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A reproducible and empirical approach for estimating spatially-referenced depths of seagrass 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-referenced approach to estimate seagrass depth of {acro:doc}
76 colonization (DoC) relied extensively on data and partially on methods described in [Hagy, In](#)
77 [review](#). The following is a summary of locations and data sources, methods and rationale for
78 incorporating spatial information in seagrass DoC estimates, and evaluation of the approach
79 including relationships with water clarity.

80 **2.1 Locations and data sources**

81 Four unique locations were chosen for the analysis: Choctowatchee Bay (Panhandle), Big
82 Bend region (northeast Gulf of Mexico), Tampa Bay (central Gulf Coast of Florida), and Indian
83 River Lagoon (east coast) ([Table 1](#) and [Fig. 1](#)). These locations represent different geographic
84 regions in the state, in addition to having available data and observed gradients in water clarity
85 that contribute to heterogeneity in seagrass growth patterns. For example, the Big Bend region
86 was chosen based on location near an outflow of the Steinhatchee River where higher
87 concentrations of dissolved organic matter are observed. Seagrasses near the outflow were
88 observed to grow at shallower depths as compared to locations far from the river source. Coastal
89 regions and estuaries in Florida are partitioned as distinct spatial units based on a segmentation
90 scheme developed by US Environmental Protection Agency (EPA) for the development of {acro:EPA}
91 numeric nutrient criteria. One segment from each geographic location was used to describe the
92 approach for estimating seagrass DoC and to evaluate variation in growth patterns DoC. The
93 segments included 0303 (Choctowatchee Bay), 0820 (Big Bend region), 0902 (Tampa Bay), and

94 1502 (Indian River Lagoon), where the first two digits indicate the estuary and the last two digits
95 indicate the segment within the estuary. Each segment was a smaller unit within a larger estuary
96 or coastal region.

97 Data used to estimate seagrass DoC were primarily obtained from publically available {acro:GIS}
98 Geographic Information System (GIS) products. At the most generic level, spatially-referenced
99 information describing seagrass aerial coverage combined with co-located bathymetric depth
100 information were used to estimate DoC. These data products are available in coastal regions of
101 Florida through the US Geological Survey, Florida Department of Environmental Protection, and
102 watershed management districts. Data are generally more available in larger estuaries that are of
103 specific management concern. For example, seagrass coverage data are available from 1950
104 (Tampa Bay) to present day (multiple estuaries), with more recent products available at annual or
105 biennial intervals. Seagrass coverage maps are less frequent in areas with lower population
106 densities (e.g., Big Bend region) or where seagrass is naturally absent (northeast Florida).

107 Seagrass maps were produced using photo-interpretations of aerial images to categorize coverage
108 as absent, discontinuous (patchy), or continuous. For this analysis, we considered seagrass
109 coverage as being only present (continuous and patchy) or absent since the former did not
110 represent unequivocal categories between regions.

111 Seagrass coverage maps were combined with bathymetric depth layers to characterize
112 location and depth of growth in each location. Bathymetric depth layers for each location were
113 obtained from the National Oceanic and Atmospheric Administration's (NOAA) National
114 Geophysical Data Center as either Digital Elevation Models (DEMs) or raw sounding data from {acro:DEM}
115 hydroacoustic surveys. Tampa Bay data provided by the Tampa Bay National Estuary Program
116 are described in [Tyler et al. \(2007\)](#). Bathymetric data for the Indian River Lagoon were obtained

117 from the St. John's Water Management District ([Coastal Planning and Engineering 1997](#)). NOAA
118 products were referenced to mean lower low water, whereas Tampa Bay data were referenced to
119 the North American Vertical Datum of 1988 (NAVD88) and the Indian River Lagoon data were
120 referenced to mean sea level. Depth layers were combined with seagrass coverage layers using
121 standard union techniques for raster and vector layers in ArcMap 10.1 ([Environmental Systems](#)
122 [Research Institute 2012](#)). To reduce computation time, depth layers were first masked using a 1
123 km buffer of the seagrass coverage layer. The final layer used for analysis was a point layer with
124 attributes describing location (latitude, longitude, segment), depth (m), and seagrass (present,
125 absent). All spatial data were referenced to the North American Datum of 1983 as geographic
126 coordinates. Depth values in each seagrass layer were further adjusted from the relevant vertical
127 reference datum to local mean sea level (MSL) using the NOAA VDatum tool
128 (<http://vdatum.noaa.gov/>).
129 {acro:NAVD88}

2.2 Segment-based estimates of seagrass depth of colonization

130 [Hagy, In review](#) describe an approach to estimate seagrass DoC for individual coastal
131 segments. The approach described herein is theoretically similar to the initial method, although
132 the latter technique has a spatial resolution that uses segments as the smallest measurable unit.
133 Seagrass depth data described above are used to estimate maximum (Z_{cMax}) and median ($Z_{c50\%}$)
134 seagrass DoC, where the maximum depth is defined as the deepest depth at which a “significant”
135 coverage of seagrasses occurred in a segment and the median depth is defined as the median depth
136 occurring at the deep water edge. The seagrass depth points are grouped into bins and the
137 proportion of points within each depth bin that contain seagrass are quantified. Both seagrass
138 DoC estimates are obtained from a plot of proportion of points occupied at each depth bin. In

139 general, the plot is characterized by a decreasing trend such that the proportion of occupied points
140 by depth bin decreases and eventually flattens with increasing depth. A regression is fit on this
141 descending portion of the curve such that the intercept point on the x-axis is considered the
142 maximum depth of colonization. The median portion of this curve is considered the median depth
143 of the deepwater edge of seagrass.

144 Considerable spatial heterogeneity in the observed seagrass growth patterns suggests that
145 a segment-wide estimate of seagrass DoC may be inadequate for fully characterizing growth
146 patterns, particularly for the examples in the current analysis. Fig. 2 illustrates spatial variation in
147 seagrass distribution for a location in the Big Bend region of Florida. Using methods in Hagy, In
148 review, the estimate for median seagrass DoC for the segment is over- and under-estimated for
149 different locations. In particular, DoC is greatly over-estimated at the outflow of the Steinhatchee
150 River where high concentrations of dissolved organic matter reduce water clarity and naturally
151 limit seagrass growth. This example suggests that estimates of DoC may be needed at finer spatial
152 scales to provide a more robust determination of restoration targets and nutrient criteria. Although
153 the current example is immediately relevant for the Big Bend region of Florida, the remaining
154 examples discussed throughout also provide a justification for a more comprehensive assessment
155 of seagrass growth patterns.

