

1 **Seagrass light requirements using an algorithm to spatially**
2 **resolve depth of colonization**

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1 Introduction

Issues related to excessive nutrient pollution have motivated a substantial amount of research to understand and address impacts on coastal waters. Eutrophication, defined as an increase in the rate of supply of organic matter to an ecosystem (Nixon 1995), is primarily caused by anthropogenic inputs of limiting nutrients that exceed background concentrations of receiving waters. Adverse impacts on aquatic resources are well-documented and have included increased occurrence in the frequency and severity of harmful algal blooms (Cloern 1996), reduction of dissolved oxygen necessary to support heterotrophic organisms (Justic et al. 1987, Diaz and Rosenberg 2008), and loss of ecosystem functioning through food web simplification (Tewfik et al. 2007). Although management activities have been successful in mitigating or reversing eutrophication impacts (e.g., Greening and Janicki 2006), the evaluation of response endpoints remains an important topic given that ecosystem changes in relation to different nutrient regimes are not fully understood nor anticipated (Duarte et al. 2009). The most appropriate indicators of ecosystem response may be those that exhibit clear biological linkages with water quality changes, such that the potential effects of management actions can be unambiguously characterized through known cause and effect pathways. Critical management decisions may be forced by tentative assessments, political or societal pressures, or qualitative criteria in the absence of empirical methods to identify adequate indicators of ecosystem response (Duarte et al. 2009).

The ecosystem services provided by seagrasses as well as their sensitivity to water quality changes has contributed to their proliferation as biological response endpoints for eutrophication. Seagrasses are ecosystem engineers (Jones et al. 1994, Koch 2001) that serve a structural and

26 functional role in altering aquatic habitat often through multiple feedback mechanisms with other
27 ecosystem components. For example, seagrass beds create habitat for juvenile fish and crabs by
28 reducing wave action and stabilizing sediment (Williams and Heck 2001, Hughes et al. 2009).
29 Seagrasses also respond to changes in water clarity through direct physiological linkages with
30 light availability. In short, increased nutrient loading contributes to reductions in water clarity
31 through increased algal concentrations, inhibiting the growth of seagrass through light limitation
32 (Duarte 1995). Empirical relationships between nutrient loading, water clarity, light requirements,
33 and the maximum depth of seagrass colonization have been identified (Duarte 1991, Kenworthy
34 and Fonseca 1996, Choice et al. 2014), such that quantitative standards can be developed to
35 maintain light regimes sufficient for seagrass growth targets (Steward et al. 2005). Conversely,
36 seagrass depth limits have formed the basis of quantitative criteria for nutrient load targets
37 (Janicki and Wade 1996). Contrasted with numeric standards for nutrients and phytoplankton,
38 seagrass-based criteria may be more practical for developing water quality standards given that
39 seagrasses are integrative of system-wide conditions over time and less variable with changes in
40 nutrient regimes (Duarte 1995).

41 The development of numeric criteria and standards for coastal waters has been a
42 management priority within the United States (USEPA, 1998) and internationally (WFD 2000).
43 Numerous agencies and management programs have developed a variety of techniques for
44 estimating seagrass depth limits as a basis for establishing numeric criteria, either as restoration
45 targets or for identifying critical load limits. Such efforts have been useful for site-specific
46 approaches where the analysis needs are driven by a particular management or research context
47 (e.g., Iverson and Bittaker 1986, Hale et al. 2004). However, a lack of standardization among
48 methods has prevented broad-scale comparisons between regions and has even contributed to

49 discrepancies between measures of depth limits based on the chosen technique. For example,
50 seagrass depth limits based on in situ techniques can vary with the sampling device (Spears et al.
51 2009). Despite the availability of data, techniques for estimating seagrass depth of colonization
52 using remotely sensed data have not been extensively developed. Such techniques have the
53 potential to facilitate broad-scale comparisons between regions given the spatial coverage and
54 annual availability of many products. For example, recent analyses by Hagy, In review have
55 shown that standardized techniques using seagrass coverage maps and bathymetric data can be
56 developed to compare growth patterns over time among different coastal regions of Florida. Such
57 methods show promise, although further development to improve the spatial resolution of the
58 analysis are needed. Specifically, methods for estimating seagrass depth limits should be
59 reproducible for broad-scale comparisons, while also maintaining flexibility for site-specific
60 estimates depending on management needs.

61 Reproducible and empirical approaches can be developed to provide more consistent
62 estimates of seagrass depth limits for restoration targets or criteria development. We describe a
63 method for estimating seagrass depth of colonization using information-rich datasets to create a
64 spatially explicit and repeatable estimate. In particular, methods described in Hagy, In review are
65 improved upon by creating a flexible and repeatable technique for estimating seagrass depth
66 limits from coverage maps and bathymetric data. The specific objectives are to 1) describe the
67 method for estimating seagrass depth limits within a relevant spatial context, 2) apply the
68 technique to four distinct regions of Florida to illustrate improved clarity of description for
69 seagrass growth patterns, and 3) develop a spatially coherent relationship between depth limits
70 and water clarity for the case studies. Overall, these methods are expected to inform the
71 development of water quality criteria based on empirical relationships of seagrass depth limits

72 with water clarity over time. The method is applied to data from Florida although the technique is
73 transferable to other regions with comparable data.

74 **2 Methods**

75 Development of a spatially-resolved approach to estimate seagrass depth of {acro:doc}
76 colonization (Z_c) relied extensively on data and partially on methods described in Hagy, In
77 review. The following is a summary of data sources, methods and rationale for improving spatial
78 resolution in seagrass Z_c estimates, and evaluation of the approach including relationships with
79 water clarity.

80 **2.1 Data sources**

81 **2.1.1 Study sites**

82 Four locations in Florida were chosen for the analysis: Choctawhatchee Bay (Panhandle),
83 Big Bend region (northeast Gulf of Mexico), Tampa Bay (central Gulf Coast of Florida), and
84 Indian River Lagoon (east coast) (Table 1 and Fig. 1). These locations represent different
85 geographic regions in the state, in addition to having available data and observed gradients in
86 water clarity that contribute to heterogeneity in seagrass growth patterns. For example, the Big
87 Bend region was chosen based on location near an outflow of the Steinhatchee River where higher
88 concentrations of dissolved organic matter are observed. Seagrasses near the outflow were
89 observed to grow at shallower depths as compared to locations far from the river source. Coastal
90 regions and estuaries in Florida are partitioned as distinct spatial units based on a segmentation
91 scheme developed by US Environmental Protection Agency (EPA) for the development of {acro:EPA}
92 numeric nutrient criteria. One segment from each geographic location was used to estimate
93 seagrass Z_c and to evaluate variation in growth patterns. The segments included portions of

94 Choctawhatchee Bay (segment 303), the big bend region (820), Old Tampa Bay (902), and Indian
95 River Lagoon (1502) (Fig. 1).

96 **2.1.2 Seagrass coverage and bathymetry**

{sec: data_}

97 Spatial data describing seagrass aerial coverage combined with co-located bathymetric
98 depth information were used to estimate Z_c . These geospatial data products are publicly
99 available in coastal regions of Florida through the US Geological Survey, Florida Department of
100 Environmental Protection, Florida Fish and Wildlife Conservation Commission, and watershed
101 management districts. Seagrass coverage maps were obtained for recent years in each of the study
102 sites described above (Table 1). Coverage maps were produced using photo-interpretations of
103 aerial images to categorize seagrass as absent, discontinuous (patchy), or continuous. For this
104 analysis, we considered seagrass as only present (continuous and patchy) or absent since
105 differences between continuous and patchy coverage were often inconsistent between data
106 sources.

