# Improved modelling of the impacts of sea level rise on coastal wetland plant communities

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## Abstract

This study presents an enhanced methodology for modelling the impacts of sea level rise on coastal wetlands. The tool integrates dGPS calibrated LiDAR data, isostatic uplift and sediment accretion rates to predict the location and extent of plant communities at three non-contiguous micro-topographical coastal wetlands in Estonia by 2100 in response to global sea level rise. Results showed an increase in surface elevation (related to sediment accretion and isostatic uplift) resulting in a decrease in local sea level in the majority of sites and scenarios in the north of the country although a rise in sea level is predicted in sites with limited allochthonous sediment supply predominantly impacting higher elevation plant communities. Wetlands situated on the west coast are likely to maintain equilibrium with sea level as result of lower sedimentation and isostatic uplift than more northerly sites. This study shows that dGPS calibrated LiDAR data and sediment accretion are essential to maintain model validity in Baltic coastal wetlands due to their low relief and could considerably improve current sea level rise impact models for other regions.

## Keywords

Coastal wetlands; Climate change impacts; Sea level rise modelling tool; LiDAR; Coastal plant communities

## Introduction

Coastal wetlands are among the most productive ecosystems in the world containing specialist plant species and providing a habitat for a wide diversity of taxa (Allen & Pye, 1998). They also provide important ecosystem services such as coastal protection (Gedan et al., 2011), carbon sequestration (Hopkinson et al., 2012), and nutrient cycling (Barbier et al., 2011). However, coastal wetlands are under threat from sea level rise (SLR) (Nicholls & Cazenave, 2010; Weisse et al., 2014) particularly those located in low lying countries with maritime borders (IPCC, 2013). Current predictions of global sea level rise suggest that SLR will be in the region of 0.26m – 0.82m by 2100 (IPCC, 2013).

In order to make an assessment of the threats to coastal wetlands from sea level rise a variety of models have been developed (Bertrand et al., 2011; Moeslund et al., 2011; Stratonovitch et al., 2012; Bellafiore et al., 2014). Typically, ecological modelling is based on knowledge of environmental gradients, which are used as ecological predictors (Burnside & Waite, 2011). Many sea level rise impact models developed for coastal wetlands utilise elevation data as a proxy for hydrology (Moeslund et al., 2011), and the most accurate remotely sensed elevation data available are LiDAR (Gesch, 2009). However, LiDAR elevation data have inherent inaccuracies due to the impenetrability of laser pulses through vegetation (Sadro et al., 2007; Ward et al., 2013). To overcome these inaccuracies Ward et al. (2013) developed a model that can accurately estimate the current distribution of plant communities in micro-topographical coastal wetlands using dGPS calibrated LiDAR data.

The recent IPCC (2013) report suggests that climate change will not affect only sea level and temperature, but is also likely to lead to increased storminess in many areas, particularly in northern Europe and the Baltic (Rozynski & Pruszak, 2010). Previous studies have shown that in predominantly depositional areas, increased storminess and rising sea levels can facilitate wetland development through sediment deposition (Friedrichs & Perry, 2001; French, 2006; Schuerch et al., 2012; Tsompanglou et al., 2012; Ward et al., 2014). A variety of studies have suggested that sediment deposition alone could, in a wide variety of coastal wetlands, keep pace with SLR, thus preventing any large scale wetland loss (Friedrichs & Perry, 2001; French, 2006; Kirwan and Temmerman, 2009; Mudd et al., 2009;). However, many predictive SLR impact models (Poulter & Halpin, 2008; Kont et al., 2008; Moeslund et al., 2011) neglect to take into account sediment accretion as a factor even where these data are available.

This study tested the hypotheses:

1) Does dGPS calibration improve modelling current plant community types in Baltic coastal wetlands?

2) How does the consideration of dGPS LiDAR correction, sediment accretion rates and the impacts of increased storminess influence plant community distribution by 2100?

3) What do these findings mean for assessing the impacts of sea level rise on coastal wetlands?

Baltic coastal wetlands have been selected for this study as (i) they require greater model accuracy due to the low gradients [typically <1.2m above mean sea level], (ii) they are extensive [extending up to 2 km inland], (iii) they are of ecological importance (EC Habitats Directive, 1992) and (iv) they show micro-topographic variation between the range of wetland plant communities.

## Materials and Methods

### Study area

Post glacial isostatic rebound has caused much of the landmass of northern and western Estonia to rise from the sea (Eronen et al., 2001), producing a long shallow coastline. Average isostatic uplift rates of 2.5 mm/yr are found on the west coast with a maximum of 2.8 mm/yr in the far north west (figure 1).

The Baltic Sea along the Estonian coast has almost no regular tide (0.02 m) (Suursaar et al., 2001). However, major fluctuations in sea level do occur due to seasonally changing meteorological conditions facilitating storm surges and variations in barometric pressure, causing an irregular influx of sediment to the coastal wetlands. The highest recorded sea level was during the 2005 storm Gudrun, which caused a 2.75 m storm surge in Pärnu, Estonia. More typically, water levels do not vary more than between 0.3 m below and 0.4 m above m.s.l. (EMHI, 2012). The generally low relief of Baltic coastal wetlands (between -0.28 m and +1.2 m) means that they can be inundated during periods of elevated sea level. Burnside et al. (2007) identified six main plant communities with indicator species for Estonian coastal wetlands. These were: Clubrush Swamp (CS), Reed Swamp (RS), Lower Shore (LS), Upper Shore (US), Tall Grass (TG), and Scrub and developing Woodland (SW). Plant community distribution is characterised by different elevations above m.s.l. related to differing inundation frequencies and durations (Ward et al. 2010) (table 1).

