

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

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8 **Abstract**

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

23 **Keywords**

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

## 26 **Introduction**

27 Coastal wetlands are among the most productive ecosystems in the world containing  
28 specialist plant species and providing a habitat for a wide diversity of taxa (Allen &  
29 Pye, 1998). They also provide important ecosystem services such as coastal  
30 protection (Gedan et al., 2011), carbon sequestration (Hopkinson et al., 2012), and  
31 nutrient cycling (Barbier et al., 2011). However, coastal wetlands are under threat from  
32 sea level rise (SLR) (Nicholls & Cazenave, 2010; Weisse et al., 2014) particularly  
33 those located in low lying countries with maritime borders (IPCC, 2013). Current  
34 predictions of global sea level rise suggest that SLR will be in the region of 0.26m –  
35 0.82m by 2100 (IPCC, 2013).

36 In order to make an assessment of the threats to coastal wetlands from sea level rise  
37 a variety of models have been developed (Bertrand et al., 2011; Moeslund et al., 2011;  
38 Stratonovitch et al., 2012; Bellafiore et al., 2014). Typically, ecological modelling is  
39 based on knowledge of environmental gradients, which are used as ecological  
40 predictors (Burnside & Waite, 2011). Many sea level rise impact models developed for  
41 coastal wetlands utilise elevation data as a proxy for hydrology (Moeslund et al., 2011),  
42 and the most accurate remotely sensed elevation data available are LiDAR (Gesch,  
43 2009). However, LiDAR elevation data have inherent inaccuracies due to the  
44 impenetrability of laser pulses through vegetation (Sadro et al., 2007; Ward et al.,  
45 2013). To overcome these inaccuracies Ward et al. (2013) developed a model that  
46 can accurately estimate the current distribution of plant communities in micro-  
47 topographical coastal wetlands using dGPS calibrated LiDAR data.

48 The recent IPCC (2013) report suggests that climate change will not affect only sea  
49 level and temperature, but is also likely to lead to increased storminess in many areas,

50 particularly in northern Europe and the Baltic (Rozynski & Pruszek, 2010). Previous  
51 studies have shown that in predominantly depositional areas, increased storminess  
52 and rising sea levels can facilitate wetland development through sediment deposition  
53 (Friedrichs & Perry, 2001; French, 2006; Schuerch et al., 2012; Tsompanglou et al.,  
54 2012; Ward et al., 2014). A variety of studies have suggested that sediment deposition  
55 alone could, in a wide variety of coastal wetlands, keep pace with SLR, thus preventing  
56 any large scale wetland loss (Friedrichs & Perry, 2001; French, 2006; Kirwan and  
57 Temmerman, 2009; Mudd et al., 2009;). However, many predictive SLR impact models  
58 (Poulter & Halpin, 2008; Kont et al., 2008; Moeslund et al., 2011) neglect to take into  
59 account sediment accretion as a factor even where these data are available.

60 This study tested the hypotheses:

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

63 2) How does the consideration of dGPS LiDAR correction, sediment accretion rates  
64 and the impacts of increased storminess influence plant community distribution by  
65 2100?

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

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

## 73 **Materials and Methods**

### 74 **Study area**

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

79 The Baltic Sea along the Estonian coast has almost no regular tide (0.02 m) (Suursaar  
80 et al., 2001). However, major fluctuations in sea level do occur due to seasonally  
81 changing meteorological conditions facilitating storm surges and variations in  
82 barometric pressure, causing an irregular influx of sediment to the coastal wetlands.  
83 The highest recorded sea level was during the 2005 storm Gudrun, which caused a  
84 2.75 m storm surge in Pärnu, Estonia. More typically, water levels do not vary more  
85 than between 0.3 m below and 0.4 m above m.s.l. (EMHI, 2012). The generally low  
86 relief of Baltic coastal wetlands (between -0.28 m and +1.2 m) means that they can be  
87 inundated during periods of elevated sea level. Burnside et al. (2007) identified six  
88 main plant communities with indicator species for Estonian coastal wetlands. These  
89 were: Clubrush Swamp (CS), Reed Swamp (RS), Lower Shore (LS), Upper Shore  
90 (US), Tall Grass (TG), and Scrub and developing Woodland (SW). Plant community  
91 distribution is characterised by different elevations above m.s.l. related to differing  
92 inundation frequencies and durations (Ward et al. 2010) (table 1).

