
# Images à très haute resolution pour la gestion des ressources du sol et la conservation durable de la biodiversité dans la savanne semi-aride

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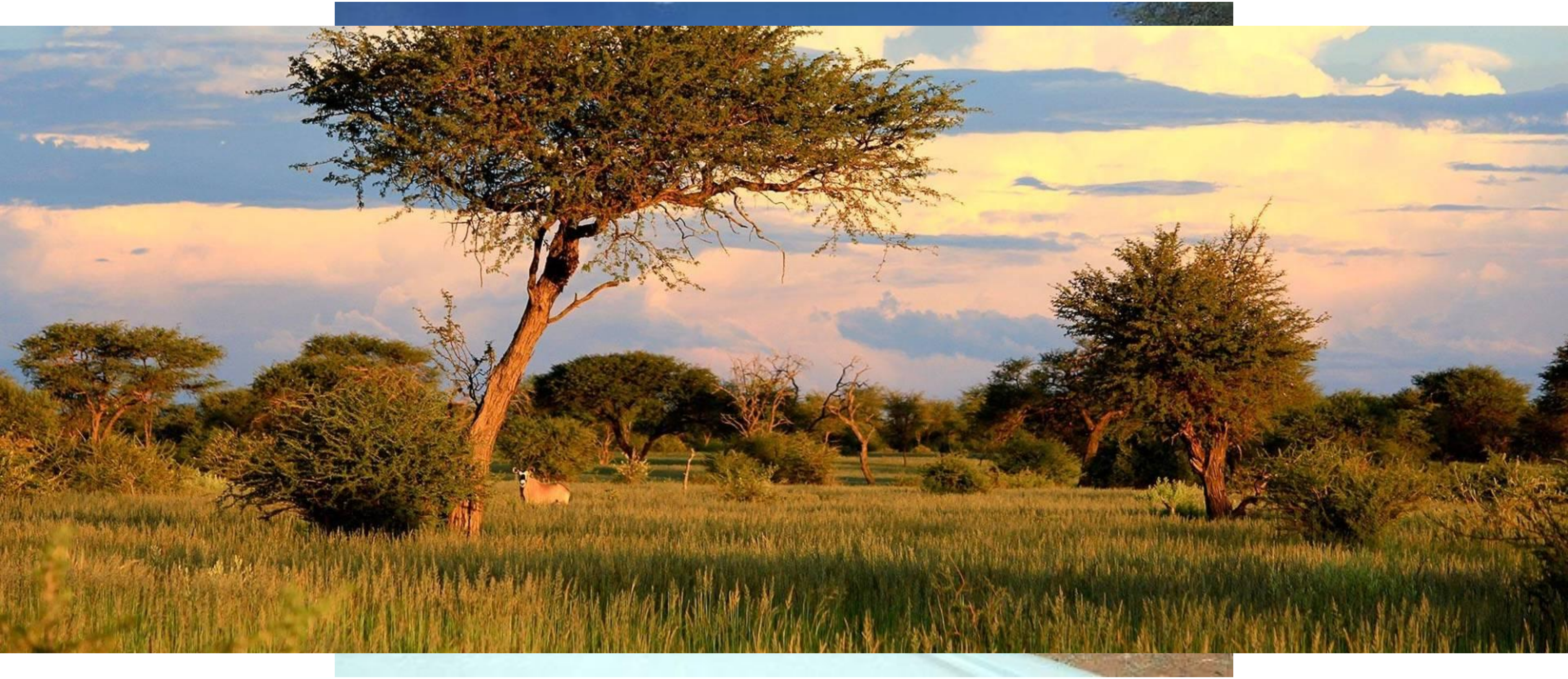
Kuzikus
WILDLIFE • RESERVE • NAMIBIA

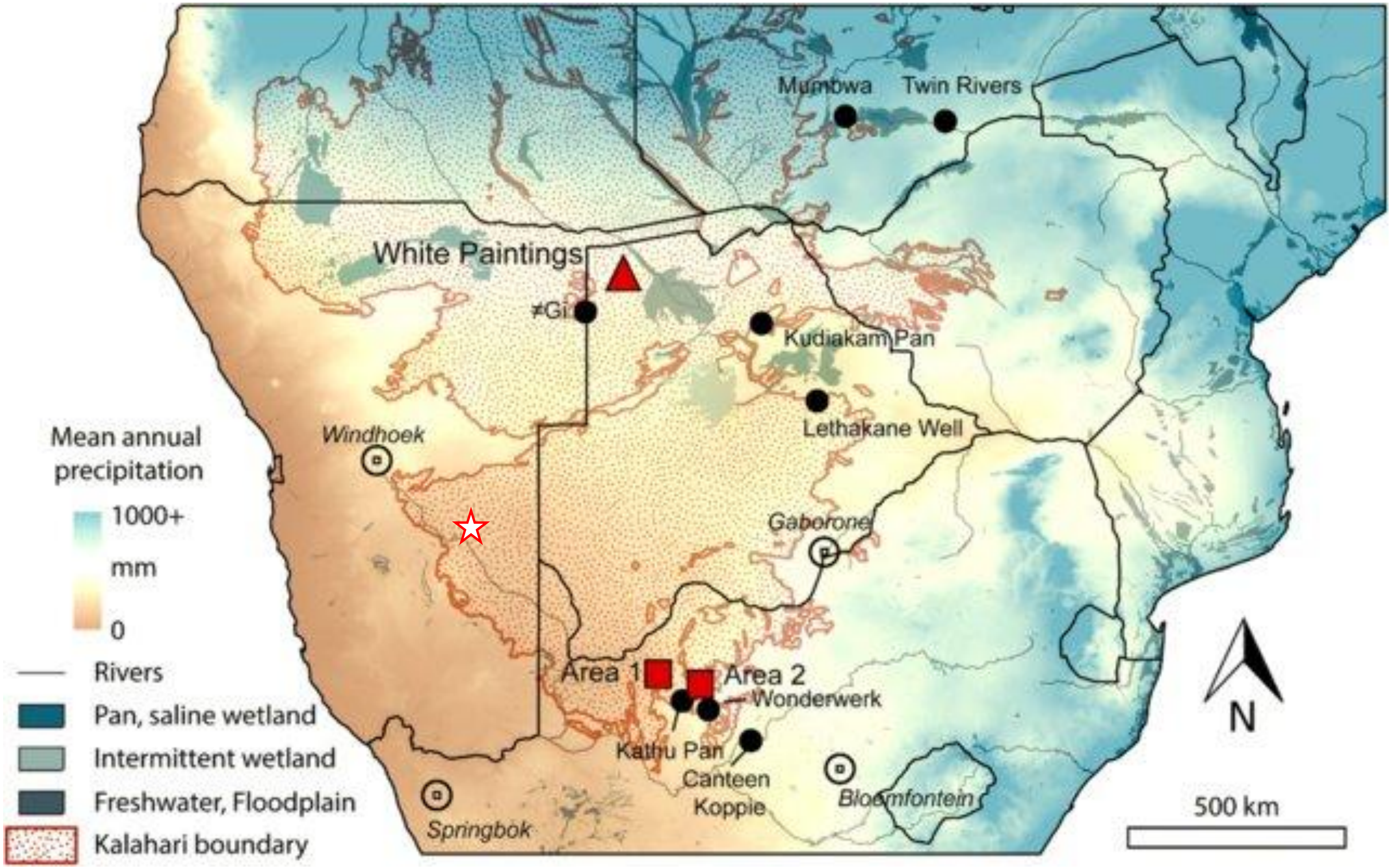


# Réserve de faune sauvage Kuzikus en Namibie

- Kuzikus: région du Kalahari riche en animaux sauvages
- Développée sous la forme d’une réserve de faune et de flore sauvages  - Accréditée par l'État namibien
- Combine tourisme, formation et recherche
- En lien avec des projets dans le domaine de la conservation de l’intégrité écologique de l’écosystème du Kalahari


Angola
Zambia
Zimbabwe
Ohangwena
Zambezi
Omusati
Oshikoto
Kavango
Kunene
Otjozondjupa
Namibia
Omaheke
Windhoek
Khomas
Botswana
Kuzikus Wildlife Reserve
Hardap
Karas
South Africa