Three study sites were selected to model the potential effects of sea level rise on Estonian coastal wetlands in order to represent a range of controlling factors. The Tahu and Kudani wetlands (figure 1) are located in the Silma Nature Reserve in the northwest of Estonia along the south coast of the Baltic Sea. These two sites are influenced by higher isostatic uplift rates than the third site, Matsalu. Tahu has access to an allochthonous sediment supply and sediment accretion rate data for this site are available. Kudani is cut off from an allochthonous sediment source, and autochthonous soil formation through plant decomposition is considered to be very low in these wetlands (Puurmann & Ratas, 1998). At both Tahu and Kudani, all of the six main plant community types were present. The Matsalu coastal wetland (figure 1) is located in Matsalu National Park and has both lower isostatic uplift and sediment accretion rates than Tahu but greater sediment accretion rates than Kudani. At Matsalu, the Clubrush Swamp plant community is not found at the lower elevations due to greater wave energy than at Tahu and Kudani. The Scrub and developing Woodland plant community is also absent from Matsalu due to a different management history to the other sites.

**Baseline plant community modelling**

In order to test hypothesis 1, does DGPS LiDAR calibration improve plant community modelling in Baltic coastal wetlands, and model the potential effects of sea level rise (hypothesis 2), a baseline digital elevation model was required. Ward et al. (2013) developed a methodology to produce an accurate (0.02 m) digital elevation model (DEM) for use in Baltic coastal wetlands using dGPS calibrated LiDAR data. The DEM was derived from medium point density LiDAR data with a footprint of 0.54 m and an average point density of 0.45 points/$m^2$ collected by the Estonian Land Board in 2009 using an ALS50-II laser/detector. dGPS calibration data were collected using a Trimble 5700 system (accuracy 0.02 m). Calculations for dGPS calibration of the LiDAR elevation data were conducted in Matlab R2010a using the Ward et al. (2013) methodology. DEM interpolation was conducted based upon raw values for LiDAR within ArcGIS 10.1 and using a Delaunay triangulated irregular network (TIN). dGPS calibration data were added to the last return LiDAR point values. DEMs for each site were categorised using plant community elevation preferences (table 1) (Ward et al., 2010) (baseline scenario a). The dGPS calibrated plant community model was used as a baseline for modelling the location of the plant communities by 2100 using modelling parameters explained in the following section. Validation of the baseline plant community models was conducted using a stratified random ground truth survey in July, 2010. At each site 15 points were selected within each predicted plant community yielding ninety 1m$^2$ quadrats at both Tahu and Kudani and sixty at Matsalu (due to the lower number of plant communities) and the presence and abundance of all plant species recorded. Validity of plant community models compared to ground-truthed data was assessed using a Fleiss' Kappa coefficient (Landis & Koch, 1972).

**Environmental modelling parameters**

The baseline model was modified by integrating isostatic uplift rates (Eronen et al. 2001), sea level rise data (IPCC 2013) and sediment accretion estimates (Ward et al. 2014) (figure 2) to predict the location and extent of the plant communities in response to local sea level by 2100 (hypothesis 2). Current IPCC (2013) estimates of global sea level rise are between 0.26 m and 0.82 m by 2100 dependant on scenario. Therefore a mid-range SLR figure of 0.54 m was selected to represent climate driven sea level rise. At the Tahu and Kudani coastal wetlands, isostatic uplift rates were included based on studies by Vallner et al. (1988) and Eronen et al. (2001) (figures 1 and 2). Both the sea level rise and isostatic uplift data were utilised in scenarios b, c, d and e. In scenario b only sea level rise and isostatic uplift were utilised (sediment accretion data not incorporated) to identify changes in plant community location using the dGPS calibrated baseline model.

A further parameter incorporated into the model was sediment accretion, [Nolte et al., (2013) terminology]. Past rates of sediment accretion for the Tahu and Matsalu coastal wetlands were based on data derived from $^{210}$Pb radionuclide dating of sediment cores and independently verified using the $^{137}$Cs dating method (Ward et al., 2014). Mean accretion rates for Tahu were 1.9 mm/yr, and for Matsalu 0.9 mm/yr. No accretion rates were used for Kudani (figure 2) as it is largely separated from the sea, and hence lacks a significant allochthonous sediment source and is unlikely to have significant autochthonous organic production. These mean accretion rates were utilised in scenarios c and e, although in scenario e the dGPS correction to the LiDAR was not used for comparison.

Increased storminess has been linked to greater sediment accretion in predominantly depositional wetlands (Allen, 2000; Kolker et al., 2009; Schuerch et al., 2012). Ward et al. (2014) have shown that increased sedimentation occurs during periods of greater storminess at both the Tahu and Matsalu sites. The IPCC (2013) report states that there is likely to be an increase in the frequency of extreme weather events. In order to take this into account in the model the number of elevated accretion periods recorded in the sedimentary record (Ward et al., 2014) for each site was doubled, as has been suggested by Bender et al. (2010), and a new mean for sedimentation calculated. Scenario d incorporated the increased storminess sediment accretion data to the dGPS calibrated baseline plant community model to predict the location of the plant communities by 2100.

The plant community extent outputs using each of these parameters were compared and the results discussed in terms of current models in order to assess the impacts of the individual parameters on model outputs (hypothesis 3).

## Results

### Baseline plant community modelling

The dGPS calibrated LiDAR based plant community models were able to accurately describe the location of the plant communities at Tahu (κ coefficient 0.63, 70.6% correctly identified), Matsalu (κ coefficient 0.89, 91.7% correctly identified) and Kudani (κ coefficient 0.81, 80.0% correctly identified) (table 2) providing a robust static plant community model as a baseline for scenario model development.

At Tahu the model was able to accurately predict the location of the plant community types in only 25% of cases (κ = 0.10), at Matsalu only 14.2% of cases (Kappa coefficient 0.03) and at Kudani 27.8% of cases (κ = 0.13), a substantial deterioration in model validity. In the majority of cases incorrect identification of the plant communities was due to the overestimation of elevation due to interference in LiDAR penetrability through the vegetation canopy. This resulted, in the majority of cases, in the model predicting the adjacent higher elevation plant community e.g. RS in place of CS.