156 **2.3 Estimating seagrass depth of colonization using spatial information**

157 The approach used to estimate seagrass DoC with spatial information has several key
158 differences that make it distinct from the original method. As before, seagrass DoC estimates are
159 based on empirical measures of the frequency occurrence of seagrass with increasing depth. The
160 first difference is that maximum DoC is estimated using a logistic growth curve fit through the

161 data, as compared to a simple linear regression in the previous example. Second, a third measure
162 describing the minimum depth of colonization was defined, in addition to median and maximum
163 depth of growth. The third and most important difference is that the estimates are assigned to
164 discrete cartesian locations, using either a grid of points or as a single location of interest.
165 Methods and implications of these differences are described below.

166 The spatially-referenced approach for estimating DoC begins by creating a grid of points
167 within the segment where the same process for estimating DoC is used for each point.
168 Alternatively, a single location of interest can be chosen rather than a grid-based design. Seagrass
169 depth data (i.e., merged bathymetric and seagrass coverage data) that are located within a set
170 radius from the chosen locations are selected for estimating seagrass DoC values (Fig. 3). The
171 estimate for each location is quantified from a plot of the proportion of bathymetric soundings
172 that contain seagrass at each depth bin (Fig. 4a). Although the chosen radius for selecting depth
173 points is problem-specific, the minimum radius must sample a sufficient number of points for
174 estimating DoC. In general, an appropriate radius will produce a plot that indicates a decrease in
175 the proportion of points that are occupied by seagrass with increasing depth. An appropriate
176 radius is also one that creates a sample area around each point that has minimal overlap with the
177 seagrass depth data sampled by adjacent points.

178 A curve is fit to the sampled depth points using non-linear regression to characterize the
179 reduction in seagrass as a function of depth (Fig. 4b). Specifically, a decreasing logistic growth
180 curve is used with the assumption that seagrass decline with increasing depth is monotonic and
181 asymptotic at the maximum depth of colonization. The curve is fit by minimizing the residual
182 sums-of-squares with the Gauss-Newton algorithm (Bates and Chambers 1992) and user-supplied
183 starting parameters that are an approximate estimate of the curve characteristics. The model has

184 the following form:

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

185 where the proportion of points occupied by seagrass at each depth is defined by a logistic curve

186 with an asymptote α , a midpoint inflection β , and a scale parameter γ . Starting values α , β , and γ

187 were estimated empirically from the observed data.

188 Finally, a simple linear curve is fit through the inflection point (β) of the logistic curve to

189 estimate the three measures of depth of colonization (Fig. 4c). The inflection point is considered

190 the depth at which seagrass are decreasing at a maximum rate and is used as the slope of the linear

191 curve. Three measures describing seagrass growth characteristics are obtained. The maximum

192 depth of seagrass colonization, DOC_{max} , is the x-axis intercept of the linear curve. The minimum

193 depth of seagrass growth, DOC_{min} , is the location where the linear curve intercepts the

194 asymptote of the logistic growth curve. This depth can be considered the start of the decline in

195 seagrass coverage with increasing depth. The median depth of seagrass colonization, DOC_{med} , is

196 the depth halfway between DOC_{min} and DOC_{max} . DOC_{med} was typically the inflection point of

197 the logistic growth curve. Functionally, each measure has specific ecological significance. The

198 median and maximum depth estimates describe the growth limitations of seagrasses as a function

199 of water clarity, whereas minimum depth of growth was often where the highest percentage of

200 seagrass coverage was observed in the sample. Median and maximum depth estimates differ in

201 that the former describes the median depth of the deep water edge, whereas the latter describes a

202 nominal characterization of maximum depth independent of outliers.

203 Estimates for each of the three DoC measures are obtained only if specific criteria are met.

204 These criteria were implemented as a safety measure that ensures a sufficient amount and

appropriate quality of data were used. First, estimates were provided only if a sufficient number of seagrass depth points were present within the radius of the grid point to estimate a logistic growth curve. This criteria applies to the sample size as well as the number of points with seagrass in the sample. The curve could not be estimated for small samples or if an insufficient number of points contained seagrass regardless of sample size. Second, estimates were provided only if an inflection point was present on the logistic curve within the range of the sampled depth data. This criteria applied under two scenarios where the curve was estimated but a trend was not adequately described by the sampled data. That is, a curve could be estimated that described only the initial decrease in points occupied as a function of depth but the observed points do not occur at depths deeper than the predicted inflection point. The opposite scenario occurred when a curve was estimated but only the deeper locations beyond the inflection point were present in the sample. Finally, the estimate for DOC_{min} was set to zero depth if the linear curve through the inflection point intercepted the asymptote at x-axis values less than zero. The estimate for DOC_{med} was also shifted to the depth value halfway between DOC_{min} and DOC_{max} if DOC_{min} was fixed at zero.

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

225 **2.4 Comparison with segment-based approach and sensitivity analysis**

226 Spatially-referenced estimates for seagrass DoC were obtained for each of the four
227 segments described above. Segment-wide estimates obtained using methods in [Hagy, In review](#)
228 were used as a basis of comparison such that departures from these values were evidence of
229 spatial heterogeneity in seagrass growth patterns and improved clarity of description in depth
230 estimates using the new approach. A sampling grid of locations for estimating each of the three
231 depth values in Fig. 4 was created for each segment. The grid was masked by the segment
232 boundaries, whereas seagrass depth points used to estimate DoC extended beyond the segment
233 boundaries to allow sampling by grid points that occurred near the edge of the segment. Initial
234 spacing between sample points was chosen arbitrarily as 0.02 decimal degrees, which is
235 approximately 2 km at 30 degrees N latitude. The sampling radius around each sampling location
236 in the grid was also chosen as 0.02 decimal degrees to allow for complete coverage of seagrass
237 within the segment while also minimizing redundancy of information described by each location.
238 In other words, radii were chosen such that the seagrass depth points sampled by each grid
239 location were only partially overlapped by those sampled by neighboring points.

240 The ability to characterize heterogeneity in seagrass growth patterns using the grid-based
241 approach can be informed by evaluating the level of confidence associated with DoC estimates.
242 Confidence intervals for non-linear regression can be estimated using a Monte Carlo simulation
243 approach that considers the variance and covariance between the model parameters and the depth
244 measurements ([Hilborn and Mangel 1997](#)). For simplicity, we assume that the variability
245 associated with parameter estimates is the dominant source of uncertainty. A 95% confidence
246 interval for each DoC estimate was constructed by repeated sampling of a multivariate normal

247 distribution followed by prediction of the proportion of points occupied by seagrass as in eq. (1).