107 Seagrass coverage maps were combined with bathymetric depth layers to characterize
108 location and depth of growth in each location. Bathymetric depth layers for each location were
109 obtained from the National Oceanic and Atmospheric Administration's (NOAA) National
110 Geophysical Data Center (<http://www.ngdc.noaa.gov/>) as either Digital Elevation
111 Models (DEMs) or raw sounding data from hydroacoustic surveys. Tampa Bay data provided by
112 the Tampa Bay National Estuary Program are described in Tyler et al. (2007). Bathymetric data
113 for the Indian River Lagoon were obtained from the St. John's Water Management District

{acro: DEM}

114 (Coastal Planning and Engineering 1997). NOAA products were referenced to mean lower low
115 water, whereas Tampa Bay data were referenced to the North American Vertical Datum of
116 1988 (NAVD88) and the Indian River Lagoon data were referenced to mean sea level. Depth

{acro: NAVD}

117 layers were combined with seagrass coverage layers using standard union techniques for raster
118 and vector layers in ArcMap 10.1 (Environmental Systems Research Institute 2012). To reduce
119 computation time, depth layers were first masked using a 1 km buffer of the seagrass coverage
120 layer. The final layer used for analysis was a point layer with attributes describing location
121 (latitude, longitude, segment), depth (m), and seagrass (present, absent). All spatial data were
122 referenced to the North American Datum of 1983 as geographic coordinates. Depth values in
123 each seagrass layer were further adjusted from the relevant vertical reference datum to local mean sea level (MSL) using the NOAA VDatum tool (<http://vdatum.noaa.gov/>).
124 {acro:MSL}

125 **2.1.3 Water clarity**

126 Seagrass light requirements can be estimated by evaluating spatial relationships between
127 depth of colonization and water clarity. Secchi measurements provide a precise estimate of water
128 clarity and have been obtained at numerous locations documented in the Florida Department of
129 Environmental Protection's Impaired Impaired Waters Rule (IWR) database. Secchi data for
130 Florida coastal waters were obtained from update 40 of the IWR database for all of Tampa Bay
131 (2010 coverage) and the Indian River Lagoon (2009 coverage) given the spatial extent of secchi
132 observations for the two locations relative to the Big Bend and Choctawhatchee segments. Secchi
133 data within the previous ten years of the seagrass coverage data were evaluated to capture water
134 quality trends from the most recent decade (i.e., 1999–2009 for the Indian River Lagoon and
135 2000–2010 for Tampa Bay). Secchi data were screened to exclude observations that were flagged
136 indicating that the value was lower than the maximum depth of the observation point. Secchi data
137 were also compared with bathymetric data to verify unflagged values were not missed by initial
138 screening. Secchi observations that were measured at the same geographic location were
139 averaged across all dates. This approach was preferred given that seagrass depth patterns are more
{acro:IWR}

¹⁴⁰ representative of long-term trends in water clarity as opposed to individual secchi measures that
¹⁴¹ may be highly variable (Dennison 1987, Dennison et al. 1993).

¹⁴² 2.2 Segment-based estimates of seagrass depth of colonization

¹⁴³ [Hagy, In review](#) describe an approach to estimate seagrass Z_c as a segment-wide median.
¹⁴⁴ Seagrass depth data described above can be used to estimate maximum (Z_{cMax}) and median
¹⁴⁵ ($Z_{c50\%}$) seagrass Z_c , where the maximum depth is defined as the deepest depth at which a
¹⁴⁶ “significant” coverage of mappable seagrasses occurred in a segment and the median depth is
¹⁴⁷ defined as the median depth occurring at the deep water edge. The seagrass depth points are
¹⁴⁸ grouped into bins and the proportion of points within each depth bin that contain seagrass are
¹⁴⁹ quantified. Both seagrass Z_c estimates are obtained from a plot of proportion of points occupied
¹⁵⁰ at each depth bin. In general, the plot is characterized by a decreasing trend such that the
¹⁵¹ proportion of occupied points by depth bin decreases and eventually flattens with increasing
¹⁵² depth. A regression is fit on this descending portion of the curve such that the intercept point on
¹⁵³ the x-axis is considered the maximum depth of colonization. The median portion of this curve is
¹⁵⁴ considered the median depth of the deepwater edge of seagrass.

¹⁵⁵ A segment-wide average of seagrass Z_c , although unbiased, may potentially reduce the
¹⁵⁶ ability to relate patterns in Z_c to relevant water quality variables. Considerable spatial
¹⁵⁷ heterogeneity in the observed seagrass growth patterns suggests that a segment-wide estimate of
¹⁵⁸ seagrass Z_c may not fully describe variation at relevant spatial scales. Fig. 2a illustrates variation
¹⁵⁹ in seagrass distribution for a location in the Big Bend region of Florida. Using methods in [Hagy](#),
¹⁶⁰ [In review](#), the segment-wide estimate for maximum depth of seagrass colonization (shown as a
¹⁶¹ red contour line) does not adequately describe within-segment variation in depth limits. Z_c is

162 greatly over-estimated at the outflow of the Steinhatchee River where high concentrations of
163 dissolved organic matter reduce water clarity and naturally limit seagrass growth. This example
164 suggests that it may be useful to have improved spatial resolution in estimates of Z_c , particularly
165 when site-specific characteristics may require a more detailed description of seagrass growth
166 patterns. Although the current example is immediately relevant for the Big Bend region of
167 Florida, the remaining examples discussed throughout also provide a justification for a more
168 comprehensive assessment of seagrass growth patterns.

169 **2.3 Estimating seagrass depth of colonization for finite and arbitrary areas**

170 The approach used to estimate seagrass Z_c with improved spatial resolution has several
171 key differences that make it distinct from the original method. As before, seagrass Z_c estimates
172 are based on empirical measures of the frequency occurrence of seagrass with increasing depth.
173 The first difference is that maximum Z_c is estimated using a logistic growth curve fit through the
174 data, as compared to a simple linear regression in the previous example. Second, a third measure
175 describing the minimum depth of colonization was defined, in addition to median and maximum
176 depth of growth. The third and most important difference is that the estimates are assigned to
177 discrete cartesian locations, using either a grid of points or as a single location of interest. The
178 area around each point within which seagrass depth data are used to estimate Z_c is based on a
179 fixed, arbitrary radius that can be increased or decreased depending on the question of interest.
180 Methods and implications of these differences are described below.

181 The spatially-resolved approach for estimating Z_c begins by creating a grid of points
182 within the segment where the same process for estimating Z_c is used for each point. Alternatively,
183 a single location of interest can be chosen rather than a grid-based design. Seagrass depth data

184 (i.e., merged bathymetric and seagrass coverage data) that are located within a set radius from the
185 chosen locations are selected for estimating seagrass Z_c values (Fig. 2). The estimate for each
186 location is quantified from a plot of the proportion of bathymetric soundings that contain seagrass
187 at each depth bin (Fig. 3a). Although the chosen radius for selecting depth points is
188 problem-specific, the minimum radius must sample a sufficient number of points for estimating
189 Z_c . In general, an appropriate radius will produce a plot that indicates a decrease in the proportion
190 of points that are occupied by seagrass with increasing depth. An appropriate radius is also one
191 that creates a sample area around each point that has minimal overlap with the seagrass depth data
192 sampled by adjacent points.

193 A curve is fit to the sampled depth points using non-linear regression to characterize the
194 reduction in seagrass as a function of depth (Fig. 3b). Specifically, a decreasing logistic growth
195 curve is used with the assumption that seagrass decline with increasing depth is monotonic and
196 asymptotic at the maximum depth of colonization. The curve is fit by minimizing the residual
197 sums-of-squares with the Gauss-Newton algorithm (Bates and Chambers 1992) and user-supplied
198 starting parameters that are an approximate estimate of the curve characteristics. The model has
199 the following form:

$$Proportion = \frac{\alpha}{1 + e^{(\beta - Depth)/\gamma}} \quad (1) \quad \{eqn:prop\}$$

200 where the proportion of points occupied by seagrass at each depth is defined by a logistic curve
201 with an asymptote α , a midpoint inflection β , and a scale parameter γ . Starting values α , β , and γ
202 were estimated empirically from the observed data.

203 Finally, a simple linear curve is fit through the inflection point (β) of the logistic curve to
204 estimate the three measures of depth of colonization (Fig. 3c). The inflection point is considered

205 the depth at which seagrass are decreasing at a maximum rate and is used as the slope of the
206 linear curve. Three measures describing seagrass growth characteristics are obtained. The
207 maximum depth of seagrass colonization, $Z_{c, max}$, is the x-axis intercept of the linear curve. The
208 minimum depth of seagrass growth, $Z_{c, min}$, is the location where the linear curve intercepts the
209 asymptote of the logistic growth curve. This depth can be considered the start of the decline in
210 seagrass coverage with increasing depth. The median depth of seagrass colonization, $Z_{c, med}$, is
211 the depth halfway between $Z_{c, min}$ and $Z_{c, max}$. $Z_{c, med}$ was typically the inflection point of the
212 logistic growth curve. Functionally, each measure has specific ecological significance. The
213 median and maximum depth estimates describe the growth limitations of seagrasses as a function
214 of water clarity, whereas minimum depth of growth was often where the highest percentage of
215 seagrass coverage was observed in the sample. Median and maximum depth estimates differ in
216 that the former describes the median depth of the deep water edge, whereas the latter describes a
217 nominal characterization of maximum depth independent of outliers.

