AFRICAN VULTURE HOTSPOT MAPPING PROJECT

MAPPING METHODOLOGIES

1. SIGHTINGS DATA AND SPECIMEN LOCATIONS MAP

Our sightings and specimen records for African vultures are drawn from the African Raptor Databank (ARDB). A secure, live data observatory for the distribution and movements of African raptors. Habitat Info Ltd, Solva, UK. Available: http://www.habitatinfo.com/ardb (Access date = 15 February 2017). Considerable efforts were made by Ralph Buij and numerous observers to draw in new vulture data for areas identified as gaps in the database, notable examples being Zambia, Northern Mozambique, Sudan, South Sudan and throughout West Africa. Much new data were gathered during 2014-2017. At the time of analysis (15/2/2017) the ARDB held 11,543 records of African vultures (separated before and after 31/12/1977 into 1914 historic records and 9629 recent records). These were comprised by species as follows: Bearded Vulture (70 recent and 83 historic), White-backed Vulture (3943 recent and 304 historic), Rüppell's Vulture (661 recent and 140 historic), Cape Vulture (474 recent and 98 historic), Griffon Vulture (18 recent and no historic), White-headed Vulture (482 recent and 251 historic), Lappet-faced Vulture (1292 recent and 228 historic), Hooded Vulture (2090 recent and 368 historic), and Egyptian Vulture (219 recent and 178 historic). A point density analysis was conducted on all the recent data points summing, for each 1 km^2 grid cell, all records within 20 km. We used a natural logarithm value of this density grid to reveal both low and very high density values and exclude areas with no observations. Areas with values > 0.3 (points per km^2) were considered to be potential stronghold areas.

2. MOVEMENT AREA MAPS

The collation of movement data on African vultures was coordinated by Corinne Kendall, Ralph Buij, Rob Davies, Ara Monadjem with assistance from Lutfor Rahman. Movement data from satellite / GPS tracking were provided for 228 tagged African vultures of eight species representing > 6 million kms travelled by African vultures by the following researchers: Keith Bildstein, Claire Bracebridge, Evan Buechley, Andre Botha, Ralph Buij, Maria Diekmann, Nina Farwig, Toby Galligan, Beckie Garbett, Roi Harel, Ohad Hatzofe, Constant Hoogstad, Gregory Kaltenecker, Adam Kane, Chris Kelly, Corinne Kendall, Glyn Maude, John Mendelsohn, Mike McGrady, Ara Monadjem, Campbell Murn, Ran Nathan, Stoyan Nikolov, Darcy Ogada, Steffen Oppel, Louis Phipps, Sascha Rösner, Andrea Santangeli, Dana Schabo, Orr Spiegel, Munir Virani, and Kerri Wolter (Vulpro); and by the following organisations: BOISE STATE UNIVERSITY, ENDANGERED WILDLIFE TRUST, HAWK CONSERVANCY TRUST, HAWK MOUNTIAN SANCTUARY, MOVEBANK, NORTH CAROLINA ZOO, RAPTORS BOTSWANA, RARE AND ENDANGERED SPECIES TRUST, ROYAL SOCIETY FOR THE PROTECTION OF BIRDS, THE PEREGRINE FUND, UNIVERSITY OF UTAH, VULPRO, WILDLIFE ACT, WILDLIFE CONSERVATION SOCIETY. The tagged individuals comprised 69 Egyptian Vultures (2,450,833 km travelled), 53 White-backed Vultures (973,062 km), 36 Cape Vultures (1,195,490 km), 22 Rüppell's Vultures (432,175 km), 20 Hooded Vultures (324,584 km), 16 Lappet-faced Vultures (255,300 km), 10 Griffon Vultures (493,926 km), and 2 White-headed Vultures (17,045 km). These data were received as georeferenced points (latitude and longitude in decimal degrees WGS84). We projected the points into Web Mercator Auxillary Sphere projection to check against online background mapping from Bing in ArcGIS. Much time was spent formatting the data fields especially to ensure all records had a consistent date and time stamp, species, source and a unique individual ID tag. Then all point datasets were processed into tracklogs using ArcGIS Tracking Analyst Tools extension: Make Tracking Layer and Track Intervals to Line. By comparing distance with duration of these lines we created a speed field and we were able to identify and filter out invalid travel lines for each bird (speeds > 100kph and abnormally straight flight lines over very large distances). After cleaning these data, we performed a line density analysis which for each 1 km^2 grid cell summed all tracklines within a 20 km radius to reveal areas of intensive use. Data were still highly concentrated for long duration recordings of birds not moving very far so we also took logarithms of the results to be able to clearly discern sporadic movements from concentration areas. Areas with values > -1 (log line density per km^2) were considered to be concentration areas.