### Plant community model for 2100

### Tahu 2100

Tahu has the highest sediment accretion and isostatic uplift rates of the studied sites and thus is likely to experience the least impact from SLR. Scenario b predictions (discounting sediment accretion but utilising the calibrated LiDAR) suggest a 9.7% loss of the total wetland area and considerable decrease in the extent of the higher elevation plant communities, namely TG -42.4% and SW -37.7% (table 4). However, scenario c (utilising the sediment accretion data and the dGPS calibration of the

LiDAR) suggests a progradation of the wetland into the Baltic Sea (figure 3c) and a consequent increase in the wetland area of 1.7% by 2100 (table 4). In scenario d assuming an increase in storminess, sediment accretion rates (2.5 mm/yr averaged over a 100 year period) are almost as high as isostatic uplift (2.8 mm/yr) (figure 2) suggesting that during storm events sediment accretion is even higher. The model predicts that there will be an increase of 12.6% of the current wetland area (table 4, figure 3d). The model output including sediment accretion estimates but not utilising the calibrated LiDAR (figure 3e, scenario e) predicts progradation of the wetland, with an increase of 28.5% of the total wetland area by 2100 (table 2).

**Matsalu 2100**

Matsalu is typified by lower uplift and sediment accretion rates than Tahu. In scenario b (dGPS calibration but discounting sediment accretion) there is a small predicted loss of the wetland area (-1.0%, table 4 and figure 4b). In this model output the greatest predicted losses occur in the US (-53.0%) and TG (-27.1%) plant communities (table 4). In model output c (utilising the dGPS correction and assuming no change in sediment accretion rates), there is a predicted loss of 0.8% of the wetland area by 2100 (table 4, figure 4 c). The greatest losses are expected in the higher elevation plant communities US (-29.5%) and TG (-18.9%). In model output d, averaged sediment accretion rates over a 100 year period assuming an increase in storminess are 1.6mm/yr comparable with those of isostatic uplift 2.0mm/yr, suggesting that during storm events sediment accretion exceeds the rates of isostatic uplift as at Tahu (figure 2). In this model output, the model predicts a 0.5% decrease in the total area of wetland by 2100 (table 4, figure 4d). In model output e (taking into account sedimentation but not including the dGPS calibration), there is predicted to be little change in plant community extent and no increase in the total wetland area (table 4, figure 4e).

### Kudani 2100

The Kudani site along with Tahu has the highest isostatic uplift rates in Estonia and in the modelling an assumption was made that there was no significant sediment accretion (figure 2). Model output b (utilising the dGPS calibration) suggests a decrease of 10.1% in the total extent of the wetland by 2100 (figure 5b, table 4). The lower elevation plant communities, although of limited extent, are expected to increase (CS 150.6%, RS 160.7% and LS 5.8%) at the expense of the higher elevation communities (US -35.9%, TG -26.0% and SW -32.0%) at Kudani by 2100. Model output e not using the dGPS calibration are substantially different, predicting an increase in the total extent of the wetland of 2.1% (figure 5e, table 4).

## Discussion

### Hypothesis 1: 'does dGPS calibration improve modelling current plant community types in Baltic coastal wetlands?'

The relationship between elevation above mean sea level and plant community type provided a basis for developing predictive plant community models for coastal wetlands (Ward et al., 2010). However, elevation differences between some of the plant communities in these Baltic coastal wetlands were small, with a minimum of 0.04 m. Hence it was necessary to obtain highly accurate elevation data that covered a variety of Baltic coastal wetland sites. Due to the small size of some of the plant community patches, as is typical in many mosaic coastal wetlands, it was also necessary to obtain high resolution data for the study areas. The most widely available data that fulfil these conditions are LiDAR elevation. The results of this study have shown that plant communities can be accurately identified using dGPS calibrated LiDAR data. LiDAR data have been successfully used in several studies to develop plant community models over large field areas (Morris *et al*., 2005; Prisloe et al., 2006; Sadro et al., 2007; Chust et al., 2008; Moeslund et al., 2011). However, none of these studies modelled plant communities at such a fine scale as that developed in this study for micro-topographical coastal wetlands, hence the requirement for the dGPS calibration.

This study has shown that in environments with a strong relationship between plant community type and small changes in elevation, dGPS calibrated LiDAR is a robust data choice due to its elevation accuracy and the density of the point cloud and a significant improvement on models utilising non-calibrated LiDAR. In this study plant community models run without the dGPS correction provided a substantially inferior outcome (with dGPS calibration $\kappa$ = 0.63-0.89 and without $\kappa$ = 0.03-0.13), addressing hypothesis 1 (does dGPS calibration improve modelling current plant community types in Baltic coastal wetlands?).

In previous studies in tidal coastal wetlands, with a greater range in relief, calibration and adjustment have not been used and are perhaps not necessary to produce a robust model able to distinguish plant communities based on their elevation range (Morris *et al*., 2005; Prisloe *et al*., 2006; Poulter & Halpin, 2008; Moeslund *et al*., 2011). However, the improvements in the accuracy of the model developed in this study could significantly enhance the accuracy of models developed by using dGPS calibration data for any tidal coastal wetlands with a greater relief. This suggests that dGPS integration would also improve the robustness of correlative plant community models in wetlands with greater relief such as tidal salt marshes.

