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Development of Land-Cover Classification Focusing on Wetlands Impacted by Subsistence Farming Using Satellite Remote Sensing

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Introduction

Wetlands provide essential ecosystem services, especially in countries affected by drought. They are often the only suitable sites for subsistence farming within barren landscapes. On the other hand, non-sustainable farming causes irreversible degradation of these wetlands. Within the Maputaland Coastal Plain (MCP) in KwaZulu-Natal, South Africa, the interdisciplinary project AllWet-RES (Alliance for Wetlands, 2012-2015) aimed at the development of intervention strategies for restoration and wise use of wetlands (mainly interdunal peatlands) under pressures of farming, forest plantations and urban expansion. Using a holistic approach AllWet-RES investigates socio-cultural acceptance and economic viability of restoration measures, and adapted farming practices that are necessary for the sustainable use of natural resources and biodiversity conservation.

A significant part of the project was the development of tools for the assessment and evaluation of existing human interventions, especially smallholder farming, on wetlands of the research area. Hence, a study has been carried out to assess the possibility of delineating different wetland types (amongst other land-cover classes) using satellite remote sensing data. This data was used to elaborate the landscape composition with special regard to their use.

Material and Methods

The study area covers 345 km² around the town of Manguzi (KwaNgwanase) situated within the uMhlabuyalingana Local Municipality. The landscape is characterised by flat undulating sandy terrain (<70 m a.s.l.). Wetlands with fertile organic-rich soils can be found only in interdunal depressions and valleys. Mean annual temperature is at 22°C with a precipitation of 1000–1300 mm. The climate is characterised by tropical summers (60% of precipitation) and subtropical winters (Watkeys et al. 1993). The eastwards flowing upper aquifer is the main supplier for the wetlands (Grundling et al. 2012).

Supervised pixel-based classification of multi-temporal, multispectral and multisource satellite imagery was carried out using the machine learning algorithm ‘Random Forests’ (RF) (Liaw & Wiener 2002) on the open statistic platform R (R Core Team 2014). A customized classification scheme was compiled to suit the special scope of the study. It was based on the standard land-cover classification proposed by Thompson (1996) and extended by wetland specific classes following the approach of Rivers-Moore & Goodman (2010) based on vegetation descriptions introduced by Mucina & Rutherford (2006). The wetland-specific classes were ‘tall sedge

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wetlands', 'short sedge wetlands' and 'swamp forest' as typical representatives of natural wetland systems as well as 'wetland subsistence cultivation', i.e. as a class describing land-use and therefore human intervention.

During a field campaign from October 2nd to November 22nd 2014 about 900 individual training points at different sites spread over the project area were recorded on-site and classified to train and validate the algorithm. Points were reviewed, aggregated and extended to regions, leaving 611 training and 202 validation areas. The classification system was also reviewed during field work to coincide with on ground conditions.

Two separate classification models were constructed: one for a general land-cover classification using the full system and the second specialized on using only the wetland-specific classes (Table 1) and trying to create a most reliable picture of wetland conditions and use. Normalized difference indices were constructed from the three SPOT4, eight SPOT5 and one WorldView2 scene acquired over a period from 15.05.2011 to 24.07.2014 at varying climatic and seasonal conditions. For the SPOT imagery NDVI, NGRDI and NDMI and for WV2 scene NDVI, NGRDI, NDWI, NDSI, NDBSI, NDRE and NHFD indices were created (Barnes et al. 2000, Gitelson et al. 2002, Tucker 1980, Wolf 2010). The RF variable importance measure in a repetition of 20 RF runs summed over the indices, similar to a method proposed by Genuer et al. (2010), was used to filter out the most important scenes for both classification models. Basic descriptive statistics about class cover proportions were extracted from the latter classification. Using spatial pattern statistics (pcf-analysis as derivative of Ripley's *K* tested against a Monte Carlo simulation of complete spatial randomness) both classifications were combined to examine the spatial correlation between the occurrence of 'settlement' features and 'wetland subsistence agriculture' (Diggle 2003).

The classification system constructed proved to be appropriate and useful. A necessary simplification was the merger of two different swamp forest classes, i.e. *Ficus trichopoda*- and *Raphia australis*-forest as the latter was hardly present in the area and not distinguishable with the algorithm chosen.

Results and Discussion

For both classification models (general and wetland specific) seven out of the twelve satellite scenes were selected by the variable reduction method. This left 25 index bands (6x3 SPOT indices plus 7 WV2 indices) for the final prediction. Especially for the wetland specific classification it was noticeable that the most important scenes were to be found amongst dry and cooler seasonal periods (Figure 1).

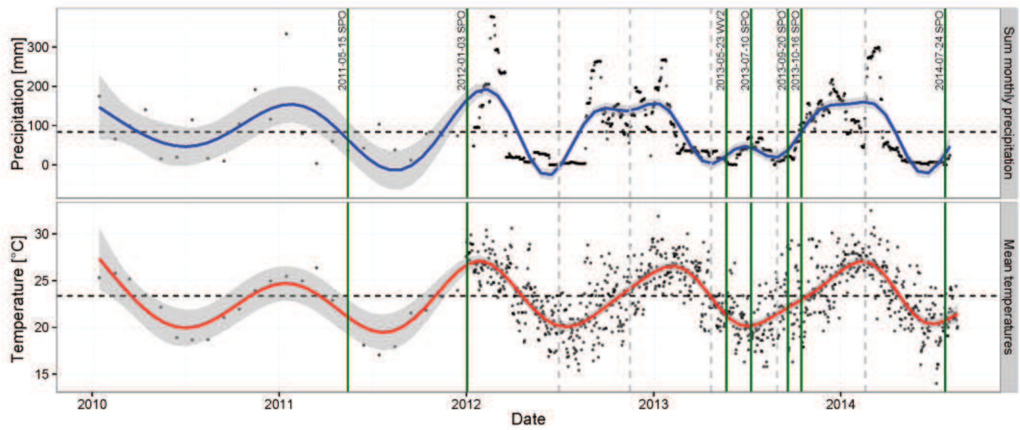

Figure 1: Recording datum of the satellite images chosen for wetland specific classification (green) in respect to the weather conditions around the time of recording. Grey dashed lines indicate omitted scenes.