Dr Friedrich Reinhard




Schoville et al. 2022

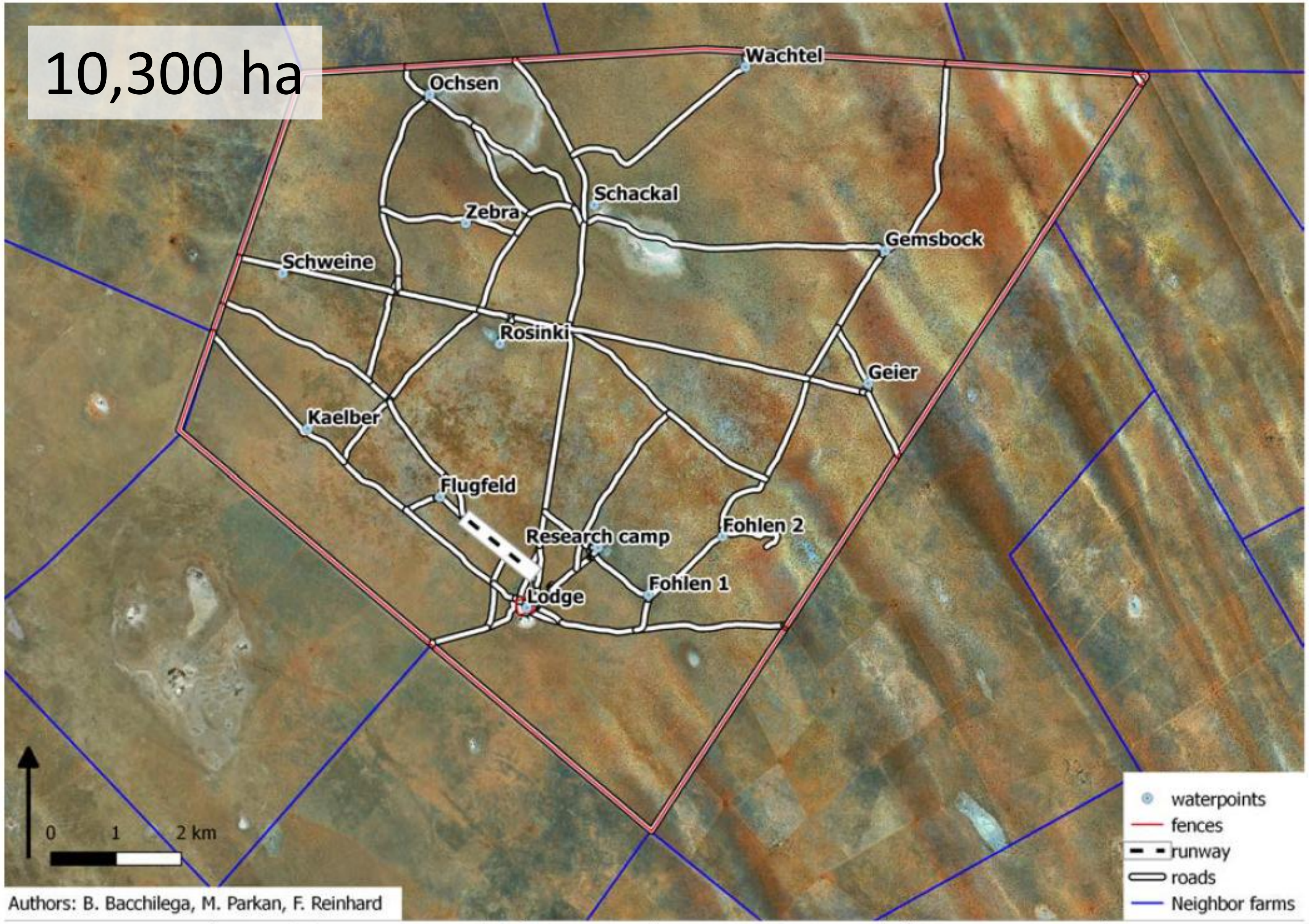


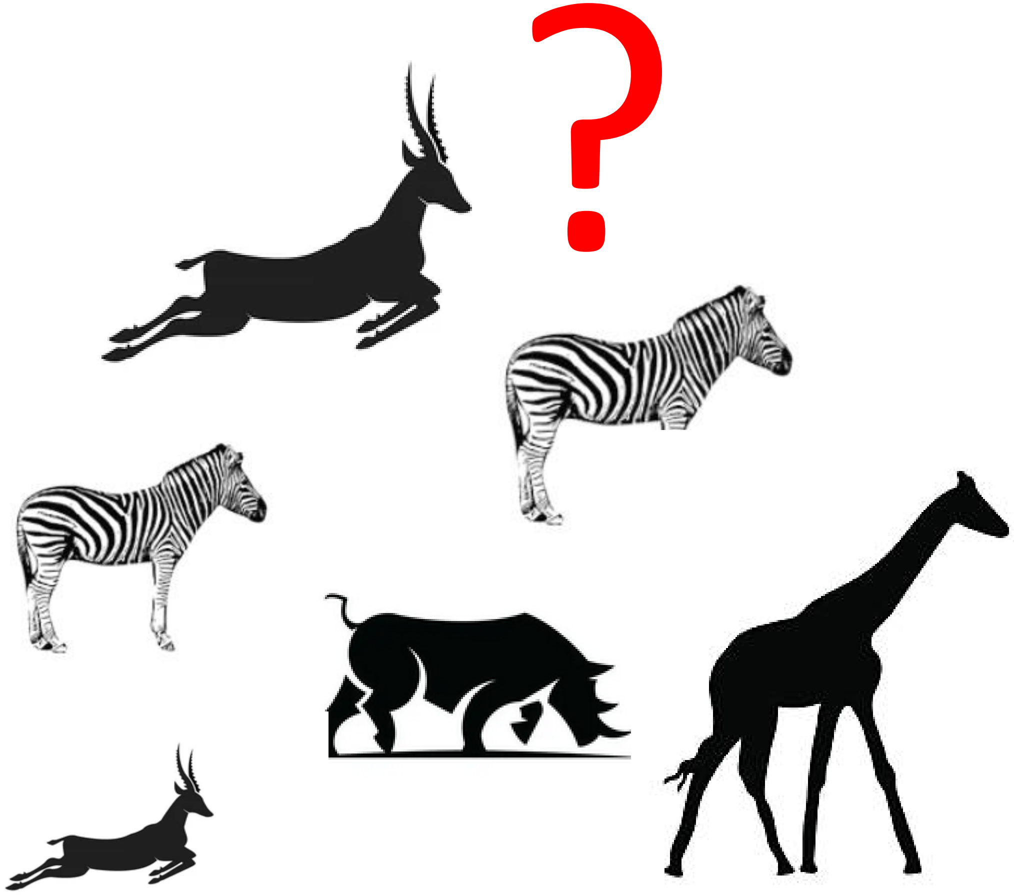

**Figure 1.2:** Kuzikus Wildlife Reserve [DigitalGlobe, 2018], [SAVMAP, 2017]



**Images**: Friedrich Reinhard and Karin Falk, Kuzikus 2015

# Problématique

- La savane semi-aride est un écosystème fragile
- Toute modification de l'équilibre entre les **précipitations**, la pression du pâturage (=consommation d’herbe par les animaux) et les feux de brousse peut entraîner une dégradation à long terme des terres
- La dégradation se traduit par une réduction de la couverture herbacée et l’apparition de broussailles
- Pour éviter le surpâturage, l’effectif des populations de brouteurs doit être maintenu en adéquation avec la disponibilité en herbe
- Les gestionnaires de Kuzikus doivent régulièrement estimer la quantité d'animaux sauvages présents sur leur territoire
- Ils doivent régulièrement estimer la quantité de végétation disponible



Combien y en-a-t-il ?

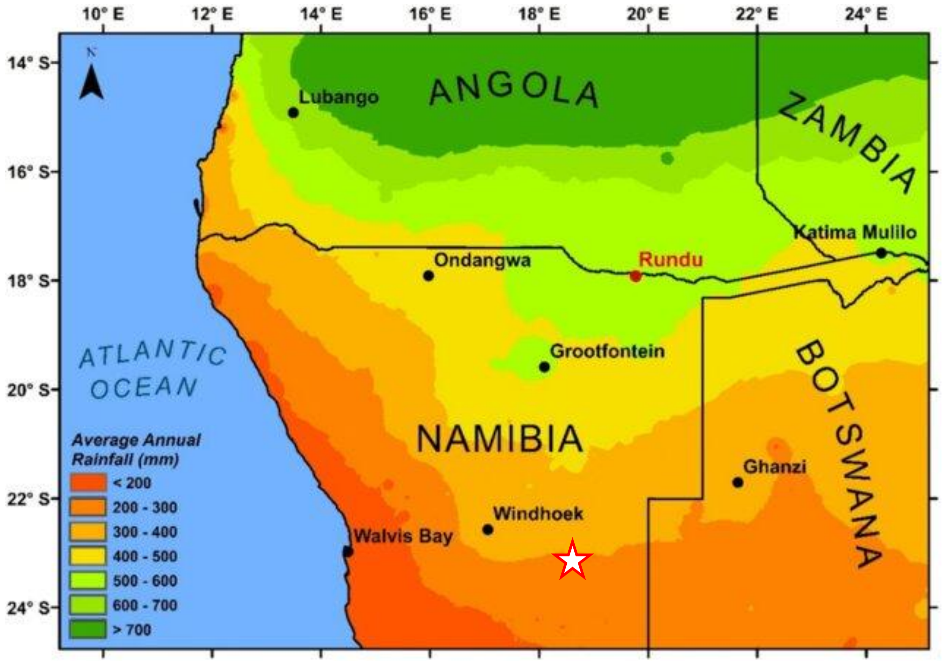
Est-ce qu'il y en a assez ?

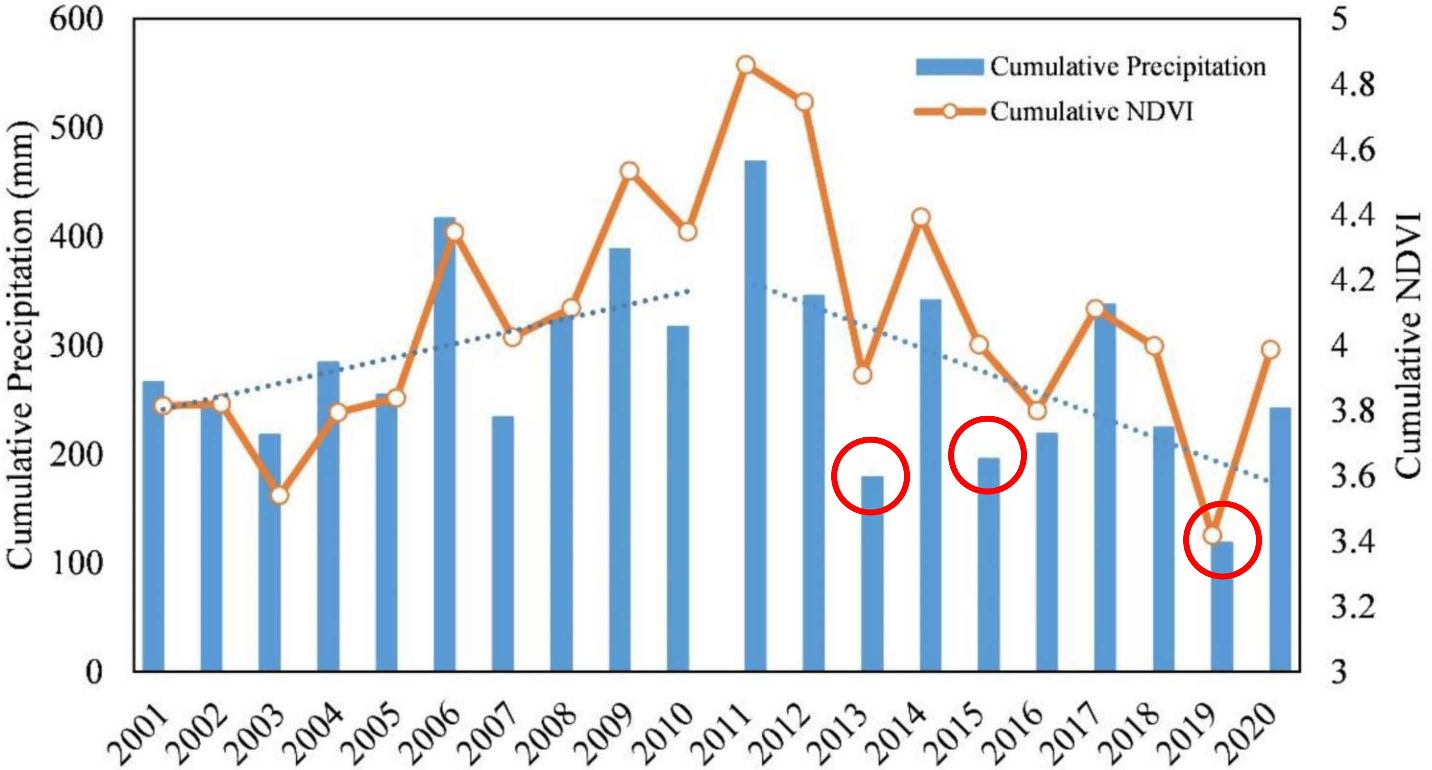
# Changement climatique

- Dans le contexte du changement climatique, l'intensité, la fréquence et la durée des épisodes de sécheresse ont augmenté de manière significative
- Impact très important sur les écosystèmes naturels et les systèmes socio-économiques en général

- Dans les régions arides et semi-arides, les **précipitations** sont le principal facteur limitant la croissance de la végétation, et les écosystèmes sont très sensibles au changement climatique

# Evolution récente des précipitations en Namibie



# Sécheresse et changement climatique


## Etat d'urgence déclaré 3 fois en 6 ans (2013, 2016, 2019)

La dernière fois le 7 mai 2019 par le Président Hage Geingob:

*"I declare under Article 26 of the Namibian Constitution that a State of Emergency exists on account of the natural disaster of drought in all regions of the Republic of Namibia."*