93 Three study sites were selected to model the potential effects of sea level rise on  
94 Estonian coastal wetlands in order to represent a range of controlling factors. The  
95 Tahu and Kudani wetlands (figure 1) are located in the Silma Nature Reserve in the  
96 northwest of Estonia along the south coast of the Baltic Sea. These two sites are

97 influenced by higher isostatic uplift rates than the third site, Matsalu. Tahu has access  
98 to an allochthonous sediment supply and sediment accretion rate data for this site are  
99 available. Kudani is cut off from an allochthonous sediment source, and  
100 autochthonous soil formation through plant decomposition is considered to be very  
101 low in these wetlands (Puurmann & Ratas, 1998). At both Tahu and Kudani, all of the  
102 six main plant community types were present. The Matsalu coastal wetland (figure 1)  
103 is located in Matsalu National Park and has both lower isostatic uplift and sediment  
104 accretion rates than Tahu but greater sediment accretion rates than Kudani. At  
105 Matsalu, the Clubrush Swamp plant community is not found at the lower elevations  
106 due to greater wave energy than at Tahu and Kudani. The Scrub and developing  
107 Woodland plant community is also absent from Matsalu due to a different management  
108 history to the other sites.

### 109 **Baseline plant community modelling**

110 In order to test hypothesis 1, does DGPS LiDAR calibration improve plant community  
111 modelling in Baltic coastal wetlands, and model the potential effects of sea level rise  
112 (hypothesis 2), a baseline digital elevation model was required. Ward et al. (2013)  
113 developed a methodology to produce an accurate (0.02 m) digital elevation model  
114 (DEM) for use in Baltic coastal wetlands using dGPS calibrated LiDAR data. The DEM  
115 was derived from medium point density LiDAR data with a footprint of 0.54 m and an  
116 average point density of 0.45 points/m<sup>2</sup> collected by the Estonian Land Board in 2009  
117 using an ALS50-II laser/detector. dGPS calibration data were collected using a Trimble  
118 5700 system (accuracy 0.02 m). Calculations for dGPS calibration of the LiDAR  
119 elevation data were conducted in Matlab R2010a using the Ward et al. (2013)  
120 methodology. DEM interpolation was conducted based upon raw values for LiDAR  
121 within ArcGIS 10.1 and using a Delaunay triangulated irregular network (TIN). dGPS

122 calibration data were added to the last return LiDAR point values. DEMs for each site  
123 were categorised using plant community elevation preferences (table 1) (Ward et al.,  
124 2010) (baseline scenario a). The dGPS calibrated plant community model was used  
125 as a baseline for modelling the location of the plant communities by 2100 using  
126 modelling parameters explained in the following section. Validation of the baseline  
127 plant community models was conducted using a stratified random ground truth survey  
128 in July, 2010. At each site 15 points were selected within each predicted plant  
129 community yielding ninety 1m<sup>2</sup> quadrats at both Tahu and Kudani and sixty at Matsalu  
130 (due to the lower number of plant communities) and the presence and abundance of  
131 all plant species recorded. Validity of plant community models compared to ground-  
132 truthed data was assessed using a Fleiss' Kappa coefficient (Landis & Koch, 1972).

### 133 **Environmental modelling parameters**

134 The baseline model was modified by integrating isostatic uplift rates (Eronen et al.  
135 2001), sea level rise data (IPCC 2013) and sediment accretion estimates (Ward et al.  
136 2014) (figure 2) to predict the location and extent of the plant communities in response  
137 to local sea level by 2100 (hypothesis 2). Current IPCC (2013) estimates of global sea  
138 level rise are between 0.26 m and 0.82 m by 2100 dependant on scenario. Therefore  
139 a mid-range SLR figure of 0.54 m was selected to represent climate driven sea level  
140 rise. At the Tahu and Kudani coastal wetlands, isostatic uplift rates were included  
141 based on studies by Vallner et al. (1988) and Eronen et al. (2001) (figures 1 and 2).  
142 Both the sea level rise and isostatic uplift data were utilised in scenarios b, c, d and e.  
143 In scenario b only sea level rise and isostatic uplift were utilised (sediment accretion  
144 data not incorporated) to identify changes in plant community location using the dGPS  
145 calibrated baseline model.

