Multi-source data fusion of optical satellite imagery to characterize habitat selection from wildlife tracking data

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Abstract

Wildlife tracking data allow monitoring of how organisms respond to spatio-temporal changes in resource availability. Remote sensing data can be used to quantify and qualify these variations to understand how movement is related to these changes. The use of remote sensing data with concurrent high levels of spatial and temporal detail may hold potential to improve our understanding of habitat selection. However, no current orbital sensor produces data with simultaneous high temporal and high spatial resolution, therefore alternative methods are required to generate remote sensing data that matches the high spatial-temporal resolution of

modern wildlife tracking data. We present an analytical framework, not yet used in movement ecology, for data fusion of optical remote sensing data from multiple satellites and wildlife tracking data to study the impact of seasonal vegetation patterns on the movement of maned wolves *(Chrysocyon brachyurus)*. We use multi-source data fusion to combine MODIS data with higher spatial resolution data (ASTER, Landsat 4-5-7-8, CBERS 2-2B) and create a synthetic NDVI product with a 15 m spatial detail and daily temporal resolution. We also use the higher spatial resolution data to create a multi-source NDVI product with same level of spatial detail but coarser temporal resolution and data from MODIS to create a single-source NDVI product with high temporal resolution but coarse spatial resolution. We combine the three different spatial-temporal resolution NDVI products with GPS tracking data of maned wolves to create step-selection functions (SSF), which are models used in ecology to investigate and predict habitat selection by animals. The SSF model based on multi-source NDVI had the best performance predicting the probability of use of visited locations given its NDVI value. The SSF based on the raw MODIS NDVI product, one which is commonly employed by ecologists, had the poorest performance for our study species. These findings indicate that, in contrast with current practice in movement ecology, a detailed spatial resolution of contextual environmental variable may be more important than a detailed temporal resolution, when investigating wildlife habitat selection regarding vegetation, although this result will be highly dependent on species. The choice of data set should therefore take into account not only the scale of movement but also the spatial and temporal scales at which dynamic environmental variables are changing.

Keywords: movement analysis, remote sensing, NDVI, MODIS, Landsat, data fusion, multi-source.

1. Introduction

Technological advances in GPS (Global Positioning Systems) have recently made it possible to collect movement data from animals at an unprecedented level of spatio-temporal detail (Demšar *et al.*, 2015). At the same time, Earth observation data are increasing in availability and quality (*e.g*, at various spatio-temporal resolutions over the last four decades (Neumann *et al.*, 2015)) and can be used to quantify and qualify the context associated with movement (Dodge *et al.*, 2013). Movement data can be used to monitor changes in behaviour by organisms adapting to spatio-temporal variations in resource availability. Remote sensing data can be used to understand how movement is associated with these variations.

In the last fifteen years many studies have demonstrated the potential of remotely sensed indicators for researching animal movement (Kerr and Ostrovsky, 2003; Turner *et al.*, 2003; Pettorelli *et al.*, 2011). Remotely sensed data has been used to understand zebra migration (Bartlam-Brooks *et al.*, 2013), waterfowl movement (Henry, Ament and Cumming, 2015) and human movement context (Brum-Bastos, Long and Demšar, 2018). Surface temperature retrieved by satellites have been used to explore foraging strategies of albatrosses (Kappes *et al.*, 2015) and investigating the habitat use of sharks (Howey *et al.*, 2017).

Amongst all remotely sensed data, NDVI (Normalized Difference Vegetation Index) is one of the most widely used to contextualize movement, particularly for understanding the effects of vegetation on wildlife movement (Pettorelli *et al.*, 2011). NDVI is a proxy for the content and state of the live green vegetation (Rouse *et al.*, 1973) and one of the most successfully used remote sensing products in movement research (Pettorelli *et al.*, 2011). NDVI is often used to assess the primary productivity distribution of an area, which has been shown to correlate with

behaviour of several species (Pettorelli *et al.*, 2011). It has been successfully combined with movement data of many species for varied purposes, such as understanding long-distance bird migration (Thorup *et al.*, 2017), exploring the movement of waterfowl in arid landscapes (Henry, Ament and Cumming, 2015), studying the effects of environment on the movement of monkeys and birds (Buchin *et al.*, 2015) and investigating the effects of vegetation productivity on roe deer performance (Pettorelli *et al.*, 2006). However, almost all of these studies only use remotely sensed data from a single source, which can lead to high uncertainties in either spatial or temporal dimension of the context of movement, particularly for studies lasting months or years.

A single satellite source can provide NDVI data with either high spatial resolution or high temporal resolution. For example, sensors providing daily data have spatial resolutions varying between 250 - 5000 m. On the other hand, sensors providing higher spatial resolution data (0.5 - 30 m), have temporal resolutions between 15 days and several months, which is temporally much coarser than most wildlife tracking data. This trade-off means that either the spatial or temporal resolution component will often be prioritized when linking environmental to movement data (Neumann *et al.*, 2015), which can be problematic for certain types of movement behaviour analysis.

We propose that the use of remote sensing data with concurrent high level of spatial and temporal detail has potential to improve our understanding of movement behaviour. To date, most studies linking wildlife tracking data with Earth observation data use only a single-source of satellite data (Bühne and Pettorelli, 2017). Alternative methods are therefore required to develop new remote sensing products for movement analysis, specifically methods that match the spatial and temporal scales of Earth observation products to those required to link movement processes with changes in the environment at the scale that both makes sense from data point of view and biological context. In particular, multi-source data fusion methods, which

systematically combine remote sensing data from multiple sensors to capitalize on their complementary characteristics (Wald, 1999), offer a substantial opportunity for developing new lines of analysis and answering increasingly complex questions at the intersection of wildlife movement and environmental change. These methods have only recently been applied movement ecology (Berman *et al.*, 2019) and are not widely known or used.

In this work, we propose a methodology for data fusion of multi-source optical satellite imagery and tracking data to investigate movement patterns of a specific animal species. We evaluate three different approaches for calculating NDVI (Normalized Difference Vegetation Index) at different spatial and temporal resolutions and combine these products with wildlife tracking data. Specifically, we hypothesize that by fusing high spatial and temporal resolution Earth observation data, we will be able to better predict the movement and habitat selection of wildlife species that respond dynamically to environmental conditions. We used data from seven different sensors to create a synthetic daily and spatially detailed NDVI series with high temporal and spatial detail (the Multi-source data Fusion product, MF-NDVI), NDVI from MODIS with high temporal and low spatial resolution (the Single Source product, SS-NDVI), and NDVI data from ASTER, Landsat 4-5-7-8 and CBERS 2-2B, with low temporal and high spatial resolution (the Multi-Source product, MS-NDVI). We demonstrate the use of our proposed methodology on a case study of maned wolves *(Chrysocyon brachyurus)* in the Brazilian Cerrado to investigate habitat selection relative to primary productivity across the landscape (defined by NDVI). We used Step-Selection Functions (SSFs), which are a common approach for studying habitat selection from wildlife tracking data (Thurfjell, Ciuti and Boyce, 2014) to test the relationship between NDVI and habitat selection by maned wolves.

The rest of the paper is structured as follows: First we describe related work on movement contextualization with remote sensing data and provide a description of the biology of our case study species. In section 3 we describe the data, the Multi-Source (MS), the Single Source (SS),

and the Multi-source data Fusion (MF) approaches and explain how we link wildlife tracking data to the resulting NDVI data sets to compare their performance. This is followed by results. We conclude with a discussion on how advanced remote sensing techniques such as our new methodology could improve spatial analysis of wildlife movement.