218 Estimates for each of the three Z_c measures are obtained only if specific criteria are met.
219 These criteria were implemented as a safety measure that ensures a sufficient amount and
220 appropriate quality of data were used. First, estimates were provided only if a sufficient number
221 of seagrass depth points were present within the radius of the grid point to estimate a logistic
222 growth curve. This criteria applies to the sample size as well as the number of points with
223 seagrass in the sample. The curve could not be estimated for small samples or if an insufficient
224 number of points contained seagrass regardless of sample size. Second, estimates were provided
225 only if an inflection point was present on the logistic curve within the range of the sampled depth
226 data. This criteria applied under two scenarios where the curve was estimated but a trend was not
227 adequately described by the sampled data. That is, a curve could be estimated that described only

228 the initial decrease in points occupied as a function of depth but the observed points do not occur
229 at depths deeper than the predicted inflection point. The opposite scenario occurred when a curve
230 was estimated but only the deeper locations beyond the inflection point were present in the
231 sample. Third, the estimate for $Z_{c, min}$ was set to zero depth if the linear curve through the
232 inflection point intercepted the asymptote at x-axis values less than zero. The estimate for $Z_{c, med}$
233 was also shifted to the depth value halfway between $Z_{c, min}$ and $Z_{c, max}$ if $Z_{c, min}$ was fixed at zero.
234 Finally, estimates were considered invalid if the 95% confidence interval for $Z_{c, max}$ included
235 zero. Methods used to determine confidence bounds on Z_c estimates are described below.

236 All estimates were obtained using custom-made functions in program R that were based
237 on the `nls` and `SSlogis` functions to fit nonlinear least squares using a self-starting logistic
238 growth model (Bates and Chambers 1992, R Development Core Team 2014). All seagrass depth
239 shapefiles were imported and processed in R using functions in the `rgeos` and `sp` packages
240 (Bivand et al. 2008, Bivand and Rundel 2014).

241 2.4 Comparison with segment-based approach and sensitivity analysis

242 Spatially-resolved estimates for seagrass Z_c were obtained for each of the four segments
243 described above. Segment-wide estimates obtained using methods in Hagy, In review were used
244 as a basis of comparison such that departures from these values were evidence of spatial
245 heterogeneity in seagrass growth patterns and improved clarity of description in depth estimates
246 using the new approach. A sampling grid of locations for estimating each of the three depth
247 values in Fig. 3 was created for each segment. The grid was masked by the segment boundaries,
248 whereas seagrass depth points used to estimate Z_c extended beyond the segment boundaries to
249 allow sampling by grid points that occurred near the edge of the segment. Initial spacing between

250 sample points was chosen arbitrarily as 0.02 decimal degrees, which is approximately 2 km at 30
251 degrees N latitude. The sampling radius around each sampling location in the grid was also
252 chosen as 0.02 decimal degrees to allow for complete coverage of seagrass within the segment
253 while also minimizing redundancy of information described by each location. In other words,
254 radii were chosen such that the seagrass depth points sampled by each grid location were only
255 partially overlapped by those sampled by neighboring points.

256 The ability to characterize heterogeneity in seagrass growth patterns using the grid-based
257 approach can be informed by evaluating the level of confidence associated with Z_c estimates.
258 Confidence intervals for non-linear regression can be estimated using a Monte Carlo simulation
259 approach that considers the variance and covariance between the model parameters and the depth
260 measurements (Hilborn and Mangel 1997). For simplicity, we assume that the variability
261 associated with parameter estimates is the dominant source of uncertainty. A 95% confidence
262 interval for each Z_c estimate was constructed by repeated sampling of a multivariate normal
263 distribution followed by prediction of the proportion of points occupied by seagrass as in eq. (1).
264 The sampling distribution assumes:

$$x \sim N(\mu, \Sigma) \quad (2)$$

265 where x is a predictor variable used in eq. (1) (depth) that follows a multivariate normal
266 distribution with mean μ , and variance-covariance matrix Σ . The mean values are set at the depth
267 value corresponding to the inflection point on the logistic curve and the predicted model
268 parameters (i.e., α , β , and γ), whereas Σ is the variance-covariance matrix of the model
269 parameters. A large number of samples ($n = 10000$) were drawn from the distribution to
270 characterize the uncertainty of the depth value at the inflection point. The 2.5th and 97.5th quantile

271 values of the sample were considered bounds on the 95% confidence interval.

272 The uncertainty associated with the Z_c estimates were based on the upper and lower limits
273 of the estimated inflection point on the logistic growth curve. This approach was used because
274 uncertainty in the inflection point is directly related to uncertainty in each of the Z_c estimates that
275 are based on the linear curve fit through the inflection point. Specifically, linear curves were fit
276 through the upper and lower estimates of the depth value at the inflection point to identify upper
277 and lower limits for the estimates of $Z_{c,min}$, $Z_{c,med}$, and $Z_{c,max}$. These values were compared
278 with the initial estimates from the linear curve that was fit through the inflection point on the
279 predicted logistic curve (i.e., Fig. 3c). This approach provided an indication of uncertainty for
280 individual estimates for the chosen radius. Uncertainty estimates were obtained for each Z_c
281 estimate for the grids in each segment.

282 **2.5 Developing a spatially coherent relationship of water clarity with depth 283 of colonization**

284 The relationship between seagrass depth limits and secchi measurements were explored
285 using established light requirements and attenuation equations. The traditional Lambert-Beer
286 equation describes the exponential decrease of light availability with depth:

$$I_z = I_O \cdot \exp(-K_d \cdot Z) \quad (3) \quad \{eqn:lambert\}$$

287 such that the irradiance of incident light at depth Z (I_z) can be estimated from the irradiance at
288 the surface (I_O) and a light extinction coefficient (K_d). Duarte (1991) indicate that minimum light
289 requirements for seagrass are on average 11% of surface irradiance. Light requirements may also
290 be species-specific and variable by latitude such that value may range from less than 5% to

291 greater than 30% (Dennison et al. 1993). Light requirements of seagrass at a specific location can
292 be estimated by rearranging eq. (3):

$$\%light = \exp(-K_d \cdot Z_{c,max}) \quad (4) \quad \{\text{eqn:perc}\}$$

293 where the percent light requirements of seagrass at $Z_{c,max}$ are empirically related to light
294 extinction. A conversion factor is often used to estimate the light extinction coefficient from
295 secchi depth Z_d , such that such that $c = K_d \cdot Z_d$, where c has been estimated as 1.7 (Poole and
296 Atkins 1929, Idso and Gilbert 1974). Thus, K_d can be replaced with the conversion factor and the
297 equation is rearranged to describe $Z_{c,max}$ as a function of secchi depth Z_d :

$$Z_{c,max} = \frac{-\log(0.20)}{1.7} \cdot Z_d \quad (5) \quad \{\text{eqn:sgrid}\}$$

298 A regression of seagrass depth estimates against secchi measurements is expected to have a slope
299 corresponding to the constant in eq. (5). For the current analysis, 20% light requirements were
300 assumed to be an approximate median requirement for seagrasses in Florida. Scatter in the
301 regression through these points can be considered biologically meaningful, such that points below
302 the curve are locations where seagrasses are observed at maximum depth with less irradiance than
303 expected given eq. (5), whereas points above the curve are those where seagrasses are growing
304 deeper than expected. The geographic coordinates for each secchi measurement in Tampa Bay
305 and the Indian River Lagoon were used as locations for estimating $Z_{c,max}$. These estimates were
306 compared with the averaged secchi estimates to identify light requirements at each location.
307 However, the relationship is expected to vary depending on the specific radius around each

308 sample point for estimating $Z_{c, max}$. An appropriate radius was chosen that minimized the
309 difference between the empirically estimated slope and that in eq. (5). The estimated light
310 requirements of each point were also plotted using the cartesian coordinates of each secchi
311 observation to evaluate spatial variation in seagrass growth as a function of light-limitation. Light
312 requirements were also summarized by individual segments in each bay to identify spatial trends
313 for relevant management units.

