Impact of remote sensing characteristics for biodiversity monitoring

A case study of Southern Myanmar mangroves

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Discussion

The application of remote sensing data plays an increasingly important role in the field of biodiversity monitoring for conservation. However, the availability of various sensor types and analysis techniques complicates an informed selection of the most appropriate remote sensing based methodology. This study compared high-resolution RapidEye data and medium-resolution Landsat 8 imagery to assist applied conservationists in this highly complex decision-making process. Referring to the main research questions of this study, it was specifically investigated which sensor and spatial resolution lead to the most accurate land cover predictions in the context of mangrove mapping in Southern Myanmar. It was furthermore examined whether the selection of specific classifiers and predictor combinations distinctly influences land cover classification accuracies.
Previously presented results will be summarized and discussed in the following paragraphs and the main findings will be associated with already existing literature. Additionally, potential limitations and possibilities for improvement will be addressed. Moreover, practical recommendations are formulated for applied conservationists with regard to each influencing element. This is done for the purpose of bridging the widely acknowledged gap between conservation science and its implementation in applied conservation and ecology (Sunderland 2009: 549; Knight et al. 2008). As it is assumed that practi-

tioners often face a lack of e.g. time, financial resources, software or technical facilities, it is attempted to make these recommendations as convenient, applicatory and simple as possible. Therefore, only one specific sensor, spatial resolution, model and predictor combination is recommended. However, it has to be considered that these recommendations represent simplifications of the rather complex and multi-faceted results.

Sensor Comparison

Comparing RapidEye and Landsat 8 sensors with their original spectral and spatial capabilities, it was found that the utilization of medium-resolution Landsat 8 imagery led to higher land cover classification accuracies than the application of high-resolution RapidEye data in the context of mangrove mapping in Myanmar. Although RapidEye images led to negligible higher overall accuracies when discriminating between the general land cover classes 'Water', 'Non-vegetated' and 'Vegetation', Landsat 8 derived classifications considerably outperformed RapidEye based land cover classifications when discriminating between mangrove and terrestrial vegetation as well as different mangrove land cover classes. Therefore, taking only initial spectral and spatial capabilities into account, medium-resolution Landsat 8 imagery can be identified as being more suitable for mangrove forest monitoring in Tanintharyi Region than high-resolution RapidEye imagery. These results fit with several previously published literature contributions. Green et al. (1998: 935, 946) found for example that mapping eastern Caribbean mangroves was possible using Landsat TM data with a spatial resolution of 30 meters, while SPOT XS/PAN data with a spatial resolution of 10 and 20 meters "failed to discriminate satisfactorily between mangrove and non-mangrove vegetation". A similar pattern was discovered by Gao (1999) when also comparing Landsat TM and SPOT images with XS and PAN mode. Investigating mangroves in the western Waitemata Harbour in New Zealand, the study found that the most accurate classification results were derived from medium-resolution Landsat TM images, whereas SPOT-generated results were considerably less accurate. A further study of Lee & Yeh (2009) adds to these findings by comparing Landsat, SPOT and Quickbird imagery. Based on investigations of estuary mangrove communities in Taiwan (Danshui River), the authors report highest user accuracy values for Landsat imagery followed by SPOT and QuickBird data (Lee & Yeh 2009).

Recommendations for Practitioners:

Considering RapidEye and Landsat 8 sensors with their original spectral and spatial capabilities, it is recommended to utilize Landsat 8 imagery for mangrove mapping in Southern Myanmar. Especially when discriminating between mangrove and terrestrial vegetation as well as different mangrove land cover classes, Landsat 8 derived classifications exhibit considerably higher overall accuracy values than RapidEye based classifications.

However, the pure sensor comparison could not reveal any information about whether the identified differences were caused by discrepancies either in spatial or spectral resolution.