146 A further parameter incorporated into the model was sediment accretion, [Nolte et al.,  
147 (2013) terminology]. Past rates of sediment accretion for the Tahu and Matsalu coastal  
148 wetlands were based on data derived from  $^{210}\text{Pb}$  radionuclide dating of sediment cores  
149 and independently verified using the  $^{137}\text{Cs}$  dating method (Ward et al., 2014). Mean  
150 accretion rates for Tahu were 1.9 mm/yr, and for Matsalu 0.9 mm/yr. No accretion  
151 rates were used for Kudani (figure 2) as it is largely separated from the sea, and hence  
152 lacks a significant allochthonous sediment source and is unlikely to have significant  
153 autochthonous organic production. These mean accretion rates were utilised in  
154 scenarios c and e, although in scenario e the dGPS correction to the LiDAR was not  
155 used for comparison.

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

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

## 170 **Results**

### 171 **Baseline plant community modelling**

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

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

### 185 **Plant community model for 2100**

#### 186 **Tahu 2100**

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

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

## 202 **Matsalu 2100**

203 Matsalu is typified by lower uplift and sediment accretion rates than Tahu. In scenario  
204 b (dGPS calibration but discounting sediment accretion) there is a small predicted loss  
205 of the wetland area (-1.0%, table 4 and figure 4b). In this model output the greatest  
206 predicted losses occur in the US (-53.0%) and TG (-27.1%) plant communities (table  
207 4). In model output c (utilising the dGPS correction and assuming no change in  
208 sediment accretion rates), there is a predicted loss of 0.8% of the wetland area by  
209 2100 (table 4, figure 4 c). The greatest losses are expected in the higher elevation  
210 plant communities US (-29.5%) and TG (-18.9%). In model output d, averaged  
211 sediment accretion rates over a 100 year period assuming an increase in storminess  
212 are 1.6mm/yr comparable with those of isostatic uplift 2.0mm/yr, suggesting that  
213 during storm events sediment accretion exceeds the rates of isostatic uplift as at Tahu  
214 (figure 2). In this model output, the model predicts a 0.5% decrease in the total area  
215 of wetland by 2100 (table 4, figure 4d). In model output e (taking into account  
216 sedimentation but not including the dGPS calibration), there is predicted to be little

217 change in plant community extent and no increase in the total wetland area (table 4,  
218 figure 4e).

## 219 **Kudani 2100**

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

## 229 **Discussion**

### 230 **Hypothesis 1: 'does dGPS calibration improve modelling current plant** 231 **community types in Baltic coastal wetlands?'**

232 The relationship between elevation above mean sea level and plant community type  
233 provided a basis for developing predictive plant community models for coastal  
234 wetlands (Ward et al., 2010). However, elevation differences between some of the  
235 plant communities in these Baltic coastal wetlands were small, with a minimum of 0.04  
236 m. Hence it was necessary to obtain highly accurate elevation data that covered a  
237 variety of Baltic coastal wetland sites. Due to the small size of some of the plant  
238 community patches, as is typical in many mosaic coastal wetlands, it was also  
239 necessary to obtain high resolution data for the study areas. The most widely available

240 data that fulfil these conditions are LiDAR elevation. The results of this study have  
241 shown that plant communities can be accurately identified using dGPS calibrated  
242 LiDAR data. LiDAR data have been successfully used in several studies to develop  
243 plant community models over large field areas (Morris *et al.*, 2005; Prisløe *et al.*, 2006;  
244 Sadro *et al.*, 2007; Chust *et al.*, 2008; Moeslund *et al.*, 2011). However, none of these  
245 studies modelled plant communities at such a fine scale as that developed in this study  
246 for micro-topographical coastal wetlands, hence the requirement for the dGPS  
247 calibration.

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

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

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

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

278 In many coastal wetlands sediment accretion is a primary driver of wetland  
279 development (Webb et al., 2013) and accretion rates are therefore an important factor  
280 to be taken into account when modelling the effects of sea level rise on coastal  
281 environments (McFadden et al., 2007). This study has utilised historical sediment  
282 accretion rates derived from  $^{210}\text{Pb}$  dating (Ward et al., 2014) and extrapolated the  
283 results for sea level rise modelling (Craft et al., 2009). The results showed that  
284 sediment accretion has a considerable effect on modelling local sea level rise impacts  
285 on wetland plant communities, highlighted by the substantial differences in the  
286 predicted distribution of the plant communities (figure 3b, c, d, e), particularly at Tahu.  
287 Many previous studies of the impacts of sea level rise in coastal wetlands have ignored  
288 sediment accretion (Suursaar et al., 2006; Kont et al., 2008, Moeslund et al., 2012).  
289 Moeslund et al. (2011) justify this exclusion from their dynamic correlative model by