**Images** : Friedrich Reinhard, Kuzikus 2019

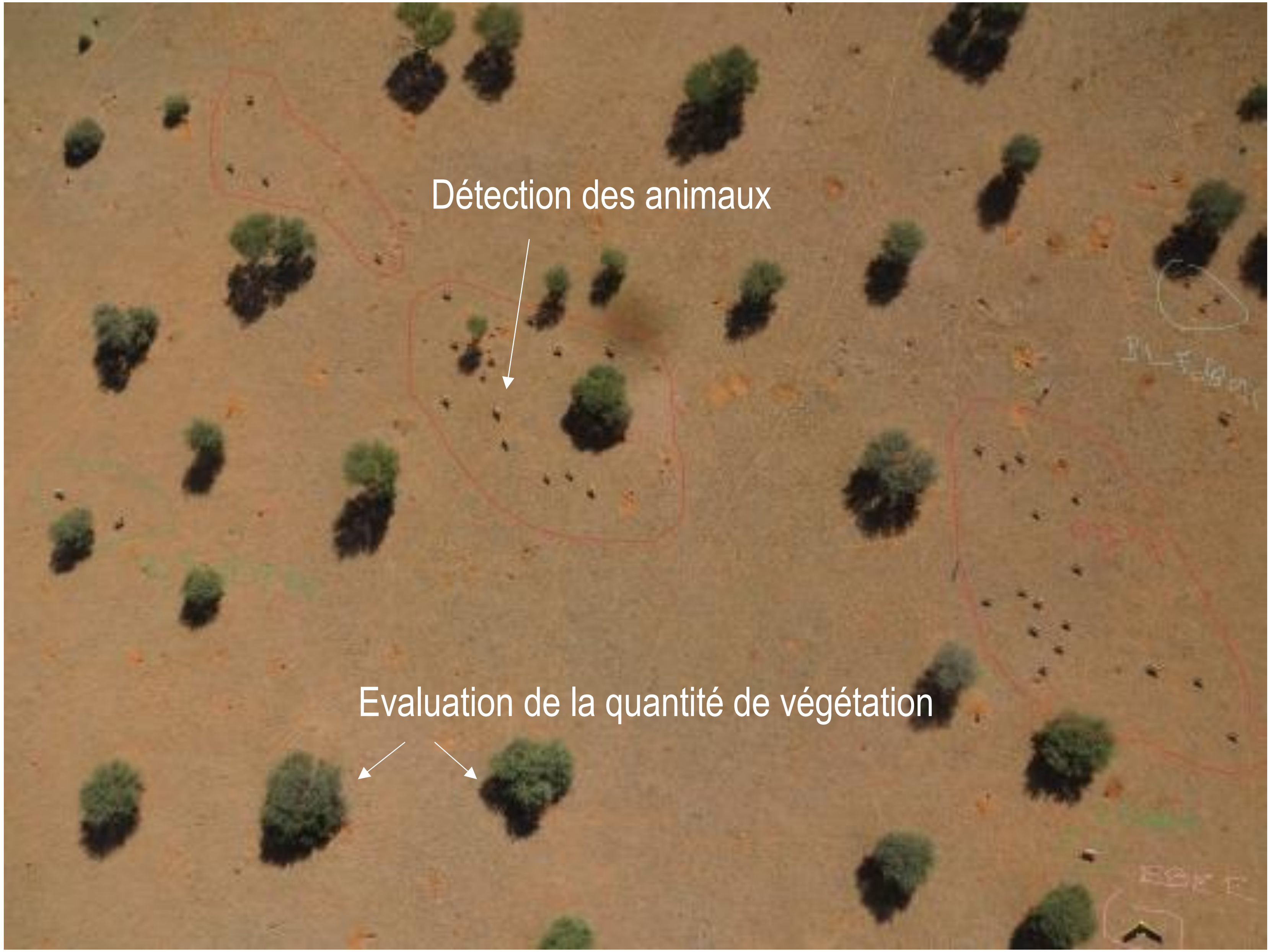
Opportunité de recherche dans le domaine de l'information géographique. Peut-on utiliser des drones et des images géoréférencées à haute résolution pour 1) compter les animaux et 2) estimer la quantité de fourrage?

# Projets CODEV

- Centre de Coopération et de Développement  de  l'EPFL (CODEV)
- Janvier 2014 rédaction d'un projet
- Collaboration entre Kuzikus Wildlife Reserve (Dr Friedrich Reinhard), la Namibia University of Science and Technology (Dr Morgan Hauptfleisch), GIS Lab de l'EPFL, Drone Adventure (foundation créée par la société SenseFly) (droneadventures.org)
- "Ultrahigh-resolution imaging for developing a monitoring tool for land managers facilitating sustainable resource management and rare species conservation (black rhinoceros)"
- Former les gestionnaires du parc et des étudiants de la NUST

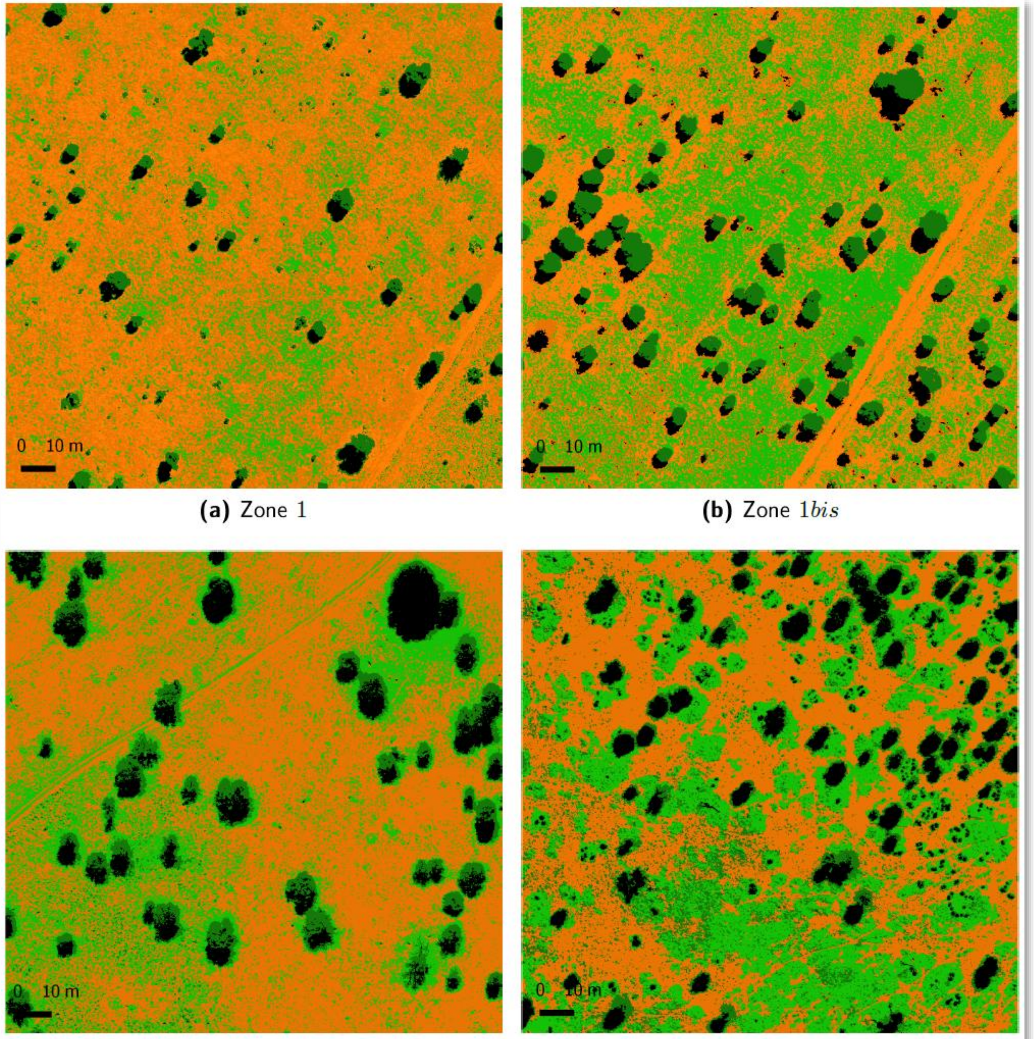
# Peu d'argent mais…

- 1x CHF 16'000.-
- 1x CHF 19'000.-
- 3 missions
- 21'400 RGB images
- 17'100 NIR images
- Terrabytes…



# Première mission


Timothée Produit (LASIG) au Gobabeb Research & Training Center, Namibia - Mai 2014