Spatial Resolution

a) RapidEye (5 - 30 m)

To test whether performance discrepancies were a matter of spatial resolution, RapidEye imagery was resampled to coarser resolutions of 5, 10, 15, 20, 25 and 30 meters. The comparison of aggregated RapidEye imagery with the initial 5 meter image could show that classification accuracies inversely increased with spatial resolution when discriminating between the land cover classes 'Water', 'Non-vegetated', 'Vegetation' or 'Mangrove vegetation' and 'Terrestrial vegetation'. This trend was less pronounced when discriminating between the different mangrove land cover classes 'Intact to slightly degraded mangroves', 'Degraded mangroves', 'Heavily degraded mangroves' and 'Nipa'. The reason might be that the patch size of the mapping objects was – due to the high level of detail – relatively small within the third classification scheme. Pixel aggregation did therefore not necessarily improve classification accuracies. However, aggregated RapidEye images still led to higher accuracies than the initial 5 meter image. It can therefore be inferred that the aggregation of high resolution RapidEye data to lower spatial resolutions resulted in an increase of classification accuracies. The reason for this might be that in high-resolution satellite images one pixel does not represent a specific land cover type anymore (e.g. terrestrial vegetation), but rather represents only a single component of the relevant land cover class (e.g. rubber plantation) (Horning et al. 2016). A fine spatial resolution of remote sensing data might therefore lead to an increase of the number of identifiable subclass features. Consequently, the resulting increase of within-class spectral variability may hamper the satisfactory discrimination of spectrally mixed land cover classes (Wang et al. 2004: 5656). Therefore, this study's main results suggest, that the appropriate spatial resolution is strongly coherent with the patch size and spectral variability of the relevant mapping objects.

Klemas (2011) verifies this finding by indicating that high-resolution images are more sensitive to "within-class spectral variance, making separation of spectrally mixed land cover types more difficult" (Klemas 2011: 426). Moreover, these results are confirmed by Horning et al. (2016) who allude to the "popular misconception that it is always best to get the finest resolution imagery you can afford" (Horning et al. 2016: 172). They refer again to the problem of high-resolution satellite imagery to cause high within-class spectral variability based on the increase of identifiable sub-class components. The authors point in this context to image segmentation methods which aim at clustering pixels to meaningful objects but admit at the same time that "those algorithms have difficulty in gradient dominated natural ecosystems and they add an extra layer of effort" (Horning et al. 2016).
However, there is also published literature which puts these findings into question. Kuenzer et al. (2011: 896) point e.g. at new opportunities in the area of mangrove mapping which were opened up by the launch of high-resolution QuickBird and IKONOS-2 satellites. The authors state, that high-resolution sensors enable an improved discrimination between mangrove forest patches and other plant species assemblages (Kuenzer et al. 2011). Studying black mangroves *(Avicennia germinans)* along the south Texas Gulf Coast, Everitt et al. (2008: 1585) found that high-resolution satellite imagery is suitable for the effective discrimination of black mangrove populations with good to excellent accuracy assessment results. However, relatively little research has so far been published on the use of high-resolution satellite imagery for mangrove ecosystem mapping (Kuenzer et al. 2011: 896). Therefore, this study considerably contributes to fill this research gap.

b) RapidEye (30 m) vs. Landsat 8 (30 m)

Comparing Landsat 8 and RapidEye imagery, each with a spatial resolution of 30 meters, it was found that both datasets performed similarly with respect to the accurate prediction of vegetation in general and the discrimination of different mangrove classes. However, despite featuring the same spatial resolution, Landsat 8 imagery led to a notably higher mean overall classification accuracy (~95 %) than RapidEye data (~87 %) when discriminating between mangrove and terrestrial vegetation (cp. Table 3.2). Therefore, it can be assumed that the different spectral resolution of both sensor types was responsible for their unequal performance with respect to the mapping of mangrove forests in Tanintharyi Region. This assumption is supported by the comparison of Landsat TM and SPOT images by Gao (1999) which found that Landsat TM images are more suitable for the accurate mapping of mangrove forests than SPOT satellite data. Referring to the differences in spectral res-

olution, Gao (1999) concludes that spectral capabilities of satellite sensors play a more important role for mangrove mapping in a temperate zone than a high spatial resolution (Gao 1999: 2823). However, Wang & Sousa (2009) argue, that spatial resolution is more important than spectral resolution for an effective mangrove mapping with regard to the differentiation between individual mangrove species.
Taking results from all three classification schemes into account, a spatial resolution of 30 meters was identified as being most suitable for mangrove mapping in Southern Myanmar. However, in the scope of this study, it was not possible to investigate whether a pixel aggregation to resolutions of e.g. 40, 50 or 60 meters could even further enhance classification accuracies.

