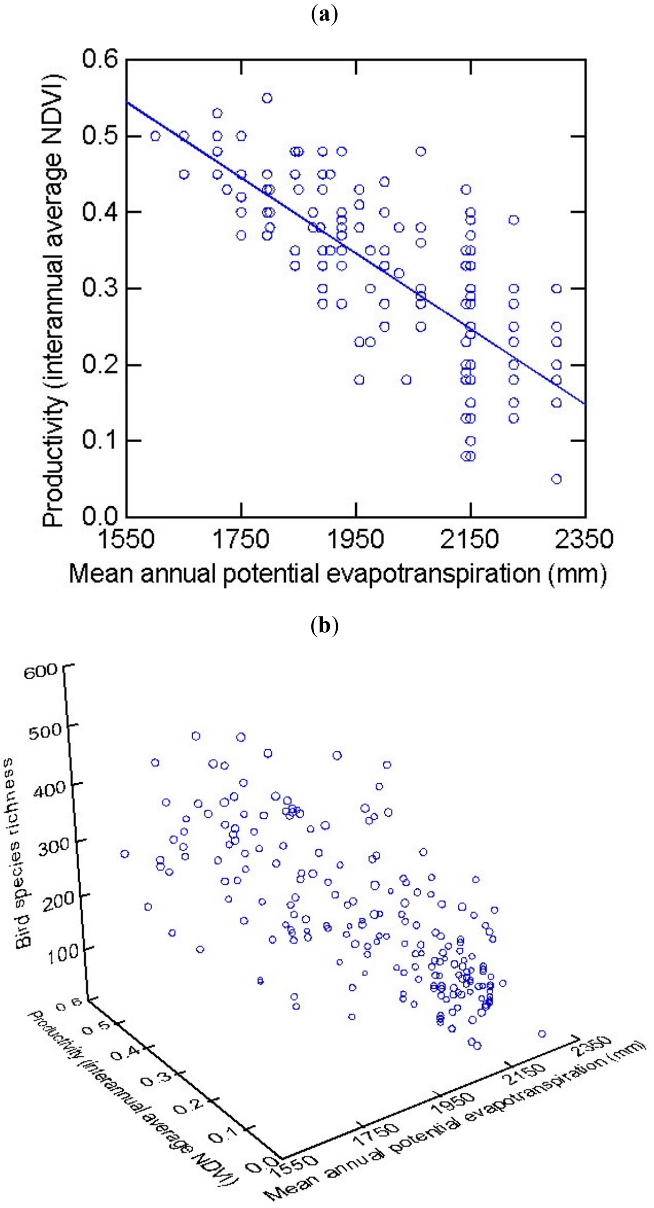

Fig. (4). (**a**) Scatterplots of productivity (interannual maximum average NDVI) versus mean annual potential evapotranspiration (r=-0.800, n=212). (**b**) Three-dimension relationships among bird species richness versus mean annual potential evapotranspiration versus productivity (interannual maximum average NDVI).

Conversely, mean annual potential evapotranspiration has a significant negative relationship with bird species richness, which accounts for 46 percent (r^2=0.463) of the variability of species richness. The least squares fit for the relationship between bird species richness and mean annual potential evapotranspiration (Fig. **3b**) shows that higher mean annual potential evapotranspiration depresses bird species richness [9]. Fig. (**4a**) shows that mean annual potential evapotranspiration is highly correlated (r^2=0.641) with net primary productivity [5]. The three-dimensional plot (Fig. **4b**) demonstrates that bird species richness is higher at high levels of net primary productivity but low at high levels of mean annual potential evapotranspiration.

