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# Above and beyond the helicopter; using remote sensed imagery and machine learning to improve the accuracy and precision of aerial census in African savannas


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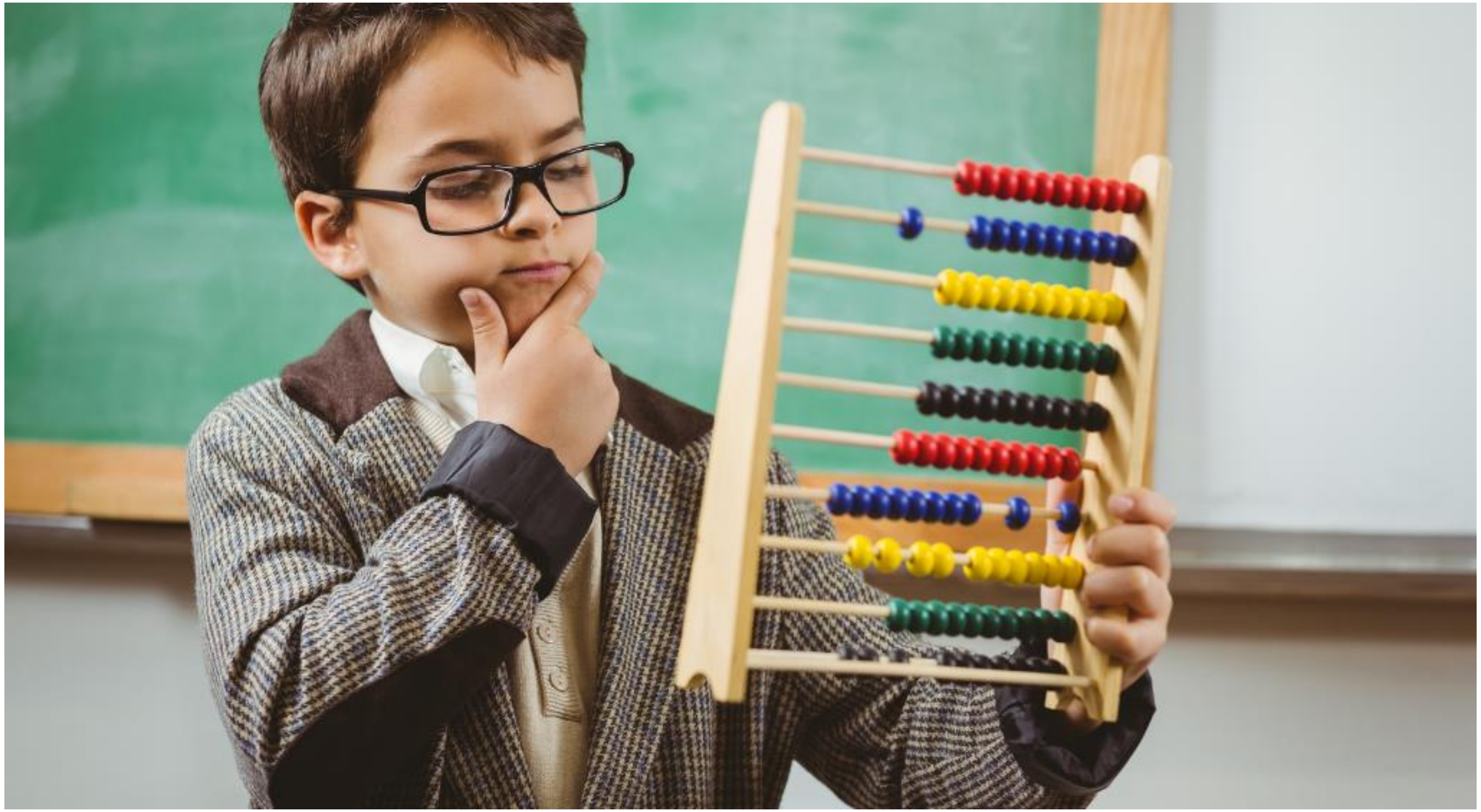
# Why count???



Inform decision making:

- Population management
- Conservation policy
- Carrying capacity
- Offtakes and (re)introductions
- Economic value
- Research questions
- Many more…