2. Methods

We propose and test three methodologies to produce contextual data on vegetation for movement analysis (Figure 2).

In Step 1, we create three NDVI products at three different levels of resolution: a Multi-Source product (MS), a Single Source (SS) product, and a Multi-Source Data Fusion product (MF). For this we acquired and fuse high spatial resolution images from seven sensors (MS) and daily MODIS NDVI (250 m) (SS) to produce daily NDVI data at a higher spatial granularity (15m - 30 m) (MF). We create the MF-NDVI by adapting the method proposed by (Rao *et al.*, 2015), in which multi-temporal MODIS NDVI, higher resolution NDVI and land cover classification are used to obtain a NDVI temporal series with high spatial detail.

In Step 2, we use the three NDVI products to annotate maned wolves' GPS tracking data and create Step-Selection Function (SSF) models to evaluate the suitability of each NDVI dataset for predicting habitat selection of used areas in regard to vegetation greenness. In the rest of this section we describe the data, the MS and MF approaches and finally how we linked NDVI data sets to movement data using SSFs to evaluate their use for movement analysis.

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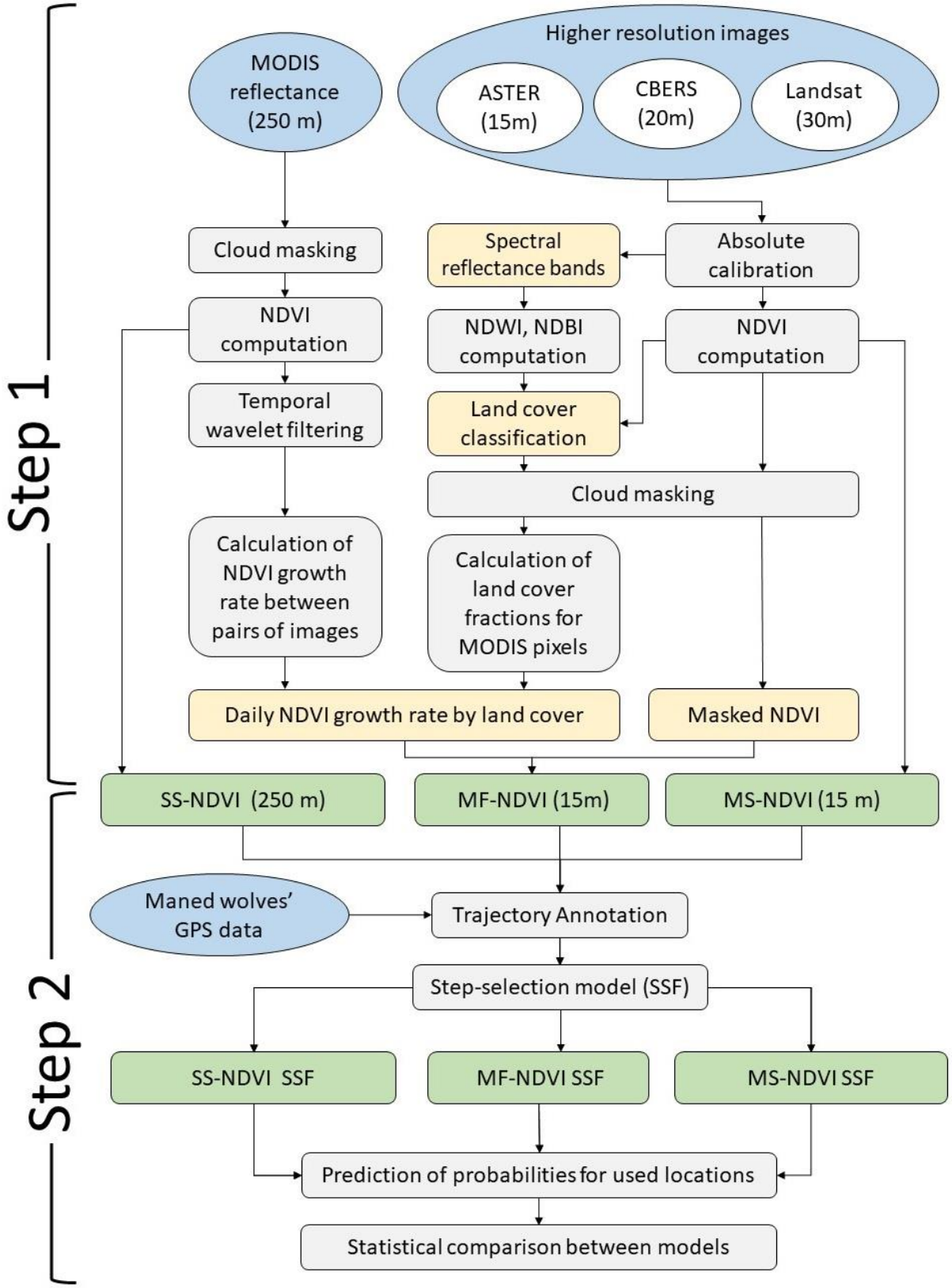
Step 1
Step 2
MODIS reflectance (250 m)
Higher resolution images
ASTER (15m)
CBERS (20m)
Landsat (30m)
Cloud masking
Spectral reflectance bands
Absolute calibration
NDVI computation
NDWI, NDBI computation
NDVI computation
Temporal wavelet filtering
Land cover classification
Cloud masking
Calculation of NDVI growth rate between pairs of images
Calculation of land cover fractions for MODIS pixels
Daily NDVI growth rate by land cover
Masked NDVI
SS-NDVI (250 m)
MF-NDVI (15m)
MS-NDVI (15 m)
Maned wolves' GPS data
Trajectory Annotation
Step-selection model (SSF)
SS-NDVI SSF
MF-NDVI SSF
MS-NDVI SSF
Prediction of probabilities for used locations
Statistical comparison between models

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Figure 2 - The overview of our framework for producing and testing the performance of SS-, MF-, and MS NDVI for context-aware movement analysis of maned wolves' tracking data. Step 1 shows how each of the NDVI data sets were produced and Step 2 shows how tracking data were linked to NDVI data sets for performance assessment through Step-Selection Functions. Blue ellipses show inputs, grey rectangles show processing steps, yellow rectangles are secondary outputs and green rectangles show primary outputs, i.e., the final products.

2.1. Study Area and Species

Maned wolves (*Chrysocyon brachyurus*) are the largest South American canid (de Paula and Desbiez, 2014) and are savannah-adapted omnivores found south of the Amazon Forest. Their range extends from Bolivia into eastern Brazil, through northern Argentina and Uruguay, to central Paraguay (Deem and Emmons, 2005) (Figure 1A). Considered "vulnerable" until 1996 by IUCN (International Union for Conservation of Nature), the species is currently classified as "near threatened" (de Paula and DeMatteo, 2015) and "vulnerable" by the Brazilian environmental authorities (ICMBio, 2016).