Recommendations for Practitioners:

As classification accuracies inversely increased with spatial resolution within the first and second classification scheme, it is recommended to use satellite imagery with a spatial resolution of 30 meters when discriminating between the land cover classes 'Water' 'Non-vegetated', 'Vegetation', 'Mangrove vegetation' or 'Terrestrial vegetation. Although RapidEye imagery with a spatial resolution of 10 meters led to the most accurate classification results when discriminating between different mangrove classes (82.9 %), its minor superiority compared to Landsat 8 data (82.4 %) with a spatial resolution of 30 meters does not legitimate its cost-intensive acquisition. Therefore, it is recommended to use freely available satellite data with a spatial resolution of 30 meters in the context of mangrove mapping in Southern Myanmar.

To find out whether this resulting pattern was caused by the different spectral capabilities of both sensors, a comparative analysis of different predictor combinations was conducted. Prior to this, the best model was identified within each classification scheme.

Model Comparison

The evaluation of four different classifiers – RF, SVM, NNET and PLS – revealed that there are distinct differences in variability and mean overall accuracies depending on the selected algorithm. This finding is confirmed by several previously published studies, investigating e.g. support vector machines (SVMs), decision trees (DTs), Random Forests (RFs) or the maximum likelihood classifier (MLC) (Duro et al. 2012, Huang et al. 2002).
The land cover predictions of the SVM classifier were identified as being

most accurate in the first and third classification scheme, whereas the PLS classifier led to the most accurate results within the second classification scheme. Therefore, the SVM classifier was identified as being most suitable for mangrove forest mapping in Tanintharyi Region. This is based on the fact, that it exhibited the lowest variability within all three investigated classification schemes by revealing simultaneously the highest mean overall accuracy values within two of three classification schemes (cp. Tab. 3.3). Furthermore, a detailed model comparison suggested avoiding the application of the NNET model, since it featured the highest variability within all classification schemes as well as lowest mean overall accuracies within two of three classification schemes. However, model tuning and parameter adjustments could possibly enhance model performances for all algorithms including the NNET, but were not applied in the course of this study for reasons mentioned in section 2.5.

Recommendations for Practitioners:

The SVM model exhibits the lowest variability within all three investigated classification schemes by revealing simultaneously the highest mean overall accuracy values within two of three classification schemes (cp. Tab. 3.3). Hence, the SVM classifier with a radial basis kernel is identified as being the most suitable model for mangrove mapping in Southern Myanmar and is therefore recommended for practical mangrove mapping activities.

Predictor Comparison

The comparative analysis of different predictor combinations revealed, that the number and properties of utilized predictor layers crucially affects land cover classification accuracies. Strikingly, overall accuracy values do not automatically increase with the number of predictor layers. Overall accuracies derived from RapidEye imagery rather increased within the second and third classification scheme when the Red Edge band was excluded from the classifying process. It can therefore be inferred that RapidEye's Red Edge band is not necessarily required for the effective mapping of Southern Myanmar mangroves. In contrast, it might be even advantageous to exclude the Red Edge band from particular mapping procedures.

The comparison of different predictor combinations further revealed that the superiority of the Landsat 8 sensor in discriminating between mangrove and terrestrial vegetation is mainly attributable to its additional spectral bands (Fig. 19 (b)). Omitting all Landsat 8 bands which are not provided by the RapidEye constellation – coastal aerosol, SWIR 1, SWIR 2 and Cirrus band – Landsat 8 images led to even less accurate classification results than aggregated RapidEye images. Therefore, these bands provide valuable additional information which considerably enhance the accurate discrimination between mangrove and terrestrial vegetation. However, it was not possible in the scope of this study to investigate more closely which of these four bands is distinctly responsible for the increase of Landsat 8 derived classification accuracies.