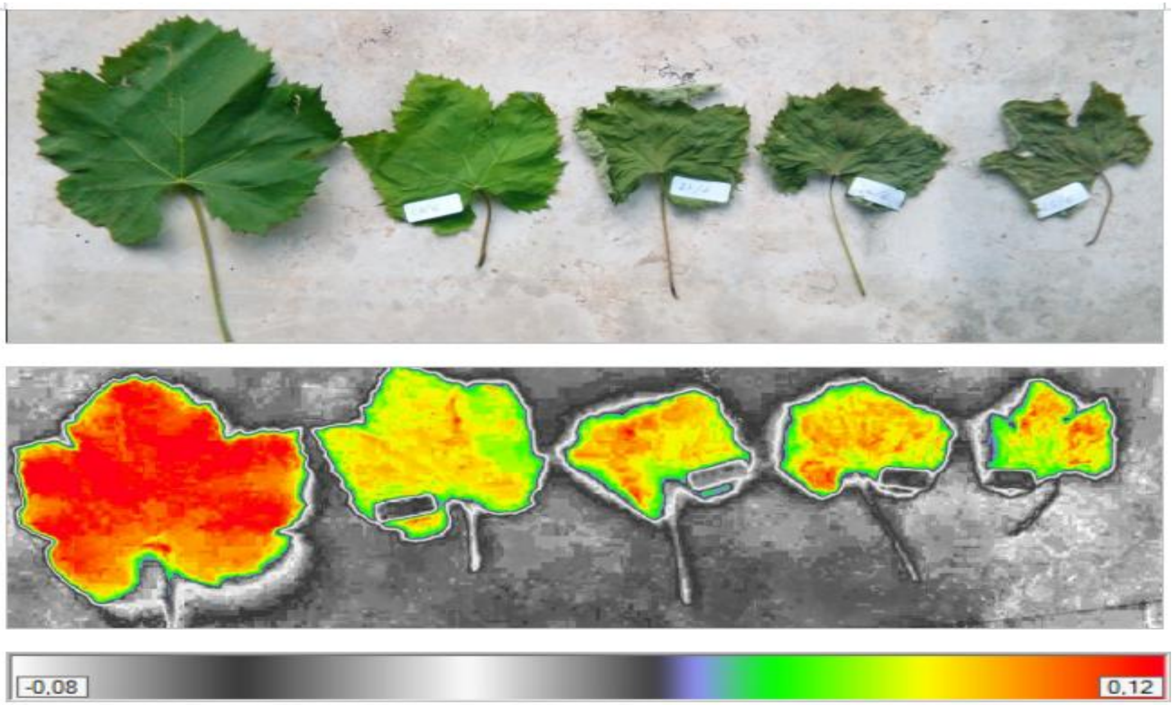

(a) Zone 1 (b) Zone 1*bis* (c) Zone 2 (d) Zone 3

Normalized Difference Vegetation Index

# Normalized Difference Vegetation Index (NDVI)

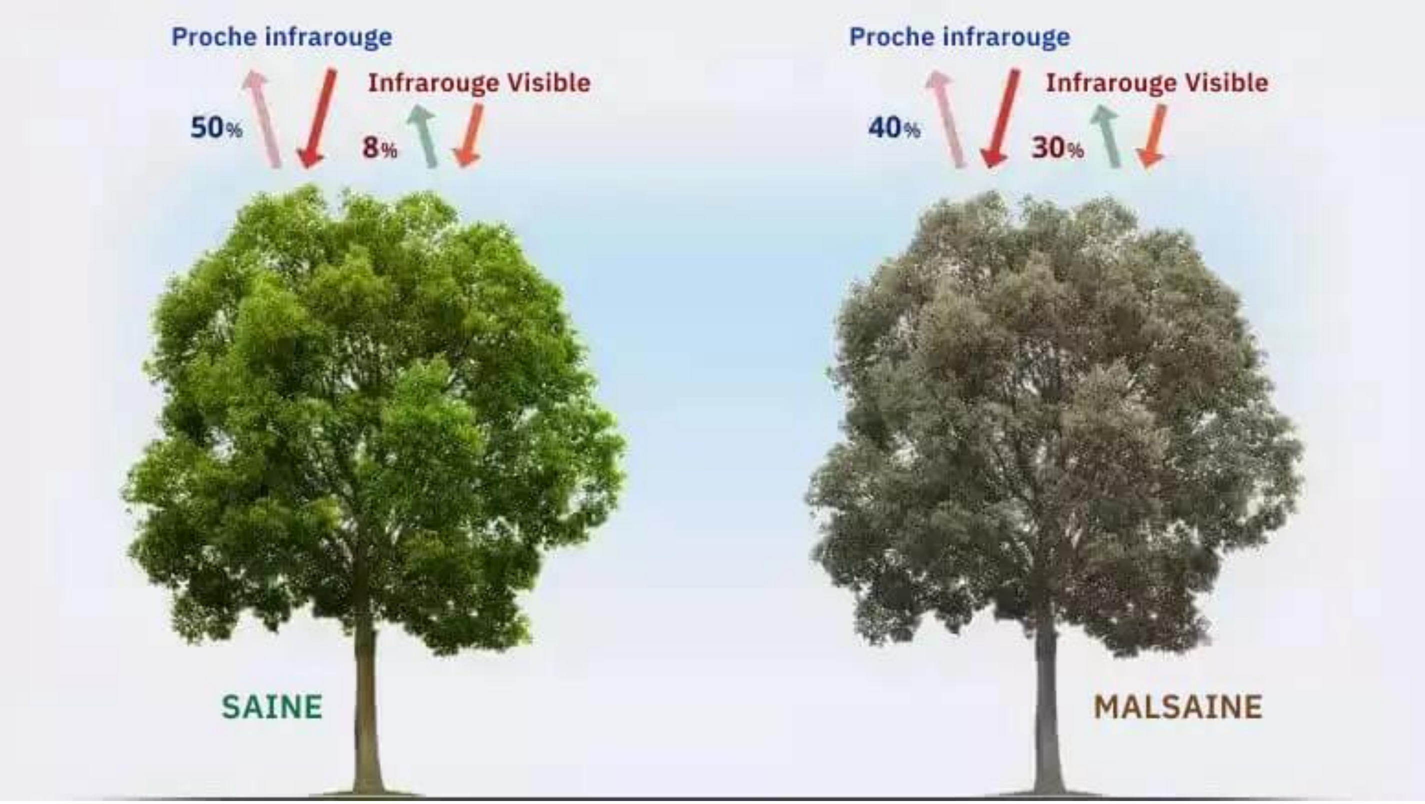
- Le NDVI est un indicateur de la santé de la végétation basé sur la façon dont les plantes reflètent certaines gammes du spectre électromagnétique

- Le NDVI est un indice sans dimension qui décrit la différence entre la réflectance visible et la réflectance dans le proche infrarouge (NIR) de la couverture végétale et qui peut être utilisé pour estimer la densité de végétation sur une zone de la terre




Goswami, 2022

$$NDVI = \frac{NIR - Red}{NIR + Red}$$




- La chlorophylle absorbe fortement la lumière visible et la structure cellulaire des feuilles réfléchit fortement la lumière proche infrarouge
- Lorsque la plante est déshydratée, malade, etc., la couche spongieuse se détériore et la plante absorbe davantage de lumière proche infrarouge au lieu de la réfléchir

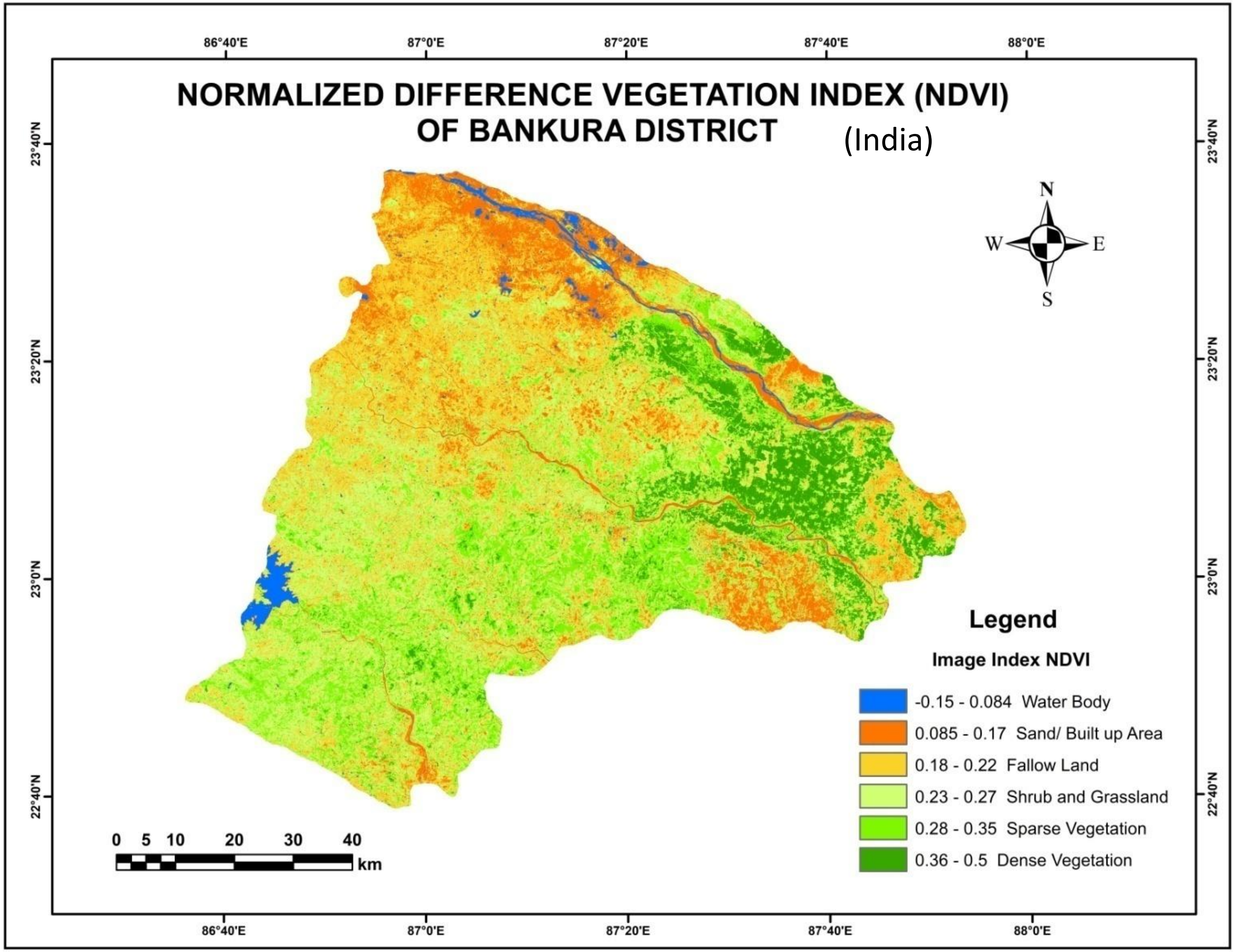
# Sources de données pour calculer le NDVI

- Imagerie satellite

- Landsat (30m de résolution spatiale)
- MODIS
- NOAA
- SPOT
- **Sentinel-2** (10m)

- Exemples avec Landsat 7 et Landsat 8

| S.N. | Landsat 7 Enhanced Thematic Mappers Plus (ETM +) | | | Band | Landsat 8 Operational Land Imagers (OLI) & Thermal Infrared Sensor (TIRS) | | |
|---|---|---|---|---|---|---|---|
| | **Resolution (meter)** | **Wavelength (micrometer)** | **Band Name** | | **Band Name** | **Wavelength (micrometers)** | **Resolution (meter)** |
| 1 | 30 | 0.45-0.52 | Blue | **Band 1** | Ultra-Blue | 0.435-0.451 | 30 |
| 2 | 30 | 0.52-0.60 | Green | **Band 2** | Blue | 0.452-0.512 | 30 |
| 3 | 30 | 0.63-0.69 | Red | **Band 3** | Green | 0.533-0.590 | 30 |
| 4 | 30 | 0.77-0.90 | NIR | **Band 4** | Red | 0.636-0.673 | 30 |
| 5 | 30 | 1.55-1.75 | SWIR 1 | **Band 5** | NIR | 0.851-0.879 | 30 |
| 6 | 60* (30) | 10.40-12.50 | Thermal | **Band 6** | SWIR 1 | 1.566-1.651 | 30 |
| 7 | 30 | 2.09-2.35 | SWIR 2 | **Band 7** | SWIR 2 | 2.107-2.294 | 30 |
| 8 | 15 | 0.52-0.90 | Panchromatic | **Band 8** | Panchromatic | 0.503-0.676 | 15 |
| 9 | | | | **Band 9** | Cirrus | 1.363-1.384 | 30 |
| 10 | | | | **Band 10** | TIRS 1 | 10.60-11.19 | 100 * (30) |
| 11 | | | | **Band 11** | TIRS 2 | 11.50-12.51 | 100 * (30) |


NORMALIZED DIFFERENCE VEGETATION INDEX (NDVI)
OF BANKURA DISTRICT
(India)
86°40'E
87°0'E
87°20'E
87°40'E
88°0'E
23°40'N
23°20'N
23°0'N
22°40'N
N
S
W
E
Legend
Image Index NDVI
-0.15 - 0.084 Water Body
0.085 - 0.17 Sand/ Built up Area
0.18 - 0.22 Fallow Land
0.23 - 0.27 Shrub and Grassland
0.28 - 0.35 Sparse Vegetation
0.36 - 0.5 Dense Vegetation
0 5 10 20 30 40
km

# Deuxième mission

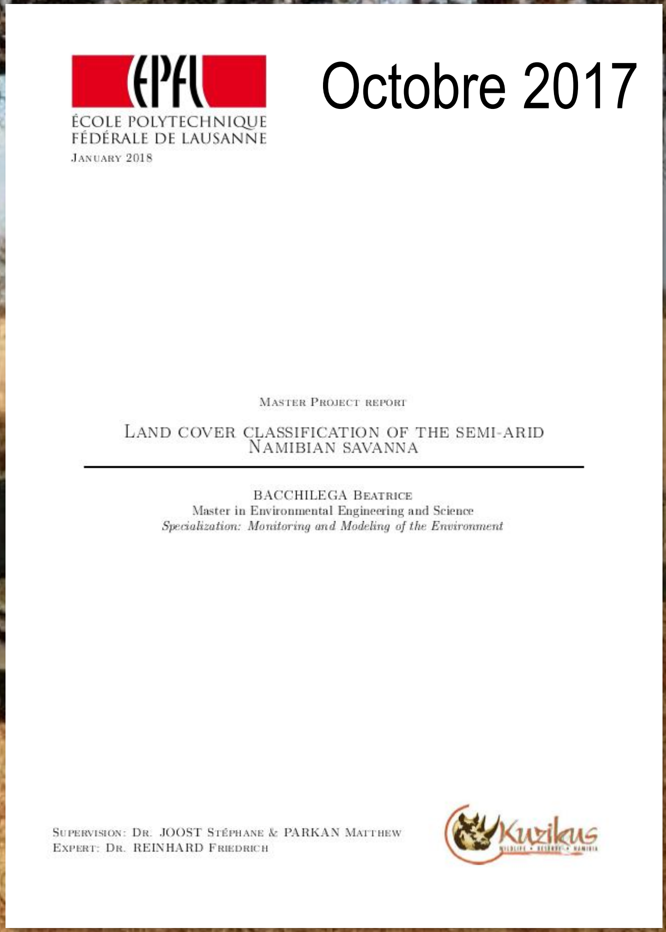
Poursuite de la couverture cartographique de Kuzikus