314 **3 Results**

315 **3.1 Segment characteristics and seagrass depth estimates**

316 Each of the four segments varied by several key characteristics that potentially explain
317 within-segment variation of seagrass growth patterns (Table 1). Mean surface area was 191.2
318 square kilometers, with area decreasing for the Big Bend (271.4 km), Indian River Lagoon (NA
319 km), Old Tampa Bay (205.5 km), and Choctawhatchee Bay (59.4 km) segments. Seagrass
320 coverage as a percentage of total surface area varied considerably by segment. Seagrasses covered
321 a majority of the surface area for the Big Bend segment (74.8 %), whereas coverage was much
322 less for Indian River Lagoon (NA %), Old Tampa Bay (11.9 %), and Choctawhatchee Bay (5.9
323 %). Visual examination of the seagrass coverage maps for the respective year of each segment
324 suggested that seagrasses were not uniformly distributed (Fig. 1). Seagrasses in the
325 Choctawhatchee Bay segments were generally sparse with the exception of a large patch located
326 to the west of the inlet connection with the Gulf of Mexico. Seagrasses in the Big Bend segment
327 were located throughout the segment with noticeable declines near the outflow of the
328 Steinhatchee River, whereas seagrasses in Old Tampa Bay and the Indian River Lagoon segment
329 were generally confined to shallow areas near the shore. Seagrass coverage showed a partial

330 decline toward the northern ends of both Old Tampa Bay and the Indian River Lagoon segments.
331 Mean depth was less than 5 meters for each segment, excluding Choctawhatchee Bay which was
332 slightly deeper than the other segments on average (5.3 m). Maximum depths were considerably
333 deeper for Choctawhatchee Bay (11.9 m) and Old Tampa Bay (10.4 m), as compared to the Big
334 Bend (3.6 m) and Indian River Lagoon (NA m) segments. Water clarity as indicated by average
335 secchi depths was similar between the segments (1.5 m), although Choctawhatchee Bay had a
336 slightly higher average (2.1 m).

337 Estimates of seagrass Z_c using a segment-wide approach that did not consider spatially
338 explicit locations indicated that seagrasses generally did not grow deeper than three meters in any
339 of the segments (Table 2). Maximum and median depth of colonization were deepest for the Big
340 Bend segment (3.7 and 2.5 m, respectively) and shallowest for Old Tampa Bay (1.1 and 0.9 m),
341 whereas the minimum depth of colonization was deepest for Choctawhatchee Bay (1.8 m) and
342 shallowest for Old Tampa Bay (0.6 m). Averages of all grid-based estimates for each segment
343 were different than the segment wide estimates, which suggests potential bias associated with
344 using a whole segment as a relevant spatial unit for estimating depth of colonization. In most
345 cases, the averages of all grid-based estimates were less than the whole segment estimates,
346 suggesting the latter provided an over-estimate of seagrass growth limits. For example, the
347 average of all grid estimates for $Z_{c, max}$ in the Big Bend region suggested seagrasses grew to
348 approximately 2 m, which was 1.6 m less than the whole segment estimate. This reduction is
349 likely related to improved resolution of seagrass depth limits near the outflow of the Steinhatchee
350 river. Although reductions were not as severe for the average grid estimates for the remaining
351 segments, considerable within-segment variation was observed depending on grid location. For
352 example, the deepest estimate for $Z_{c, min}$ (2 m) in the Indian River Lagoon exceeded the average

353 of all grid locations for $Z_{c, max}$ (1.7 m). $Z_{c, min}$ also had minimum values of zero meters for the
354 Big Bend and Old Tampa Bay segments, suggesting that seagrasses declined continuously from the
355 surface for several locations.

356 Visual interpretations of seagrass depth estimates using the grid-based approach provided
357 further information on the distribution of seagrasses in each segment (Fig. 4). Spatial
358 heterogeneity in depth limits was particularly apparent for the Big Bend and Indian River Lagoon
359 segments. As expected, depth estimates indicated that seagrasses grew deeper at locations far
360 from the outflow of the SteinHatchee River in the Big Bend segment. Similarly, seagrasses were
361 limited to shallower depths at the north end of the Indian River Lagoon segment near the Merrit
362 Island National Wildlife Refuge. Seagrasses were estimated to grow at maximum depths up to 2.1
363 m on the eastern portion of the Indian River Lagoon segment. Spatial heterogeneity was less
364 distinct for the remaining segments. Seagrasses in Old Tampa Bay grew deeper in the northeast
365 portion of the segment and declined to shallower depths near the inflow at the northern edge.
366 Spatial variation in the Choctawhatchee Bay segment was not apparent, although the maximum
367 Z_c estimate was observed in the northeast portion of the segment. Z_c values were not available for
368 all grid locations givne the limitations imposed in the estimation method. Z_c could not be
369 estimated in locations where seagrasses were sparse or absent, nor where seagrasses were present
370 but the sampled points did not exhibit a sufficient decline with depth. The latter scenario was
371 most common in Old Tampa Bay and Choctawhatchee Bay where seagrasses were unevenly
372 distributed or confined to shallow areas near the shore. The former scenario was most common in
373 the Big Bend segment where seagrasses were abundant but locations near the shore were
374 inestimable given that seagrasses did not decline appreciably within the depths that were sampled.

375 Uncertainty for estimates of $Z_{c, max}$ indicated that confidence intervals were generally

376 acceptable (i.e., greater than zero), although the ability to discriminate between the three depth
377 estimates varied by segment (Fig. 5 and Table 3). Mean uncertainty for all estimates in each
378 segment measured as the width of a 95% confidence interval was 0.2 m. Greater uncertainty was
379 observed for Choctawhatchee Bay (mean width of all confidence intervals was 0.7 m) and Old
380 Tampa Bay (0.4 m), compared to the Big Bend (0.1 m) and Indian River Lagoon (0.1 m)
381 segments. The largest confidence interval for each segment was 1 m for Old Tampa Bay, 2.5 m for
382 Choctawhatchee Bay, 0.4 m for the Big Bend, and 0.3 m for the Indian River Lagoon segments.
383 However, most confidence intervals for the remaining grid locations were much smaller than the
384 maximum in each segment. A comparison of overlapping confidence intervals for $Z_{c,min}$, $Z_{c,med}$,
385 and $Z_{c,max}$ at each grid location indicated that not every measure was unique. Specifically, only
386 12.5% of grid points in Choctawhatchee Bay and 38.9% in Old Tampa Bay had significantly
387 different estimates, whereas 84% of grid points in the Indian River Lagoon and 94.1% of grid
388 points in the Big Bend segments had estimates that were significantly different. By contrast, all
389 grid estimates in Choctawhatchee Bay and Indian River Lagoon had $Z_{c,max}$ estimates that were
390 significantly greater than zero, whereas all but 10% of grid points in Old Tampa Bay and 5.6% of
391 grid points in the Big Bend segment had $Z_{c,max}$ estimates significantly greater than zero.

392 **3.2 Evaluation of seagrass light requirements**

393 Estimates of seagrass light requirements for all segments of Tampa Bay and the Indian
394 River Lagoon indicated substantial variation, both between and within the different bays (Table 4
395 and Figs. 6 and 7). Seagrass Z_c estimates were obtained for 51 locations in Tampa Bay and 80
396 locations in the Indian River Lagoon where secchi observations were available in the Florida IWR
397 database. Mean secchi depth for all recorded observations was 1.8 m ($n = 51$) for Tampa Bay and

398 1 m ($n = 80$) for Indian River Lagoon. Mean light requirements were significantly different
399 between the bays (two-sided t-test, $t = 8.1$, $df = 104.1$, $p < 0.001$) with a mean requirement of
400 21.9% for Tampa Bay and 10.7% for Indian River Lagoon. Within each bay, light requirements
401 were significantly different between segments (ANOVA, $F = 3.5$, $df = 3, 47$, $p = 0.02$ for Tampa
402 Bay, $F = 4.0$, $df = 7, 72$, $p = 0.001$ for Indian River Lagoon). However, post-hoc evaluation of
403 all pair-wise comparisons of mean light requirements indicated that significant differences were
404 only observed between a few segments within each bay. Significant differences in Tampa Bay
405 were observed between Old Tampa Bay and Hillsborough Bay (Tukey multiple comparisons, $p =$
406 0.119). Significant differences in the Indian River Lagoon were observed between the Upper
407 Indian River Lagoon and Banana River ($p = 0.998$), the Upper Indian River Lagoon and Lower
408 Indian River Lagoon ($p = 0.023$), and Upper Indian River Lagoon and Lower St. Lucie ($p =$
409 0.018) segments. In general, spatial variation of light requirements in Tampa Bay suggested that
410 seagrasses were less light-limited (i.e., lower percent light requirements at $Z_{c,max}$) in
411 Hillsborough Bay and western areas of Lower Tampa Bay near the Gulf of Mexico (Fig. 6).
412 Seagrassess in the Indian River Lagoon were generally less light-limited towards the south and in
413 the Banana River segment (Fig. 7).