248 The sampling distribution assumes:

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

249 where x is a predictor variable used in eq. (1) (depth) that follows a multivariate normal
250 distribution with mean μ , and variance-covariance matrix Σ . The mean values are set at the depth
251 value corresponding to the inflection point on the logistic curve and the predicted model
252 parameters (i.e., α , β , and γ), whereas Σ is the variance-covariance matrix of the model
253 parameters. A large number of samples ($n = 10000$) were drawn from the distribution to
254 characterize the uncertainty of the depth value at the inflection point. The 2.5th and 97.5th quantile
255 values of the sample were considered bounds on the 95% confidence interval.

256 The uncertainty associated with the DoC estimates were based on the upper and lower
257 limits of the estimated inflection point on the logistic growth curve. This approach was used
258 because uncertainty in the inflection point is directly related to uncertainty in each of the DoC
259 estimates that are based on the linear curve fit through the inflection point. Specifically, linear
260 curves were fit through the upper and lower estimates of the depth value at the inflection point to
261 identify upper and lower limits for the estimates of DOC_{min} , DOC_{med} , and DOC_{max} . These
262 values were compared with the initial estimates from the linear curve that was fit through the
263 inflection point on the predicted logistic curve (i.e., Fig. 4c). This approach provided an
264 indication of uncertainty for individual estimates for the chosen radius. Uncertainty estimates
265 were obtained for each DoC estimate for the grids in each segment.

266 **2.5 Developing a spatially coherent relationship of water clarity with depth
267 of colonization**

268 Information describing seagrass light requirements can be obtained from the maximum
269 depth estimates by evaluating spatial relationships with water clarity. In particular, increased
270 resolution of seagrass depth estimates compared with measures of water clarity can potentially
271 improve the ability to empirically describe light requirements and areas where seagrass are
272 growing at depths deeper or shallower than expected. Secchi measurements provide a precise
273 estimate of water clarity and have been obtained at numerous locations documented in the Florida

274 Department of Environmental Protection's Impaired Impaired Waters Rule (IWR) database.

{acro:IWR}

275 Secchi data for Florida coastal waters were obtained from update 40 of the IWR database for all
276 of Tampa Bay (2010 coverage) and the Indian River Lagoon (2009 coverage) given the spatial
277 extent of secchi observations for the two locations. All seagrass data for a given year and all
278 secchi data regardless of date were evaluated. Secchi data were screened to exclude observations
279 that were flagged indicating that the value was lower than the maximum depth of the observation
280 point. Secchi data were also compared with bathymetric data to verify unflagged values were not
281 missed by initial screening. Secchi observations that were measured at the same geographic
282 location were averaged across all dates. This approach was preferred given that seagrass depth
283 patterns are more representative of long-term trends in water clarity as opposed to individual
284 secchi measures that may be highly variable (Dennison 1987, Dennison et al. 1993).

285 The relationship between seagrass depth limits and secchi measurements were explored
286 using established light requirements and attenuation equations. The traditional Lambert-Beer

287 equation describes the exponential decrease of light availability with depth:

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

288 such that the irradiance of incident light at depth Z (I_Z) can be estimated from the irradiance at
289 the surface (I_O) and a light extinction coefficient (K_d). Duarte (1991) indicate that minimum light
290 requirements for seagrass are on average 11% of surface irradiance. Light requirements may also
291 be species-specific and variable by latitude such that value may range from less than 5% to
292 greater than 30% (Dennison et al. 1993). Light requirements of seagrass at a specific location can
293 be estimated by rearranging eq. (3):

$$\%light = \exp(-K_d \cdot DOC_{max}) \quad (4) \quad \{\text{eqn:percent}\}$$

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

$$DOC_{max} = \frac{-\log(0.20)}{1.7} \cdot Z_d \quad (5) \quad \{\text{eqn:sgregression}\}$$

299 A regression of seagrass depth estimates against secchi measurements is expected to have a slope
300 corresponding to the constant in eq. (5). For the current analysis, 20% light requirements were
301 assumed to be an approximate median requirement for seagrasses in Florida. Scatter in the

302 regression through these points can be considered biologically meaningful, such that points below
303 the curve are locations where seagrasses are observed at maximum depth with less irradiance than
304 expected given eq. (5), whereas points above the curve are those where seagrasses are growing
305 deeper than expected. The geographic coordinates for each secchi measurement in Tampa Bay
306 and the Indian River Lagoon were used as locations for estimating DOC_{max} . These estimates
307 were compared with the averaged secchi estimates to identify light requirements at each location.
308 However, the relationship is expected to vary depending on the specific radius around each
309 sample point for estimating DOC_{max} . An appropriate radius was chosen that minimized the
310 difference between the empirically estimated slope and that in eq. (5). The estimated light
311 requirements of each point were plotted using the cartesian coordinates of each secchi observation
312 to evaluate spatial variation in seagrass growth as a function of light-limitation. Light
313 requirements were also summarized by individual segments in each bay to identify spatial trends
314 for relevant management units.

315 **3 Results**

316 **3.1 Segment characteristics and seagrass depth estimates**

317 Each of the four segments varied by several key characteristics that potentially explain
318 within-segment variation of seagrass growth patterns (Table 1). Mean surface area was 191.2
319 square kilometers, with area decreasing for the Big Bend (271.4 km), Indian River Lagoon
320 (228.5 km), Old Tampa Bay (205.5 km), and Choctawhatchee Bay (59.4 km) segments. Seagrass
321 coverage as a percentage of total surface area varied considerably by segment. Seagrasses covered
322 a majority of the surface area for the Big Bend segment (74.8 %), whereas coverage was much
323 less for Indian River Lagoon (32.8 %), Old Tampa Bay (11.9 %), and Choctawhatchee Bay (5.9

324 %). Visual examination of the seagrass coverage maps for the respective year of each segment
325 suggested that seagrasses were not uniformly distributed (Fig. 1). Seagrasses in the
326 Choctawatchee Bay segments were generally sparse with the exception of a large patch located to
327 the west of the inlet connection with the Gulf of Mexico. Seagrasses in the Big Bend segment
328 were located throughout the segment with noticeable declines near the outflow of the
329 Steinhatchee River, whereas seagrasses in Old Tampa Bay and the Indian River Lagoon segment
330 were generally confined to shallow areas near the shore. Seagrass coverage showed a partial
331 decline toward the northern ends of both Old Tampa Bay and the Indian River Lagoon segments.
332 Mean depth was less than 5 meters for each segment, excluding Choctawhatchee Bay which was
333 slightly deeper than the other segments on average (5.3 m). Maximum depths were considerably
334 deeper for Choctawhatchee Bay (11.9 m) and Old Tampa Bay (10.4 m), as compared to the Big
335 Bend (3.6 m) and Indian River Lagoon (1.4 m) segments. Water clarity as indicated by average
336 secchi depths was similar between the segments (1.5 m), although Choctawhatchee Bay had a
337 slightly higher average (2.1 m).