**Hypothesis 2: 'how does the consideration of dGPS LiDAR correction, sediment accretion rates and the impacts of increased storminess influence plant community distribution by 2100?'**

The predictive plant community models developed in this study, incorporated the main factors predicted to influence the future location and extent of vegetation in coastal wetlands: isostatic uplift, eustatic sea level rise, and sediment accretion (McFadden et al., 2007). Previous studies assessing the effects of sea level rise on coastal wetlands have been limited due partly to the use of inaccurate elevation data, whereas greater accuracy is required for micro-topographical coastal wetlands, and especially the exclusion of sediment accretion data. In the model outputs not utilising dGPS calibrated LiDAR (model output e) to predict plant community distribution by 2100 progradation of the wetland is seen (figures 3, 4 and 5) a significant difference to the dGPS calibrated model outputs.

In many coastal wetlands sediment accretion is a primary driver of wetland development (Webb et al., 2013) and accretion rates are therefore an important factor to be taken into account when modelling the effects of sea level rise on coastal environments (McFadden et al., 2007). This study has utilised historical sediment accretion rates derived from $^{210}$Pb dating (Ward et al., 2014) and extrapolated the results for sea level rise modelling (Craft et al., 2009). The results showed that sediment accretion has a considerable effect on modelling local sea level rise impacts on wetland plant communities, highlighted by the substantial differences in the predicted distribution of the plant communities (figure 3b, c, d, e), particularly at Tahu. Many previous studies of the impacts of sea level rise in coastal wetlands have ignored sediment accretion (Suursaar et al., 2006; Kont et al., 2008, Moeslund et al., 2012). Moeslund et al. (2011) justify this exclusion from their dynamic correlative model by suggesting that accretion rates vary greatly within sites and that the majority of sediment accretion data available are generalised from few samples. However, whilst extrapolation of accretion data from few samples can be problematic due to the spatial variability of sediment deposition the exclusion of these data is likely to provide greater dynamic model prediction errors. Results from this study have shown that sediment accretion rates taking into account increased storminess are of a similar magnitude to isostatic uplift (1.6-2.5 mm/yr compared with 2.0-2.8 mm/yr respectively). Ward et al. (2014) have estimated that during periods of elevated sediment accretion, rates can be as high as 5 mm/yr, well in excess of isostatic uplift. In the model outputs assuming an increase in storminess (output d in figures 3, 4 and 5) the impacts of sea level rise are reduced and in the case of Tahu progradation is predicted to take place. This has been predicted to be the case in sheltered coastal wetlands in many areas of the world including the Baltic (Schuerch et al., 2013; Tweel and Turner, 2014; Schindler et al., 2014; Ward et al., 2014) suggesting that this is a useful addition to plant community modelling parameters.

**Hypothesis 3: 'what do these findings mean for assessing the impacts of sea level rise on coastal wetlands?'**

The model developed in this study accurately predicted the location and extent of plant communities in micro-topographic non-tidal Baltic coastal wetlands. The model also has potential applications in other appropriate open environments such as floodplains, tidal coastal marshes or for the restoration of wetlands. It does however, have limitations that should be taken into account when interpreting the results. As with any correlative model, there is regional specificity and hence the particular model developed in this study is unlikely to be valid in locations other than Estonia without further ground-truthing. The model is also based on the assumption that sea level and sediment accretion will be the only environmental variables that will change due to climate effects by 2100. However, IPCC (2013) climate change scenarios suggest that temperature will also increase and several studies have suggested that this could cause a northward migration of some plant species (Dullinger et al., 2004; Aitken et al., 2008; Hilyer & Silman, 2010), which is likely to affect community composition in coastal wetlands, particularly at the extreme geographical ranges of individual species.

Salt marshes are an obvious environment for the further application of the dynamic plant community model presented in this study. Several authors have related the zonation of marsh communities to elevation above mean sea level and hence tidal range (Cutini et al., 2010; Moffett et al., 2010; Suchrow & Jensen, 2010; Moffett et al., 2012). However, tidal ranges vary greatly, so any plant community model would likely be valid only for areas with similar tidal regimes. As correlative plant community models have been suggested to be location specific (Franklin, 1995) in localities with different tidal regimes model parameters will need to be adjusted. Furthermore, salt marshes, whilst retaining a similar zonal character typically consisting of a low marsh, middle marsh and a high marsh (Nottage & Robertson, 2005), have a geographically varying species composition requiring the use of different plant community classifications dependent on location (Pennings et al., 2003). Ellenberg (1988), Rodwell (1992) and Isaach et al. (2006) have produced plant community classifications for continental European, UK and South American salt marshes respectively, which would be suitable for use as base model development. With regards to the geomatic stages involved in applying the plant community tool to salt marshes, the conceptual model developed in this study (figure 2) would be applicable for other coastal wetland systems.

## Conclusions

Remotely sensed data have been successfully used in many studies to develop plant community models over large field areas. However, previously developed models are unable to work effectively at such a fine scale as that developed in this study. The addition of the dGPS calibration to the model represents an improvement to previous LiDAR based models (Morris et al., 2005; Chust et al., 2008; Moeslund et al., 2011). Without dGPS calibration, this study reported Kappa values of only 0.03-0.13 for Baltic coastal wetlands, compared to Kappa 0.63-0.89, dependant on site, when the calibration was used. Moreover, previous studies investigating the effects of sea level rise on coastal wetlands have neglected to include sediment accretion data (Morris et al., 2005; Chust et al., 2008; Moeslund et al., 2011). The results of this study have shown that sediment accretion in some Baltic coastal wetland sites can contribute to greater vertical growth at the littoral edge of the wetland than isostatic uplift, particularly during periods of increased storminess. Thus, dGPS calibrated LiDAR and sediment accretion data are essential to maintain model validity in Baltic coastal wetlands due to their low relief. These data could also considerably improve sea level rise impact models for coastal wetlands in other geographical areas including micro, meso and macro-tidally influenced saltmarshes and wet grasslands.

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Figure 1: Study sites in a regional and national context. Isostatic uplift rates are shown in millimetres (rates reproduced from Eronen et al., 2001).