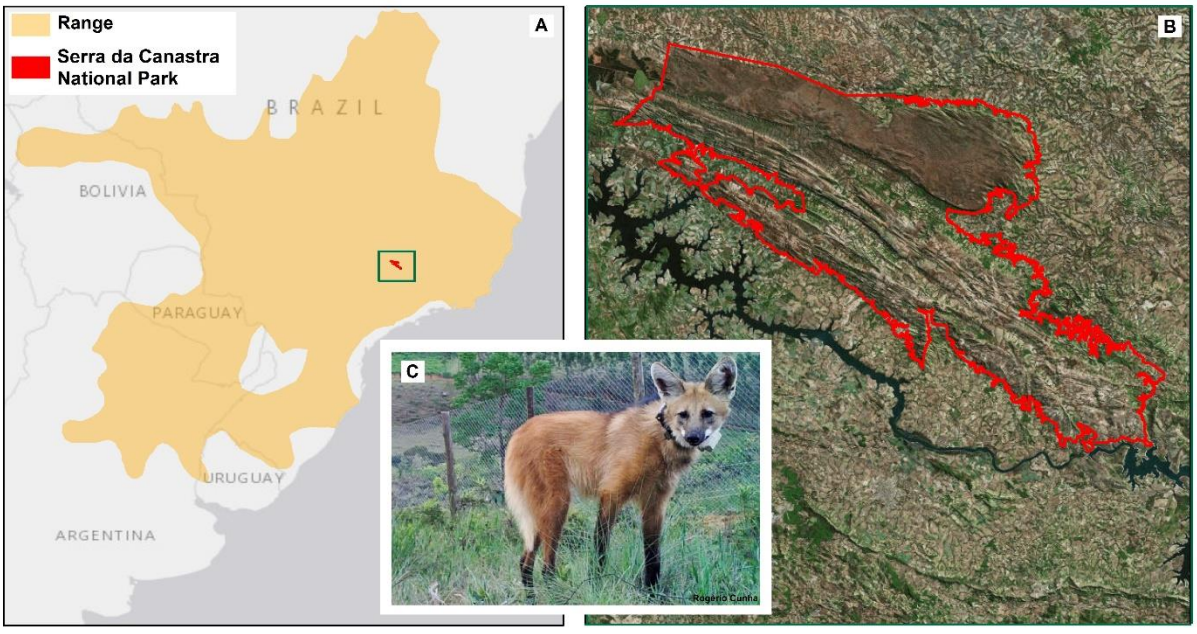

Figure 1 - A) The range of the maned wolf *(Chrysocyon brachyurus)* in South America. B)

Borders of Serra da Canastra National Park (CNP) in Minas Gerais state in Brazil, home of the wolves whose tracking data are used in this study. C) Lobinha (one of the individuals from our study), a female maned wolf of approximately two years old, wearing a GPS tracking collar.

The main threat to the species comes from the continuous large scale habitat loss (Noss and Lima, 2007) which is especially significant in Brazil because of the extensive conversion of the Cerrado (Brazilian savannah) into farmland (Fonseca *et al.*, 1994). Only 20% of Cerrado is still covered by native vegetation (Myers *et al.*, 2000) and less than 2.5% is protected by law. One of the protected areas, the Serra da Canastra National Park (CNP) (Figure 1B) has been key to the preservation of maned wolves. The extensive conversion of the park's surroundings into farmland has exposed the wolves to many anthropogenic threats, such as road traffic, culling and disease contamination by domestic animals (Deem and Emmons, 2005), all of which can result in large fluctuations in population size, eventually leading to extinction (de Paula and Desbiez, 2014).

Understanding interactions with the environment and relevance of different habitats for survival is of prime importance for preserving a species (Garshelis, 2000). There has been only one study based on GPS and satellite data on the habitat use by maned wolves, and it was restricted to one male and one female (Coelho *et al.*, 2008). Most studies on maned wolves were performed in a captive population and little is known about maned wolves in the wild (Bueno and Motta-Junior, 2009; de Paula *et al.*, 2013).

2.2. GPS tracking data

Tracking data were collected using GPS collars - (Pinnacle Lite G5C 275D by Sirtrac, 3300S and Iridium Track 1D by Lotek Wireless Inc) for 13 maned wolves between March 2007 and

July 2015 (see Table 1 in Supplementary information A for a summary of the tracking data), the most complete attempt to study this species to date (de Paula, 2016). Our sample included seven females and six males, with the tracking period varying from 59 to 841 days per individual. We calculated home ranges of each individual as the 95% isopleth from kernel density utilisation distribution (UD) surfaces to show the extent of territories (Worton, 1989) of each individual's GPS tracking data (Figure 3). A home range is defined as a set of bounded areas used by an animal in the course of its normal activities, such as foraging and mating (Burt, 1943) and is typically calculated as an isopleth of the UD density estimate.

Home ranges varied in size with an average of 64.5 $km^2 \mp 34.5$ km^2 standard deviation but were generally compact in shape. Only two individuals stay completely within the CNP, five transit between the CNP and its surrounding areas, and the remaining six are based outside the park in landscapes extremely influenced by anthropogenic activity (primarily agriculture) (Figure 3). Maned wolves are known to be territorial, and we found that home ranges had generally little overlap, except between mates (Figure 3).