338 Estimates of seagrass DoC using a segment-wide approach that did not consider spatially
339 explicit locations indicated that seagrasses generally did not grow deeper than three meters in any
340 of the segments (Table 2). Maximum and median depth of colonization were deepest for the Big
341 Bend segment (3.7 and 2.5 m, respectively) and shallowest for Old Tampa Bay (1.1 and 0.9 m),
342 whereas the minimum depth of colonization was deepest for Choctawhatchee Bay (1.8 m) and
343 shallowest for Old Tampa Bay (0.6 m). Averages of all grid-based estimates for each segment
344 were different than the segment wide estimates, which suggests potential bias associated with
345 using a whole segment as a relevant spatial unit for estimating depth of colonization. In most
346 cases, the averages of all grid-based estimates were less than the whole segment estimates,

347 suggesting the latter provided an over-estimate of seagrass growth limits. For example, the
348 average of all grid estimates for DOC_{max} in the Big Bend region suggested seagrasses grew to
349 approximately 1.9 m, which was 1.7 m less than the whole segment estimate. This reduction is
350 likely related to improved resolution of seagrass depth limits near the outflow of the Steinhatchee
351 river. Although reductions were not as severe for the average grid estimates for the remaining
352 segments, considerable within-segment variation was observed depending on grid location. For
353 example, the deepest estimate for DOC_{min} (2 m) in the Indian River Lagoon exceeded the
354 average of all grid locations for DOC_{max} (1.7 m). DOC_{min} also had minimum values of zero
355 meters for the Big Bend and Old Tampa Bay segments, suggesting that seagrasses declined
356 continuously from the surface for several locations.

357 Visual interpretations of seagrass depth estimates using the grid-based approach provided
358 further information on the distribution of seagrasses in each segment (Fig. 5). Spatial
359 heterogeneity in depth limits was particularly apparent for the Big Bend and Indian River Lagoon
360 segments. As expected, depth estimates indicated that seagrasses grew deeper at locations far
361 from the outflow of the SteinHatchee River in the Big Bend segment. Similarly, seagrasses were
362 limited to shallower depths at the north end of the Indian River Lagoon segment near the Merrit
363 Island National Wildlife Refuge. Seagrasses were estimated to grow at maximum depths up to 2.1
364 m on the eastern portion of the Indian River Lagoon segment. Spatial heterogeneity was less
365 distinct for the remaining segments. Seagrasses in Old Tampa Bay grew deeper in the northeast
366 portion of the segment and declined to shallower depths near the inflow at the northern edge.
367 Spatial variation in the Choctowatchee Bay segment was not apparent, although the maximum
368 DoC estimate was observed in the northeast portion of the segment. DoC values were not
369 available for all grid locations givne the limitations imposed in the estimation method. DoC could

370 not be estimated in locations where seagrasses were sparse or absent, nor where seagrasses were
371 present but the sampled points did not exhibit a sufficient decline with depth. The latter scenario
372 was most common in Old Tampa Bay and Choctawhatchee Bay where seagrasses were unevenly
373 distributed or confined to shallow areas near the shore. The former scenario was most common in
374 the Big Bend segment where seagrasses were abundant but locations near the shore were
375 inestimable given that seagrasses did not decline appreciably within the depths that were sampled.

376 Uncertainty for estimates of DOC_{max} indicated that confidence intervals were generally
377 acceptable (i.e., greater than zero), although the ability to discriminate between the three depth
378 estimates varied by segment (Fig. 6 and Table 3). Mean uncertainty for all estimates in each
379 segment measured as the width of a 95% confidence interval was 0.3 m. Greater uncertainty was
380 observed for Choctawhatchee Bay (mean width of all confidence intervals was 0.7 m) and Old
381 Tampa Bay (0.7 m), compared to the Big Bend (0.2 m) and Indian River Lagoon (0.1 m)
382 segments. The largest confidence interval for each segment was 4.6 m for Old Tampa Bay, 2.5 m
383 for Choctawhatchee Bay, 2.4 m for the Big Bend, and 0.3 m for the Indian River Lagoon
384 segments. However, most confidence intervals for the remaining grid locations were much
385 smaller than the maximum in each segment. A comparison of overlapping confidence intervals for
386 DOC_{min} , DOC_{med} , and DOC_{max} at each grid location indicated that not every measure was
387 unique. Specifically, only 12.5% of grid points in Choctawhatchee Bay and 35% in Old Tampa
388 Bay had significantly different estimates, whereas 84% of grid points in the Indian River Lagoon
389 and 88.9% of grid points in the Big Bend segments had estimates that were significantly different.

390 By contrast, all grid estimates in Choctawhatchee Bay and Indian River Lagoon had DOC_{max}
391 estimates that were significantly greater than zero, whereas all but 10% of grid points in Old
392 Tampa Bay and 5.6% of grid points in the Big Bend segment had DOC_{max} estimates significantly

³⁹³ greater than zero.

³⁹⁴ **3.2 Evaluation of seagrass light requirements**

³⁹⁵ Estimates of seagrass light requirements for the entire areas of Tampa Bay and the Indian
³⁹⁶ River Lagoon indicated substantial variation, both between and within the different bays (Figs. [7](#)
³⁹⁷ and [8](#)). Seagrass DoC estimates were obtained for 81 locations in Tampa Bay and 134 locations in
³⁹⁸ the Indian River Lagoon where secchi observations were available in the Florida IWR database.
³⁹⁹ Mean light requirements were significantly different between

⁴⁰⁰ **4 Discussion**

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Table 1: Characteristics of coastal segments used to evaluate seagrass depth of colonization estimates. Segments are spatial units defined by US EPA for nutrient criteria development (see Fig. 1). 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, update number 40.^{tab:seg_summ}

	Choctawhatchee Bay	Big Bend	Old Tampa Bay	Indian River Lagoon
Segment	0303	0820	0902	1502
Latitude	30.43	29.61	27.94	28.61
Longitude	-86.54	-83.48	-82.62	-80.77
Surface area	59.41	271.37	205.50	228.52
Seagrass area	3.51	203.02	24.48	74.89
Depth (mean)	5.31	1.41	2.56	1.40
Depth (max)	11.90	3.60	10.40	3.70
Secchi (mean)	2.13	1.34	1.34	1.34
Secchi (se)	0.07	0.19	0.01	0.01