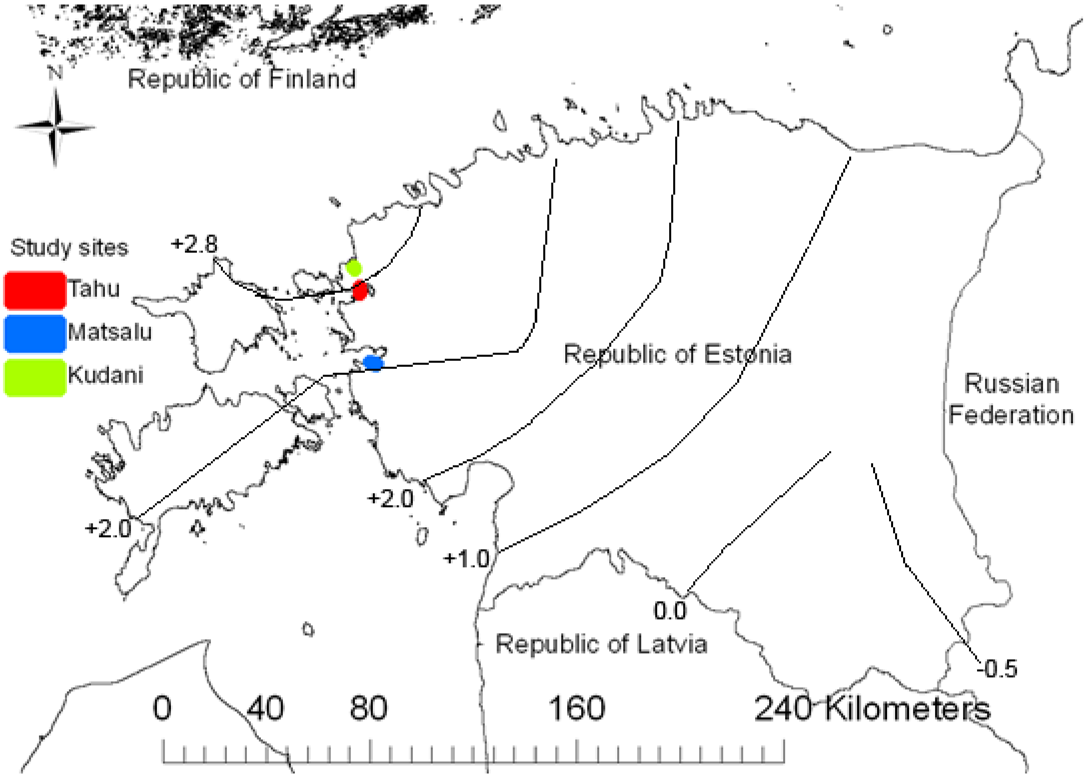


Figure 2: Conceptual model of local sea level rise at Tahu, Kudani and Matsalu study sites by 2100. Factors decreasing local sea level are denoted with a minus and those increasing local sea level are denoted with a plus sign.