290 suggesting that accretion rates vary greatly within sites and that the majority of  
291 sediment accretion data available are generalised from few samples. However, whilst  
292 extrapolation of accretion data from few samples can be problematic due to the spatial  
293 variability of sediment deposition the exclusion of these data is likely to provide greater  
294 dynamic model prediction errors. Results from this study have shown that sediment  
295 accretion rates taking into account increased storminess are of a similar magnitude to  
296 isostatic uplift (1.6-2.5 mm/yr compared with 2.0-2.8 mm/yr respectively). Ward et al.  
297 (2014) have estimated that during periods of elevated sediment accretion, rates can  
298 be as high as 5 mm/yr, well in excess of isostatic uplift. In the model outputs assuming  
299 an increase in storminess (output d in figures 3, 4 and 5) the impacts of sea level rise  
300 are reduced and in the case of Tahu progradation is predicted to take place. This has  
301 been predicted to be the case in sheltered coastal wetlands in many areas of the world  
302 including the Baltic (Schuerch et al., 2013; Tweel and Turner, 2014; Schindler et al.,  
303 2014; Ward et al., 2014) suggesting that this is a useful addition to plant community  
304 modelling parameters.

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

307 The model developed in this study accurately predicted the location and extent of plant  
308 communities in micro-topographic non-tidal Baltic coastal wetlands. The model also  
309 has potential applications in other appropriate open environments such as floodplains,  
310 tidal coastal marshes or for the restoration of wetlands. It does however, have  
311 limitations that should be taken into account when interpreting the results. As with any  
312 correlative model, there is regional specificity and hence the particular model  
313 developed in this study is unlikely to be valid in locations other than Estonia without  
314 further ground-truthing. The model is also based on the assumption that sea level and

315 sediment accretion will be the only environmental variables that will change due to  
316 climate effects by 2100. However, IPCC (2013) climate change scenarios suggest that  
317 temperature will also increase and several studies have suggested that this could  
318 cause a northward migration of some plant species (Dullinger et al., 2004; Aitken et  
319 al., 2008; Hilyer & Silman, 2010), which is likely to affect community composition in  
320 coastal wetlands, particularly at the extreme geographical ranges of individual species.

321 Salt marshes are an obvious environment for the further application of the dynamic  
322 plant community model presented in this study. Several authors have related the  
323 zonation of marsh communities to elevation above mean sea level and hence tidal  
324 range (Cutini et al., 2010; Moffett et al., 2010; Suchrow & Jensen, 2010; Moffett et al.,  
325 2012). However, tidal ranges vary greatly, so any plant community model would likely  
326 be valid only for areas with similar tidal regimes. As correlative plant community  
327 models have been suggested to be location specific (Franklin, 1995) in localities with  
328 different tidal regimes model parameters will need to be adjusted. Furthermore, salt  
329 marshes, whilst retaining a similar zonal character typically consisting of a low marsh,  
330 middle marsh and a high marsh (Nottage & Robertson, 2005), have a geographically  
331 varying species composition requiring the use of different plant community  
332 classifications dependent on location (Pennings et al., 2003). Ellenberg (1988),  
333 Rodwell (1992) and Isaach et al. (2006) have produced plant community  
334 classifications for continental European, UK and South American salt marshes  
335 respectively, which would be suitable for use as base model development. With  
336 regards to the geomatic stages involved in applying the plant community tool to salt  
337 marshes, the conceptual model developed in this study (figure 2) would be applicable  
338 for other coastal wetland systems.

## 339 **Conclusions**

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

### 357 **Acknowledgements**

358 This research was funded, in part, by the University of Brighton. This research was  
359 also supported by the European Social Fund's Doctoral Studies and  
360 Internationalisation Programme DoRa, Estonia; and the Estonian Land Board.

361 We would also like to thank Henri Järv, Tiina Järv, Samuel Bastable, Darren Ward,  
362 Taaniel Sepp, Martin Leppik, Kuldar Kuusik, Mae-Liis Sepp, Triin Jaagus and the staff  
363 of the Matsalu National Park and the Silma Nature Reserve.