Table 2: Summary of seagrass depth estimates (m) for each segment using all grid locations in Fig. 5. Whole segment estimates were obtained from all seagrass depth data for each segment.^{tab:est_summ}

Segment	Whole segment	Mean	St. Dev.	Min	Max
0303					
DOC_{min}	1.82	1.57	0.72	0.00	2.27
DOC_{med}	2.16	1.98	0.46	1.19	2.48
DOC_{max}	2.50	2.40	0.32	1.86	2.74
0820					
DOC_{min}	1.25	1.26	0.85	0.00	2.64
DOC_{med}	2.46	1.60	0.84	0.10	2.85
DOC_{max}	3.66	1.93	0.89	0.20	3.31
0902					
DOC_{min}	0.61	0.47	0.32	0.00	0.98
DOC_{med}	0.88	0.80	0.30	0.30	1.24
DOC_{max}	1.15	1.13	0.40	0.37	1.81
1502					
DOC_{min}	1.25	1.32	0.23	1.00	2.02
DOC_{med}	1.51	1.49	0.21	1.12	2.08
DOC_{max}	1.77	1.66	0.21	1.23	2.14

Table 3: Summary of uncertainty for seagrass depth estimates (m) for each segment using all grid locations in Fig. 6. The uncertainty values are equally applicable to each seagrass depth measure (DOC_{min} , DOC_{med} , DOC_{max}).^{tab:sens_summ}

Segment	Mean	St. Dev	Min	Max
0303	0.72	0.74	0.22	2.52
0820	0.24	0.56	0.01	2.43
0902	0.67	1.05	0.11	4.57
1502	0.09	0.06	0.01	0.30

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 dates within each bay. Minimum year, maximum year, sample size (n), and mean values (m) of secchi data by segment are shown. Mean DOC_{max} ^{tab:sec_c_summ} and estimated % light requirements for each segment are based on data in Figs. 7 and 8.^{tab:sec_c_summ}

Bay segment ^a	Min year	Max year	n	Secchi	DOC_{max}	% light
Indian River Lagoon						
BR	1973	2009	1786	1.10	1.55	0.10
LCIRL	1977	2009	1735	1.04	1.38	0.12
LIRL	1976	2005	244	0.90	1.65	0.06
LML	1979	2009	414	1.01	1.24	0.12
LSL	1973	2005	163	0.97	3.16	0.01
UCIRL	1973	2009	2301	1.30	1.30	0.12
UIRL	1973	2009	1269	1.34	1.12	0.18
UML	1973	2009	544	1.04	2.36	0.02
Tampa Bay						
HB	1972	2003	3963	1.08	1.11	0.14
LTB	1972	2009	3880	2.42	2.28	0.19
MTB	1972	2009	4901	1.84	1.78	0.19
OTB	1972	2003	5383	1.43	1.17	0.22

^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.

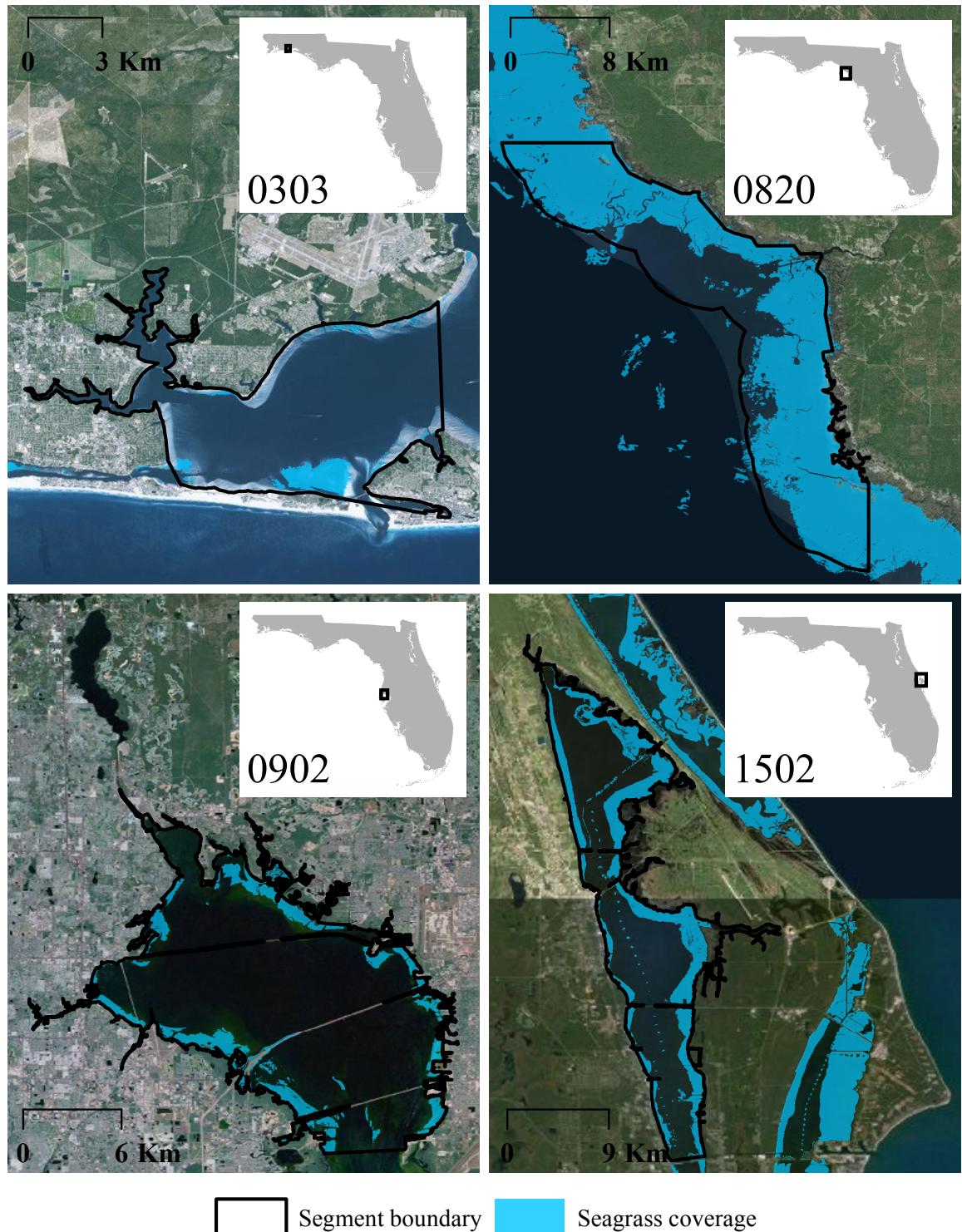


Fig. 1: Locations and seagrass coverage of estuary segments used to evaluate depth of colonization estimates. Seagrass coverage layers are from 2007 (Choctowatchee Bay, 0303), 2006 (Big Bend, 0820), 2010 (Old Tampa Bay, 0902), and 2009 (Indian River Lagoon, 1502).