3. HABITAT MODELS

Recent ARDB data are patchy reflecting biases in observer effort; specific regions (e.g. Tanzania, Kenya, South Africa) have been well-covered by observers recently while most other regions have not been visited at all (Sudans, most of West Africa). We used another output of the ARDB to help identify habitat strongholds for African vultures notably in areas not visited by observers. Distribution models were developed by the ARDB and refined for this project on African vultures using Maxent software (Phillips *et al.* 2017). Special efforts were made to update environmental datasets and introduce new anthropogenic datasets that would be ecologically relevant to vultures. In total 97 such datasets were created or refined to span the entire African continent and Arabian Peninsula plus offshore islands at exactly 1km2 resolution. These datasets are listed in Appendix I. Habitat Info specializes in such Africa-wide datasets and has compiled these over twenty years. We projected all data into Lambert Azimuth Equal Area projection using 20 degrees as the central meridian. This projection is best suited for measuring areas and distances at a continent scale. We ran two modelling exercises for each vulture species – one for historical records from the ARDB and not using anthropogenic datasets; and a second run using recent records together with all environmental and anthropogenic datasets (for sample sizes see Sightings Data and Specimen Locations). To overcome sampling bias we developed an observer bias dataset by buffering 10km around all the records in the database and around all the roads driven in the surveys data table. This bias dataset is used by Maxent to constrain the selection of background points (Phillips *et al.* 2017). We used all variables in initial runs of the models to determine which measures may be the most important in describing vulture distribution. These models are then tuned by removal of related variables. Models return values ranging from 0 to 1 representing the likelihood of a species occurring in any cell. We used the value 0.3 approximating the 10 percentile training presence value of most models (Phillips *et al.* 2017) as a logistic threshold to extract all areas where each species was likely to occur. These datasets could be summed for eight species (Egyptian-, White-backed-, Cape-, Rüppell's-, Hooded-, Lappet-faced-, Bearded-, White-headed Vultures) to offer a summary dataset showing important areas for vultures in Africa. In the analysis using recent records with anthropogenic datasets included, we extracted values of over 0.45 in this summary dataset to indicate current habitat strongholds. We also conducted a subtraction of the recent summary map from the historic summary map to reveal the extent of loss of previously suitable habitat.

4. STRONGHOLDS ANALYSIS MAP

We used three lines of evidence to inform the African vulture habitat strongholds map: two forms of empirical data, from recent sightings and from tracklogs; and one form of predicted data from the distribution models. Strongholds from each method (as described above) were overlain and symbolized in accordance with whether 0, 1, 2, or 3 lines of evidence coincided. In different versions of this map we include main movement areas indicated by tracklogs in between strongholds and in the Overview map we also include as background the loss of previously suitable habitat. These tools are offered to help conservationists accurately place activities to be of maximal benefit to existing vulture populations and also perhaps to facilitate maintenance of corridors of vulture movement in between existing good patches.

5. RANGE MAPS

As part of the African Raptor Databank project, range maps were captured from Kemp and Kemp (1998) and compared with Birdlife range maps (Birdlife International and NatureServe 2015). Historic ranges were inferred by digitizing all 16k data points from the Snow Atlas (Snow, D.W. 1978) which represent collections in the British Museum of Natural History up to the end of 1977. Historic points were buffered by 100km to estimate formerly inhabited areas. Some additional historic records were sourced elsewhere particularly for Namibia (Chris Brown in litt. 2017). Current ranges were derived from the afore-mentioned range maps plus 100km buffers around recent (1978 onwards) sighting data points from the African Raptor Databank. In 2015 the ARDB rangemaps for vultures were updated by expert consultation using online webmaps, organized by Darcy Ogada and The Peregrine Fund and supplied to Birdlife to inform uplisting for certain species on the IUCN RedList. In 2016-2017 a concerted effort was made to collate new vulture sightings from surveys and new tracklog data from movement studies of tagged vultures into the ARDB. Tracklogs were sourced on > 200 tagged individuals of eight species. ARDB rangemaps were finally reviewed and edited to incorporate these new data. Range types were classified into: resident (green), present only in the breeding season (orange), present only in the non-breeding season (blue), vagrant or movement only (lilac) and historic occurrence (grey). Distribution modelling using Maxent software (Phillips *et al.* 2017) was performed on historic and recent observations of vultures from the ARDB. Occupied habitat for each species was defined by extracting likelihood values > 0.25 which approximated the 10 percentile training presence in most of the models. These extracts were used to colour code the range maps further whereby dark colours indicate likely occupancy within the range and pale colours indicate sparse occurrence.