DISCUSSION

Net primary productivity is the rate at which energy flows through an ecosystem [3]. Ecologists normally use an index of productivity rather than measuring it directly. It has been shown that normalized difference vegetation index (NDVI) is closely related to net primary productivity and actual evapotranspiration for many vegetation types [8]. Hence, the interannual maximum average NDVI (1982-1993) was integrated as an index for net primary productivity. The integrated vegetation index is representative of rate of photosynthetic plant activity, its integration over time should tell us more about the productive history of the plants, and by inference about production [26]. The interannual maximum average NDVI has been shown to be positively correlated with the climatic variables, mean annual rainfall and moisture availability [9, 16]. This indicates that interannual maximum average NDVI is closely related with plant growth and production. Consequently, higher interannual maximum average NDVI represents higher net primary productivity.

The relationship between interannual maximum average NDVI and bird species richness is positive and moderately strong (r = 0.595). This implies that higher net primary productivity results in higher bird species richness. Why does high net primary productivity tend to increase species richness of birds? Apparently, in natural habitats bird populations are positively correlated with the amount of woody vegetation [15]. Since there is increased production of woody species in highly productive ecosystems [27], bird species richness too increases with woody vegetation [15]. Moreover, many species of landbirds use trees as a source of food, or for nesting or as a perch and even many waterbirds nest or perch in trees. In non-forested areas too, the number of bird species increases in proportion to the amount of woody vegetation, that is, trees and shrubs. However, by far the greatest bulk of woody vegetation is to be found in forests, which in the tropics are extraordinarily rich in insect species. These in turn support a rich diversity of birds, almost all of them breeding in the forest [11]. On the contrary, whilst semiarid woodlands may support as many species of birds as a forest, far fewer of them breed in any particular woodland so the overall diversity of species is lower in Savannah woodland [12].

By contrast, higher mean annual potential evapotranspiration results in lower bird species richness. Why does high potential evapotranspiration tend to decrease species richness of birds? One possible explanation could be that there is often a striking decrease in net primary productivity with mean annual potential evapotranspiration (Fig. **4a**). Thus regions receiving low rainfall with high potential evapotranspiration due to high temperatures have drier soil conditions, which minimize potential for growth of woody vegetation. Since bird species diversity is correlated with the amount of woody vegetation in natural habitats [15], the scarcity of woody species reduces bird species richness. Other factors induce variability around the limits determined by energy: for example, physically complex environments, like mountains, may favour more equal energy partitioning among species, and thus permit relatively more species to occur together [5]. Thus, for a given level of mean annual potential evapotranspiration in Kenya, bird species richness is greater in moist mountainous areas that can support the growth of trees thereby providing nesting habitat and food for bird populations.

The authenticity of the regional data layers needs to be confirmed. The high correlations (Fig. **4a**) between mean annual potential evapotranspiration and net primary productivity (r = -0.800) is in agreement with other studies [5] that potential evapotranspiration is highly correlated with terrestrial primary productivity. However, predicting bird species richness requires precise environmental data. Thus, the regional perspective requires the sacrifice of ecological precision for the sake of the generality, as well as the provision of more data thereby allowing statistical predictions. Species-energy relationships, documented by regression statistics, can be used to identify areas more likely characterized by high bird species diversity. These areas will be recognizable only on the regional scale, and field observations will be required for precise boundary determination [28].

CONCLUSION

The study demonstrated that bird species richness increases with net primary productivity (i.e. realized energy captured in plants) and decreases with mean annual potential evapotranspiration (i.e. community energy used). Thus, the most productive regions in Kenya such as central and western highlands support the highest bird species richness [9]. However, most Kenya's agriculture and populace are also concentrated in most productive regions, and most of the existing protected areas are small. The small size of these protected areas, their scattered location, their progressive isolation through the loss of connecting habitat and increasing edge to area ratios, are cause for concern [13]. Therefore, management plans are needed to prevent a confrontation between conservation and human interests [9]. Whereas the less productive areas with more protected areas for conservation of biodiversity support less bird species richness due to high potential evapotranspiration. Planning of conservation priorities does not only require the knowledge of species-energy relationships but also an understanding of interaction between historical and ecological processes [29]. The results obtained from this study are applicable to Kenya and cannot necessarily be extended beyond Kenya.

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