{fig:seg_a}

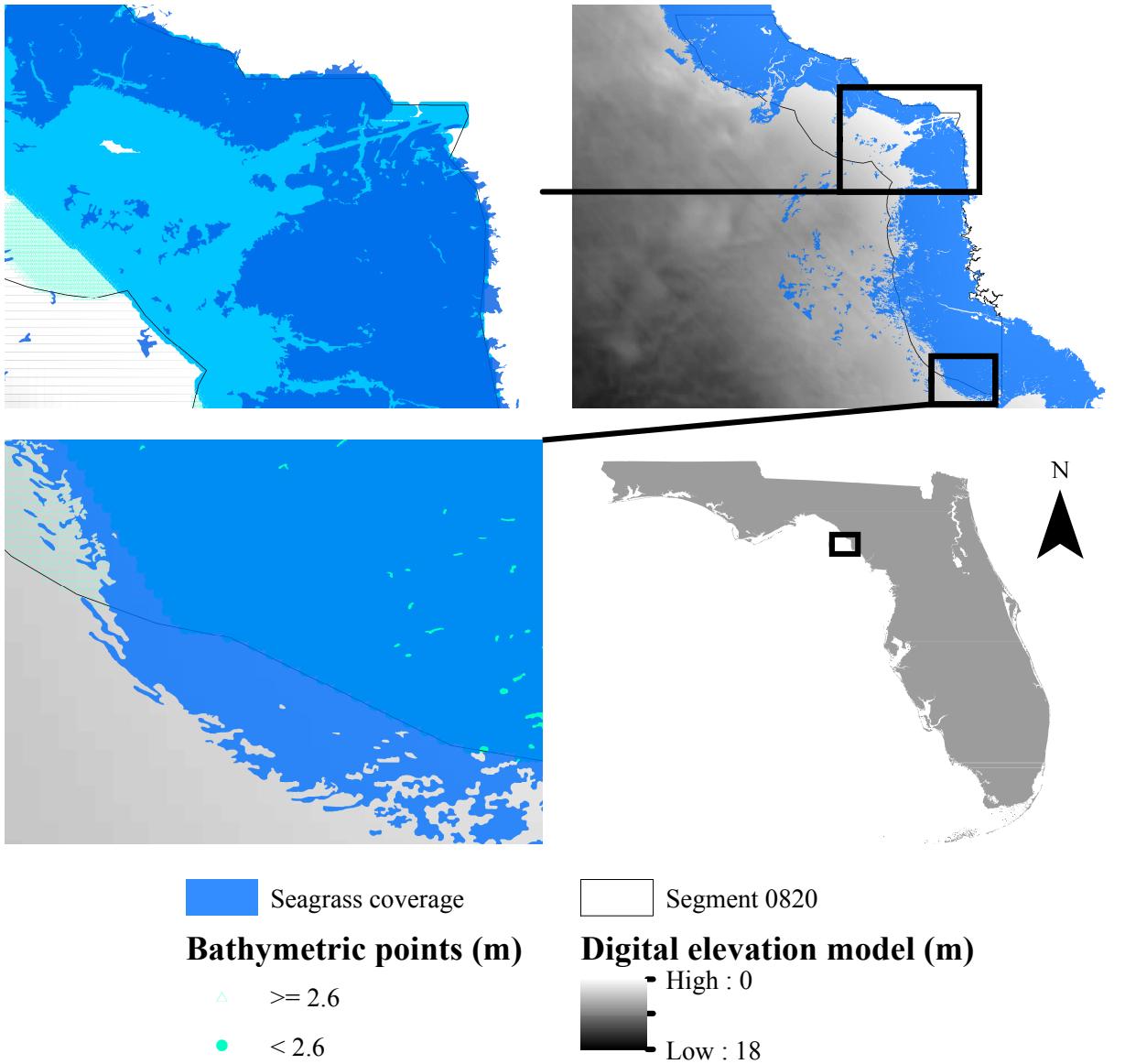
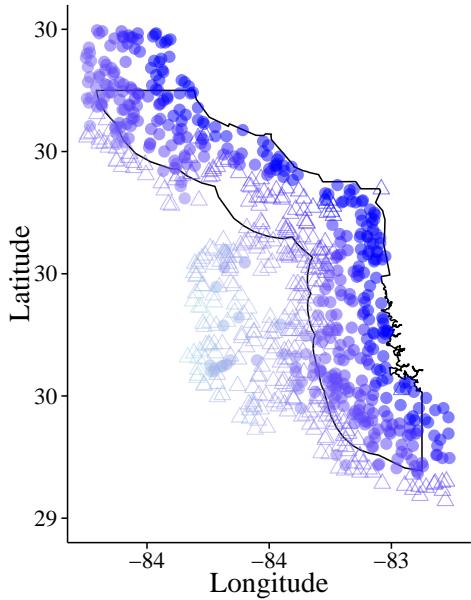


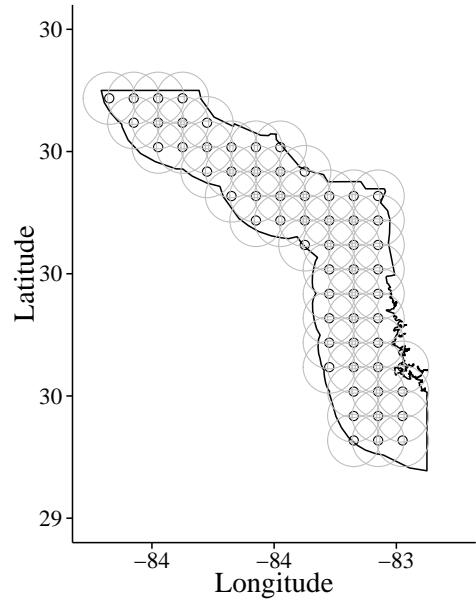
Fig. 2: Example of over- and under-estimates for seagrass depth of colonization for segment 820 in the Big Bend region, Florida. Layers include a seagrass coverage layer, bathymetric depth points, bathymetric digital elevation model, and spatial extents for the segment and Florida. The top-left figure indicates over-estimation and the bottom-left indicates under-estimation. Bathymetric points are color-coded by the median depth of colonization estimate for seagrass using data from the whole segment (2.6 m).