414 **4 Discussion**

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Table 1: Characteristics of coastal segments used to evaluate seagrass depth of colonization estimates (see Fig. 1 for spatial distribution). Year is the date of the seagrass coverage and bathymetric data. Latitude and longitude are the geographic centers of each segment. Area and depth values are meters and square kilometers, respectively. Secchi measurements (m) were obtained from the Florida Department of Environmental Protection’s Impaired Waters Rule (IWR), update number 40. Secchi mean and standard errors are based on all observations within the ten years preceding each seagrass survey.^{tab:seg_summ}

	Big Bend	Choctawhatchee Bay	Old Tampa Bay	Upper Indian R. Lagoon
Year ^a	2006	2007	2010	2009
Latitude	29.61	30.43	27.94	28.61
Longitude	-83.48	-86.54	-82.62	-80.77
Surface area	271.37	59.41	205.50	228.52
Seagrass area	203.02	3.51	24.48	74.89
Depth (mean)	1.41	5.31	2.56	1.40
Depth (max)	3.60	11.90	10.40	3.70
Secchi (mean)	1.34	2.14	1.41	1.30
Secchi (se)	0.19	0.08	0.02	0.02

^a Seagrass coverage data sources, see section 2.1.2 for bathymetry data sources:

Big Bend: http://atoll.floridamarine.org/Data/metadata/SDE_Current/seagrass_bigbend_2006_poly.htm

Choctawhatchee Bay: http://atoll.floridamarine.org/data/metadata/SDE_Current/seagrass_chotawhatchee_2007_poly.htm

Tampa Bay: http://www.swfwmd.state.fl.us/data/gis/layer_library/category/swim

Indian R. Lagoon: <http://www.sjrwmd.com/gisdevelopment/docs/themes.html>

Table 2: Summary of seagrass depth estimates (m) for each segment using all grid locations in Fig. 4. Whole segment estimates were obtained from all seagrass depth data for each segment.^{tab:est_summ}

Segment ^a	Whole segment	Mean	St. Dev.	Min	Max
BB					
$Z_{c,min}$	1.25	1.33	0.82	0.00	2.64
$Z_{c,med}$	2.46	1.68	0.77	0.66	2.85
$Z_{c,max}$	3.66	2.03	0.80	0.86	3.31
CB					
$Z_{c,min}$	1.82	1.57	0.72	0.00	2.27
$Z_{c,med}$	2.16	1.98	0.46	1.19	2.48
$Z_{c,max}$	2.50	2.40	0.32	1.86	2.74
OTB					
$Z_{c,min}$	0.61	0.52	0.29	0.05	0.98
$Z_{c,med}$	0.88	0.85	0.27	0.30	1.24
$Z_{c,max}$	1.15	1.18	0.39	0.37	1.81
UIRL					
$Z_{c,min}$	1.25	1.32	0.23	1.00	2.02
$Z_{c,med}$	1.51	1.49	0.21	1.12	2.08
$Z_{c,max}$	1.77	1.66	0.21	1.23	2.14

^aBB: Big Bend, CB: Choctawhatchee Bay, OTB: Old Tampa Bay, UIRL: Upper Indian River Lagoon.

Table 3: Summary of uncertainty for seagrass depth estimates (m) for each segment using all grid locations in Fig. 5. The uncertainty values are equally applicable to each seagrass depth measure ($Z_{c,min}$, $Z_{c,med}$, $Z_{c,max}$).^{tab:sens_summ}

Segment ^a	Mean	St. Dev	Min	Max
BB	0.11	0.10	0.01	0.35
CB	0.72	0.74	0.22	2.52
OTB	0.36	0.28	0.11	1.04
UIRL	0.09	0.06	0.01	0.30

^aBB: Big Bend, CB: Choctawhatchee Bay, OTB: Old Tampa Bay, UIRL: Upper Indian River Lagoon.

Table 4: Summary of water clarity data and estimated light requirements for all bay segments of the Indian River Lagoon and Tampa Bay. Water clarity data were obtained from secchi observations in the Florida Impaired Waters Rule database for all available locations and dates within ten years of the seagrass survey in each bay. Values are minimum and maximum years of secchi data, sample size of secchi data (n_{Secchi}), sample size of seagrass depth estimates (n_Z) at each unique secchi location, mean values (m) of secchi data, mean $Z_{c,max}$, and estimated % light requirements for each segment. Summaries are based primarily on data in Figs. 6 and 7.^a

Segment ^a	Min year	Max year	n_{Secchi}	n_Z	Secchi	$Z_{c,max}$	% light
Indian River Lagoon							
BR	2000	2009	909	21	1.06	1.27	17.91
LCIRL	2000	2009	656	19	1.03	1.36	11.62
LIRL	2000	2005	111	6	0.93	1.88	3.68
LML	2000	2009	239	13	1.11	1.13	14.07
LSL	2000	2005	52	3	0.94	2.90	0.97
UCIRL	2000	2009	1165	35	1.13	1.21	9.33
UIRL	2000	2009	599	15	1.30	1.15	22.30
UML	2000	2009	258	11	1.03	1.42	14.96
Tampa Bay							
HB	2001	2003	412	10	1.25	1.25	16.24
LTB	2001	2009	807	26	2.47	2.06	19.18
MTB	2001	2009	571	16	2.18	1.76	25.27
OTB	2001	2003	671	15	1.44	1.18	23.78

^aBR: Banana R., LCIRL: Lower Central Indian R. Lagoon, LIRL: Lower Indian R. Lagoon, LML: Lower Mosquito Lagoon, LSL: Lower St. Lucie, UCIRL: Upper Central Indian R. Lagoon, UIRL: Upper Indian R. Lagoon, UML: Upper Mosquito Lagoon, HB: Hillsborough Bay, LTB: Lower Tampa Bay, MTB: Middle Tampa Bay, OTB: Old Tampa Bay.

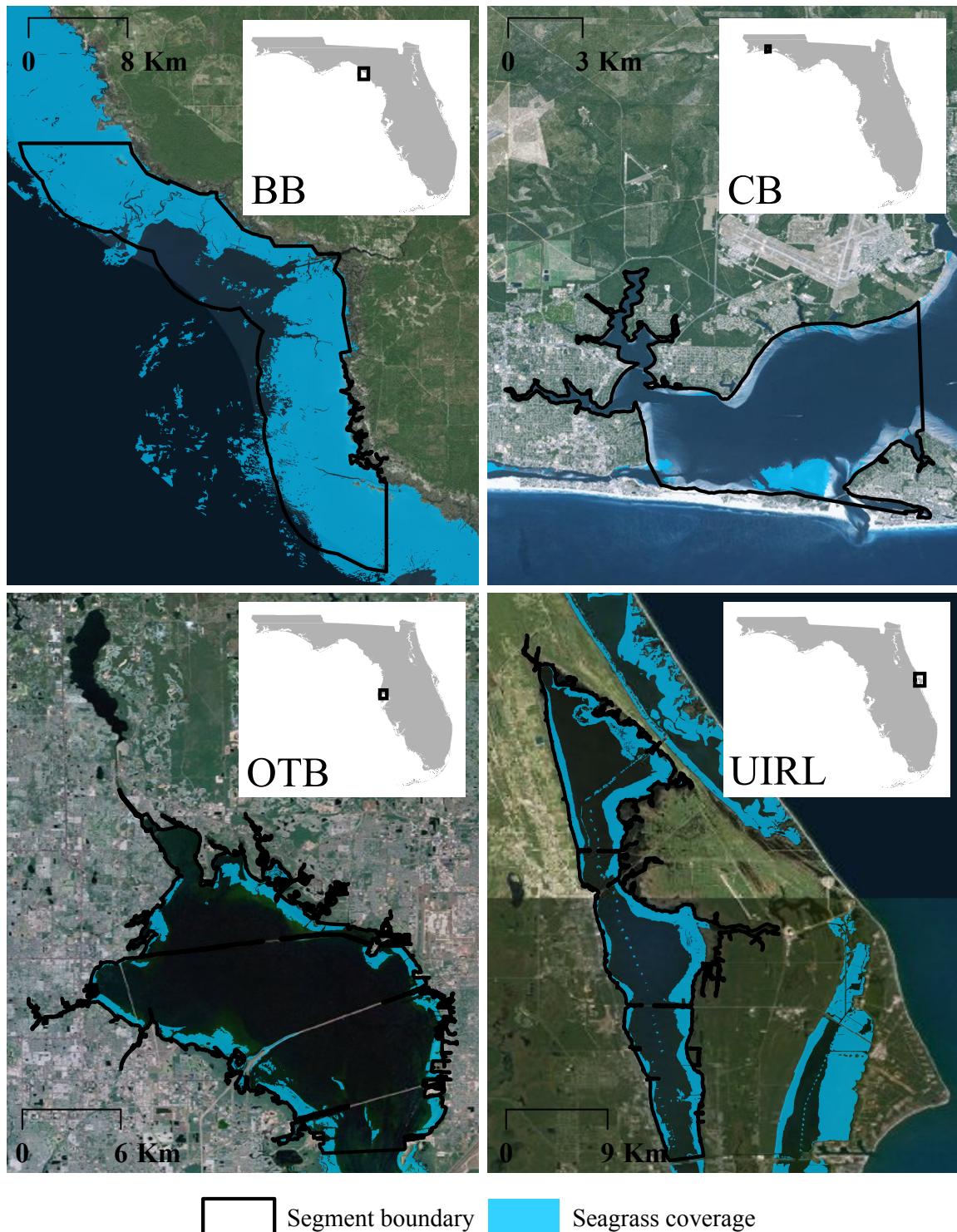
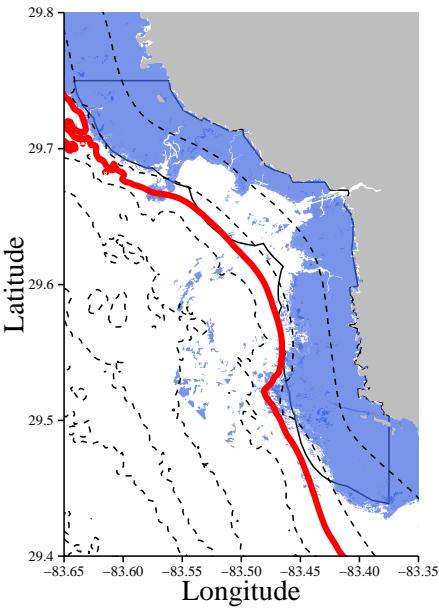