Analyse des traces des animaux dans le sol avec les Bushmen

Mai 2015

*Friedrich Reinhard et Matthew Parkan (GIS Lab EPFL) à Kuzikus avec des rangers et des enfants pour une démo avec un drone*

# Troisième mission


ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE
JANUARY 2018

MASTER PROJECT REPORT

LAND COVER CLASSIFICATION OF THE SEMI-ARID NAMIBIAN SAVANNA

BACCHILEGA BEATRICE
Master in Environmental Engineering and Science
*Specialization: Monitoring and Modeling of the Environment*

SUPERVISION: DR. JOOST STÉPHANE & PARKAN MATTHEW
EXPERT: DR. REINHARD FRIEDRICH

Octobre 2017

Sentinel-2 satellite data

# Evaluation de la disponibilité du fourrage

- Chaque année, à la fin de la période de végétation (fin mai), les responsables du parc évaluent les disponibilités en fourrage
- L'estimation de la quantité de nourriture pour les animaux est longue et compliquée
- Les évaluations basées sur les observations au sol ne fournissent pas de d'estimation fiable de la disponibilité sur tout le domaine

# Importance de la précision de l'estimation

- S'il n'y a pas assez de fourrage, alors tirs de régulation des effectifs
- Pertes financières
- Vente des animaux sauvages à des pays tiers (e.g. Angola)

**Constat**

- Difficile d'exploiter les images de drones pour l'évaluation du fourrage
- Temps d'acquisition (300 ha par jour/10'300 ha, donc 34 jours) et de traitement
- Autres sources de données?
- Apports des images des drones pour validation?

# Sentinel-2

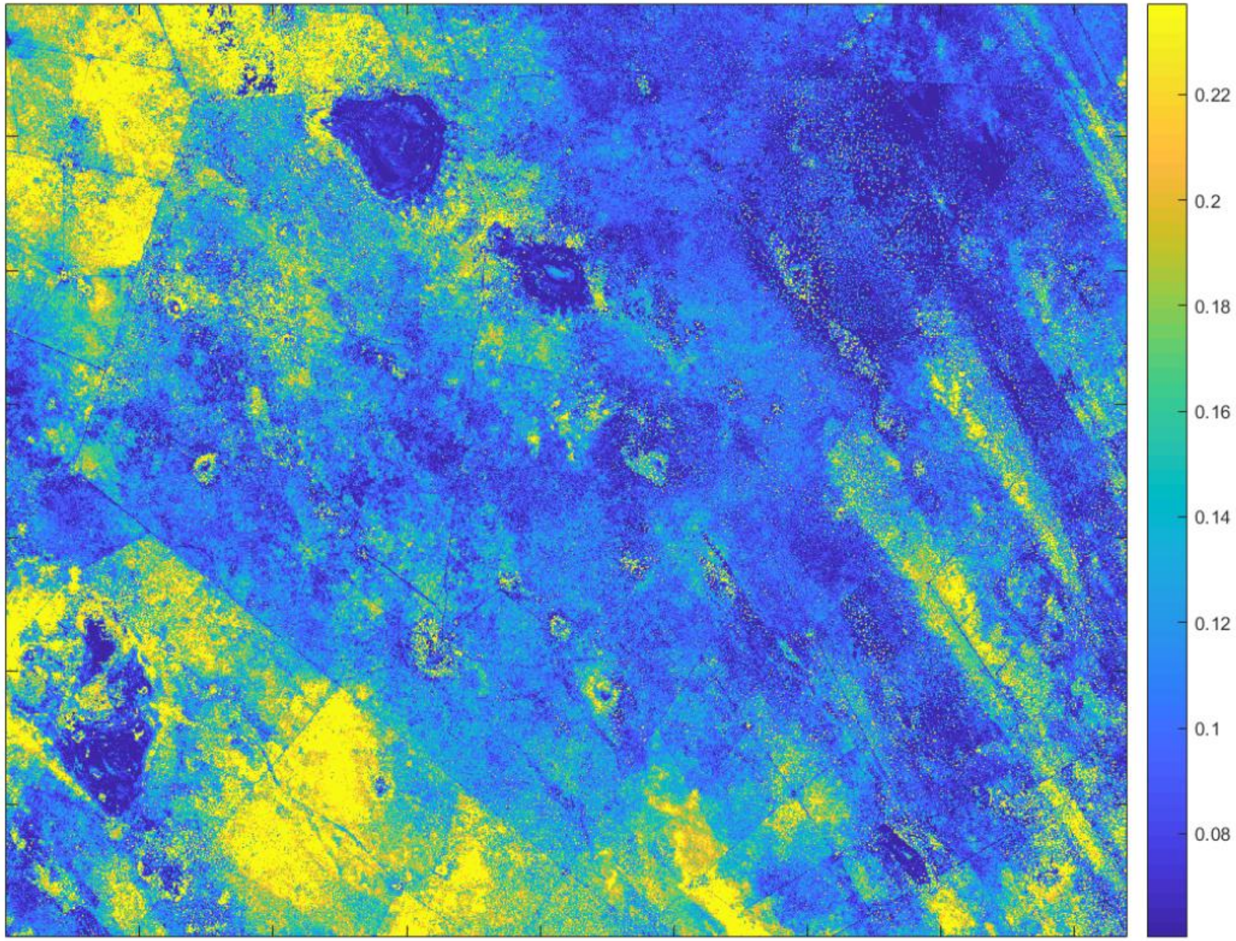



**Figure 5.31:** Standard deviation of the Difference Vegetation Index over 1 year, from November 2016 to November 2017

- Projet COPERNICUS des pays européens (2015, 2017)
- Imagerie optique haute résolution pour l'observation des sols (utilisation des sols, végétation, zones côtières, fleuves, etc.) et le traitement des situations d'urgence (catastrophes naturelles...)
- Fréquence de revisite élevée de 5 jours (à l'équateur)
- Résolution spatiale de 10m
- 13 bandes spectrales

- Évaluer la précision des estimations basées sur Sentinel-2 (10m2) avec les images de la VHR obtenues par drone (4 cm2)
- Par classification (forêts d'arbres décisionnels ou random forest)
- Méthode d'apprentissage