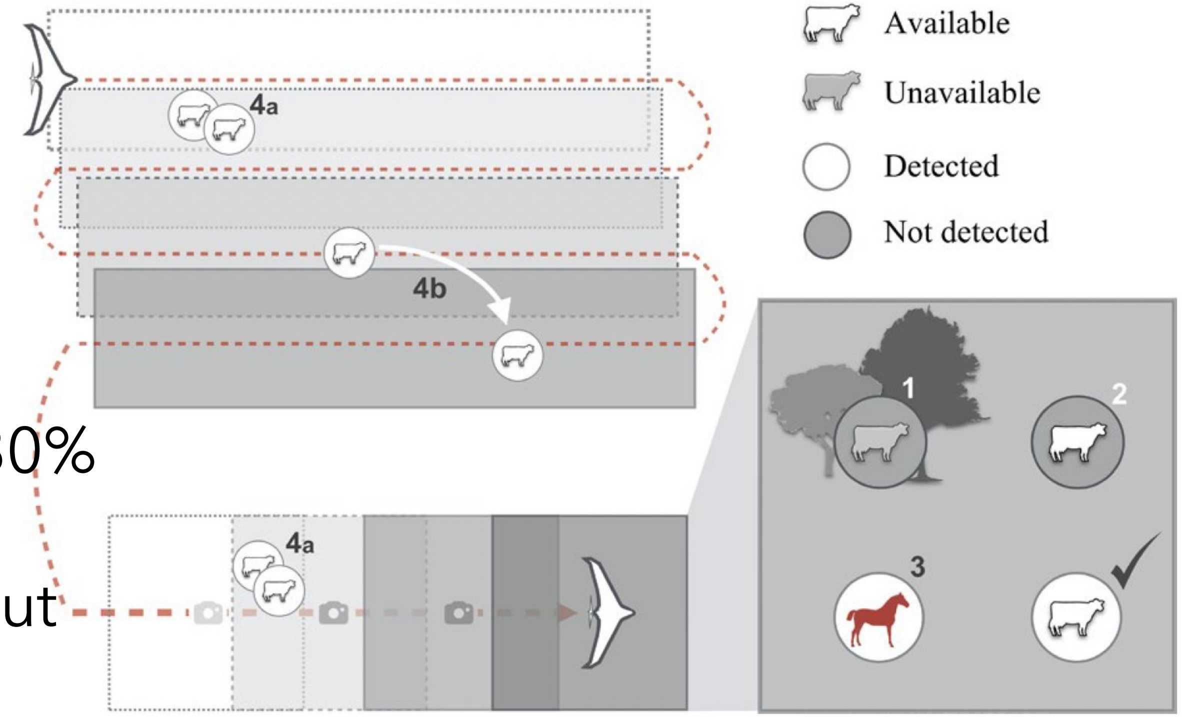
# How hard can counting be?
## Main sources of error in aerial counts

- Poor survey design
- Availability bias
- Detection bias

Brockett (2000) accuracy 46%-109%
Redfern (2002) detection 45%-95%
Lamprey et al. (2020) detection 5%-80%

Correction using statistics possible but seldom applied in practice

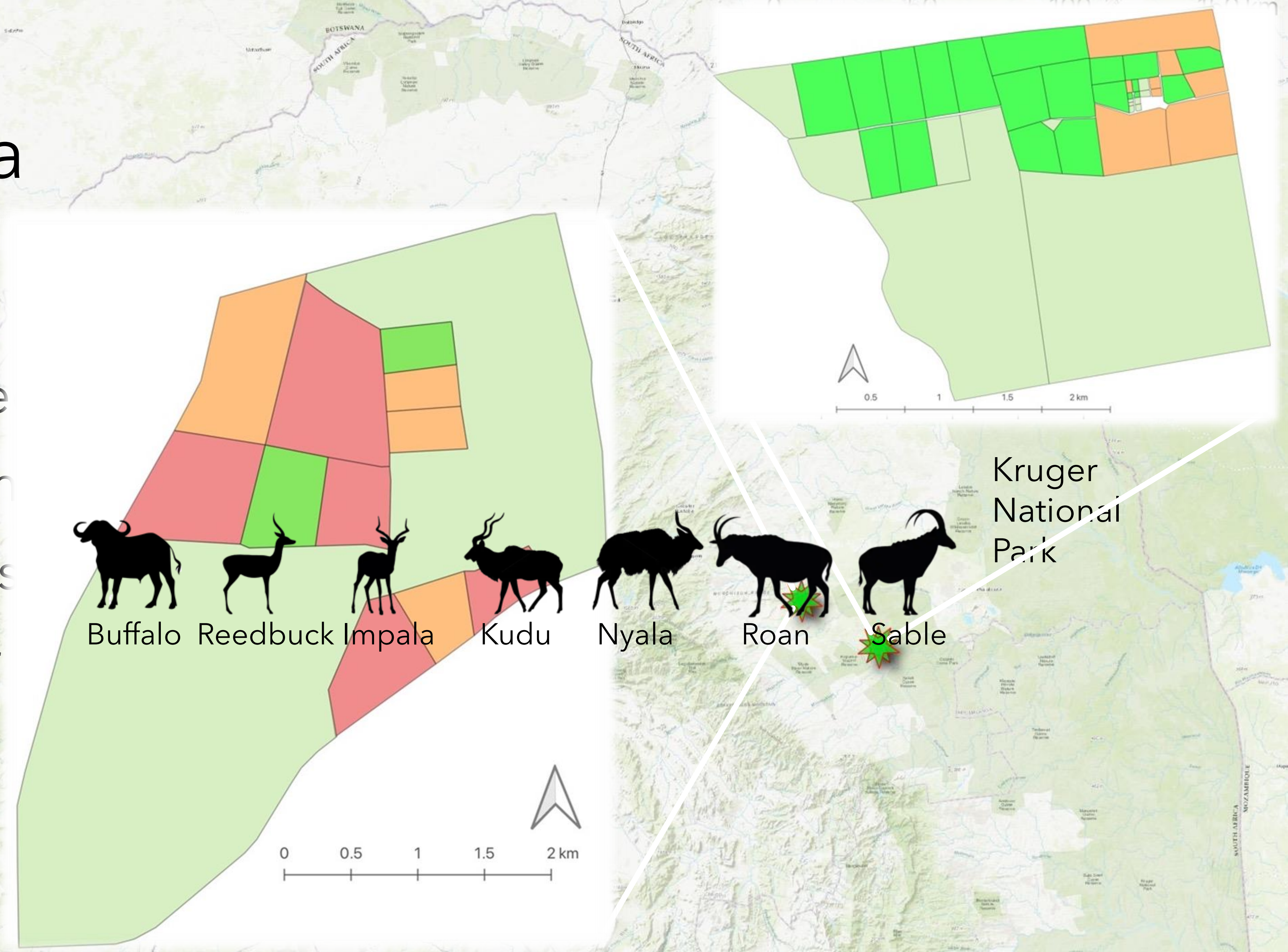
Removal of biases where possible
→ Drones, Remote sensing, AI