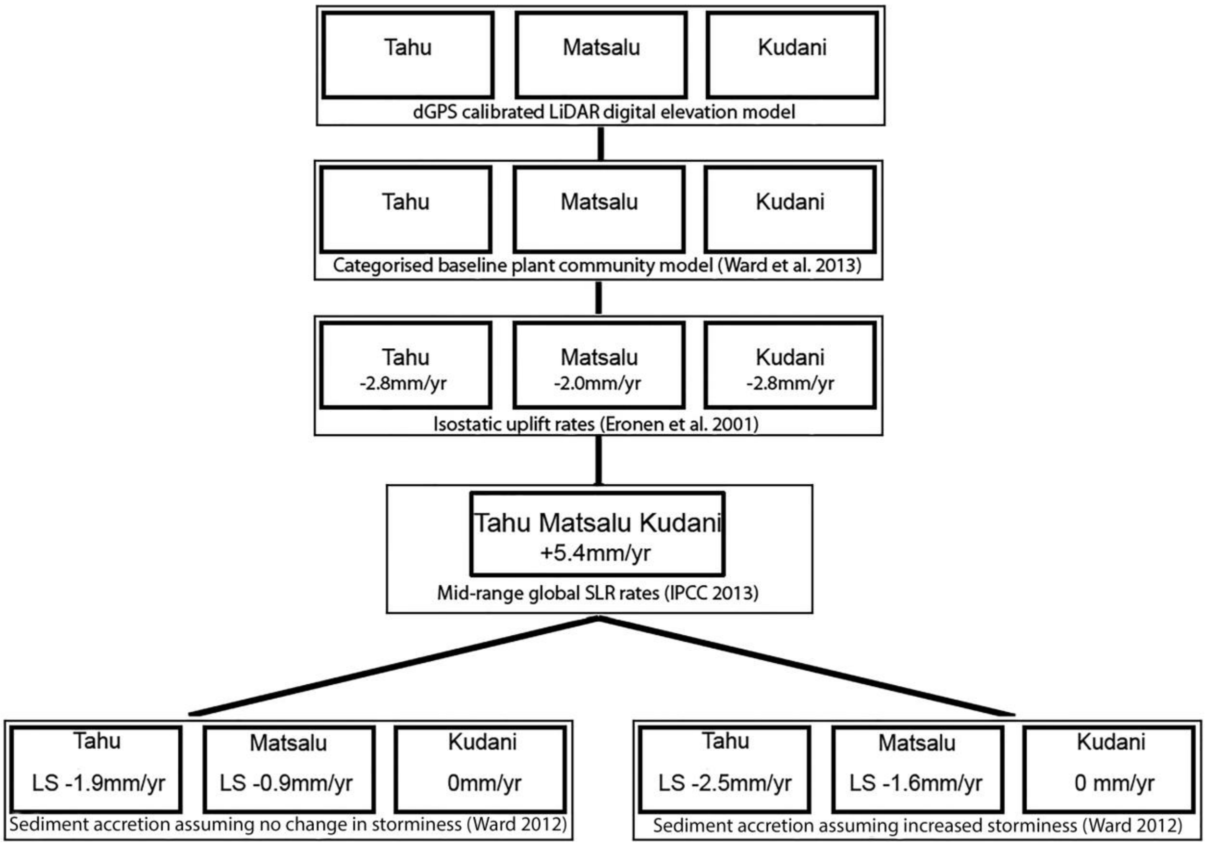


Figure 3: Tahu plant community model output. Plant community location is mapped showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by 2100 using the dGPS correction but no sediment data, (c) changes by 2100 using the dGPS correction and assuming no change in sedimentation rates, (d) changes by 2100 using the dGPS correction and assuming an increase in sedimentation rates due to greater storm activity, (e) changes by 2100 not using the dGPS correction and assuming no change in sedimentation rates. See table 1 for explanation of plant community codes.

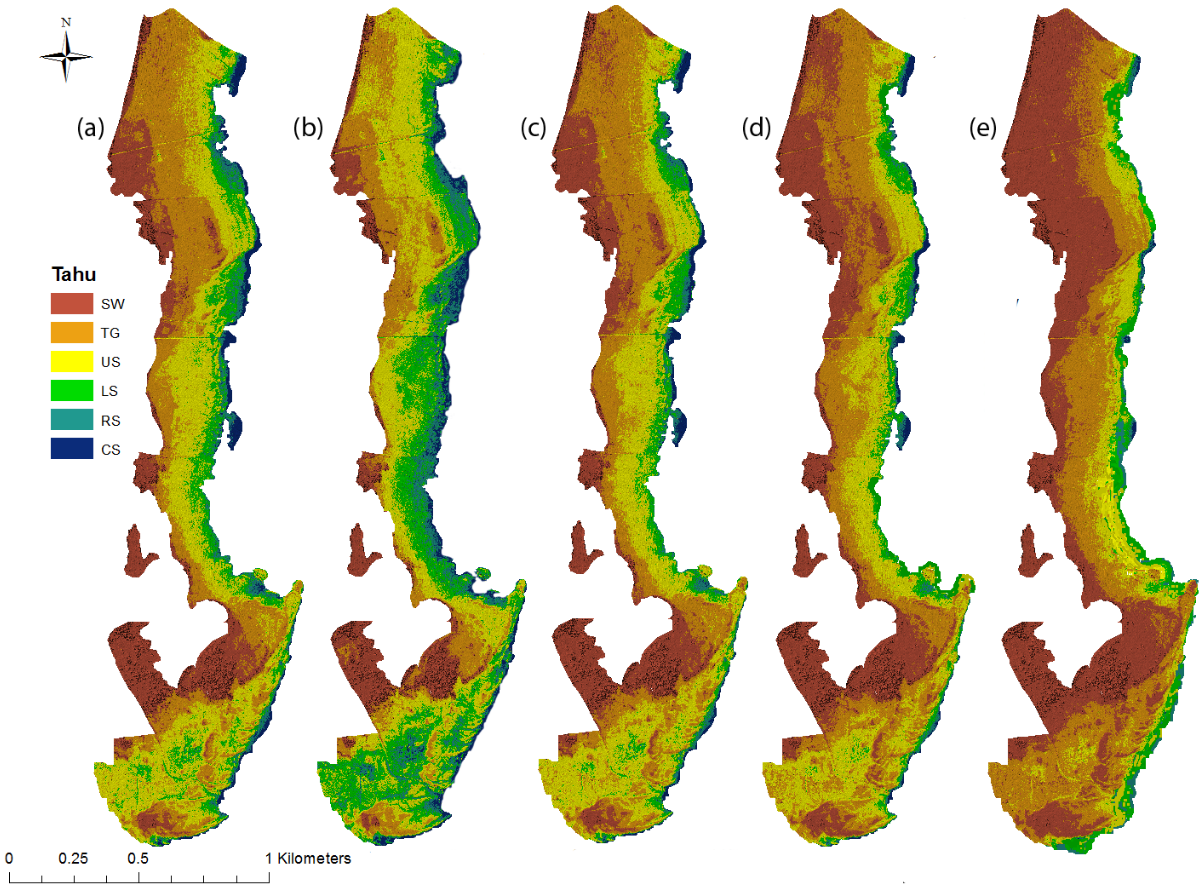


Figure 4: Matsalu plant community model output. Plant community location is mapped showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by 2100 using the dGPS correction but no sediment data, (c) changes by 2100 using the dGPS correction and assuming no change in sedimentation rates, (d) changes by 2100 using the dGPS correction and assuming an increase in sedimentation rates due to greater storm activity, (e) changes by 2100 not using the dGPS correction and assuming no change in sedimentation rates. See table 1 for explanation of plant community codes.

