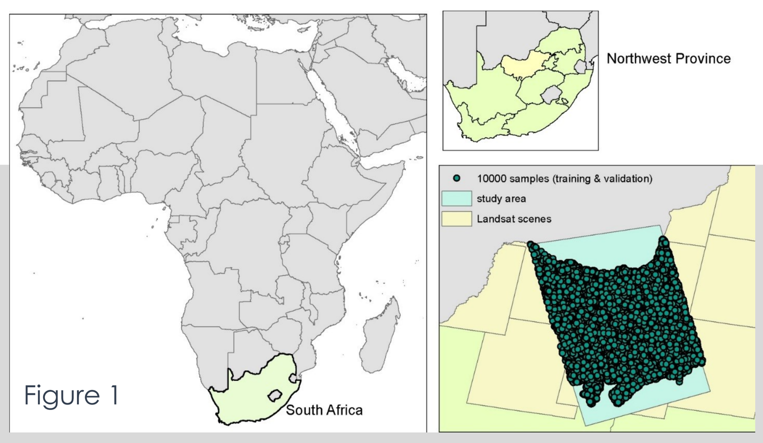

Figure 1

Optimisation of Woody Vegetation Cover Mapping with Optical, Thermal and Radar data

Elías Symeonakis, K. Petroulaki, T. Higginbottom, Á. Marqués-Mateu[2]
School of Science and the Environment, Manchester Metropolitan University, UK
[2]School of Engineering in Geodesy, Cartography and Surveying, Universitat Politècnica de València, Spain
E.Symeonakis@mmu.ac.uk, Kyriaki.Petroulaki@stu.mmu.ac.uk, T.Higginbottom@mmu.ac.uk
www.land-degradation.org

Rationale

- **Woody perennial vegetation** is an integral part of **savannah** ecosystems
- Accurately mapping its presence can provide useful input to global carbon emissions models as well regional policy decision making efforts regarding **bush control** or the **overexploitation of fuelwood**
- Recent attempts to map the extent of savannah woody cover over the regional scale have employed Earth observation data either from **optical** or **radar** sensors, and most commonly from the **dry season** when the spectral difference from the 'background' grasses is maximised
- By far the most common practice has been the use of **Landsat optical bands**, but some studies have also used **vegetation indices** or **L-band** or **C-band SAR data**
- However, **conflicting reports** with regards to the effectiveness of the different approaches have emerged leaving the respective land cover mapping community with **unclear methodological pathways** to follow
- We address this issue by employing **Landsat** and **ALOS PALSAR** data, together with **colour aerial photography** for training and validation of random forest regressions, to **assess the accuracy** of mapping woody vegetation when:
  - **(a) data from either or both (wet and dry) seasons are considered**
  - **(b) PALSAR data are used on their own or together with the optical data**
  - **(c) vegetation indices are calculated and are used either on their own or together with the Landsat bands**
  - **(iv) thermal infrared information is not discarded but included in the parameterisation**

Study area (Figure 1)

Falls within the **Northwest Province** (NWP), **South Africa**:

- Covers an area **>53,000 km²**
- **6 Landsat scenes** required for mosaic
- **Temperatures**:
  - 17° to 31 °C summer
  - 3° to 21 °C winter
- **Annual rainfall**:
  - ~360 mm, ~all in summer months, (October to April)

Datasets

Aerial photos

- **0.5m-pixel colour aerial photography** (free for 2008 onwards by South African National Geospatial Information (**NGI**) mapping agency, http://www.ngi.gov.za/index.php)

Landsat

- The Landsat imagery employed for the mosaics are shown in **Table 1**
- Where ETM+ SLC-off data had to be used, gaps were filled in using the Gapfill plug-in for ENVI 5.2

SAR data

We used ALOS PALSAR data from the **Alaska Satellite Facility** (https://www.asf.alaska.edu/) **level 1.5** high resolution terrain corrected data in dual **HH and HV polarisation** and a **spatial resolution of 12.5m**

Season	Sensor	Path	Row	DOY	Year
Dry	5 TM	171	79	228	2007
	5 TM	172	77	200	2006
	5 TM	172	78	184	2006
	5 TM	172	79	187	2007
	5 TM	173	78	191	2006
	5 TM	173	79	223	2006
Wet	5 TM	171	79	4	2007
	7 ETM+	172	77	35	2007
	7 ETM+	172	77	19	2007
	7 ETM+	172	78	35	2007
	7 ETM+	172	78	51	2007
	7 ETM+	172	79	35	2007
	7 ETM+	172	79	19	2007
	5 TM	173	78	114	2007
	5 TM	173	79	114	2007