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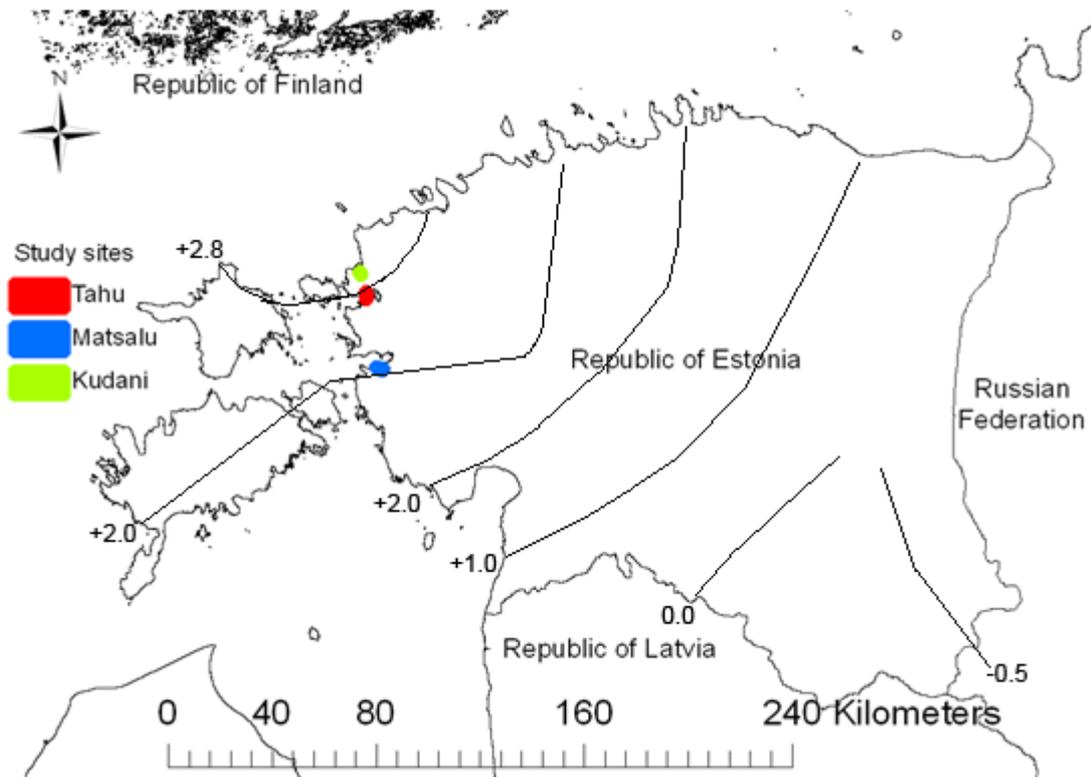
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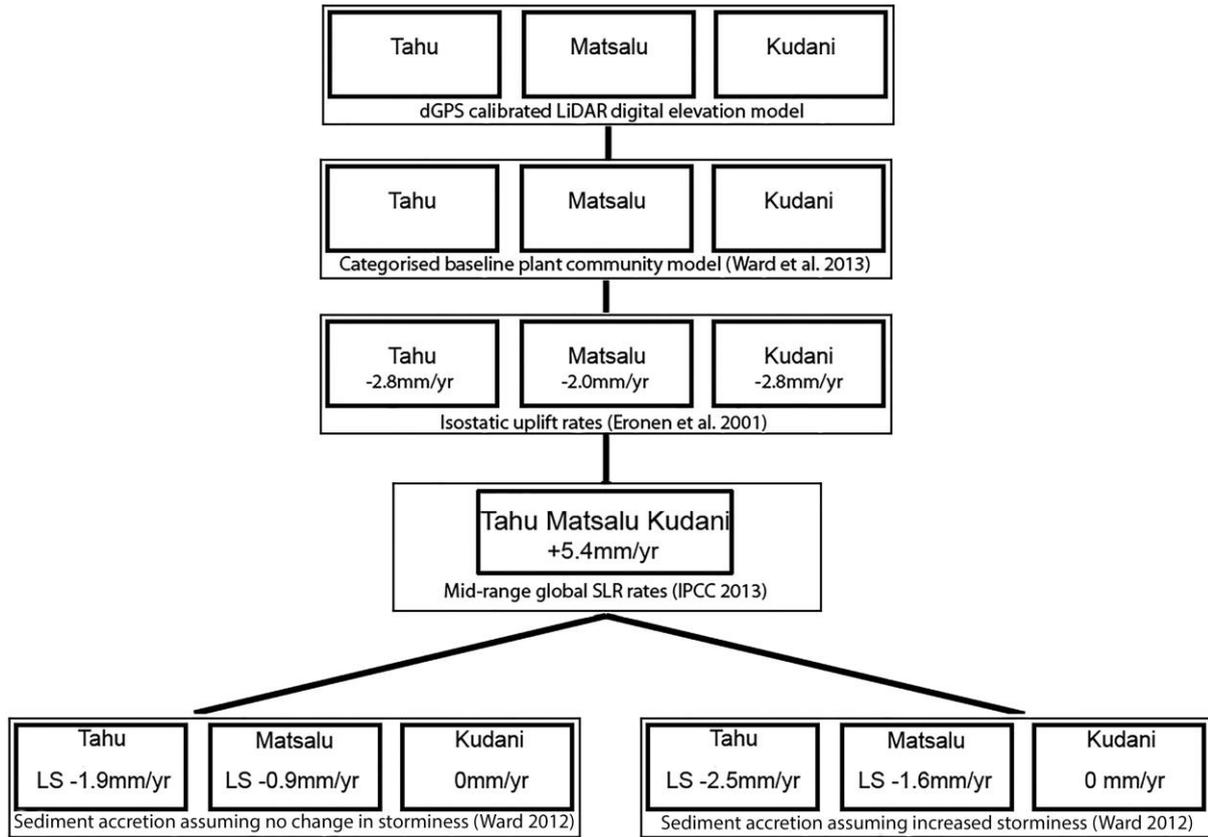
545