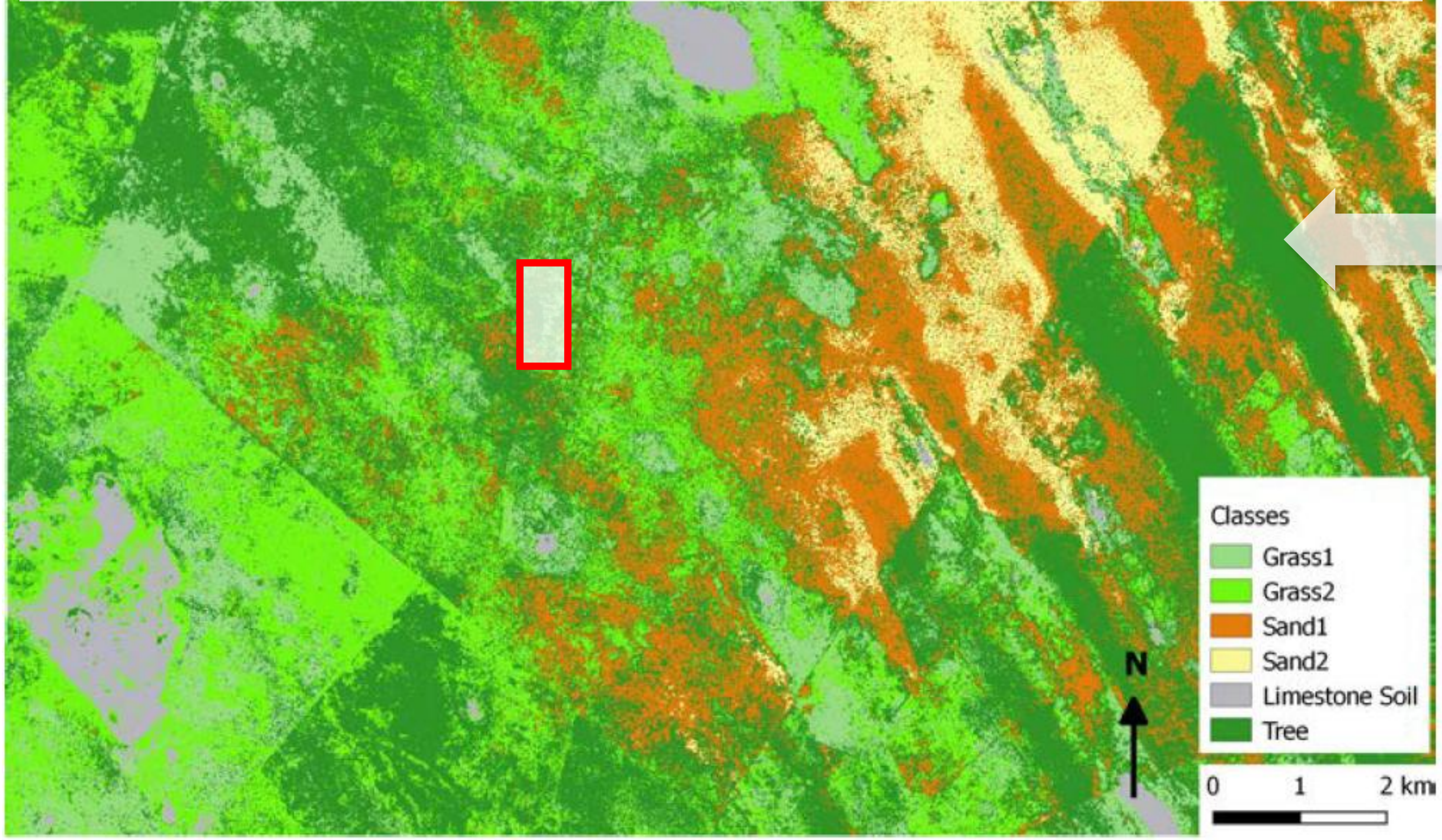



**Figure 5.17:** Random Forest classification, Sentinel-2 May 2017

# Ortho-image drone superposée à classification sur Sentinel-2

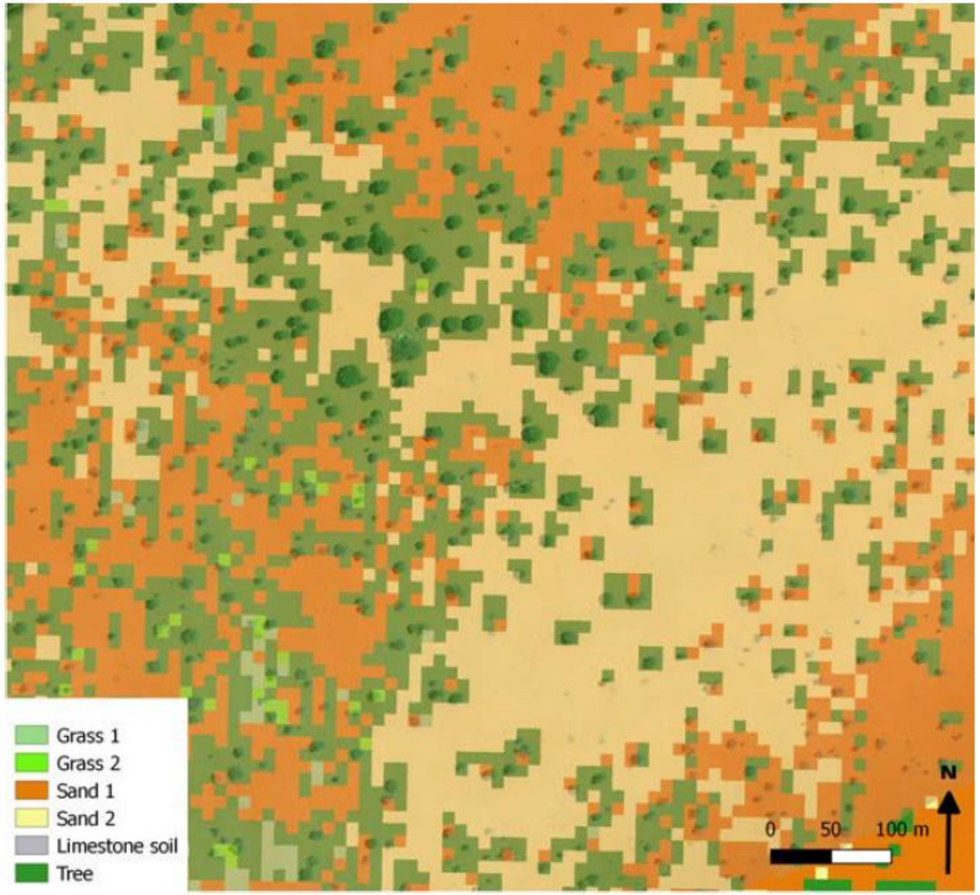



**Figure 5.21:** Comparison between RF classificatin results over the Sentinel-2 image from October 21, 2017 and an eBee Plus Orthophoto from October 16, 2017 over zone 2

- Validation par superposition
- Image Drone du 16 octobre 2017
- Image Sentinel-2 du 21 octobre 2017
- Pas de Ground Control Points (GCPs)
- Précision absolue de positionnement varie entre 1 et 5 mètres
- Malgré cela bonne correspondence apparente entre données drone et les classes Sentinel-2

| Drone 2017 | | | | |
|---|---|---|---|---|
| Area $[m^2]$ | Zone 1 (RF) | Zone 1bis (RF) | Zone 2 (RF) | Zone 3 (RF) |
| Grass 1 | 637.7 | 1176.0 | 200.6 | 159.4 |
| Grass 2 | 898.1 | 2094.1 | 5195.5 | 12397.5 |
| Total grass | 1535.7 | 3270.1 | 5396.1 | 12556.9 |
| Bush 1 | 644.7 | 156.9 | 10.2 | 8.7 |
| Bush 2 | 0.0 | 1.8 | 0.3 | 1071.5 |
| Total bush | 644.7 | 158.7 | 10.5 | 1080.2 |
| Tree 1 | 526.4 | 370.7 | 671.6 | 1518.0 |
| Tree 2 | 538.2 | 2149.4 | 1269.1 | 30.5 |
| Total tree | 1064.5 | 2520.1 | 1940.7 | 1548.5 |
| Total vegetation | 3244.9 | 5948.9 | 7347.2 | 15185.6 |

**Table 5.13:** Vegetation estimation from RF and SVM classifications results per zones, drone October 2017

| Satellite | | |
|---|---|---|
| | May [ha] | October [ha] |
| Grass 1 | 1236.1 | 1840.9 |
| Grass 2 | 1536.1 | 1765.2 |
| Total grass | 2772.9 | 3606.1 |
| Trees and bushes | 3705.8 | 3159.3 |
| Total vegetation | 6478.7 | 6765.4 |

**Table 5.14:** Vegetation estimation from RF classification results, Sentinel-2 May and October 2017

(110%)

# Complémentarité

- Les données obtenues par drone et les données satellitaires offrent des informations différentes et complémentaires sur la couverture du sol
- Drone = haut niveau de détails, mais petites zones seulement et pas de vue d'ensemble de la zone d'étude et des environs (sans compter temps d’acquisition et de traitement = coût)
- Sentinel-2 (gratuites) = plus grandes zones couvertes mais moins de détails
- Grâce à leur haute résolution, les images de drone peuvent être utilisées pour extraire des informations utiles des données satellitaires
- Les images de drones peuvent être utilisées comme vérité de terrain pour quantifier le volume des différentes espèces végétales avec les images satellite
- Ces informations facilitent l'exploitation à long terme des données satellitaires pour estimer la quantité de fourrage

# Comment compter le animaux ?

# Méthodes traditionnelles de recensement de la faune

- Comptage à terre (voiture ou pièges photographiques) ou à partir d'un hélicoptère
- Ces méthodes permettent d'estimer la densité de la population sur la base d'observations localisées le long d'un chemin prédéfini
- Ces méthodes sont coûteuses, dangereuses (hélicoptère)
- Elles nécessitent des experts humains formés
- Ne conviennent pas pour des recensements réguliers sur de vastes zones


Springbok Oryx Blue_Gnu Blesbok Black_Gnu Zebra Hartebeest Impala Strauss Eland Giraffe

| Species | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| Springbock | 1996 | 1409 | 1286 | 1545 | 2019 |
| Oryx | 890 | 620 | 802 | 576 | 1263 |
| Blue-Gnu | 639 | 348 | 329 | 304 | 418 |
| Blesbok | 362 | 272 | 184 | 143 | 35 |
| Black Gnu | 199 | 150 | 134 | 181 | 11 |
| Zebra | 191 | 191 | 237 | 175 | 81 |
| Hartebeest | 59 | 32 | 22 | 21 | 63 |
| Impala | 9 | 13 | 7 | 31 | 0 |
| Strauss | 62 | 98 | 127 | 86 | 31 |
| Eland | 10 | 9 | 15 | 19 | 51 |
| Giraffe | 16 | 18 | 21 | 20 | 22 |
| Kudu | 25 | 33 | 69 | 31 | 28 |
| **Total** | **4458** | **3193** | **3233** | **3132** | **4022** |

Girafe

Oryx

Antilope

# Science citoyenne

- Article SAVMAP sur l'usage simultané du «human computing» et du machine learning pour détecter des animaux et leur efficacité respective

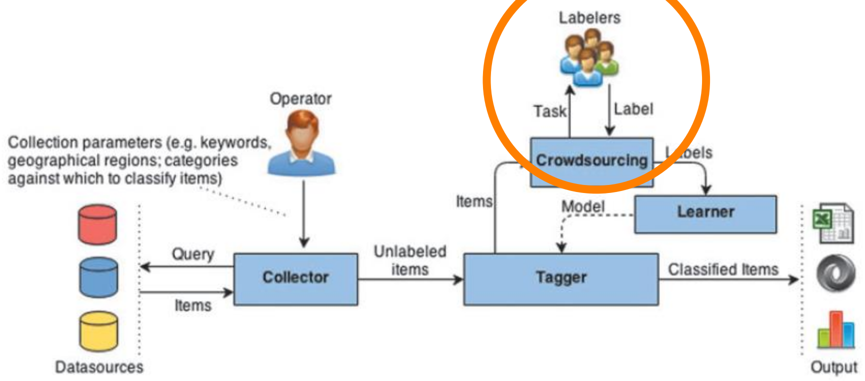
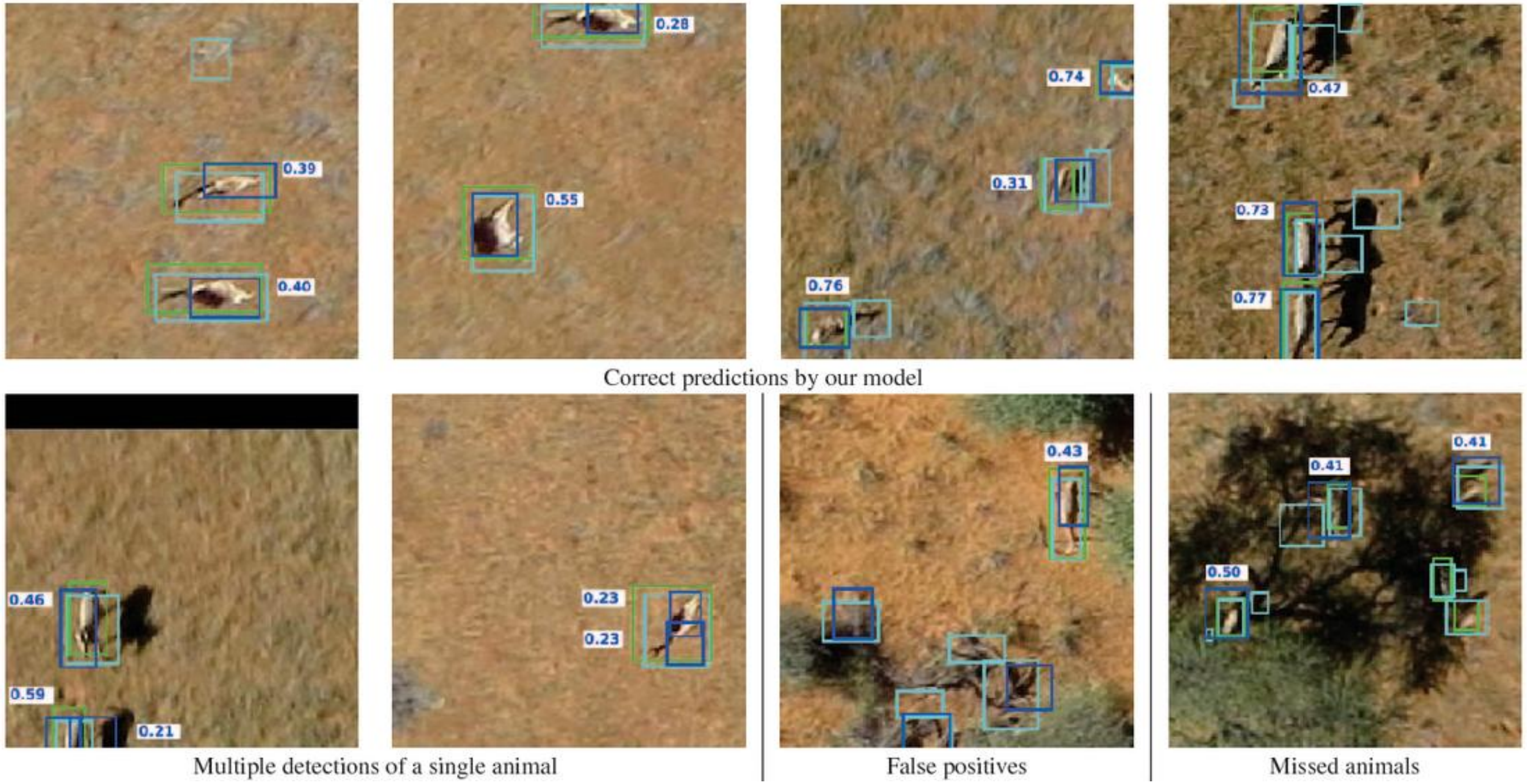



FIG. 1. Artificial Intelligence for Disaster Response (AIDR) process flow.[10]

- 500 volontaires numériques ont utilisé des «clickers» pour établir la «vérité terrain» (ou «ground truth») pour tester l'efficacité d'algorithmes de machine learning