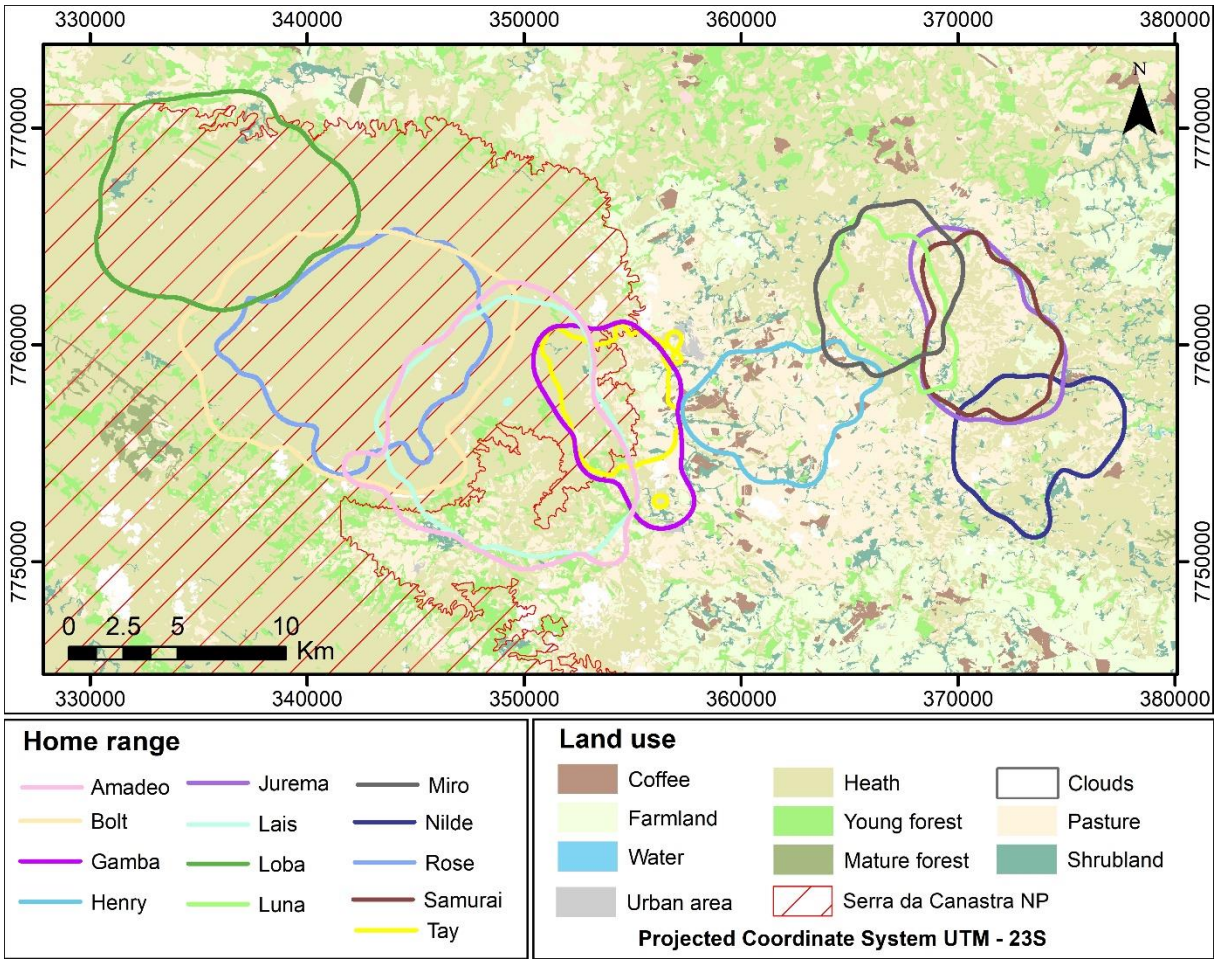

Figure 3 - Home ranges (95% utilization distribution) for each individual and Canastra National Park (CNP) limits overlaid on top of land use classes. Home ranges of the two individuals in each couple (Table 1 in Supplementary information A) intersect to a large extent. The land use map was produced by (de Paula, 2016) based on automatic and supervised multi-temporal classification (2009 - 2011) of RapidEye images with 5 m spatial resolution.

2.3. Remote sensing data

We integrate coarse spatial resolution - fine temporal resolution MODIS (Moderate Resolution Imaging Spectroradiometer) data and higher spatial resolution - coarse temporal resolution data from Terra - ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), Landsat 4-5-7-8, CBERS 2 (China-Brazil Earth Resources Satellite) and CBERS 2B) (Table 1) to create a high spatial and temporal granularity NDVI data set (Multi-Source Data Fusion

product, MF-NDVI). We use data from the same seven higher spatial resolution - coarse temporal resolution data sensor to calculate fine spatial resolution - coarse temporal resolution NDVI (Multi-Source Data product, MS-NDVI). We also use the daily reflectance (MOD09 product) to calculate coarse spatial resolution fine temporal resolution NDVI (Single-Source Data product, SS-NDVI) and cloud mask (MOD35 product) products to filter out clouds, both products from Terra - MODIS. Our study period spans from 2007 to 2013, and during this period we acquired 2260 total images, with the vast majority (2227) coming from MODIS (due to high temporal resolution) and 33 images coming from the other sensors (Table 1). We only retrieved images with cloud coverage lower than 5%.

Table 1 - Remote sensing data used as input for the SS, MS and MF approach to produce NDVI data sets. The letters along with spatial resolutions are specifying the spectral bands for sensors with multiples spatial resolutions, sensors without letters have a uniform spatial resolution along the spectral bands. R stands for red, G for green, B for blue, NIR for near infra-red, VNIR for visible (RGB) and near infra-red, SWIR for short wavelength infra-red, FI for far infra-red and TIR for thermal infra-red.

Satellite	*Sensor*	*Temporal resolution (days)*	*Spatial resolution (m)*	*Images used*
CBERS 2-2B	High Resolution CCD Camera (HRCC)	26	20	3
Landsat 4-5	Thematic Mapper (TM)	16	30	16
Landsat 7	Enhanced Thematic Mapper plus (ETM+)	16	30	

Landsat 8	Operational Land Imager (OLI)	16	30	14
Terra	Moderate Resolution Imaging Spectroradiometer (MODIS)	1 - 2	250 (R/NIR) 500 (B/G/SWIR) 1000 (VNIR/FI)	2227
Terra	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	16	15(VNIR) 30 (SWIR) 90 (TIR)	3

2.4. Step 1: Multi-source data fusion

We performed the absolute calibration of satellite data to guarantee consistency among the measurements from different satellites. NDVI growth rates were extracted from MODIS and we performed land cover classification on the finer resolution data, so that we could compute land cover fractions within each MODIS pixel. The land cover fraction and the daily NDVI growth rates from MODIS were used to calculate the NDVI growth rate for each land cover fraction, which was then applied to the finer NDVI data to generate a time series of daily NDVI with higher level of spatial detail. In this section we provide the details of this methodology, while figure 2 illustrates the proposed process.

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235 ### 2.4.1. Absolute calibration of remote sensing data

236 Absolute calibration is necessary to convert the digital numbers stored within a remotely sensed
237 image to spectral reflectance, the physical quantity of the object (Rees, 2001), which is
238 important for integrating multi-source remotely sensed data. MODIS data (MOD09) have been
239 pre-processed to spectral reflectance values, therefore we only calibrated the 33 images from
240 the other seven satellites. This was done using sensor-specific scaling parameters and equations
241 that are provided in the meta data for each image and user's handbook of each sensor. We further
242 re-sampled the 33 images, i.e. all except MODIS, to 15 m in order to match the finest spatial
243 resolution of our data sets. We used the nearest neighbour method to perform the resampling,
244 which does not create values that were not in the original data (Meneses and Almeida, 2012).
245 This is important to preserve the relationship between what was measured on the ground by the
246 satellite and the biophysical variable being analysed.

247 ### 2.4.2. Calculating SS-NDVI and MS-NDVI

248 The calibrated spectral reflectance bands were then used to compute the SS-NDVI (Single
249 Source) time series with 2227 images based on MODIS data and a MS-NDVI (Multi-Source)
250 time series with 33 images based on data from the other seven satellites. NDVI is a proxy for
251 the content and state of the live green vegetation and its computation requires information on

the spectral reflectance in the red and near infra-red portions of the electromagnetic spectrum (Rouse *et al.*, 1973):

$$NDVI = \frac{NIR_\rho - Red_\rho}{NIR_\rho + Red_\rho} \quad (1)$$

Here NIR_ρ is the reflectance in near infra-red interval (800 - 1000 nm[1]) and Red_ρ is the reflectance in the red interval (650 - 700 nm). NDVI values range from -1 to 1. Values smaller than 0.1 are usually related to bare rocks, sand, or snow; values around 0.2 to 0.5 are related to sparse vegetation such as shrub, grasslands or senescence crops; values between 0.6 and 1.0 correspond to dense vegetation, such as tropical forests or crops at their peak growth stage (Rouse *et al.*, 1973; Xue and Su, 2017).

2.4.3. Generating time-series of SS-NDVI growth rates

We calculated the daily NDVI time series, which we here call MF-NDVI (Multi-Source Data Fusion product), by adapting downscaling methods from Rao *et al.* (2015).

MODIS data have been previously used for extracting growth rates and understanding vegetation dynamics (Lu *et al.*, 2015). Their high temporal resolution allows daily monitoring of changes in vegetation, however, the extraction of accurate NDVI growth rates requires a rigorous filtering process to de-noise the data series, i.e., to reduce the known interference of clouds, atmosphere dynamics, variability on the detectors that register reflectance and other

[1] Theoretical limit according to Jensen (2006), these limits may vary from satellite to satellite but will stay within this range.

factors. A wavelet transform (WT) is particularly efficient in identifying and reducing noise while preserving useful information in time-series (Lu *et al.*, 2007) and it has been widely used in the extraction of vegetation patterns via radiometric indices (Sakamoto *et al.*, 2005; Priyadarshi *et al.*, 2017).