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



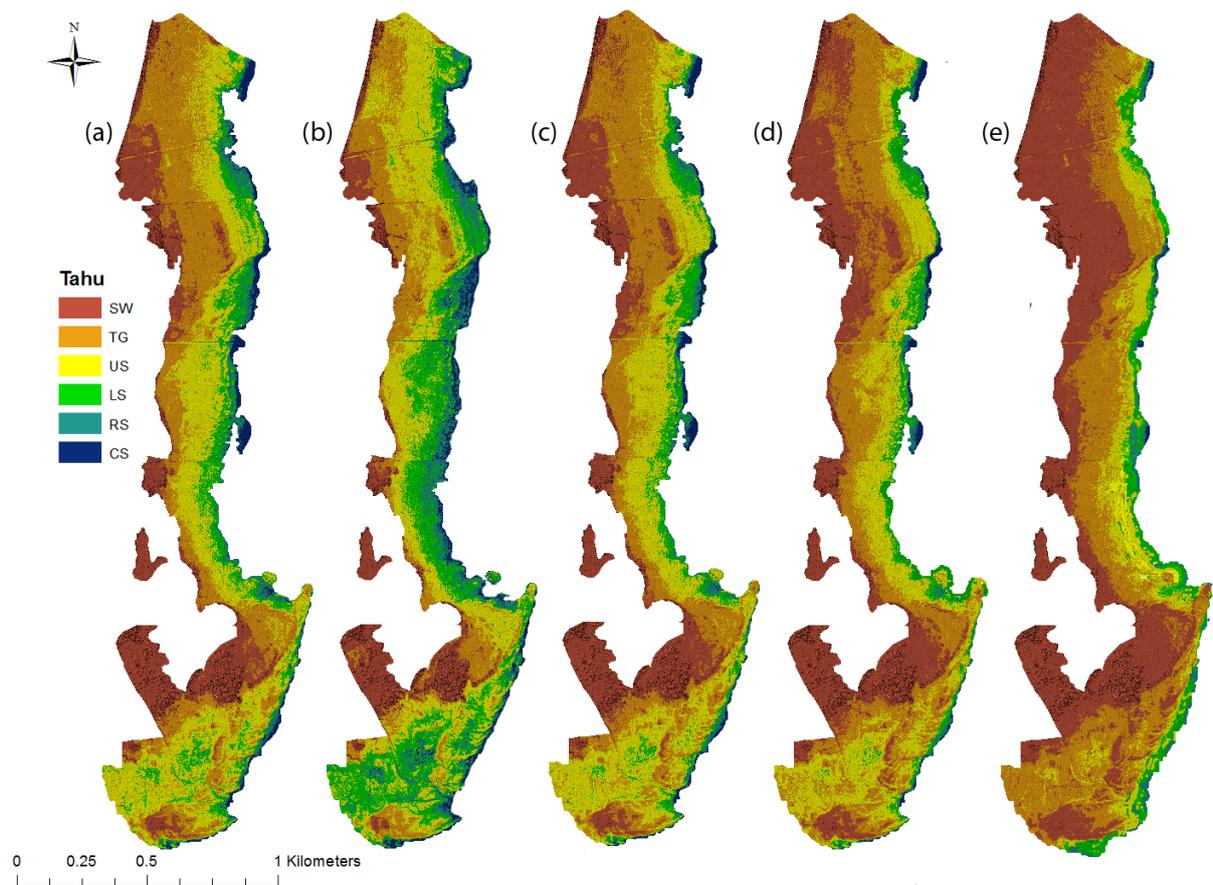
548

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



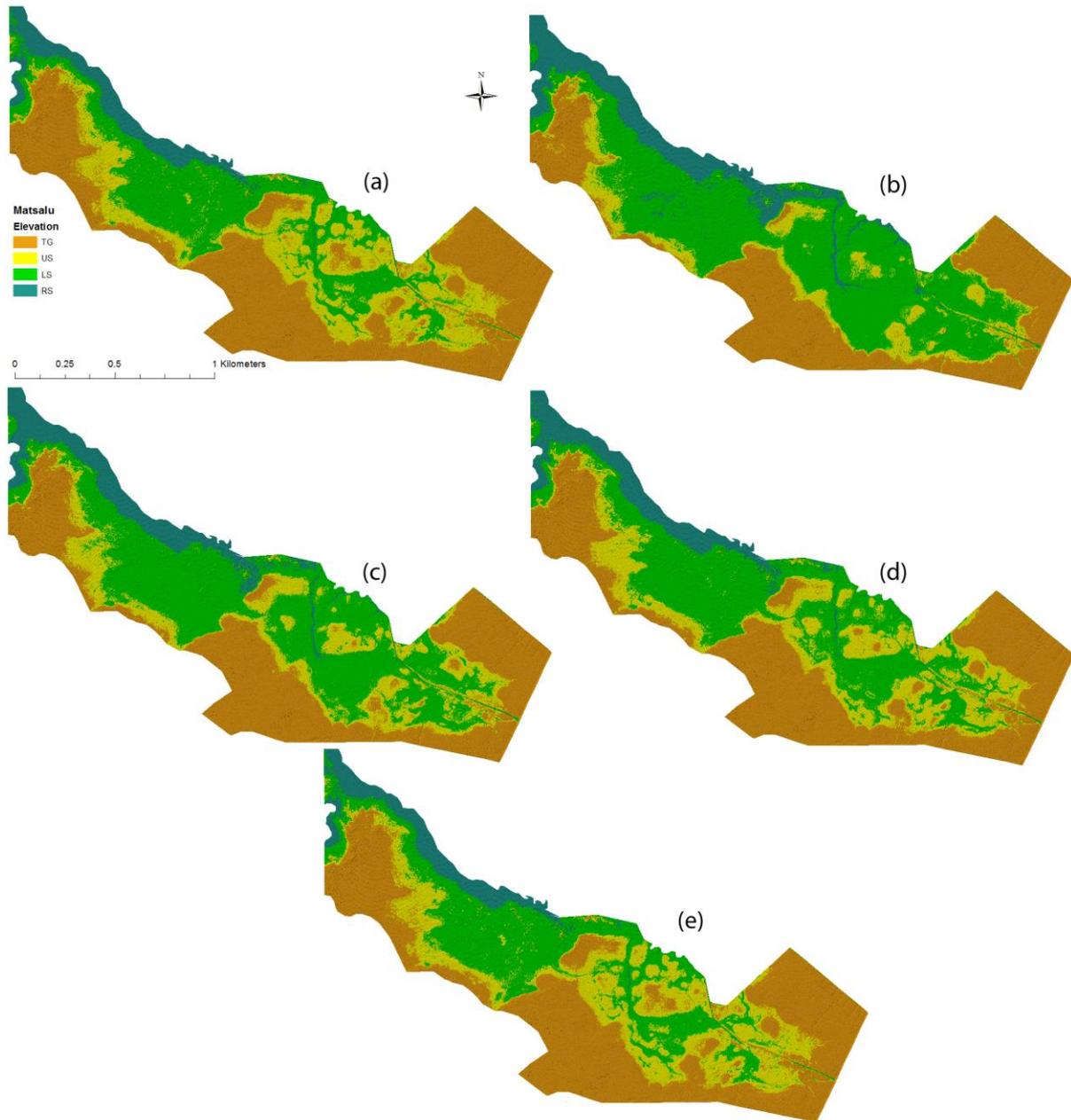
552

553 Figure 3: Tahu plant community model output. Plant community location is mapped  
 554 showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by  
 555 2100 using the dGPS correction but no sediment data, (c) changes by 2100 using the  
 556 dGPS correction and assuming no change in sedimentation rates, (d) changes by  
 557 2100 using the dGPS correction and assuming an increase in sedimentation rates due  
 558 to greater storm activity, (e) changes by 2100 not using the dGPS correction and  
 559 assuming no change in sedimentation rates. See table 1 for explanation of plant  
 560 community codes.