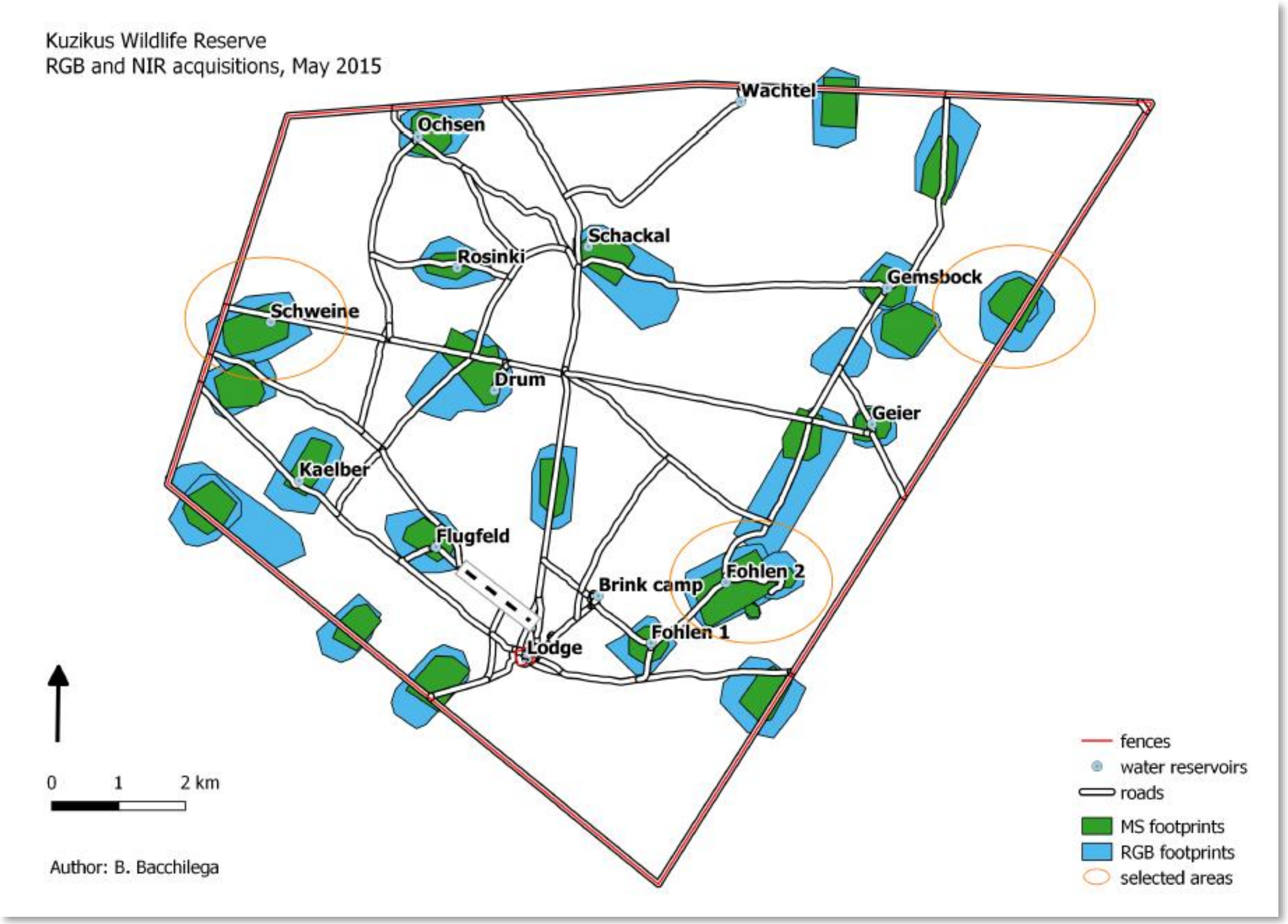

FIG. 2. User interface of Aerial Clicker (SAVMAP image).


ARTICLE / 18 FEBRUARY 2019
Using Swiss AI and Drones to Count African Wildlife
After a promising first run in Namibia, a Swiss project could aid savanna conservation using drones and automatic image analysis.


0.39
0.40
0.28
0.55
0.74
0.31
0.76
0.47
0.73
0.77
Correct predictions by our model
0.46
0.59
0.21
0.23
0.23
0.43
0.41
0.41
0.50
Multiple detections of a single animal
False positives
Missed animals

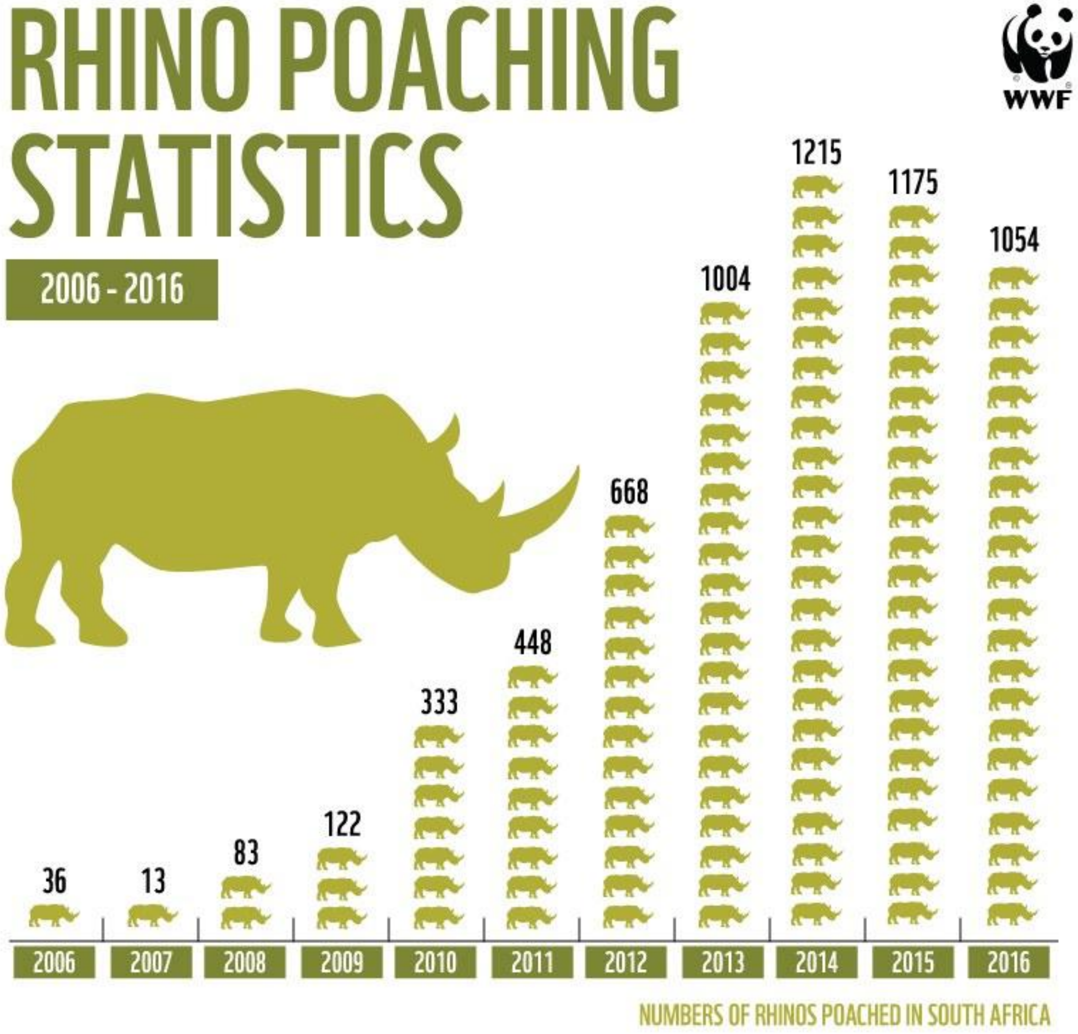
# Masses d'information générées et stockage open access

- Paradoxe
- Beaucoup d'images (plus de 30% de couverture)
- Open access pour favoriser la recherche sur le même sujet
- Dilemme: information riche, précisément référencée
- Danger: donner des pistes aux braconniers



# Braconnage

- Problème de la publication de ces images en tant que données ouvertes
- Le braconnage des rhinocéros menace de faire disparaître les espèces de rhinocéros d'ici une ou deux décennies
- La surveillance des rhinocéros est importante pour leur protection et les images géoréférencées sont utiles dans ce sens
- Mais les images géoréférencées avec des rhinocéros peuvent guider les braconniers.
- **Géo-anonymisation** des images avant leur mise à disposition (par tout utilisateur, aussi par les volontaires du projet de science citoyenne)
- Complication du processus



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March 29, 2015

Photo | Open Access

# Near real-time ultrahigh-resolution imaging from unmanned aerial vehicles for sustainable land use management and biodiversity conservation in semi-arid savanna under regional and global change (SAVMAP)

Reinhard, Friedrich; Hauptfleisch, Morgan L. ; Joost, Stéphane; SAVMAP, Consortium

To prevent aggravation of existing poverty in semi-arid savannas, a comprehensive concept for the sustainable adaptive management and use of these ecosystems under unprecedented conditions is needed. SAVMAP is an innovative, trans-, and inter-disciplinary initiative whose goal is to develop a valuable monitoring tool for both sustainable land-use management and rare species conservation (black rhinoceros) in semi-arid savanna in Namibia. SAVMAP uses near real-time ultrahigh-resolution photographic imaging (NURI) facilitated by unmanned aerial vehicles (UAVs) designed at EPFL.

Preview

day5_ebenhazer_burnt_geier_merged_archive.zip

| | |
|---|---|
| transparent_day_5_ebenhazer_burnt_geier_merged_mosaic_group1.tfw | 54 Bytes |
| transparent_day_5_ebenhazer_burnt_geier_merged_mosaic_group1.tif | 593.2 MB |

**Publication date:**
March 29, 2015

**DOI:**
DOI 10.5281/zenodo.16445

**Keyword(s):**
savanna, sustainable resource management, ultrahigh-resolution photographic imaging, conservation

**Communities:**
savmap

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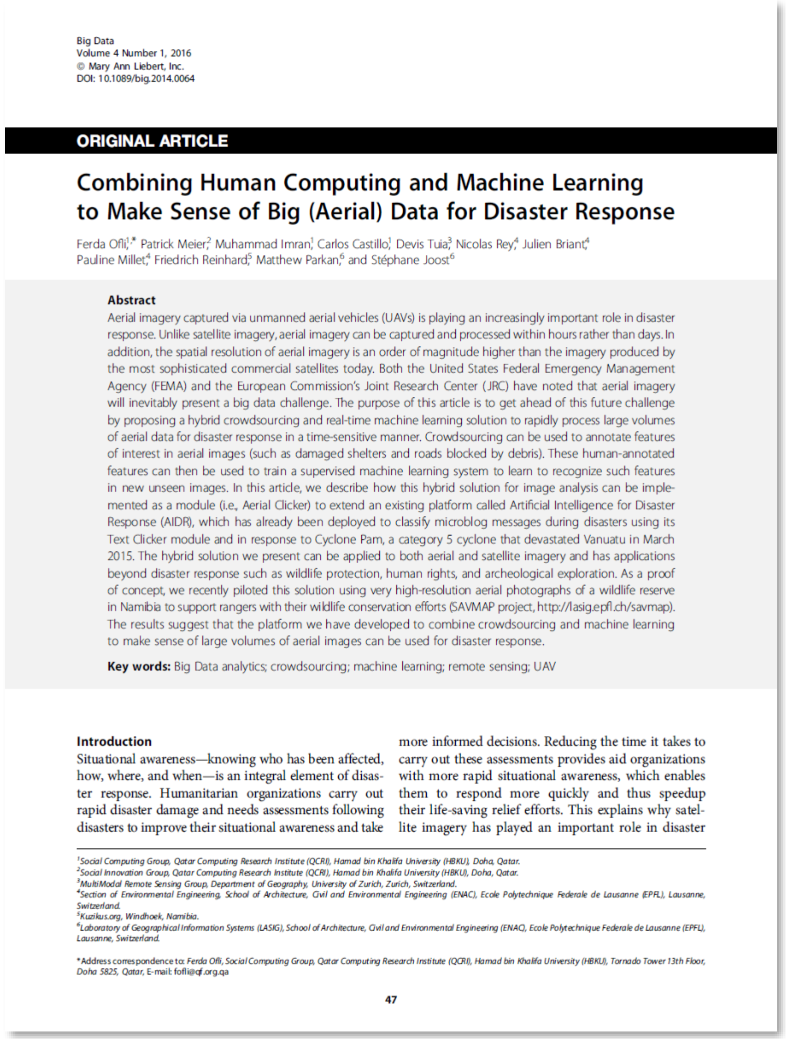
## Cite as