We used the 2227 SS-NDVI (Single Source NDVI) images to create a temporal profile of NDVI for each 250 m pixel in our study area. We first used the cloud mask product (MOD35) (Strabala, 2018) corresponding to each SS-NDVI image to remove cloud contamination. In the next step, we converted the images into 46,710 time-series of NDVI values, one time-series for each 250m pixel, and applied two consecutive WT using the Daubechies 4 mother wavelet (MW) (Daubechies, 1990). This MW has been extensively used for de-noising and it is commonly used for NDVI data (Kaddar *et al.*, 2017). We performed a four level soft threshold WT of the NDVI temporal series for each pixel (2227 samples/pixel) in the MODIS data, then we reconstructed the series, then repeated the procedure once again to obtain the final filtered NDVI pixel series. The NDVI daily growth rates were then computed for each pair of SS-NDVI images by calculating the first derivative for each filtered SS-NDVI pixel time series.

2.4.4. Calculating MF-NDVI

The filtered NDVI daily growth rates extracted from SS-NDVI (Single Source NDVI) reflect the average of the vegetation dynamics covered by each 250 m x 250 m pixel. To obtain more detailed information on the vegetation dynamics within each pixel, we calculated the contribution of each land cover fraction to the growth rates (Rao *et al.*, 2015) (Figure 5).

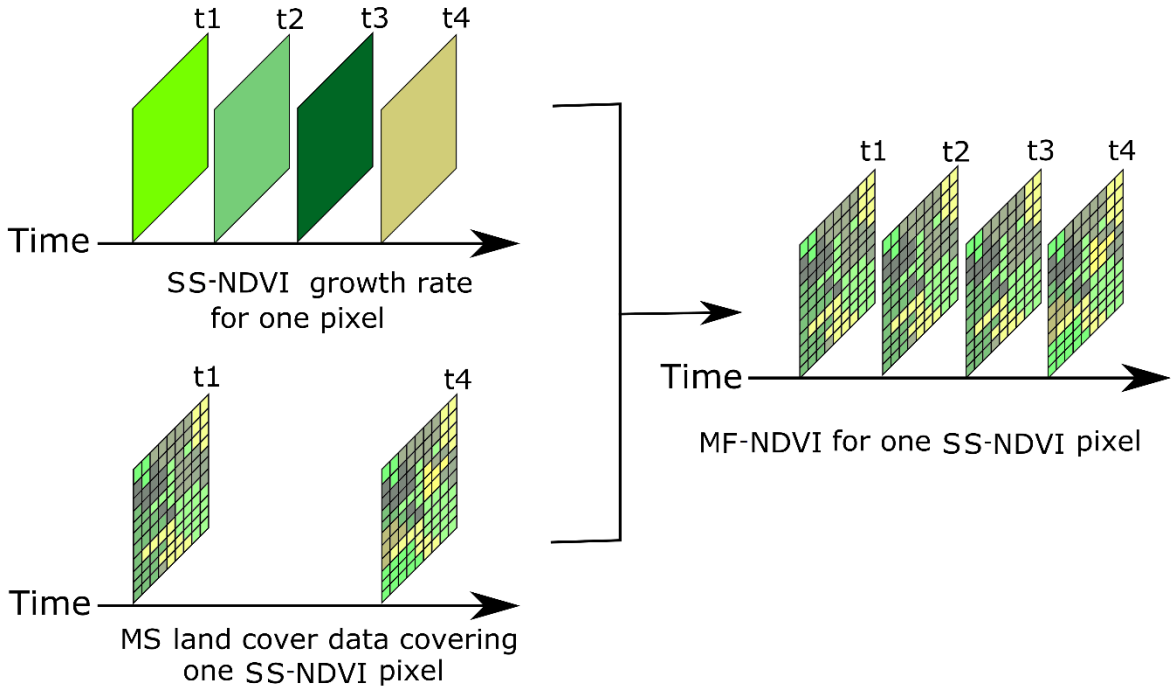

Figure 4 - The filtered SS-NDVI growth rates are combined with MS land cover data to produce the MF-NDVI, which has the same temporal resolution as the SS-NDVI and similar spatial details to the MS-NDVI. Land cover data are used to find the NDVI growth rate for each MS pixel (15 m). Growth rates are then applied to the available 33 MS-NDVI images to create the temporal series of MF-NDVI.

To calculate land cover fractions within each SS pixel, the calibrated spectral reflectance bands in the finer resolution images were used to obtain 33 land cover maps. We use the BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies) algorithm (Zhang, Ramakrishnan and Livny, 1996) to perform automatic non-supervised classification. The algorithm requires three input parameters: 1) a threshold for the maximum allowed radius for the cluster resulting from the grouping of a sub-cluster and the closest sample (the cluster is

partitioned if the radius is bigger than the chosen threshold); 2) a branching factor that determines the maximum number of sub-clusters in each node (if a new sample is added such that the number of sub-clusters exceeds the branching factor the node is split into two); and 3) the number of clusters after the final clustering step, which prunes the resulting hierarchical tree. We used a branching factor of 100 for all images, varied the threshold from 0.2 to 0.7 by 0.02 for each image and did not use pruning. For each threshold we computed the Calinski-Harabaz Index (CHI) (Calinski and Harabasz, 1974) to measure the intra- and inter-cluster quality of our land cover classes, and for each image we kept the threshold that achieved the lowest within-cluster dispersion and highest between-cluster dispersion. This produced the optimal data-driven unsupervised land cover classification for each image.

For each of the 33 land cover classifications (15 m) we then calculated the percentage of each land cover within the corresponding SS pixel (250 m), which produced 33 maps of land cover fractions for our study period. The use of multiple land cover fractions maps is important to account for possible land cover changes within a SS pixel during the study period. The contribution of each land cover fraction and the growth rates were then applied to the 33 MS-NDVI (Multi-Source Data product) images to generate the MF-NDVI (Multi-Source data Fusion product) images (Rao *et al.*, 2015). Mathematical details of our procedure are presented in Supplementary information B. The assessment of the resultant MF-NDVI time series is presented in Supplementary information C.

2.5. Step 2: Context-aware movement analysis

2.5.1. Linking NDVI data sets and wildlife tracking data

To explore which of the three different NDVI data sets better predict wolves' habitat selection, we annotated the wildlife tracking data with NDVI values from each of the three data sets and used Step Selection Functions (SSF) to assess NDVI effects on movement probability. We linked GPS fixes to the NDVI datasets by matching both the temporal and spatial coordinates using the nearest neighbour method (Dodge *et al.*, 2013; Brum-Bastos, Long and Demšar, 2016). We then created SSFs models for each NDVI data set and compared them through statistical analysis of results from 10-fold cross-validations.

SSFs statistically model the effects of landscape on movement probability by contrasting used and available resources (Equation 2). SSFs require real steps to characterize used resources and random steps to characterize available resources. Real steps are the locations registered by tracking data. Random steps are defined from each tracked location by applying a step length and turning angle, which are drawn from the distributions of step lengths and turning angles observed from all tracking data (Thurfjell, Ciuti and Boyce, 2014).

$$w(x) = exp\left(\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_n\right) \quad (2)$$

where $w(x)$ is the likelihood of a step (random or real) with the associated resources $x = x_1$ to x_n being used by the animal, and β_1 to β_p are coefficients estimated by conditional logistic regression for the associated resources (Fortin *et al.*, 2005). Steps with a higher SSF score $w(x)$ have a higher likelihood of being chosen by the tracked animal.