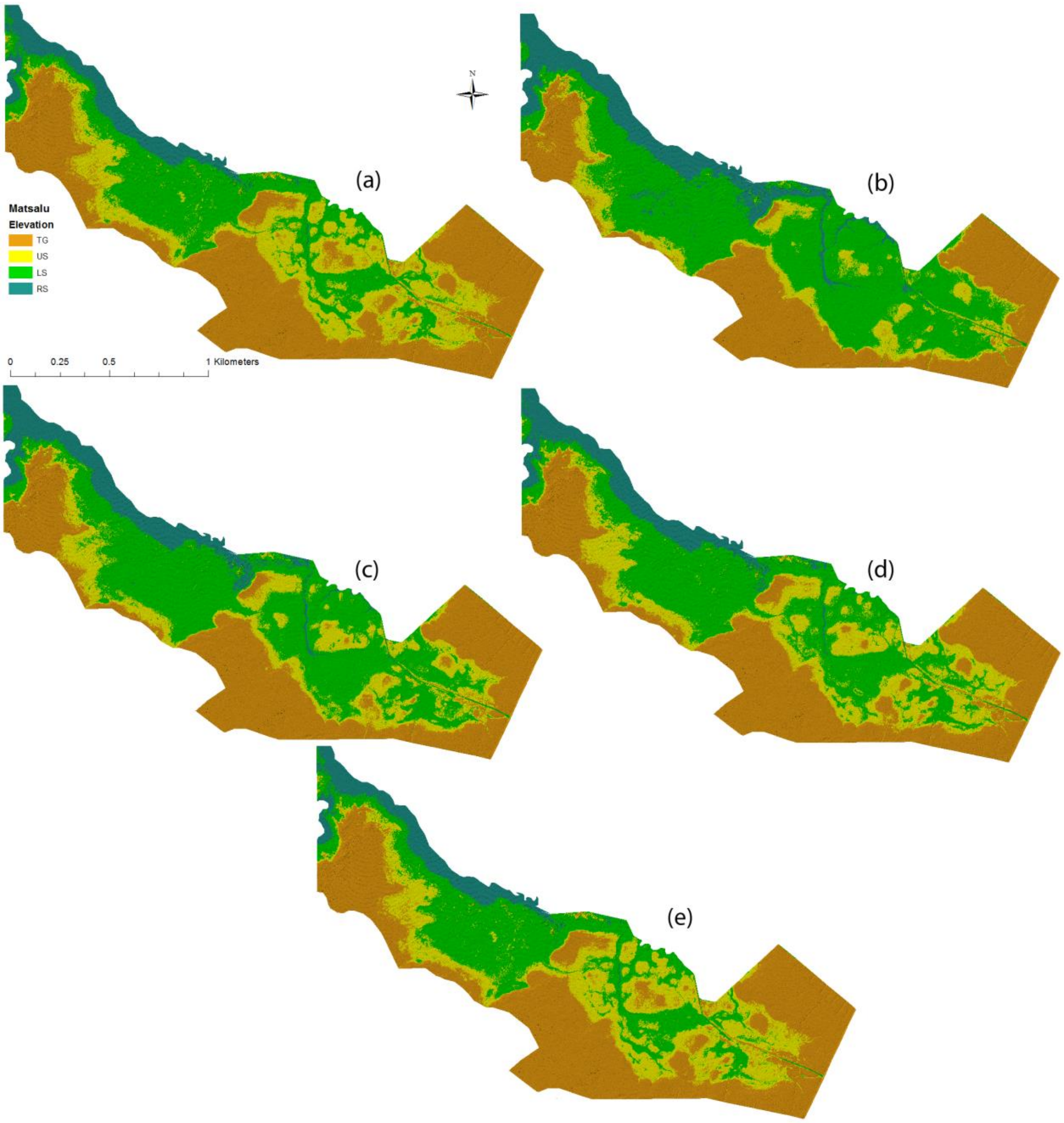


Figure 5: Kudani plant community model output. Plant community location is mapped showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by 2100 using the dGPS correction but no sediment data, (c) changes by 2100 not using the dGPS correction and assuming no change in sedimentation rates. See table 1 for explanation of plant community codes.

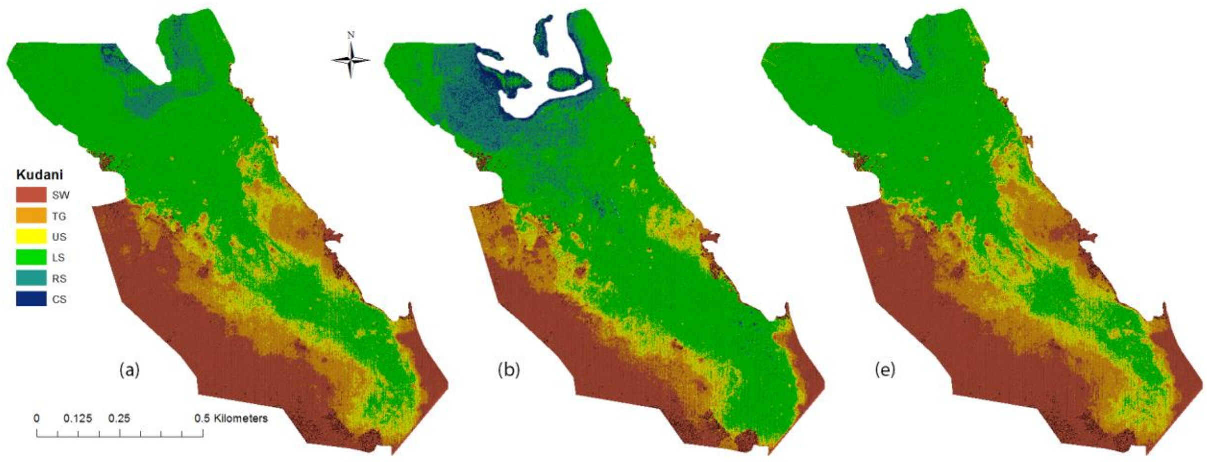


Table 1: Elevation ranges of the six plant community types above mean sea level used in the model (BK77 as measured at Kronstadt, in m). Elevation ranges calculated using a Leica rtk dGPS derived from 2100 records per plant community.

| Community | Elevation range (m) |
|---|---|
| Clubrush Swamp (CS) | -0.20 to 0.07 |
| Reed Swamp (RS) | 0.07 to 0.15 |
| Lower Shore (LS) | 0.15 to 0.27 |
| Upper Shore (US) | 0.27 to 0.47 |
| Tall Grass (TG) | 0.47 to 0.69 |
| Scrub Woodland (SW) | 0.69 to 1.2 |