Reinhard, F., Hauptfleisch, M. L., Joost, S., & SAVMAP, C. (2015). Near real-time ultrahigh-resolution imaging from unmanned aerial vehicles for sustainable land use management and biodiversity conservation in semi-arid savanna under regional and global change (SAVMAP). Zenodo. http://doi.org/10.5281/zenodo.16445

# Application pratique et aussi recherche fondamentale


Big Data
Volume 4 Number 1, 2016
© Mary Ann Liebert, Inc.
DOI: 10.1089/big.2014.0064

**ORIGINAL ARTICLE**

## Combining Human Computing and Machine Learning to Make Sense of Big (Aerial) Data for Disaster Response

Ferda Ofli,[1,*] Patrick Meier,[2] Muhammad Imran,[1] Carlos Castillo,[1] Devis Tuia,[3] Nicolas Rey,[4] Julien Briant,[4] Pauline Millet,[4] Friedrich Reinhard,[5] Matthew Parkan,[6] and Stéphane Joost[6]

**Abstract**

Aerial imagery captured via unmanned aerial vehicles (UAVs) is playing an increasingly important role in disaster response. Unlike satellite imagery, aerial imagery can be captured and processed within hours rather than days. In addition, the spatial resolution of aerial imagery is an order of magnitude higher than the imagery produced by the most sophisticated commercial satellites today. Both the United States Federal Emergency Management Agency (FEMA) and the European Commission's Joint Research Center (JRC) have noted that aerial imagery will inevitably present a big data challenge. The purpose of this article is to get ahead of this future challenge by proposing a hybrid crowdsourcing and real-time machine learning solution to rapidly process large volumes of aerial data for disaster response in a time-sensitive manner. Crowdsourcing can be used to annotate features of interest in aerial images (such as damaged shelters and roads blocked by debris). These human-annotated features can then be used to train a supervised machine learning system to learn to recognize such features in new unseen images. In this article, we describe how this hybrid solution for image analysis can be implemented as a module (i.e., Aerial Clicker) to extend an existing platform called Artificial Intelligence for Disaster Response (AIDR), which has already been deployed to classify microblog messages during disasters using its Text Clicker module and in response to Cyclone Pam, a category 5 cyclone that devastated Vanuatu in March 2015. The hybrid solution we present can be applied to both aerial and satellite imagery and has applications beyond disaster response such as wildlife protection, human rights, and archeological exploration. As a proof of concept, we recently piloted this solution using very high-resolution aerial photographs of a wildlife reserve in Namibia to support rangers with their wildlife conservation efforts (SAVMAP project, http://lasig.epfl.ch/savmap). The results suggest that the platform we have developed to combine crowdsourcing and machine learning to make sense of large volumes of aerial images can be used for disaster response.

**Key words:** Big Data analytics; crowdsourcing; machine learning; remote sensing; UAV

**Introduction**

Situational awareness—knowing who has been affected, how, where, and when—is an integral element of disaster response. Humanitarian organizations carry out rapid disaster damage and needs assessments following disasters to improve their situational awareness and take more informed decisions. Reducing the time it takes to carry out these assessments provides aid organizations with more rapid situational awareness, which enables them to respond more quickly and thus speedup their life-saving relief efforts. This explains why satellite imagery has played an important role in disaster

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## Detecting animals in African Savanna with UAVs and the crowds

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ABSTRACT

Unmanned aerial vehicles (UAVs) offer new opportunities for wildlife monitoring, with several advantages over traditional field-based methods. They have readily been used to count birds, marine mammals and large herbivores in different environments, tasks which are routinely performed through manual counting in large collections of images. In this paper, we propose a semi-automatic system able to detect large mammals in semi-arid Savanna. It relies on an animal-detection system based on machine learning, trained with crowd-sourced annotations provided by volunteers who manually interpreted sub-decimeter resolution color images. The system achieves a high recall rate and a human operator can then eliminate false detections with limited effort. Our system provides good perspectives for the development of data-driven management practices in wildlife conservation. It shows that the detection of large mammals in semi-arid Savanna can be approached by processing data provided by standard RGB cameras mounted on affordable fixed wings UAVs.

**1. Introduction**

In the fragile ecosystems of semi-arid Savanna, any change in the equilibrium between precipitation, grazing pressure and bush fires can lead to long-term land degradation, such as the reduction in grass cover and bush encroachment (Trodd and Dougill, 1998). To avoid overgrazing, the populations of grazers must be kept in adequacy with the grass availability, which is subject to meteorological conditions. For this purpose, land managers need to regularly estimate the amount of wildlife present on their territory. Thus, monitoring wildlife populations is crucial towards conservation in wildlife farms and parks.

To carry out wildlife censuses, traditional methods include transect counts on land or from a helicopter, and camera traps. While a total count is usually not possible over large areas, these methods estimate the population density based on observations localized along a predefined path (see (Aebischer et al., 2017; Alienor et al., 2017) and references therein). These methods are expensive (e.g. in the case of the Kuzikus reserve considered in this paper, helicopter costs for a single survey are between 1000$ and 2500$), require trained human experts to screen large amounts of data and are consequently not suitable for regular censuses over large areas.

In recent years, unmanned aerial vehicles (UAVs) have been used to detect and count wildlife such as birds, marine mammals, and large herbivores (Linchant et al., 2015). Compared to traditional methods, UAVs offer several advantages: they cover large areas in a short amount of time and can be used in inaccessible and remote areas, yet they are cheaper and easier to deploy than helicopters. Moreover, they are safer for the pilot, who can stay on the ground and avoiding retaliations from poachers.

However, UAVs collect large amounts of color images with sub-meter to sub-decimeter spatial resolution, of which only few contain animals. Furthermore, the animals cover only an infinitesimal area of the images and their color might blend in smoothly with background vegetation and soil. Therefore, identifying and counting single animals across large collections of images is extremely complex and time-consuming, preventing land managers from using UAVs on a regular basis.

Despite these challenges, recent developments in object detection pipelines in both computer vision (Girshick et al., 2014; Malisiewicz et al., 2011) and remote sensing (Akçay and Aksoy, 2016; Moranduzzo and Melgani, 2014; Tuermer et al., 2013), provide promising techniques to semi-automatically localize and count animals. We refer to these methods as semi-automated and not as fully automated since they rely on supervised learning paradigms, thus requiring annotated ground truth to be trained. Still, as the human effort required to make sense of the aerial images is reduced, the overall benefits of using UAVs are significantly increased.

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## Detecting mammals in UAV images: Best practices to address a substantially imbalanced dataset with deep learning

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ABSTRACT

Knowledge over the number of animals in large wildlife reserves is a vital necessity for park rangers in their efforts to protect endangered species. Manual animal censuses are dangerous and expensive, hence Unmanned Aerial Vehicles (UAVs) with consumer level digital cameras are becoming a popular alternative tool to estimate livestock. Several works have been proposed that semi-automatically process UAV images to detect animals, of which some employ Convolutional Neural Networks (CNNs), a recent family of deep learning algorithms that proved very effective in object detection in large datasets from computer vision. However, the majority of works related to wildlife focuses only on small datasets (typically subsets of UAV campaigns), which might be detrimental when presented with the sheer scale of real study areas for large mammal census. Methods may yield thousands of false alarms in such cases. In this paper, we study how to scale CNNs to large wildlife census tasks and present a number of recommendations to train a CNN on a large UAV dataset. We further introduce novel evaluation protocols that are tailored to censuses and model suitability for subsequent human verification of detections. Using our recommendations, we are able to train a CNN reducing the number of false positives by an order of magnitude compared to previous state-of-the-art. Setting the requirements at 90% recall, our CNN allows to reduce the amount of data required for manual verification by three times, thus making it possible for rangers to screen all the data acquired efficiently and to detect almost all animals in the reserve automatically.

**1. Introduction**

Livestock censuses play an important part in the ever-ongoing fight against the rapid decline of endangered large mammal species (Linchant et al., 2015). Knowing the exact number of individuals as well as their last known location sheds light on environmental requirements for different species (Gadiye et al., 2016), the developments of species reintroductions (Berger-Tal and Saltz, 2014), and can be of great help in anti-poaching efforts (Piel et al., 2015).

Identifying and counting animals in remote areas has traditionally been carried out manually, using methods such as surveys from manned aircrafts (Bayliss and Yeomans, 1989; Norton-Griffiths, 1978), camera traps (Silver et al., 2004) and other manual methods (Jachmann, 1991). For a long time, such campaigns were the only means of getting rough estimations of animal abundances, but they come with substantial flaws: (i.) They pose great risk on human operators who have to get close to armed poachers and wild animals; (ii.) they are expensive, requiring many man-hours of surveying, and (iii.) they might lead to accuracy deficiencies due to the limited extents that can be monitored. Camera traps have come down in cost (Nazir et al., 2017) but still require risky in-field installation and maintenance. Manned aircrafts overcome this problem, but are expensive and depend on human operators who might disagree and introduce estimation errors (Schlossberg et al., 2016, Bouché et al., 2012). Therefore, traditional methods generally lead to high monetary costs or raise safety concerns. These factors are particularly limiting in remote areas like the African savanna examined in this study.

A promising direction to address these issues is to employ Unmanned Aerial Vehicles (UAVs) for monitoring purposes (Hodgson et al., 2018). UAVs are remotely controlled, inexpensive aircrafts that can be equipped with sensing instruments such as point-and-shoot cameras. As such, UAVs alleviate both the risk on operators and the financial pressure on the data acquisition (Linchant et al., 2015). Furthermore, the bird's eye view allows reaching otherwise inaccessible areas from a safe distance. However, bypassing human counting inevitably requires more time to be spent on the analysis of the acquired data. Although the task of manual photo-interpretation does not expose the operator to the risks involved in field work, it can become prohibitively expensive for large UAV campaigns, which often generate tens of thousands of images. Works exist that employ experts to manually

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# Bilan du projet SAVMAP

- Les données SAVMAP ont permis de produire des publications qui montrent le potentiel du comptage de la faune et de la flore et de la classification de la végétation à partir d'images numériques grâce à des algorithmes d'apprentissage automatique
- L’utilisation complémentaire des images de drones et des images Sentinel-2 est un succès. Application pratique opérationnelle.
- Il n'existe pas encore d’application pratique et automatisée pour le comptage numérique de la faune
- Perspective: intégrer le comptage de la faune à partir d'images numériques dans le cadre d'un processus régulier de gestion de la faune
- La réserve Kuzikus est aussi une station de recherche et les travaux se poursuivent sur place (conservation de la biodiversité)

# Merci pour votre attention !