We created five random steps for each GPS location as recommended by (p.6 Thurfjell, Ciuti and Boyce, 2014), which were defined by randomly drawing a step length and a turning angle from the observed distributions of these parameters. Similarly, to the GPS points, random steps were also annotated with NDVI values from the three NDVI data sets. Next, we perform a 10-fold cross-validation by training the SSF model on one-fold (GPS points and random steps) and predicting only on the GPS points (used resources) of the remaining folds. As Steps with a higher SSF score $w(x)$ have a higher likelihood of being chosen by the tracked animal, we can use the prediction on used areas (GPS points only) to compare which NDVI data set is more accurate in predicting habitat use. We do this by calculating and comparing the sum of the logged odds for each fold cross-validation for the three NDVI datasets. As a used resource or GPS point should have $w(x) = 1$ and $log(1) = 0$, the best model is the one that yields the maximum of the summed log-odds. We use ANOVA and Students T-tests to assess differences between the three data sets. We also retrieve and compare the distribution of angular coefficients and p-values for the three SSF models.

3. Results

3.1. Step 1: Multi-source data fusion

The MS (Multi-Source) approach with higher spatial resolution data was able to provide more NDVI images than a single-source approach would at the same spatial resolution. However, even using multiple satellites the NDVI data retrieved covered only 1% of the wildlife tracking period (Table 2) and there were data gaps as long as almost two years (Figure 4A) due to cloud

361 coverage. The SS (Single Source) approach with coarse spatial resolution data, which is the
362 common practice in movement ecology, was able to provide daily images for 80% of the
363 wildlife tracking period (Table 2) with some gaps of approximately two months around August
364 (Figure 4A) due to cloud coverage. Finally, the MF (Multi-Source Fusion) provided daily
365 images for 100% of the wildlife tracking period (Table 2) (Figure 4A) due to cloud coverage.
366 Figure 4B shows scaled pixel sizes overlaying an image from a portion of the study area,
367 highlighting how the heterogeneity of environmental conditions might be camouflaged by the
368 spatial resolution of the SS approach, but can be captured by the MS and MF approaches.

369 Table 2 - Characteristics of the NDVI data sets produced by the SS, MS and MF approaches.

Approach	*Number of NDVI images*	*Tracking days covered (%)*	*Revisiting time (days)*	*Spatial detail (m)*
SS	2227	70	1	250
MS	33	1	< 15*	15-30
MF	3150	100	1	15-30

*If gaps due to cloud coverage are not considered

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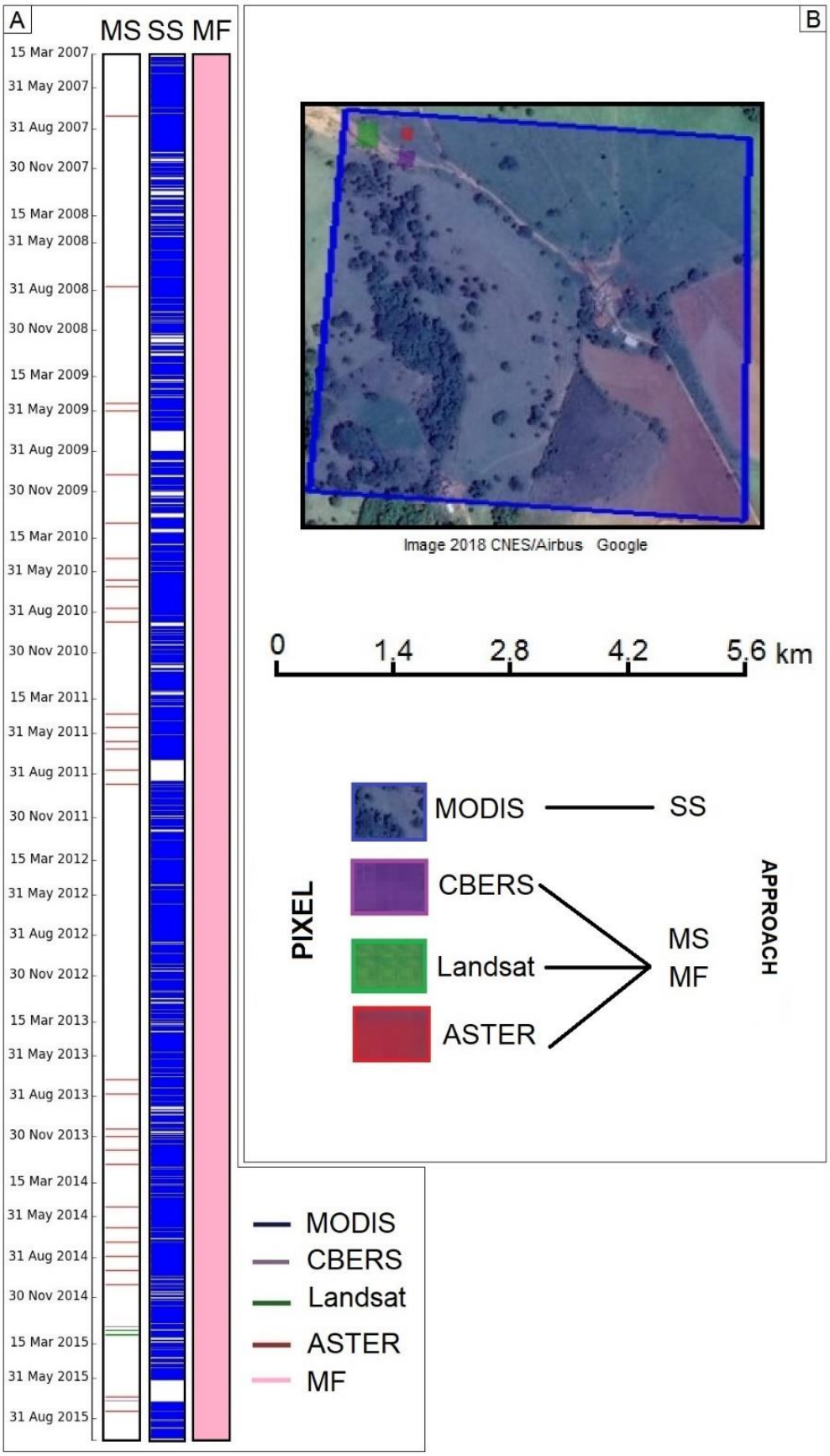
A
MS SS MF
15 Mar 2007
31 May 2007
31 Aug 2007
30 Nov 2007
15 Mar 2008
31 May 2008
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30 Nov 2008
15 Mar 2009
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31 Aug 2009
30 Nov 2009
15 Mar 2010
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MODIS
CBERS
Landsat
ASTER
MF
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0
1.4
2.8
4.2
5.6 km
MODIS
SS
CBERS
Landsat
ASTER
MS
MF
PIXEL
APPROACH

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Figure 5 - Results from the three approaches used to obtain NDVI data sets. Panel A) shows a timeline covering the wildlife tracking period, where horizontal dashes indicate availability of NDVI images from each approach. The image source is specified by the colour of the bar shown in the legend. MF images are plotted on the right timeline, SS images are plotted in the middle timeline and MS images are plotted on the left timeline. Panel B) shows scaled pixel sizes overlaying an image from a portion of the study area, highlighting how the heterogeneity of environmental conditions might be camouflaged by the spatial detail level of the SS approach. A SS pixel covers 62500 m^2 and originally the data used to produce MS and MF images were as follows: a Landsat pixel covers 900 m^2, a CBERS pixel covers 400 m^2 and an ASTER pixel covers 225 m^2. However, they were all re-sampled to 15 m pixel size covering 225 m^2.