Table 1. Landsat data used for the dry and wet seasons of 2007. When data for 2007 were not available, data for 2006 were used. Two scenes per SLC-off Landsat 7 scene were used to deal with the stripping issue

Methods

Sampling (training & validation)

~ **10,000 point samples** of three land cover types were selected:

- **Woody** vegetation cover (**WVC**)
- **Non-woody vegetation cover** (**NWVC**, including grasses and crops)
- **No vegetation** (**NVC**, urban areas and bare areas)

Regressions

Random forest (RF) regressions carried out using R

Accuracy statistics reviewed and training samples modified to achieve optimum predictive models.

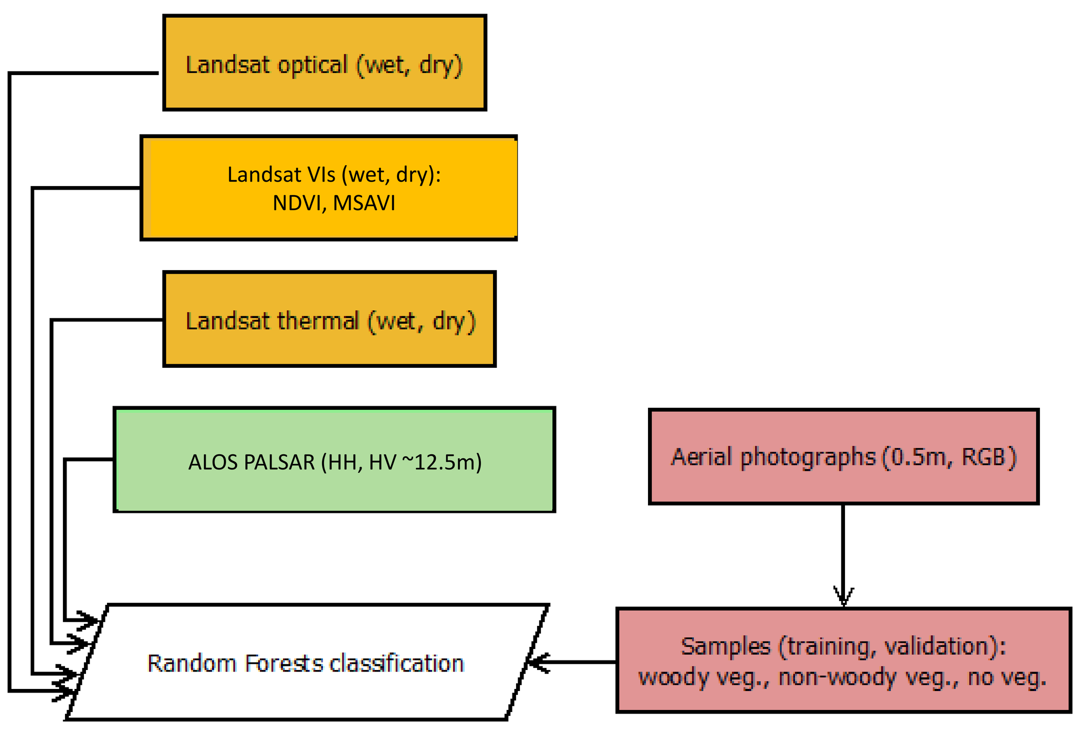

Figure 2. Flowchart of the methodological framework

Results & Discussion

- Table 2 is a summary of the **overall statistics** (accuracy and k) and the **per-class balanced accuracy** figures for the 16 models tested
- The inclusion of the **wet season** data, the **thermal** band and **vegetation indices** and, most importantly, the **radar data**, improves the overall accuracy of the classifications by **13%** and the balanced accuracy for the mapping of the woody vegetation cover by **9%**.
- Simply **adding the HV** polarized SAR data to the **dry season optical bands**, improves the **overall accuracy** by **10%** and the woody cover **balanced accuracy** by **7%**.
- The accuracies achieved are in agreement with a number of research studies comparing radar and optical data, e.g. Armston et al. (2009), Laurin et al. (2012), Lehmann et al. (2015), Higginbottom et al. (subm), Symeonakis and Higginbottom (2014)