Threat maps

6. UNINTENTIONAL POISONING THREAT MAP

Vultures are often poisoned unintentionally by livestock farmers in their efforts to protect their stock from carnivores (Ogada *et al*. 2012, Ogada 2014). This has been a prevailing problem in small-stock farming areas in southern Africa for perhaps over a century and has recently become a problem for large-stock farming areas with large carnivores in East Africa. The species most affected by poisoning are lions, hyenas (all species except aardwolf), wild dogs, leopards, and jackals and caracals (Ogada 2014); of these, lions most often prey on cattle, whereas the other predators kill mostly smaller stock or calves (e.g. Butler 2000, Kissui 2008). We assume there is a widespread level of risk of poisoned baiting throughout small-livestock (sheep and goats) areas in Africa because there will nearly always be some small carnivores present such as jackals and Caracal and also solitary larger carnivores such as Leopards, and two hyenas (Brown and Striped) which together have wide geographic ranges. The geographic ranges of large social carnivores such as Lion and Wild Dogs are much more confined now to protected areas. We obtained the latest range maps for these species from IUCN, although the range map for Spotted Hyena was very extensive across Africa and gave no accurate indication of areas of occupancy. We calculated an index of these large social carnivores by weighted overlays whereby Lion scored 3, Wild Dog scored 2 and Spotted Hyena scored 1. The scores were based on the following: Lions are the most important large livestock predators in Africa, while the other two are less important as cattle predators, although Wild Dogs are often strongly persecuted by livestock farmers where they are present (e.g. Patterson et al. 2004, Graham et al. 2005, Woodroffe et al. 2005, Kolowski and Holekamp 2006, Holmern et al. 2007, Kissui 2008, Gusset et al. 2009). We carried out focal statistics to sum the weighted overlay values within 10km radius. We then multiplied this dataset by all livestock numbers reclassified on a scale 0-30 (from Gridded Livestock of the World v2 – Robinson et al. 2014) to obtain areas of potential conflict between livestock farmers and large social carnivores. We reclassified this product into four threat levels: not present = 0 (0-1810), present = 1 (1810-10676), medium=2 (10676-23657) and high=3 (23657-57060). We compared this dataset with the small-stock farming map (value 1) and took a maximum from the two datasets as our final threat map for unintentional poisoning of vultures.

7. INTENTIONAL POISONING THREAT MAP

The intentional poisoning of vultures by poachers to be rid of vultures as sentinels used by game guards is a more recent phenomenon associated with the increase of poaching of elephant and possibly rhino (Ogada et al. 2015, 2016). It is considered that elephant poachers have more opportunity to lace carcasses with poison for vultures than rhino poachers who carry out their crimes more rapidly. But it is possible that criminal gangs are involved in both poaching activities. At present, there is more data to suggest that elephant poachers intentionally poison vultures (Ogada et al. 2016). Also, elephant range details and mortality details through criminal activities were more available to our analysis than equivalent data for rhinos, so our emphasis in this threat map is on elephant poaching but Mike Cadman assisted us in gathering initial data on rhino poaching for southern Africa. We used three datasets as inputs for our analysis: the latest African Elephant range map (known and possible range) from the African Elephant Status Report 2016 (Thouless *et al.* 2016); data on elephant mortality from Monitoring the Illegal Killing of Elephants (MIKE) Database at CITES; and Africa's major poaching hotspots revealed by genetic assignment of large seizures of elephant ivory (Wasser *et al.* 2015). Geographic assignments from the latter publication were digitized from the graphics published with this article. It should be noted that the median accuracy of these assignments is considered to be within 300km of source. So the geo-referencing can only be regarded as accurate to this crude resolution. However there are many data points from the study so a density analysis of many points, even with errors, should be useful in evaluation concentration areas. Furthermore, with vultures moving these sorts of distances in a single day, a broad-brush picture of poaching activity is highly pertinent to their conservation. We conducted a density analysis of these data points measuring the sum of assignments within a radius of 100km. This was then reclassified on a scale of four to represent threat levels: 0 = no threat, 1 = threat present, 2 = medium threat, 3 = high threat. For the MIKE data we summed values at each MIKE site for the period 2011-2015 and calculated the density of illegally killed elephants for these sites. These data have caveats in that small protected areas may be more effectively patrolled than large protected areas. Unfortunately MIKE sites do not cover the entire range of African elephants so we converted the sites to points and conducted an inverse distance weighting map to show how the density of illegally killed elephant varies across the whole continent. We then clipped this Africa-wide dataset to the possible elephant range map. Again, we reclassified these density values into four classes of threat level: 0 = no threat (0 – 0.000000993), 1 = threat present (0.000000993 – 9.029), 2 = medium threat (9.029 – 21.115), 3 = high threat (21.115 – 60.498). We obtained a final representation of intentional poisoning threat by taking the maximum value from the overlay of the two methods (MIKE map and Wasser *et al*. map).