{fig:wbid}

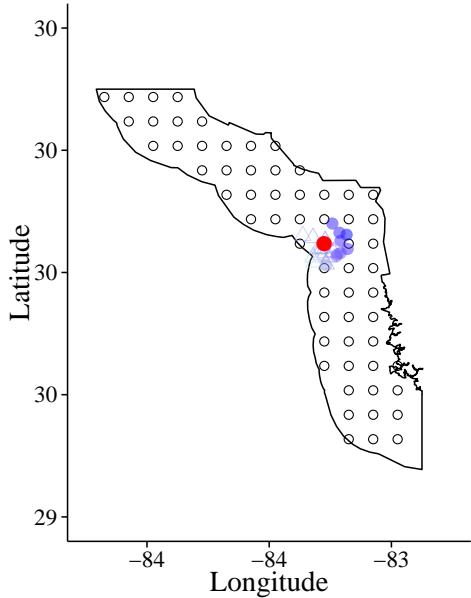
(a) Seagrass depth points for the segment



(b) Grid of locations and sample areas for estimates



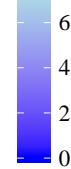
(c) Sampled observations for a test point



Seagrass

- △ Absent
- Present

Depth (m)



Points

- Estimation grid
- Test point
- Sample area

Fig. 3: Examples of data and grid locations for estimating seagrass depth of colonization for a region of the Big Bend, Florida. Fig. 3a shows the seagrass depth points that are used for sampling, Fig. 3b shows a grid of locations and sampling radii for estimating seagrass DoC, and Fig. 3c shows an example of sampled seagrass depth points for a location. Estimates in Fig. 4 were obtained from the sampled location in Fig. 3c.

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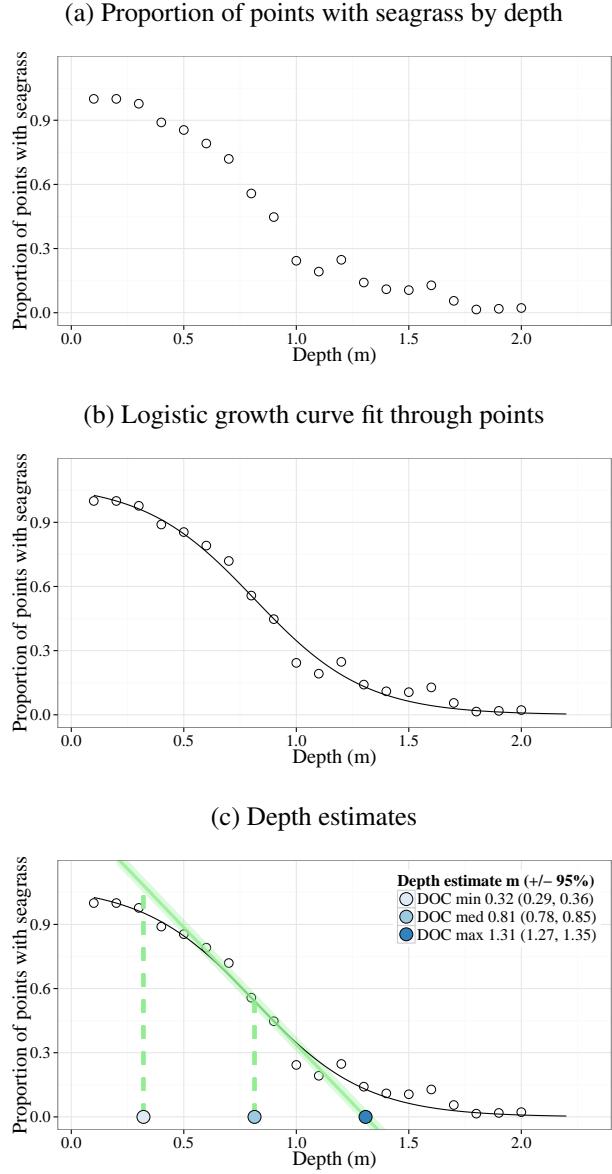


Fig. 4: Methods for estimating seagrass depth of colonization using sampled seagrass depth points around a single location. Fig. 4a is the proportion of points with seagrass by depth using depth points within the buffer of the test point in Fig. 3. Fig. 4b adds a decreasing logistic growth curve fit through the points. Fig. 4c shows three depth estimates based on a linear curve fit through the inflection point of logistic growth curve.

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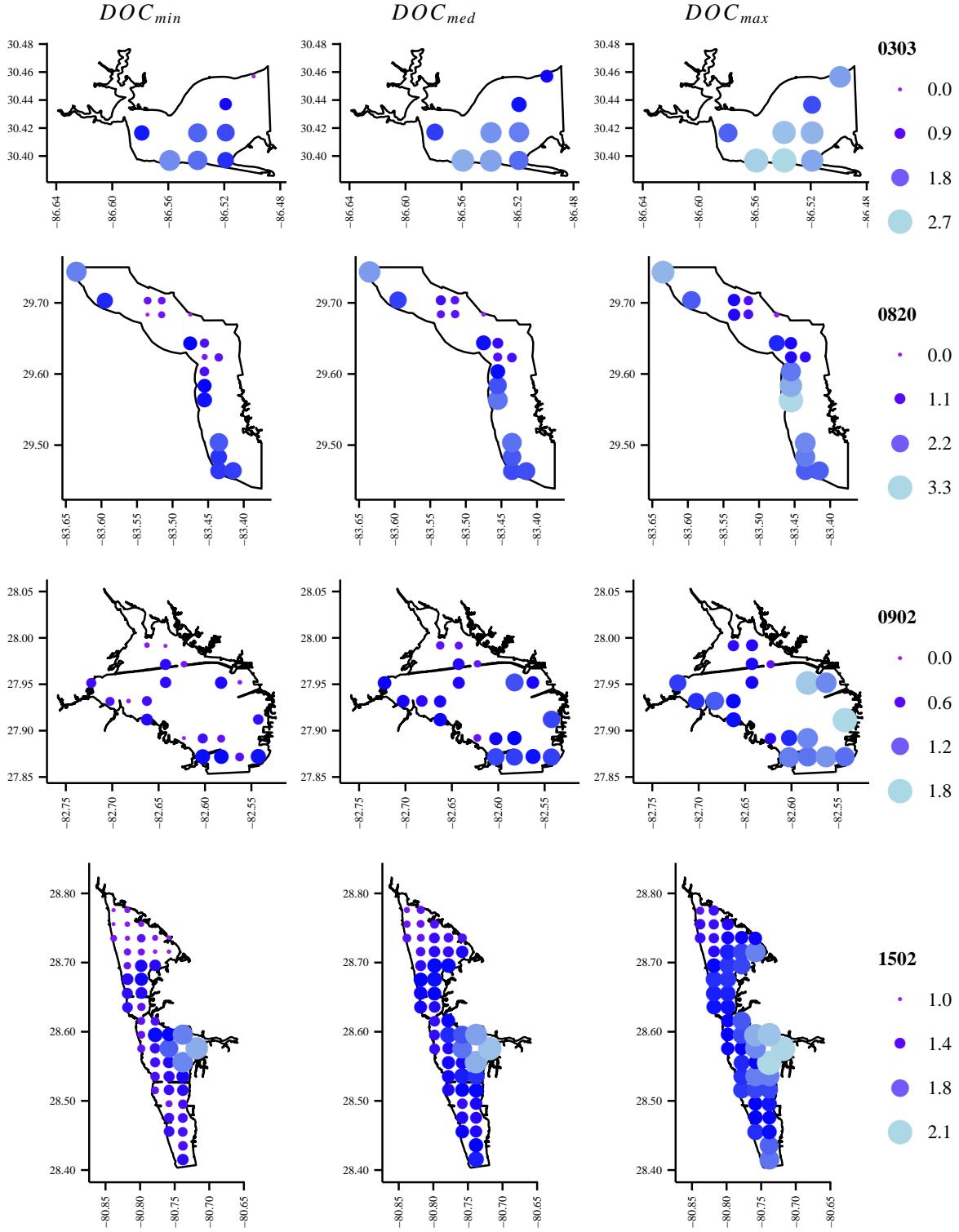