In addition, this study found that the fusion of RapidEye and Landsat 8 data each with a spatial resolution of 30 meters led to relatively high classification accuracies within all three classification schemes. Therefore, remote sensing data fusion techniques are identified as promising future opportunity in the context of mangrove mapping, which are worthy of further exploration. The identification of multi-sensor data fusion as possibility to further improve the accurate mapping of mangrove forest ecosystems also fits with previously published knowledge. Studying the data fusion of fine and coarse spatial resolution satellite images, Kempeneers et al. (2011) found that their applied data fusion approach increased "the robustness of forest-type mapping within Europe" (Kempeneers et al. 2011: 4977). Confirming these results, multi-sensor data fusion techniques have been identified as a promising research area in the field of remote sensing applications within a number of further literature contributions (e.g. Dong et al. 2009; Zhang 2010; Heumann 2011a).

Recommendations for Practitioners:

Based on overall accuracy values presented in Tab. 3.4 and Fig. 19, the 'All bands' predictor combination is identified as being most suitable for mangrove mapping in Southern Myanmar using Landsat 8 imagery. The inclusion of NDVI, SAVI, RVI or NDWI is not necessary as it does not lead to an improvement of accuracy assessment results. Hence, it is recommended to use Landsat 8 imagery with its original spectral capabilities. Although a combination of RapidEye and Landsat 8 data, each with a spatial resolution of 30 meters can slightly increase overall accuracy values, a fusion of both datasets is not recommended mainly for two reasons. First, the increase of overall accuracy values is negligibly low while complicating the classification process. Second, considering the high costs of RapidEye imagery, the minor accuracy improvement does not justify the purchase of cost-intensive RapidEye images in addition to freely available Landsat 8 imagery.

Land Cover Maps and their Variability

Thematic land cover maps resulting from the basic classification of 'Water', 'Non-Vegetated' areas and 'Vegetation' were fairly similar – irrespective of the sensor, spatial resolution, classification algorithm and predictor combination. The main reason for this is possibly the low level of detail inherent in the land cover maps generated within the first classification scheme. This is based on the fact, that a low level of detail generally leads to high classification accuracies (Horning et al. 2010: 27), which also causes a generally low variability. Nevertheless, high variability could be observed in mudflats, shallow waters or occasionally flooded areas (Fig. 21). The reason for this might be the spectral mixture of the two land cover classes 'Water' and 'Non-vegetated' within pixels representing these areas. Relatively high variability could also be found in built-up areas such as the city of Myeik. This might be caused by the fact that mapped objects (e.g. individual houses, single trees, artificial ponds) are in many cases considerably smaller than the pixel size, which leads again to a strong spectral mixing of different land cover classes within one pixel. This assumption is reinforced by the fact that the variability increases in urban areas with coarser spatial resolutions (Fig. 21). In contrast, highly pronounced differences in resulting land cover maps could be observed when discriminating between mangrove and terrestrial vegetation (Fig. 23). Results from the predictor comparison could reveal that this is mainly due to the different spectral capabilities of the RapidEye and Landsat 8 sensors. Clearly pronounced differences in thematic land cover maps can also be observed within the third classification scheme which portrays different mangrove classes. Whereas e.g. land cover maps based on fused RapidEye and Landsat 8 imagery depict a fairly realistic reproduction of the distribution of mangrove classes within the study area, other land cover maps even omit entire mangrove classes (Fig. 24). Results of the comparison of different models revealed that this is mainly caused by the poor performance of the NNET model. Variations in land cover class prediction are again evenly distributed throughout the whole study area when considering results based on high-resolution RapidEye data. In contrast, variability found in Landsat and low-resolution RapidEye based land cover maps is especially aggregated along the edges of land cover classes (Fig. 25). This aggregation might be an effect of the better filtering of within-class spectral mixing caused by lower spatial resolutions.

Recapitulating this study's main findings, the first hypothesis stating that high resolution RapidEye imagery leads to higher classification accuracies than medium-resolution Landsat 8 imagery in the context of mangrove map-

ping in Southern Myanmar cannot be confirmed. In contrast, medium-resolution Landsat 8 imagery could be identified as being more suitable for an effective mangrove mapping in Tanintharyi Region. This is mainly attributable to its additional spectral bands. Results of this study revealed that selected classification algorithms and predictor combinations crucially affect overall accuracies. Therefore, the second hypothesis stating that classification models as well as number and characteristics of predictor layers strongly influence land cover classification accuracies can be verified.
Consequently, the major findings of this study suggest that medium-resolution remote sensing data is more suitable for an accurate mapping of mangrove forests in Southern Myanmar. Moreover, a high spectral resolution was identified as being more important than a high spatial resolution of remote sensing data in the field of mangrove mapping in Tanintharyi Region. Additionally, data fusion techniques were identified as a promising opportunity to further enhance the effectiveness and accuracy of remote sensing based mangrove monitoring.