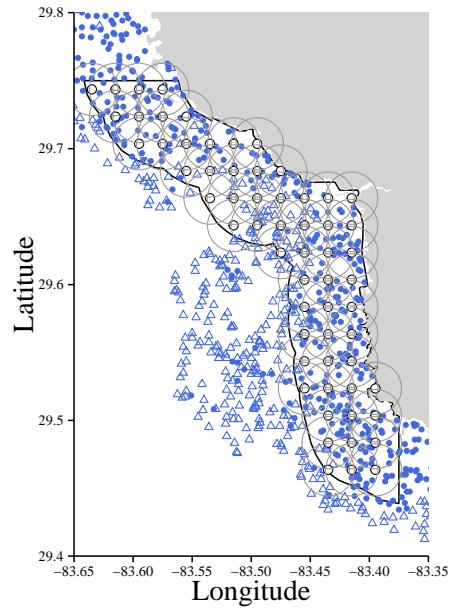
Fig. 1: Locations and seagrass coverage of estuary segments used to evaluate depth of colonization estimates. Seagrass coverage layers are from 2007 (CB: Choctawhatchee Bay), 2006 (BB: Big Bend), 2010 (OTB: Old Tampa Bay), and 2009 (UIRL: Upper Indian R. Lagoon).

{fig:seg_a}

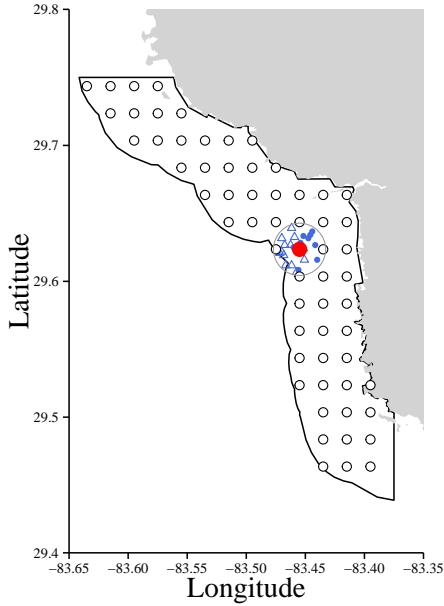
(a) Seagrass coverage and bathymetry for the segment



(b) Grid of locations and sample areas for estimates



(c) Sampled seagrass data for a test point



- Seagrass coverage
- 2 m depth contours
- Estimated depth limit for segment

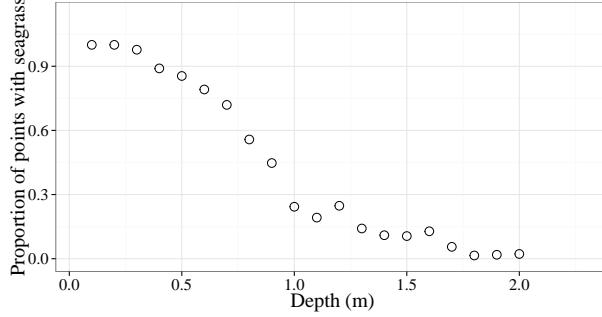
- △ Seagrass absent
- Seagrass present

- Estimation grid
- Test point
- Sample area

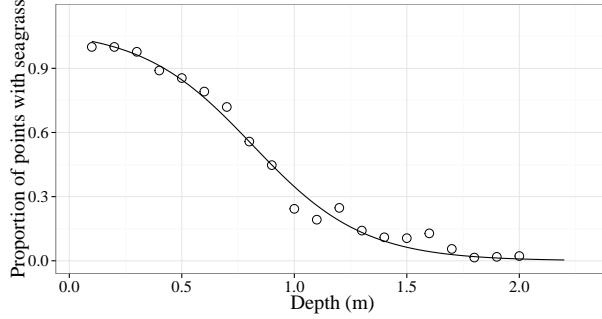
Fig. 2: Examples of data and grid locations for estimating seagrass depth of colonization for a region of the Big Bend, Florida. Fig. 2a shows the seagrass coverage and depth contours at 2 meter intervals, including the whole segment estimate for depth of colonization. Fig. 2b shows a grid of sampling locations with sampling radii for estimating Z_c and seagrass depth points derived from bathymetry and seagrass coverage layers. Fig. 2c shows an example of sampled seagrass depth points for a test location. Estimates in Fig. 3 were obtained from the test location in Fig. 2c.

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(a) Proportion of points with seagrass by depth



(b) Logistic growth curve fit through points



(c) Depth estimates

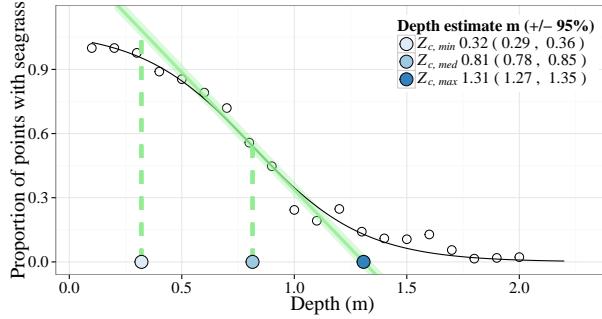


Fig. 3: Methods for estimating seagrass depth of colonization using sampled seagrass depth points around a single location. Fig. 3a is the proportion of points with seagrass by depth using depth points within the buffer of the test point in Fig. 2. Fig. 3b adds a decreasing logistic growth curve fit through the points. Fig. 3c shows three depth estimates based on a linear curve fit through the inflection point of logistic growth curve.