3.2. Step 2: Context-aware movement analysis

We found that the MS-NDVI (Multi-Source NDVI) had the highest predictive probability (largest log-odds) based on our k-fold cross validation procedure. This was followed by the MF-NDVI (Multi-Source Fusion) and lastly the SS-NDVI (Single Source) data (Figure 6A). Therefore, the model that included only the high spatial resolution satellites (but not the high temporal resolution MODIS NDVI data) was the best at predicting habitat selection in terms of NDVI. The poorest performing model was the SS-NDVI model. The MF model therefore achieved a relatively middle performance level, falling in between the MS-NDVI and the SS-NDVI (Figure 6B).

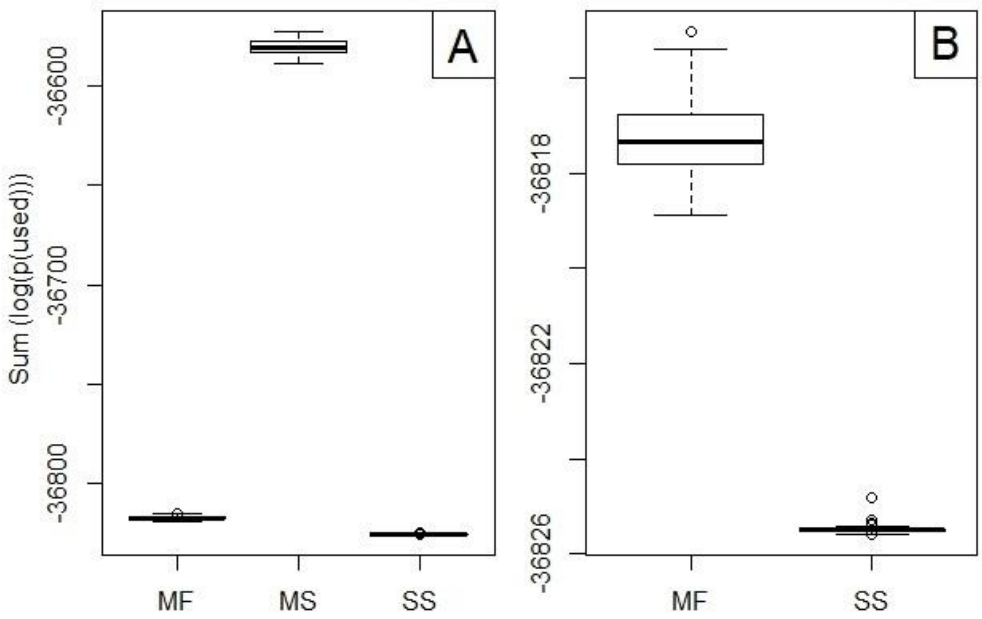

Figure 6 - Sum of logged predicted probabilities for used areas (GPS points) for each of the ten-fold cross validations performed for each step-selection model. Panel A shows the results for MF-, MS- and SS-NDVI. Panel B zooms in to the results of MF and SS-NDVI.

The ANOVA indicates that the use of different NDVI data sets have a statistically significant effect (p-value < 0.01) on the sum of the logged predicted probabilities for the GPS points (used areas). Pairwise Students T-tests indicated that the MS-NDVI produced superior models in comparison to the other two data sets (p-value < 0.01) and that the MF-NDVI performed significantly better than SS-NDVI (p-value < 0.01).

Importantly, the NDVI coefficient was not significant in the SS-NDVI SSF models but was always significant in the models using MS-NDVI and MF-NDVI (Figure 7). The coefficients for NDVI ranged between 1.9 and 2.0 in the MS-NDVI model and were always under 0.02 in the other two models MF- and SS-NDVI.

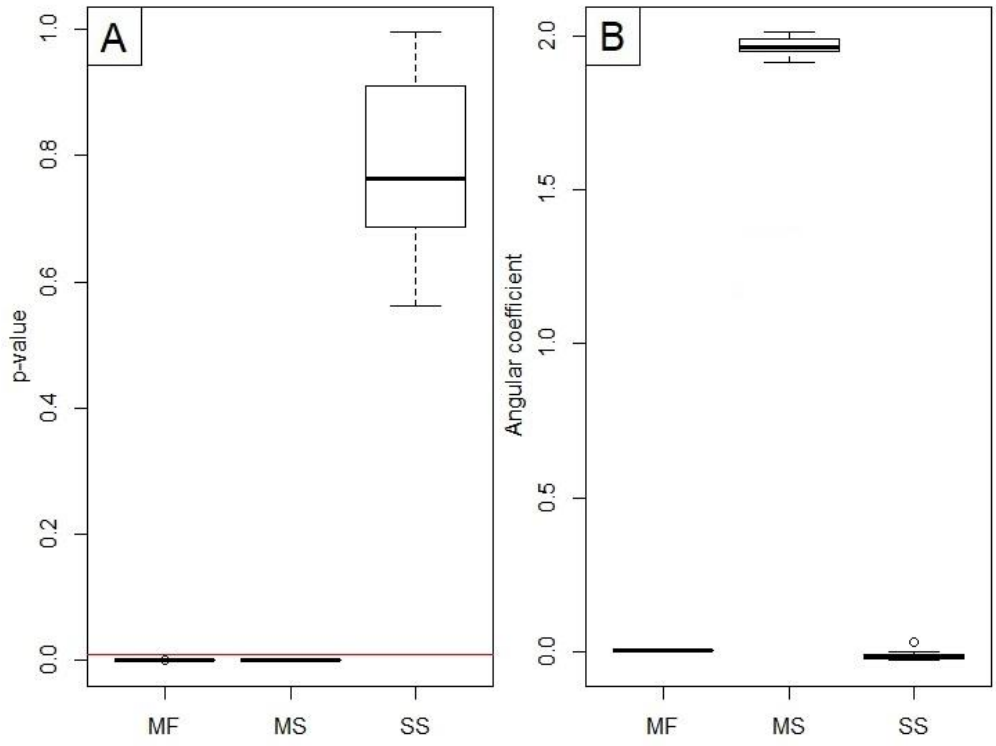

Fig 7 - Distribution of the parameters from the ten Step-Selection Functions generated for with each NDVI data set. Panel A shows the p-values for MF-, MS- and SS-NDVI; the red line indicates p-value = 0.01. Panel B shows the SSF angular coefficients for NDVI for MF-, MS- and SS-NDVI.

4. Discussion and conclusion

In this paper, we used multi-source data fusion to combine MODIS data with higher spatial resolution data (ASTER, Landsat 4-5-7-8, CBERS 2-2B) and created a synthetic NDVI product with a 15 m spatial detail and daily temporal resolution (MF-NDVI). We also used the higher spatial resolution data to create a multi-source NDVI product (MS-NDVI) with same level of spatial detail but coarser temporal resolution and data from MODIS to create a single-source NDVI product with high temporal resolution but coarse spatial resolution (SS-NDVI). We

416 combined the three different spatial-temporal resolution NDVI products with GPS tracking data
417 of maned wolves to create step-selection functions (SSF), which are models used in ecology to
418 investigate and predict habitat selection by animals. We used SSFs to investigate which data
419 approach created a NDVI dataset with higher accuracy in predicting habitat selection for maned
420 wolves. In the following we discuss some of advantages and limitations of this approach and
421 contextualise our findings.