ID	Model	~5000 samples (=50% of total, other 50% for validation)										
		Per Class Balanced Accuracy			Prod. Acc. (om.)			User. Acc. (comm.)			Overall	
		WVC	NWVC	NVC	WVC	NWVC	NVC	WVC	NWVC	NVC	Acc (%)	K
1	Lan dry	81.33	77.48	81.81	66.97	77.52	77.36	75.91	75.31	76.09	75.69	0.60
2	Lan wet	80.21	78.73	83.53	65.40	78.90	79.22	72.88	76.55	78.56	76.72	0.62
3	Lan (dry+wet)	86.53	83.91	86.44	76.52	85.46	81.24	81.93	81.01	84.63	82.41	0.71
4	$(\text{Lan+SARHH})_{dry}$	85.35	82.93	85.32	74.65	83.09	81.03	79.27	80.72	81.89	80.92	0.69
5	$(\text{Lan+SARHV})_{dry}$	88.67	88.11	87.68	80.10	88.91	83.88	85.41	85.93	85.15	85.57	0.77
6	$(\text{Lan+SAR(HH,HV)})_{dry}$	88.40	88.08	86.64	79.42	91.20	80.42	85.97	84.07	86.72	85.27	0.76
7	$(\text{Lan+SAR(HH,HV,diff,div)})_{dry}$	88.37	87.70	87.10	79.80	89.48	81.99	84.07	84.84	85.93	85.10	0.76
8	$\text{SAR(HH,HV,diff,div)}_{dry}$	60.87	82.65	65.15	31.78	86.28	54.10	39.07	78.22	56.67	65.34	0.43
9	3VIs $(\text{NDVI,MSAVI, TNDVI})_d$	82.31	69.15	71.46	69.31	69.48	62.55	75.39	65.80	64.68	66.92	0.46
10	4VIs $(\text{NDVI,MSAVI, TNDVI, GDVI}^2)_d$	81.15	67.86	71.43	67.01	66.19	64.82	74.64	65.35	62.83	65.83	0.45
11	$(\text{Lan+2VIs})_{dry}$	83.72	78.76	82.02	71.55	79.70	76.17	78.18	75.99	77.99	77.04	0.63
12	$(\text{Lan+3VIs})_{dry}$	83.80	78.84	82.80	71.52	78.25	78.84	78.87	76.74	77.43	77.32	0.63
13	$(\text{Lan+TIR})_{dry}$	84.11	81.42	85.84	72.12	81.58	82.12	79.12	79.43	81.58	80.16	0.68
14	Dry+3VIs+TIR+SAR(HH,HV)	88.78	90.09	88.87	79.71	92.56	84.38	88.26	86.42	88.26	87.36	0.79
15	Dry+wet+$3VIs_d$+$3VIs_w$ +TIR_d +TIR_w	87.20	85.13	87.78	77.14	87.46	82.73	85.22	81.57	86.89	83.98	0.74
16	Dry+wet+$3VIs_d$+$3VIs_w$ +TIR_d +TIR_w + SAR(HH,HV)_d+SAR(HH)_w	90.59	90.75	90.25	83.06	93.50	85.55	90.11	86.78	90.94	88.76	0.82

Table 2. Summary table of overall accuracies for the 16 models and the four different training sample sizes tested for the year 2007. 'dry': dry season Landsat TM or ETM+ bands; 'wet': same for wet season; 'TIR': thermal Landsat band; 'NDVI': Normalised Difference Vegetation Index; 'MSAVI': Modified Soil Adjusted Vegetation Index; 'HH' and 'HV': HH- or HV-polarised ALOS PALSAR data

Conclusions

- Remote sensing methods that accurately map woody vegetation cover in southern African savannahs are important as an initial stage in the attempt to map **bush encroachment**, a process repeatedly acknowledged as a form of **land degradation** in these areas
- Our research has identified the **combination** of **Landsat TM multi-seasonal optical** and **thermal** data, together with **ALOS PALSAR1 HH** and **HV** polarized data, as the **most accurate** in mapping woody vegetation cover in the Northwest Province of South Africa. We also concluded, however, that in the absence of other data, employing **dry season Landsat data** is able to provide **highly accurate estimates of woody cover**
- Further research is currently underway in South Africa aiming to employ the presented methodological framework to assess woody cover **change through time**, on the one hand, and the mapping and monitoring of **fractional woody cover**, on the other

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