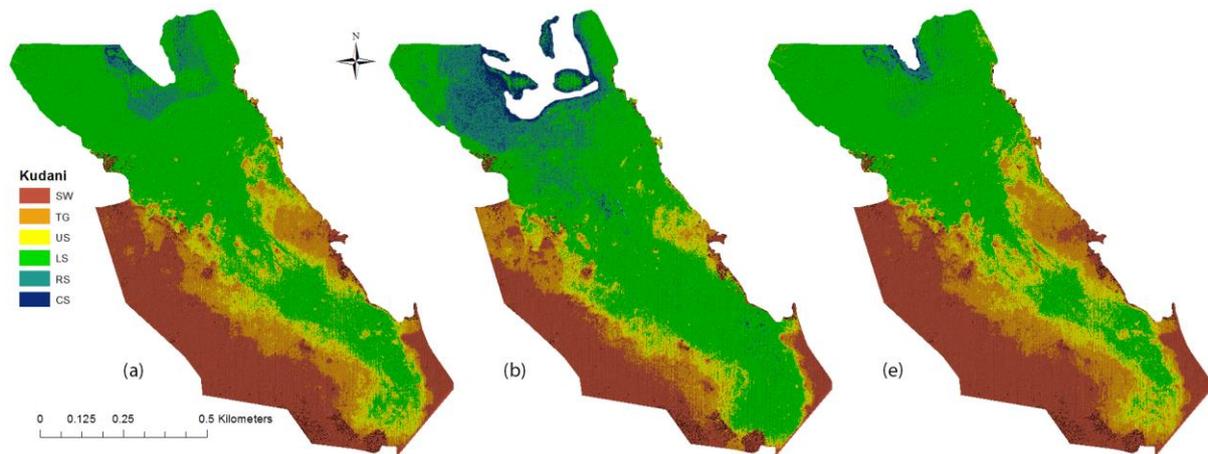
561

562 Figure 4: Matsalu plant community model output. Plant community location is mapped  
 563 showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by  
 564 2100 using the dGPS correction but no sediment data, (c) changes by 2100 using the  
 565 dGPS correction and assuming no change in sedimentation rates, (d) changes by  
 566 2100 using the dGPS correction and assuming an increase in sedimentation rates due  
 567 to greater storm activity, (e) changes by 2100 not using the dGPS correction and  
 568 assuming no change in sedimentation rates. See table 1 for explanation of plant  
 569 community codes.



570

571 Figure 5: Kudani plant community model output. Plant community location is mapped  
 572 showing the (a) baseline 2010 locations using the dGPS correction, (b) changes by  
 573 2100 using the dGPS correction but no sediment data, (c) changes by 2100 not using  
 574 the dGPS correction and assuming no change in sedimentation rates. See table 1 for  
 575 explanation of plant community codes.



576

577 Table 1: Elevation ranges of the six plant community types above mean sea level used  
 578 in the model (BK77 as measured at Kronstadt, in m). Elevation ranges calculated using  
 579 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

580

581 Table 2: Percentage of quadrats of each plant community type correctly identified at  
 582 each site utilising the dGPS calibration. A Fleiss' Kappa coefficient was used to assess  
 583 plant community model accuracy at Tahu, Matsalu and Kudani (from Ward et al.,  
 584 2013). See table 1 for explanation of plant community codes.

Interpolation	Observed community	Expected Community						Correctly identified
		CS	RS	LS	US	TG	SW	
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
$\kappa$ 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
$\kappa$ coefficient 0.81								Mean 80.0

585

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

Interpolation	Observed community	Expected Community						Correctly identified
		CS	RS	LS	US	TG	SW	
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
$\kappa$ 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
$\kappa$ 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
$\kappa$ coefficient 0.13								Mean 27.8

590

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

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

599