8. TRADITIONAL MEDICINE MARKET DEMAND MAP

We digitized and georeferenced the locations of 125 traditional medicine markets. Lou Luddington assisted with this work. These were mainly in West & Central Africa provided by Buij *et al.* (2016) but we supplemented these with several known locations for Southern and Eastern Africa from Williams *et al.* (2014), McKean et al. (2013) and other sources (Ogada, Thomsett, Monadjem, Pomeroy, Baker & Baker in litt.). We also tabulated information on the size of these markets. We do not yet have a systematic way of measuring this but we looked at the number of stalls with vulture products and the number of vultures traded over time periods (McKean et al. 2013). We classed markets as non-trading in vulture parts (weighted 1), small (weighted 5), medium (weighted 25) or large (weighted 50) – these weights were roughly based on the frequency histogram of number of stalls with vulture products. We conducted a kernel density analysis across Africa measuring the density of markets within a 500km radius and using the weights as a population field. The resultant dataset was then reclassified into four threat levels: 0 = no threat, 1 = threat present, 2 = medium threat / demand, 3 = high threat / demand.

9. COMBINED POISONING THREAT MAP

A combined poisoning likelihood threat map was derived by simply summing the threat values from the three separate maps: unintentional poisoning threat map, intentional poisoning threat map, and traditional medicine market demand map. Each had been scored on a scale of 0-4 so the range of values is the combined map is 0-12. This map represents our best deductive model for where poisoning of vultures is most likely to occur across Africa.

10. LIKELIHOOD OF POISONING MAP

We added geo-referencing information to 444 records in the poisonings database maintained by The Peregrine Fund (Darcy Ogada) and Endangered Wildlife Trust (Lizanne Roxburgh & Andre Botha). Lou Luddington assisted with this work. We added four fields to the data table: resolution (7 classes as per ARDB), georeferenced by, vultures killed (y/n) and a date-time field to enable hotspot mapping over time. These empirical data of where poisoning of vultures and other wildlife has actually occurred across Africa could be used in a separate inductive modelling exercise using the same explanatory variables and Maxent software that were used in the vulture distribution modelling. A likelihood of poisoning is presented in the map on the scale 0-9. The model yielded good results with Area Under the Curve (AUC) value of 0.846 for test records (15% of data were held back for evaluation purposes). A single variable 'poach10km' which was a crude indicator of both elephant and rhino poaching combined made the largest contribution to the model, followed by grasscover (more poisoning in grassland habitats) and percent non-Christian areas (more poisoning in Christian areas). Indicators of livestock farming and of distance to traditional medicine markets did not make important contributions to the model suggesting that intentional poisoning of vultures as sentinels may be the biggest current driver of poisoning (but it may be more reported than other types). But another variable, distance to large protected area (>1000km^2), had the greatest permutation importance, i.e. if this variable was adjusted it caused most perturbance. Clearly from the map more vulture poisoning occurs in the vicinity of large protected areas and there are some similarities to the combined poisoning threat map which was a deductive model.