Table 2: Percentage of quadrats of each plant community type correctly identified at each site utilising the dGPS calibration. A Fleiss' Kappa coefficient was used to assess plant community model accuracy at Tahu, Matsalu and Kudani (from Ward et al., 2013). See table 1 for explanation of plant community codes.

| | Observed | Expected Community | | | | | | Correctly |
|---|---|---|---|---|---|---|---|---|
| Interpolation | community | CS | RS | LS | US | TG | SW | identified |
| Tahu | CS | 86.7 | 10 | | | | | 86.7 |
| | RS | 13.3 | 90 | | | | | 90 |
| | LS | | | 80 | 53.3 | 26.7 | | 80 |
| | US | | | 20 | 46.7 | 20 | | 46.7 |
| | TG | | | | | 53.3 | 33.3 | 53.3 |
| | SW | | | | | | 66.7 | 66.7 |
| | | κ coefficient 0.63 | | | | | Mean 70.6 | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Matsalu | RS | N/A | 100.0 | | | | N/A | 70 |
| | LS | N/A | | 80.0 | 6.7 | | N/A | 80 |
| | US | N/A | | 20.0 | 86.7 | | N/A | 43.3 |
| | TG | N/A | | | 6.7 | 100.0 | N/A | 46.7 |
| | | κ coefficient 0.89 | | | | | | Mean 91.7 |
| Kudani | CS | 100.0 | | | | | | 100.0 |
| | RS | | 100.0 | | | | | 100.0 |
| | LS | | | 80.0 | 20.0 | 13.3 | | 80.0 |
| | US | | | 20.0 | 60.0 | 26.7 | 6.7 | 60.0 |
| | TG | | | | 20.0 | 60.0 | 13.3 | 60.0 |
| | SW | | | | | | 80.0 | 80.0 |
| | | κ coefficient 0.81 | | | | | | Mean 80.0 |

Table 3: Percentage of quadrats of each plant community type correctly identified at each site utilising modelling with no dGPS correction. A Fleiss' Kappa coefficient was used to assess plant community model accuracy at Tahu, Matsalu and Kudani. See table 1 for explanation of plant community codes.

| Interpolation | Observed community | Expected Community CS | RS | LS | US | TG | SW | Correctly identified |
|---|---|---|---|---|---|---|---|---|
| Tahu | CS | | | | | | | 0.0 |
| | RS | 83.3 | | | | | | 0.0 |
| | LS | 16.6 | 100.0 | | 20.0 | | | 0.0 |
| | US | | | 93.3 | 20.0 | 33.3 | | 20.0 |
| | TG | | | 6.6 | 60.0 | 30.0 | | 30.0 |
| | SW | | | | | 36.6 | 100.0 | 100.0 |
| | | κ coefficient 0.10 | | | | | | Mean 25.0 |
| Matsalu | RS | N/A | | | | | N/A | 0 |
| | LS | N/A | 80.0 | | | | N/A | 0 |
| | US | N/A | 20.0 | 50.0 | 10.0 | | N/A | 10 |
| | TG | N/A | | 50.0 | 90.0 | 100.0 | N/A | 46.7 |
| | | κ coefficient 0.03 | | | | | | Mean 14.2 |
| Kudani | CS | | | | | | | 0.0 |
| | RS | 100.0 | | | | | | 0.0 |
| | LS | | 86.6 | | | | | 0.0 |
| | US | | 13.3 | 66.6 | 26.6 | | | 26.6 |
| | TG | | | 26.6 | 10.0 | 40.0 | | 40.0 |
| | SW | | | 6.6 | 73.3 | 60.0 | 100.0 | 100.0 |
| | | κ coefficient 0.13 | | | | | | Mean 27.8 |

Table 4: Predicted changes in the extent of each plant community and total wetland area from 2010 by 2100 at Tahu, Matsalu and Kudani. Model parameters are: a = baseline situation in 2010, b = using dGPS correction but no sediment data, c = using dGPS correction and sediment data assuming no increase in storm activity, d = using dGPS correction and sediment data assuming an increase in storm activity, e = not using dGPS correction but using sediment data assuming no increase in storm activity (except Kudani where no sediment accretion is assumed). See table 1 for explanation of plant community codes.

| Plant community | a (ha) | b (% change) | c (% change) | d (% change) | e (% change) |
|---|---|---|---|---|---|
| Tahu | | | | | |
| CS | **0.6** | 133.3 | 14.7 | -6.2 | -1.1 |
| RS | **4.5** | 137.8 | 0.5 | -2.3 | 7.0 |
| LS | **11.7** | 112.8 | -23.5 | -4.6 | 2.1 |
| US | **37.8** | -2.1 | -7.1 | 2.0 | 5.7 |
| TG | **35.6** | -42.4 | 4.7 | 2.0 | 10.1 |
| SW | **26.8** | -37.7 | 17.4 | 33.2 | 71.1 |
| Total | **117.0** | -9.7 | 1.7 | 12.6 | 28.5 |
| Matsalu | | | | | |
| RS | **12.5** | 60.8 | 28.8 | 13.6 | 0.0 |
| LS | **48.9** | 76.9 | 49.9 | 24.7 | -0.1 |
| US | **45.5** | -53.0 | -29.5 | -11.6 | -0.3 |
| TG | **85.1** | -27.1 | -18.9 | -11.2 | 0.4 |
| Total | **192** | -1.0 | -0.8 | -0.5 | 0.0 |
| Kudani | | | | | |
| CS | **1.4** | 150.6 | - | - | 1.1 |
| RS | **2.1** | 160.7 | - | - | -1.8 |
| LS | **36.0** | 5.8 | - | - | -3.6 |
| US | **9.2** | -35.9 | - | - | 10.9 |
| TG | **10.0** | -26.0 | - | - | 14.0 |
| SW | **20.0** | -32.0 | - | - | 13.5 |
| Total | **78.7** | -10.1 | - | - | 2.1 |