The final classification model for the general land-cover classification resulted in a Cohen's Kappa value of κ = 0.74 and an overall accuracy of 77.8% compared to the self-produced validation data. The wetland specific classification was evaluated with a Cohen's kappa value of $\kappa = 0.79$ and an overall accuracy of 87.1% (Class details in Table 1). Only the latter will be further discussed here.

Table 1: Confusion matrix of wetland specific classification including producer's and user's accuracy.

		Reference						
		Non wetland	**Short sedge**	**Swamp**	**Tall sedge**	**Water**	**Cultivation, wetland**	**User's Acc. [%]**
Prediction	**Non wetland**	22468	272	381	320	346	263	**93.42**
	Short sedge	127	1014	0	230	10	101	**68.42**
	Swamp	219	24	2138	787	0	175	**63.95**
	Tall sedge	123	160	256	1278	34	214	**61.89**
	Water	41	3	0	110	9730	0	**98.44**
	Cultivation, wetland	516	628	69	118	4	582	**30.36**
Producer's Acc. [%]		**95.63**	**48.26**	**75.18**	**44.95**	**96.11**	**43.60**	

The overall accuracy superseded previous classifications within the study area and got close to quality requirements of 85% with no class undercutting 70% as stated in pertinent literature sources (Foody 2002). The class 'cultivation wetland' had very low accuracy values and two major confusions: In confusion with 'short sedge' it was seen as an expression of the structural and successional similarity between the systems: relatively moist, organic soils, covered by short and/or sparse vegetation. Another remarkable confusion with 'tall sedge' was mainly to be explained through moisture content in the vegetation. Keeping these insecurities in mind, the actual classification output showed a good compliance between wetland cultivation features on the ground and features classified by the algorithm, only the exact delineation was rather weak.

Nevertheless spatial descriptive statistics were created to generate an estimate of wetland use. Wetland cultivation took place in about 13.6% of the total wetland area. Neighbouring wetland classes were grouped to wetland systems. Leaving out wetland systems that included swamp forests the value rose to 27.9%. In swamp forest systems only 13.0% were covered by subsistence agriculture. This confirmed the assumption of a value of >4% postulated in Mucina & Rutherford (2006) and exceeded or got close to the estimation of 11% by Grundling et al. (2013), respectively. It had to be noted though that another 34.1% of the area of swamp forest systems were covered by 'short' and 'tall sedge' classes, which often occur as secondary vegetation after clearing, also indicating disturbance. Even with the low accuracy these are substantial numbers. Furthermore the aggregation of cultivation between the wetland systems was tested: There was a trend showing 45% of the wetland systems were used and 23% seemed to be used most intensively in contrast to others which seem to be avoided due to unascertained reasons. This could be explained through location, infrastructure, classification errors or even remaining sustainability practices (Grobler et al. 2004).

Considering spatial patterns the inhibition between 'settlement' and 'wetland cultivation' features was strongest within the first 25–50 m, indicating very little settlement directly at wetland gardens. Comparably most common pattern of settlement was at a distance of around 310 m (± 30 m) from the wetland indicated by a little spike within the $g(r)$ values into the domain >1 (Figure 2). The predominating answer from interviews conducted with farmers by Guerrero Moreno (2014) resulted in a walking time of 2–5 min to the wetland garden. This equals about 300 m for a walking time of 5 min, with sandy underground, hot weather and the assumption of weights to be carried reducing the normal walking speed. This shows an existing spatial dependency of the population upon the wetlands.

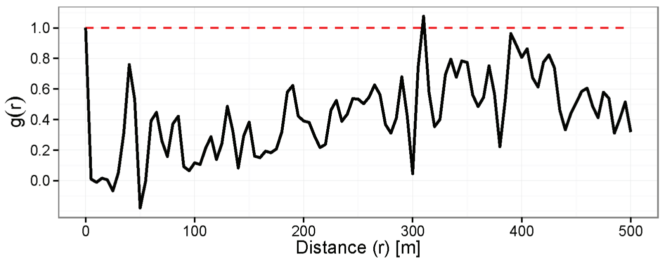

Figure 2: Graphic bivariate pcf-plot of centroids on settlement features and wetland features. Inhibition of features up to 310 m, with a spike > 1 signalizing an aggregation of features at this specific distance.

Conclusions and Outlook

On the technical side, the classification using RF via an R implementation on large datasets >18 GB was proven to be feasible. Future classifications regarding this topic should not only rely on spectral data but also incorporate elevation, soil and other ancillary data.

The results indicated the decrease of wetland systems in the study area is caused by human pressure, as repeatedly stated by various researchers in the past. The greater Manguzi area with its unique combination of various wetland types within an arid environment works well as a model for global processes. Urban development in poverty-driven societies that depend on rare and vulnerable natural systems and resources is one of the upcoming big challenges for conservation and landscape planning. In combination with the results obtained from the socio-economic studies as well as from the investigations on soil characteristics and the restorability of the wetland habitats, the landscape analyses based on remote sensing allow the development of scenarios and recommendations for sustainable use of wetlands and other natural resources.

Further applications based on the classification results could include analysis on eucalyptus timber plantations which were mapped with a high reliability.

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