*Brack et al 2018

# Study area

- Two game bre
- 605ha, 23 cam
- 7 focal specie
- Canopy cover



# Methodology  Census method comparison

3 Replicates

Traditional helicopter count
with human observers
vs
Drone with RGB + TIR camera
with machine learning
(Nadir)

# Helicopter results

Total count

Accuracy 73.8% (23.3%-100%)

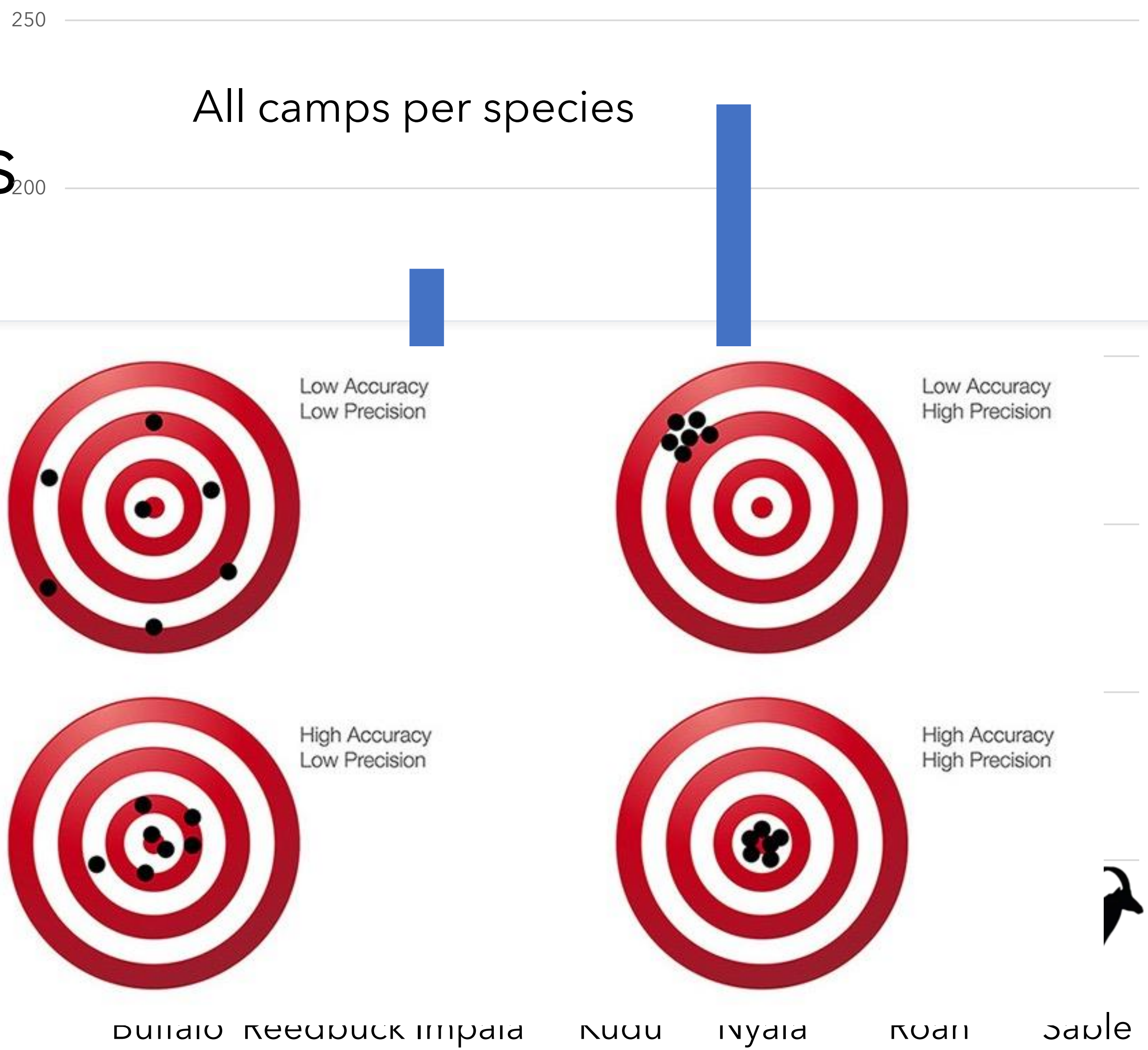
Kapiri 66.0%

Leopard rock 94.9%

Precision 91.1% (CV* 18.3%)

Kapiri 90.3%

Leopard rock 95.0%




*CV = variance of the means, values bootstrapped 3000x (Reilly 2000)

# Algorithm performance (detection)

| Model | Precision | mAP(50) | Recall | Accuracy |
|---|---|---|---|---|
| YOLOv5s | 84.0 | 80.9 | 72 | 70.8 |
| YOLOv8s-obb | 86.6 | 76.5 | 61.7 | 63.9 |
| YOLOv11s-obb | **<u>86.7</u>** | 84.4 | **<u>75.2</u>** | **<u>77.1</u>** |
| YOLOv12s-obb | 86.5 | **<u>85.0</u>** | **<u>75.2</u>** | 67.3 |
| HerdNet | 0 | 0 | 0 | 0 |

# Algorithm performance (identification)

| Model | Precision | mAP(50) | Recall | Impala* | Nyala ♀ | Nyala ♂ | Roan | Sable | Buffalo |
|---|---|---|---|---|---|---|---|---|---|
| YOLOv5s | 48.7 | 44.3 | 40.6 | 35.3 | 14.7 | **34.5** | 30.7 | 64.5 | 63.6 |
| YOLOv8s-obb | 47.5 | 44.1 | 42.1 | 26 | 12.4 | **34.5** | **37.6** | 67.1 | 75.3 |
| YOLOv11s-obb | 55.2 | 50.4 | 44.8 | 38.8 | 15.8 | 30.9 | 31.2 | **75.3** | **76.7** |
| YOLOv12s-obb | **59.4** | **55.7** | **47.4** | **50.3** | 18.5 | 41.8 | 29.3 | 70.1 | 74.6 |
| HerdNet | 53.9 | - | - | 33.4 | **29.7** | 0 | 28.3 | 70.9 | 73.5 |

Body mass

*Colour variants excluded

# Discussion

- Context of counting is important