11. POISONING INCIDENCE MAP

We used ArcGIS Space Time Pattern Mining Tools to analyse the incidence of poisoning over time. A space time cube was created from the date-time field using 5 year step intervals. We then ran emerging hotspot analyses on both the incidents of poisoning and also the number of mortalities at these incidents. We set neighborhood influence on this to be 500km and the output resolution is 100km^2. The maps reveal significant hotspots of poisoning which are new, consecutive or sporadic. Empty boxes indicate no significant trend over time.

12. POISONING DENSITY MAP

A poisoning density map was derived by conducting kernel density analysis on the 444 records of poisoning incidents using the mortality number field as the population field and a search radius of 50km.

13. ELECTROCUTION THREAT MAP

We accessed electricity grid data for the African continent from two sources: Africa Infrastructure Country Diagnostic AICD (Foster & Briceno-Garmendia 2010), and data on powerlines accessed from OpenStreet Map for North Africa and Arabia (OpenStreetMap contributors 2015). AICD data vary in detail and were augmented in certain areas e.g. from the Digital Atlas of Namibia published by the ACACIA (Arid Climate, Adaptation and Cultural Innovation in Africa) project. AICD data provided usable attribute information on voltage. All powerlines were given weighting scores. Those without useable attribute information on KV or status which included the OpenStreet Map data were given a median score of 3; existing or under construction powerlines > 40kv carried a score of 2; while powerlines that were planned, missing, proposed, under study and > 40kv were given lowest scores of 1; a maximum score of 5 was attributed to any existing powerlines of voltage < 40KV which are considered to be of greatest threat to raptors; any powerlines which were planned and of voltage < 40kv carried a median score of 3. On account of a lack of certainty for future powerlines these were thus accorded lower threat value. We conducted a line density analysis per km^2 in ArcGIS using the score values as the population field and a search radius of 20km and we reclassified this dataset to extract the following threat from electrocution classes: 0 = no threat (value 0); 1 = threat present (0 – 0.11767); 2 = medium threat (0.11767 – 0.29236); and high threat (0.29236 – 1.16760).

14. TURBINE COLLISION THREAT MAP

We loosely followed the approach of Mentis *et al.* (2015) to develop a wind energy turbine collision threat map for Africa, except that we introduced a measure for traveltime to cities (electricity demand) and we did not agree that any locations over 2000m altitude or on slopes were unsuitable (cf Lesotho). But future versions of our map could be improved by incorporating topographic suitability and compressed airflow over mountain features. First we used the new windspeed dataset for the African continent at $1km^2$ resolution from Worldclim (Fick & Hijmans 2017). Mean annual windspeeds above 1.75 msec-1 matched the pattern of suitable windspeeds for wind energy from Mentis *et al.* (2015). All values less than this were set to zero to exclude the Central African forest basin and other static airs. We divided windspeed by distance from the grid and constrained this analysis to < 100km from the existing electricity grid. Consequently areas with very limited electricity grid e.g. Somalia are considered in our map to have limited threat. This situation may change of course. Further to this we divided the dataset by our traveltime to nearest city dataset (the assumption being that demand for electricity will be higher closer to cities). This resulted in very small values but when represented as logarithms this revealed a strong rural pattern of where demand for and suitability for turbine construction is likely to be greatest. There were gaps of no data where the values for distance to grid had been zero so to fill these gaps we conducted a focal statistics analysis obtaining the average value of all data within 5km. We created masks to remove the following areas from the threat map: protected areas, lakes and urban areas. We extracted the final potential turbine collision risk map into the following classes: 0 = no threat, 1 = threat present (log values -18.9 to -15.7), 2 = medium threat (-15.7 to -13.7), and 3 = high threat (-13.7 to -5.5).

15. FUTURE THREATS

We provide a simple map showing the locations for future i.e. planned development corridors (Laurance *et al.* 2015) and powerlines (AICD). This is intended to provide a simple cross-reference for assessing the future threats posed by these features and how we have presented these or not in the other threat maps.