422 We hypothesized that the MF-NDVI data would be best at predicting habitat selection (defined
423 by NDVI) because these data capture both the fine spatial heterogeneity and temporal dynamics
424 of primary productivity. However, we found that the MS-NDVI model was the strongest
425 predictor of habitat selection by maned wolves, and that the SS-NDVI was the poorest predictor.
426 Therefore, it is perhaps unsurprising that the performance of the MF-NDVI model lied in
427 between the other two models. This seems to suggest in the case of maned-wolves in the
428 Brazilian savannah that spatial heterogeneity in the availability of primary productivity is far
429 more important than the temporal dynamics when predicting fine-scale movement and habitat
430 selection.

431 MODIS data, which were used in the SS approach, were designed for mapping vegetation at
432 global, continental or national scale, while the data used for the MS and MF approaches were
433 designed for mapping vegetation at the community and species level (Xie, Sha and Yu, 2008),
434 which is closer to the scale at which maned wolves were experiencing the landscape. In animal
435 ecology, detailed information on habitat allows the representation of the cognitive map of

436 animal's environment and the observation at approximately same spatio-temporal scale as an
437 observer's experience (Cagnacci *et al.*, 2010), which is important for understanding individual's
438 decision making processes. In addition, the MF approach had performance in between the SS
439 and the MS, which makes sense as this product is a combination of the two previous ones and
440 some of the interval we have between the MS scenes are probably too long to allow changes on
441 vegetation be modelled as a linear function, which added uncertainty to the MF-NDVI. In
442 addition, the MF approach requires a sufficient number of landcover classifications adequately
443 distributed across the study period. Ideally, there would be one landcover classification for each
444 15 days interval, but that can be especially difficult to guarantee in areas with high cloud
445 coverage, such as the Amazon forest, or during specific seasons, such as the wet season in the
446 Atlantic forest. Moreover, this approach has higher data and computational complexity, which
447 can be challenging for researchers that are no acquainted with advanced remote sensing
448 techniques. Lastly, it is difficult to obtain ground truth data to validate the product generated
449 by the MF approach, as it ideally it would require either fieldwork sampling on different days,
450 or leaving out MS images and trying to reproduce them with the MF approach for comparison.
451 The validation itself can take as much or more time than processing the data, but it is necessary
452 to know if the data will actually be representing the experience of an individual in that
453 landscape. Still, the MF approach performed better than what is traditionally used in movement
454 ecology

455 The temporal resolution of data produced using a multi-sensor approach might drastically
456 improve in areas less densely covered by clouds. We had bigger relatively large data gaps in
457 our MS-NDVI data because we were extremely conservative with the cloud coverage threshold
458 for accepting images (< 5%), particularly for an area that is known to have a concentrated and
459 seasonal rainfall regime. Another reason for our conservative threshold was the use of these
460 images for creating the MS-NDVI data set, which requires scenes with clear sky.

461 In terms of new insights into movement behaviour, the SSF model of each NDVI data set
462 reported different relationships between vegetation and maned wolves' movement. The
463 traditional SS approach reported no statistically significant relationship between vegetation and
464 habitat selection for maned wolves, whilst the MS and MF models, which had higher spatial
465 resolution, reported a statistically significant relationship. This differences in significance of
466 vegetation for habitat selection reinforce the capacity of multi-source and multi-source data
467 fusion methods to provide new insights into movement analysis when compared to the
468 traditional single-source approaches. In addition, the difference between the distributions of the
469 NDVI coefficients for each model highlights once again that much of the patterns we see are
470 related to the granularity and scale of the data we use (Laube and Purves, 2011). Therefore,
471 when selecting earth observation data for movement analysis, it is essential to consider the
472 scales of the movement but also the scales of the earth observation data being linked to
473 movement. The goal is to capture data that can portray the changes in environmental conditions
474 that closely match the reality perceived by the individual moving, i.e., at the spatial and

475 temporal scale at which the individual is interacting with environment. Multi-source and multi-
476 source data fusion methodologies offer tremendous potential in the study of wildlife movement,
477 because these data will better match the spatial heterogeneity and temporal dynamics associated
478 with environmental conditions experienced by wildlife.

479 The three approaches we tested (i.e., using single source data, combining multiple medium/high
480 resolution sensor data and fusing these data with high temporal resolution Earth observation
481 data) are not limited to optical satellite imagery, but can be used for other types of Earth
482 observation data captured using a variety of other sensors. For example, different satellite
483 systems are now collecting detailed information on environmental conditions such as, water
484 content, chlorophyll, snow coverage, vegetation type, land or sea surface temperature,
485 humidity, rainfall, air pressure and Earth's magnetic field (Sadeghi *et al.*, 2018), which can be
486 useful for explaining wildlife movement patterns. There is a potential to extend our
487 methodology beyond optical imagery and include all these different types of environmental
488 data. We note here that we found that a multi-source approach was more predictive of
489 movement and habitat selection than a multi-source fusion approach, and we recommend that
490 future research first explores the use of multi-source Earth observation data for movement
491 analysis at local and spatially detailed scales. Further, a multi-source approach is less
492 computationally demanding than multi-source data fusion methods, which may not lead to
493 improvements in predictive capability as shown here. Moreover, the need to ensure enough
494 landcover classifications at reasonable intervals it is important to highlight that

This paper is, as far as we are aware, one of the first attempts to combine data from multiple satellites and sensors for the purpose of analysing animal movement patterns (but see Berman *et al.*, 2019) . While remotely sensed data has become more widely used in movement ecology studies, using data from more than one source (either in a multi-source or a multi-source data fusion context) and linking these data to yet another complex data source (i.e., GPS tracking data) is a complicated task (as demonstrated by the procedures used in this paper) that many ecologists may still refrain from undertaking (Pettorelli *et al.*, 2014). The primary conceptual challenge in this process is the mismatch between the spatial and temporal resolutions of different sources of satellite remotely sensed data and wildlife tracking data – in this paper we demonstrated how this challenge can be tackled by applying multi-source and multi-source data fusion techniques.

Monitoring changes in the biosphere across sufficient spatial and temporal scales and linking the information on these changes with detailed *in situ* data, such as wildlife tracking data, represents an area of opportunity for further discovery in the field of movement ecology. While there are a number of tools that can support this process, methods for combining remote sensing data with wildlife tracking data are still in their infancy (Neumann *et al.*, 2015; Remelgado, Wegmann and Safi, 2019). As demonstrated here, these analyses can be undertaken using relatively simple single-source remotely sensed data but become increasingly complex as multiple sources of earth observation data are included, and further complicated when using true data fusion methods. Here we find that (in the case of a terrestrial omnivore) a multi-source

515 approach that focuses on high spatial resolution data, outperforms single source high temporal
516 resolution data, and a more complex multi-source fused dataset. Thus, future research may wish
517 to first explore multi-source high resolution datasets where the spatial heterogeneity of
518 resources is more likely to be predictive of movement and habitat selection over temporal
519 dynamics. In contrast, in species where temporal dynamics are crucial to movement and habitat
520 selection, high temporal resolution earth observation data or a more multi-source data fusion
521 approach (as demonstrated here) are likely to provide higher predictive outcomes, leading to
522 better insights in to the movement of wildlife species.

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