- Machine learning can offer significant value
- Human in the loop still needed (for now)
- Very large differences per species (both methods)
- Viewing angle (oblique vs nadir)
- Scalability and repeatability


# Acknowledgements

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TRANSFRONTIER AFRICA

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www.rufford.org @ruffordgrants

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- Brack, I. V., Kindel, A., & Oliveira, L. F. B. (2018). Detection errors in wildlife abundance estimates from Unmanned Aerial Systems (UAS) surveys: Synthesis, solutions, and challenges. *Methods in Ecology and Evolution*, *9*(8), 1864-1873
- Brockett, B. H. (2002). Accuracy, bias and precision of helicopter-based counts of black rhinoceros in Pilanesberg National Park, South Africa. *South African Journal of Wildlife*, *32*(2), 121-136
- Lamprey, R., Ochanda, D., Brett, R., Tumwesigye, C., & Douglas-Hamilton, I. (2020). Cameras replace human observers in multi-species aerial counts in Murchison Falls, Uganda. *Remote Sensing in Ecology and Conservation*, *6*(4), 529-545
- Redfern, J. V., Viljoen, P. C., Kruger, J. M., & Getz, W. M. (2002). Biases in estimating population size from an aerial census: A case study in the Kruger National Park, South Africa: Starfield Festschrift. *South African Journal of Science*, *98*(9), 455-461
- Reilly, B. K. (2000). The statistics of helicopter total counts of large ungulates in sourish mixed bushveld, northwest arid bushveld and mopane veld, Republic of South Africa (Doctoral dissertation, Stellenbosch: Stellenbosch University)