16. DEVELOPMENT THREAT MAP

We combine development growth from two datasets: development corridors (Laurance *et al.* 2015, Sloan et al. 2016) and measures of current urban growth (Habitat Info). Polygons defining major development corridors for Africa were obtained from Laurance *et al.* These polygons had already been buffered by these authors for appropriate distances considered to reflect the impact effect of major road / rail development in Africa (25km either side to yield a swathe 50km wide). Development corridors were given scores of 1 for proposed corridors and 2 for active or upgrading corridors. Impact zones for urban growth and areas of agglomeration (rural to urban migration) were previously developed by Habitat Info in the following manner: national data values for urban population growth for 2000-2015 were obtained from UNDP (UN World Population Prospects database-http://esa.un.org/unpd/wpp/index.htm) and attached to polygons of urban areas from the GRUMP urban mask for those countries (CIESIN 2014, http://sedac.ciesin.columbia.edu/data/collection/grump-v1). Using the assumption that the growth in area of the cities should be proportional to the growth in population size, the outer perimeters of the cities were buffered inside and out by a distance which was correct for that level of percent growth in area. Thus in countries showing more rapid growth the city buffers would be proportionately larger. These halos around the edges of cities are considered to be the zones where negative aspects of agglomeration e.g. slums are concentrated. Urban expansion polygons (pretty tiny on the map) were given scores of 3. These two development area layers were added together and then calculated the average score within 10km which makes the urban polygons more visible with a low score buffer area. The dataset was then reclassified into 4 classes: 0 = no threat, 1 = threat present, 2 = medium threat, and 4 = high threat. This arrangement reveals existing urban growth as hardest development especially where it overlays development corridors, existing development corridors are more dispersed so accorded lower but significant threat value, and future development corridors carry lower threat value in accordance with a lack of certainty.

17. EXPOSURE TO PEOPLE THREAT MAP

This layer is derived as the inverse values of a detailed dataset entitled 'levels of protection' developed and maintained by Habitat Info. Three datasets were combined: log traveltime to cities (http://bioval.jrc.ec.europa.eu/products/gam/download.htm - Nelson 2008), log human population density (CIESIN 2016), and log dollar spend per km^2 inside protected areas. The latter was calculated by attributing data on national spend on conservation to protected areas belonging to that country we derived a national figure for annual spend per km^2 on protected areas (WDPA: IUCN & UNEP-WCMC 2016) from data provided in: James *et al.* (1999). This publication provides data on many African countries. For a few within Africa that were missing values, these values were estimated from the known values of neighbouring states with comparable economies. Logarithm values were used throughout to overcome extreme variation and clumping of values and the domination of urban effects. This revealed more of the variation in rural areas. In the development of the levels of protection layer, the three datasets were reclassified to a scale of 1-9 and summed. In the present study we inverted the values and reclassified into the following four classes: 0 = no exposure threat, 1 = exposure threat present, 2 = medium exposure threat, and 3 = high exposure threat. So the lowest threat levels of zero are found in well protected areas with low population density and far from cities, highest threat levels are encountered outside protected areas, with high population density and readily accessible to cities.

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Still adding….

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APPENDIX I

Environmental and Anthropogenic datasets used in the Maxent Modelling exercises.

Variable	code	name	source	anthropogenic	categorical
altitude.asc		altitude	Shuttle Radar	n	n
anpp_total.asc		above-ground net primary production		n	n
aridity_inv.asc		aridity index (inverted)		n	n
baresubstrate.asc		bare substrate	Univ Maryland	n	n
bio_10_l.asc		mean temperature of warmest quarter	Worldclim	n	n
bio_11_l.asc		mean temperature of coldest quarter	Worldclim	n	n
bio_18_l.asc		precipitation of warmest quarter	Worldclim	n	n
bio_19_l.asc		precipitation of coldest quarter	Worldclim	n	n
constantland.asc		land area (to constrain the model)	Digital Chart of the World	n	y
dist_fresh.asc		distance from fresh water		n	n
ecoregions.asc		ecoregions	Worldwide Fund for Nature	n	y
fires50km.asc		fires within 50km		n	n
globcov.asc		globcover landcover		n	y
grasscover.asc		grass cover		n	y
herblayer.asc		herbaceous layer		n	n
isotherm.asc		isothermality	Worldclim	n	n
k_understorey.asc		primary production of the understorey		n	n
maxtmpwm.asc		maximum temperature of the warmest month	Worldclim	n	n
maxtreeht10k		maximum tree height within 10km		n	n
meantdq.asc		mean temperature of the driest quarter	Worldclim	n	n
meantemp.asc		mean temperature	Worldclim	n	n
meantwq.asc		mean temperature of the wettest quarter	Worldclim	n	n
mintmpcm.asc		minimum temperature of the coldest month	Worldclim	n	n
pet.asc		potential evapotranspiration rate	Worldclim	n	n
phytechoria.asc		phytechoria	Whyte	n	y
phytom_trees.asc		phytomass within trees		n	n
prec_dm.asc		precipitation of the driest month	Worldclim	n	n
prec_dq.asc		precipitation of the driest quarter	Worldclim	n	n
prec_wm.asc		precipitation of the wettest month	Worldclim	n	n
prec_wq.asc		precipitation of the wettest quarter	Worldclim	n	n
precip.asc		precipitation	Worldclim	n	n
precseas.asc		precipitation seasonality	Worldclim	n	n
prom_range5km.asc		vertical exaggeration of the landscape	Shuttle Radar	n	n
slope3km.asc		mean slope within 3km	Shuttle Radar	n	n
slope5km.asc		mean slope within 5km	Shuttle Radar	n	n
soil_cats.asc		soil categories		n	y
soil_depth.asc		soil depth		n	n
soil_orgc.asc		soil organic carbon		n	n
soil_ph.asc		soil pH		n	n
solar_new.asc		solar radiation		n	n
steepslope5km.asc		steep slope within 5km	Shuttle Radar	n	n
tempseas.asc		temperature seasonality	Worldclim	n	n
tmprngd.asc		temperature range (daily)	Worldclim	n	n
tmprngyr.asc		temperature range (annual)	Worldclim	n	n
tree_height		tree height		n	n
treecov2010		tree cover		n	n
understorey_phytom		phytomass within understorey		n	n
wetland_cats		wetland categories	Worldwide Fund for Nature	n	y
windspeed_new.asc		windspeed		n	n