Ensuring a scientifically sound research procedure, several methodological limitations of this study have to be acknowledged. The scope of this study allowed only the comparison of RapidEye and Landsat 8 remote sensing characteristics. The inclusion and comparison of further sensors, e.g. Sentinel 2, MODIS, SPOT or HyMap, could help to provide a more holistic overview about the suitability of different sensor types with respect to mangrove mapping. In this context, it is especially recommended for future research to include active remote sensing instruments (e.g. LiDAR) in mangrove monitoring investigations. The utilization of the LiDAR pulsed laser enables the collection of three-dimensional information about the surface of the Earth. This could be uniquely beneficial for the accurate separation of different mangrove degradation classes as they are discriminated in many cases by their characteristic height or density. It is also highly recommended to test the suitability of hyperspectral remote sensing data for mangrove ecosystem monitoring. With more than 100 spectral bands, HyMap data might strongly contribute to a satisfactory discrimination of different mangrove classes independent of the high level of extracted detail.
In accordance with the inclusion of further sensors, taking into account additional classifiers might also reveal further classification improvements. Likewise, there are numerous possibilities of enhancing accuracy assessment results by including further predictor layers. Using for example a principal component analysis (PCA) to create an additional predictor dataset could increase the accuracy of land cover predictions. As common and standardized PCA approach, Tasseled Cap transformation coefficients (e.g. the "green-

ness" index) could be used to improve remote sensing based land cover classifications (Horning et al. 2010: 111). A further promising predictor is the Mangrove Recognition Index (MRI) developed by Zhang & Tian (2013). Unfortunately, the MRI could not be included in this study, as multi-temporal Landsat images recorded at different tide levels are necessary for its calculation. In addition, the inclusion of texture metrics âĂŞ e.g. mean, variance or homogeneity âĂŞ as predictor variables could also contribute to an enhancement of accurate land cover predictions. However, defining the most suitable size of the moving window for texture statistic calculations could be a major challenge (Feng et al. 2015: 1080). Moreover, a multi-temporal approach which takes seasonal changes and variability in forest structure and phenological appearance into account could be a possible source of classification improvement with regard to different forest species (Jensen 2004; Wang & Sousa 2009).

Besides these methodological limitations, several potential sources of error and the introduction of a certain level of subjectivity during the research process have to be considered as well. Initially, it has to be kept in mind, that the ground truth points used within the course of this study were collected in May and June 2015. The time of sensor overpass and the field campaign are therefore not coincident. A collection of ground truth points at the same time of sensor overpass could possibly have further enhanced the precision of the classification results.

Moreover, it has to be acknowledged that the creation of training data based on visual interpretations of VHR and ground truth data is generally highly subjective. Thematic land cover classes only represent visual cues existing in the original image and resulting land cover maps can therefore only be perceived as rough abstractions of reality (Horning et al. 2010). A further level of subjectivity is inherently introduced within the process of defining important land cover classes and excluding apparently irrelevant land cover types. For instance, there are numerous different definitions of 'forest' in general as well as of more specific cover types such as 'degraded forest' (CBD 2014; FAO 2000). The choice of the applied definition is always based on a subjective decision and might strongly affect the resulting land cover map. In addition, the validation procedure of the developed classification schemes represents another potential source of error. The partitioning of gathered data from the training polygons into 70 % training and 30 % test data implies that training as well as test data are sampled within the same polygons which can introduce a certain bias. To ensure complete independence of training and test data, two datasets could e.g. be generated separately by two different people using the same land cover descriptions. As a prerequisite, these people would need to be trained well together to ensure a consistent classification. Even