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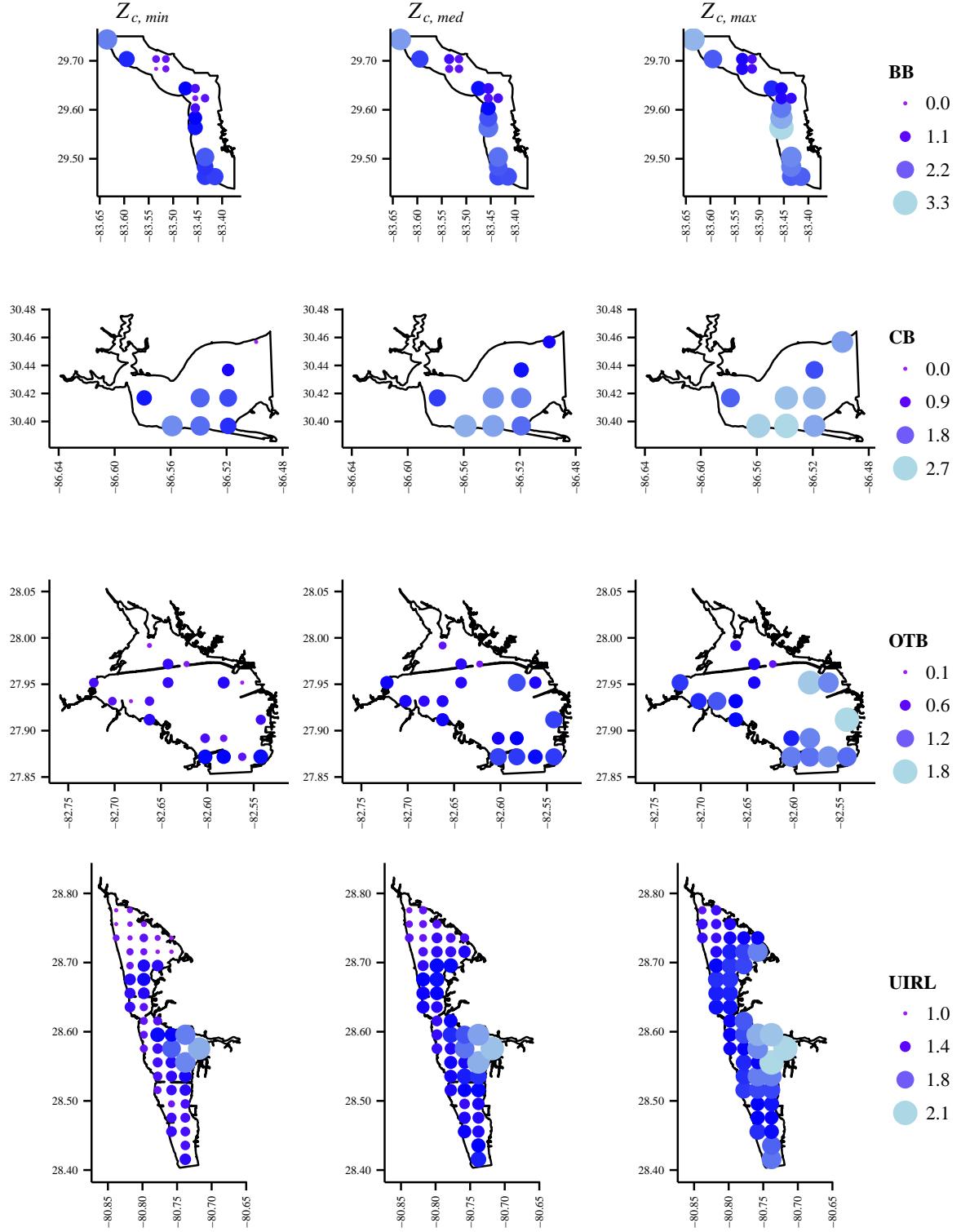


Fig. 4: Spatially-resolved estimates of seagrass depth limits (m) for four coastal segments of Florida. Estimates include minimum ($Z_{c, \text{min}}$), median ($Z_{c, \text{med}}$), and maximum depth of colonization ($Z_{c, \text{max}}$). Estimates are assigned to grid locations for each segment, where grid spacing was fixed at 0.02 decimal degrees. Radii for sampling seagrass bathymetric data around each grid location were fixed at 0.06 decimal degrees. BB: Big Bend, CB: Choctawhatchee Bay, OTB: Old Tampa Bay, UIRL: Upper Indian R. Lagoon.

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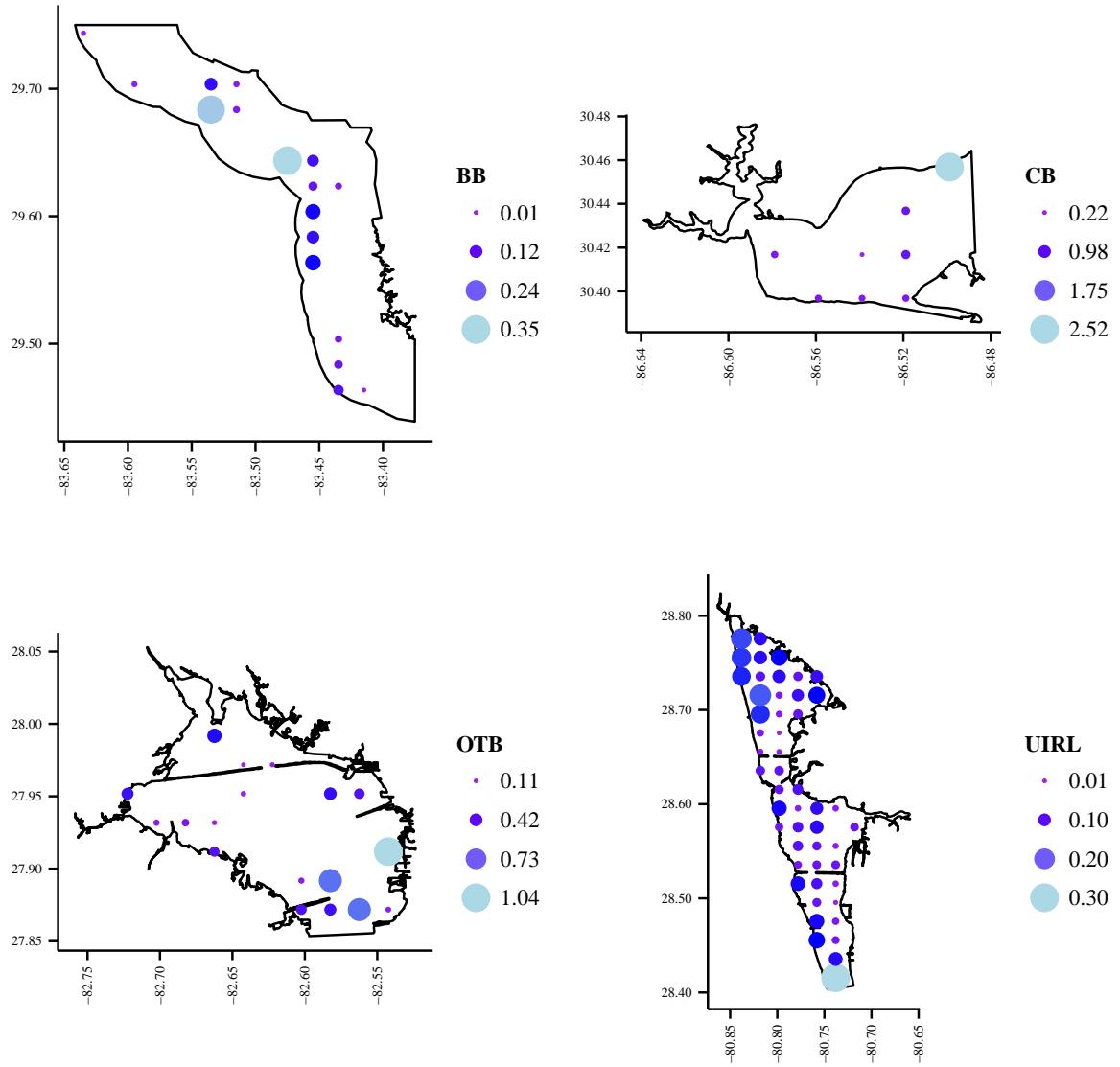


Fig. 5: Size of confidence intervals (m) for depth of colonization estimates in Fig. 4. Points are colored and sized based on the difference between the upper and lower bounds of a 95% confidence interval for all three Z_c estimates ($Z_{c,min}$, $Z_{c,med}$, $Z_{c,max}$). Bounds were obtained using Monte Carlo simulations to estimate uncertainty associated with the inflection point of the estimated logistic curve (Fig. 3) for each sample. BB: Big Bend, CB: Choctawhatchee Bay, OTB: Old Tampa Bay, UIRL: Upper Indian R. Lagoon.