Variable	code	name	source	anthropogenic	categorical
activegrowth.asc		development growth around roads and cities		y	n
agric_use.asc		zones of agricultural use		y	y
camels_n.asc		density of camels	Gridded Livestock of the World	y	n
carionl		livestock carrion		y	n
carionl100k		livestock carrion within 100km		y	n
carionl20k		livestock carrion within 20km		y	n
cariont		total carrion		y	n
cariont100k		total carrion within 100km		y	n
cariont20k		total carrion within 20km		y	n
carrionw.asc		wild carrion		y	n
carrionw100k.asc		wild carrion within 100km		y	n
carrionw20k.asc		wild carrion within 20km		y	n
cattle_n.asc		density of cattle		y	n
cropland_cat.asc		cropland categories		y	y
distpa_1000km.asc		distance from large protected areas (>1000km2)	WDPA	y	n
distpa_250km.asc		distance from medium protected areas (>250km2)	WDPA	y	n
distpa_any.asc		distance from any protected area	WDPA	y	n
forestloss10k		forest loss within 10km		y	n
forestloss1k		forest loss within 1km		y	n
gdpkm2_20km.asc		mean GDP/km2 within 20km		y	n
glw_lsu.asc		livestock stocking rate (LSU/km2)	Gridded Livestock of the World	y	n
goats_n.asc		density of goats	Gridded Livestock of the World	y	n
levelsprot.asc		levels of protection	Habitat Info	y	n
livestock_areas.asc		livestock areas	Gridded Livestock of the World	y	n
livestock_n.asc		density of livestock	Gridded Livestock of the World	y	n
nightlights.asc		night lights	NOAA	y	n
nolights10k.asc		high population density without lights within 10km		y	n
pawithin100k.asc		protected area within 100km		y	n
pct_nonc.asc		percent non-christian religion		y	n
people_press.asc		people pressure		y	n
poach10km		poaching index within 10km		y	n
popdens.asc		population density		y	n
protect_cat.asc		protected area (Y/N)		y	y
protect0.asc		dollar spend per km2 in protected areas		y	n
religioncl.asc		principal religion categories		y	y
rural_poor.asc		rural poverty		y	n
sheep_n.asc		density of sheep	Gridded Livestock of the World	y	n
smallstock_n.asc		density of small livestock	Gridded Livestock of the World	y	n
socialcarn10k		social carnivore index within 10km		y	n
soil_qual.asc		soil quality		y	n
thr_electricity2		threat of electrocution		y	n
thr_intent		threat of intentional poisoning		y	n
thr_markets500		density of traditional medicine markets within 500km		y	n
thr_poiscomb		combined poisoning threat		y	n
thr_unintent		threat of unintentional poisoning		y	n
transform.asc		habitat transformation		y	n
traveltime.asc		traveltime to nearest city		y	n
urbgrow10km.asc		urban growth within 10km		y	n