more reliable would be the coverage of all utilized land cover classes with a relatively high number of ground truth points collected during a field campaign. These sample points could be used for training as well as validation purposes. But even the assignment of ground truth points to specific land cover classes during a field campaign entails the introduction of a certain level of subjectivity, as criteria such as ground coverage are in most cases based on subjective estimations.
Furthermore, some methodological difficulties inherent in any land cover classification approach have to be considered. First of all, land cover classifications lead to thematic maps in which individual classes are mostly portrayed as discrete entities with well defined boundaries. However, the actual transition between different land cover types is in many cases rather gradient dominated (Horning et al. 2010: 83). Therefore, it is highly important in the context of biodiversity conservation management that thematic land cover maps are perceived and handled as an abstraction of the actual land cover and not as a congruent representation of reality. Reporting validation metrics and accuracy values is therefore of utmost importance. However, the presentation of accuracy statistics is complicated by the fact that accuracy terms are used inconsistently between different disciplines and research areas. Whereas 'accuracy rates' are reported in some disciplines, others announce the 'error rate' of their land cover classification (Kuhn & Johnson 2013). In order to avoid future misconceptions, a standardization of accuracy terms would be highly desirable.
Although results obtained from this study can essentially contribute to a more informed selection of appropriate remote sensing data for an effective mangrove monitoring in Southern Myanmar, it has to be acknowledged that the presented results cannot simply be transferred to any other geographic area, natural ecosystem or biodiversity monitoring context. Sensor suitability might vary strongly with respect to different conservation issues and objects or scales of interest. The careful consideration of the appropriate remote sensing data depending on each specific context plays therefore a crucial role for an informed and meaningful conservation management.
In spite of these potential limitations, this study's findings can strongly contribute to a more informed decisions of applied conservationists about the most appropriate remote sensing based methodology in the context of mangrove mapping in Southern Myanmar. Previously formulated practical recommendations represent a serious attempt of bridging the so-called 'research–implementation gap' and try to overcome the failure of science to fruitfully inform conservation practitioners (Sunderland et al. 2009; Knight et al. 2008).

Besides the mainly methodological findings, the results of this study can also have practical implications for a reasonable planning of mangrove conservation in Southern Myanmar. As only 0.1 % of Myanmar's coastline is protected so far, a meaningful expansion of the protected area network is of utmost importance (Zoeckler et al. 2013: 29). This is especially true in the current context of rapid political and economic transformations which are reshaping the country after decades of isolation. The enormous infrastructural and economic developments in Southern Myanmar (e.g. planned industrial zone in Myeik, Dawei deep sea-port and Special Economic Zone) increasingly imperil Tanintharyi's already endangered mangrove ecosystems (Myanmar Investment Guide 2013; Webb et al. 2014). The currently ongoing mismanagement and over-exploitation of Tanintharyi's mangrove forests is also reflected by the results of this study (Tab. 4.1).
Only 22 % of the mangrove forest in the study area could be identified as 'Intact to slightly degraded mangroves'. 63 % of the mangrove area was on the other hand classified as being degraded or even heavily degraded (Tab. 4.1). Interestingly, most intact mangrove areas are found in relative proximity of the two major towns in the study area (Kyunsu & Myeik). Heavy degradation of mangroves is most pronounced in the more remote areas in the Southern part of the study area (e.g. Sakanthit & Kanmaw islands). A detailed threat analysis could reveal potential reasons for this pattern and is recommended for future investigations.

Table 4.1: Area and Percentage per mangrove land cover class. Area calculations are based on the most accurate classification result within the third classification scheme (fused RapidEye and Landsat 8 dataset, RF, allbands). The area size is rounded to two decimals. Percentages are rounded to whole numbers.

Land cover class	**Area** $[km^2]$	**Percentage**
Intact to slightly degraded mangroves	280.57	22 %
Degraded mangroves	584.69	45 %
Nipa	190.28	15 %
Heavily degraded mangroves	235.18	18 %
TOTAL	1290.72	100 %

According to interviews conducted during the field campaign, the main reasons for the degradation of mangrove forests in Southern Myanmar are the large-scale production of charcoal as well as unsustainable extraction of

mangrove wood for firewood and construction materials (Appendix A.1, A.4 – A.10).
Belonging to MOECAF, Myanmar's Forest Department is very interested in the implementation of effective measures for coastal protection to ensure the provision of crucial ecosystem services (FD / MOECAF 2015). There is also a range of national and international NGOs (e.g. FFI, FREDA, BANCA) which are already engaged in ecologically meaningful conservation planning in Tanintharyi Region. Proposed Reserved Forests (RF) and Public Protected Forests (PPF) within the study area are shown in Fig. 26.