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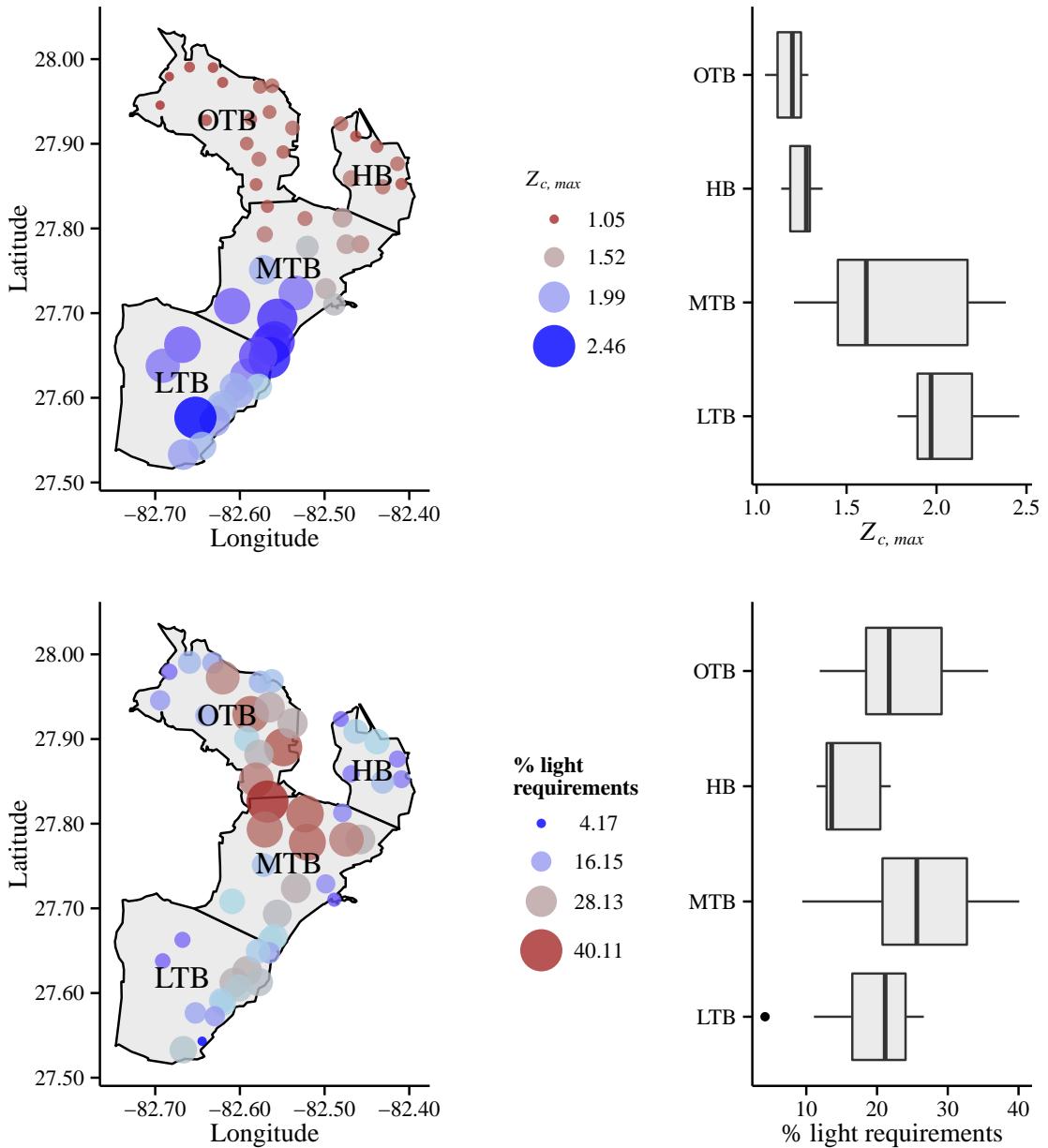


Fig. 6: Estimated maximum depths of seagrass colonization and light requirements for multiple locations in Tampa Bay, Florida. Map locations are georeferenced observations of water clarity from secchi measurements in the Florida Impaired Waters Rule database, update 40. Estimates are also summarized by bay segment as boxplots where the dimensions are the 25th percentile, median, and 75th percentile. Whiskers extend beyond the boxes as 1.5 multiplied by the interquartile range. Light requirements are based on averaged secchi values within ten years of the seagrass coverage data and estimated maximum depth of colonization using a radius of 0.02 decimal degrees for each secchi location to sample seagrass depth points. HB: Hillsborough Bay, LTB: Lower Tampa Bay, MTB: Middle Tampa Bay, OTB: Old Tampa Bay.

{fig:light}

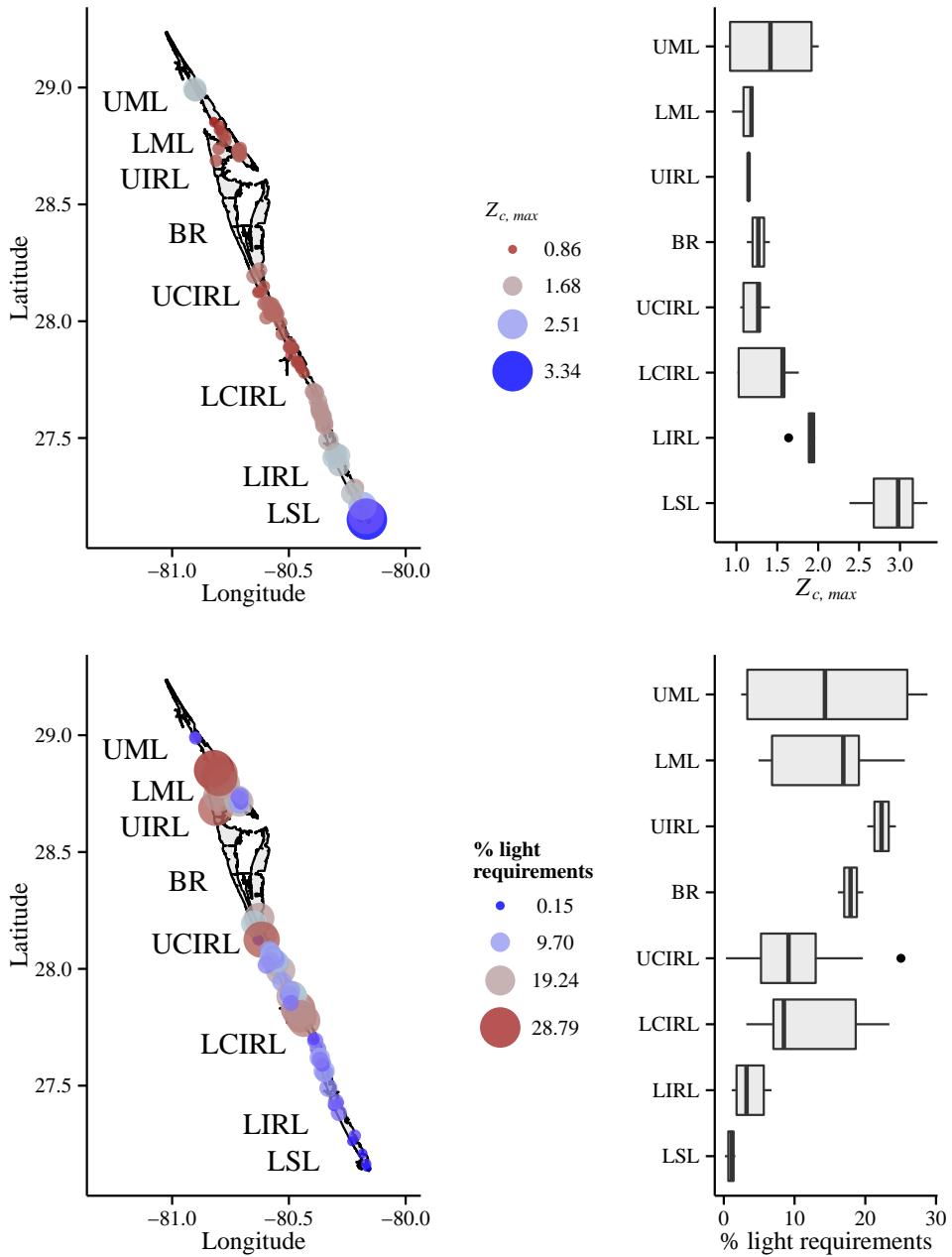


Fig. 7: Estimated maximum depths of seagrass colonization and light requirements for multiple locations in Indian River Lagoon, Florida. Map locations are georeferenced observations of water clarity in the Florida Impaired Waters Rule database, update 40. Estimates are also summarized by bay segment as boxplots as in Fig. 6. Light requirements are based on averaged secchi values within ten years of the seagrass coverage data and estimated maximum depth of colonization using a radius of 0.02 decimal degrees for each secchi location to sample seagrass depth points. BR: Banana R., LCIRL: Lower Central Indian R. Lagoon, LIRL: Lower Indian R. Lagoon, LML: Lower Mosquito Lagoon, LSL: Lower St. Lucie, UCIRL: Upper Central Indian R. Lagoon, UIRL: Upper Indian R. Lagoon, UML: Upper Mosquito Lagoon.

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