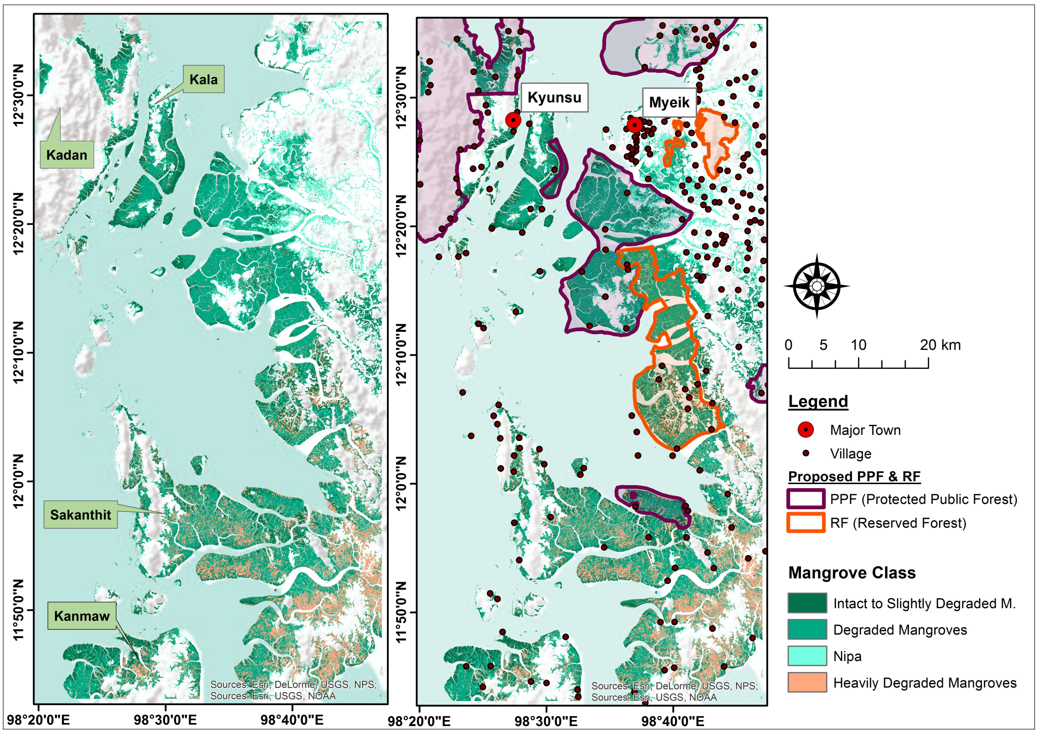

Figure 26: Left: Distribution of mangrove land cover classes based on a fused RapidEye and Landsat 8 dataset. Right: Location of proposed RF and PPF areas within the study site. Source: Forest Department Myanmar, FFI Myanmar, MIMU.

These proposed protected areas already comprise several mangrove regions which were identified in the course of this study as still being in a relatively good shape (Fig. 26 b). However, the proposed conservation areas still lack official approval. Prior to the formal demarcation of these regions as protected areas, it is essential to raise acceptance of these conservation areas within the local communities which are living along Tanintharyi's coast. A

further prerequisite is to refine the boundaries in an ecologically worthwhile way.
The remote sensing based methodology which was developed and investigated in the course of this study can be a valuable contribution to the meaningful refinement of ecologically sound protected areas in Southern Myanmar. The achievement of good to excellent accuracy assessment results within the multi-scale classification approach proves the developed methodology as being highly suitable for replication. The fact that freely available Landsat 8 imagery was identified as being more suitable for an accurate mangrove monitoring in Southern Myanmar than cost-intensive RapidEye data illustrates the great opportunities which are currently provided to conservationists by openly available databases. This is even highlighted by the very good classification results which were achieved in the course of this study by using open-source software, such as *R* or QGIS.