Fig. 5: Spatially-referenced estimates of seagrass depth limits (m) for four coastal segments of Florida. Estimates include minimum (DOC_{min}), median (DOC_{med}), and maximum depth of colonization (DOC_{max}). Estimates are assigned to grid locations for each segment, where grid spacing was fixed at 0.02 decimal degrees. Radii for sampling seagrass bathymetric data around each grid location were fixed at 0.06 decimal degrees.

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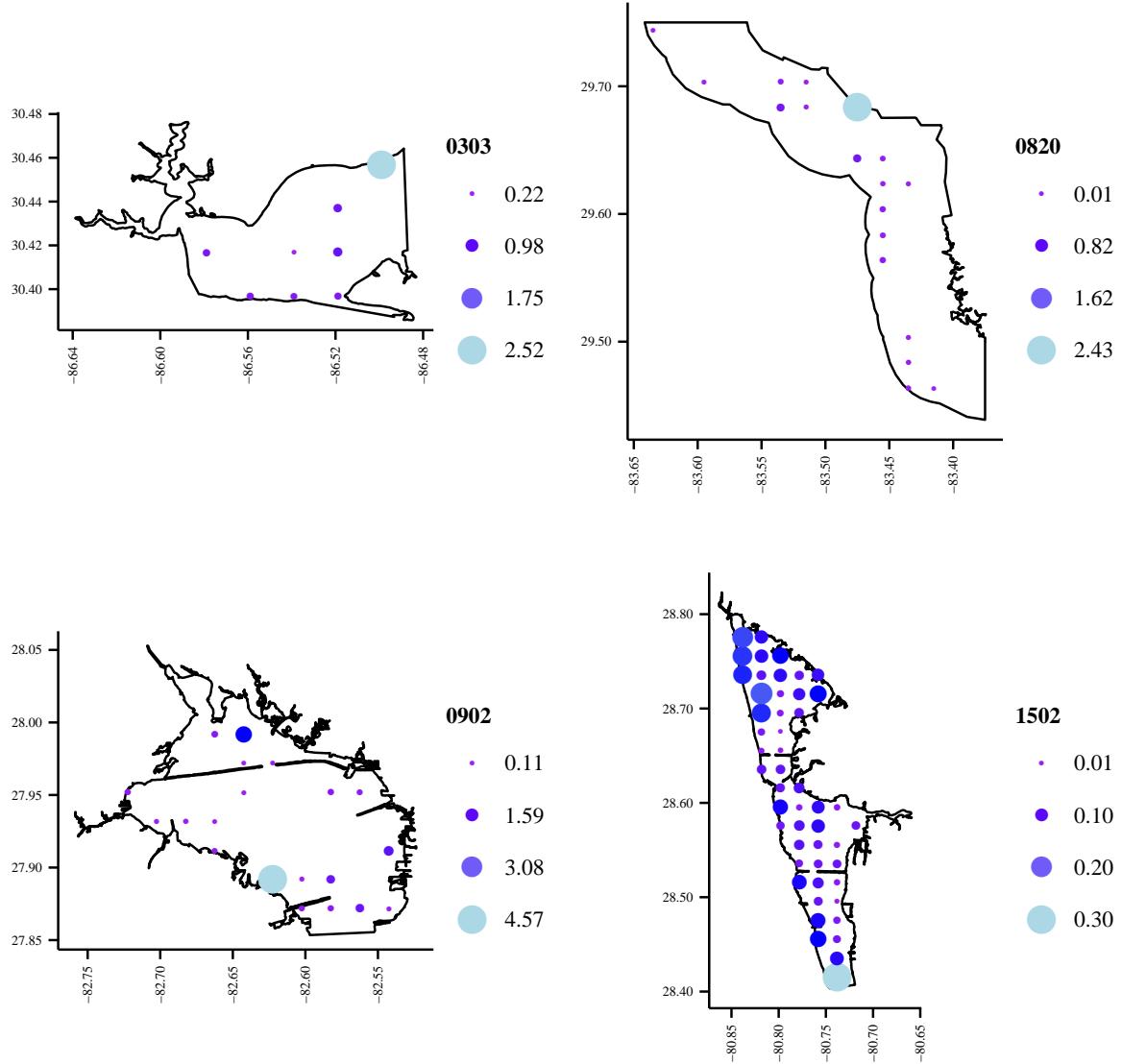


Fig. 6: Size of confidence intervals (m) for depth of colonization estimates in Fig. 5. Points are colored and sized based on the difference between the upper and lower bounds of a 95% confidence interval for all three DoC estimates (DOC_{min} , DOC_{med} , DOC_{max}). Bounds were obtained using Monte Carlo simulations to estimate uncertainty associated with the inflection point of the estimated logistic curve (Fig. 4) for each sample.

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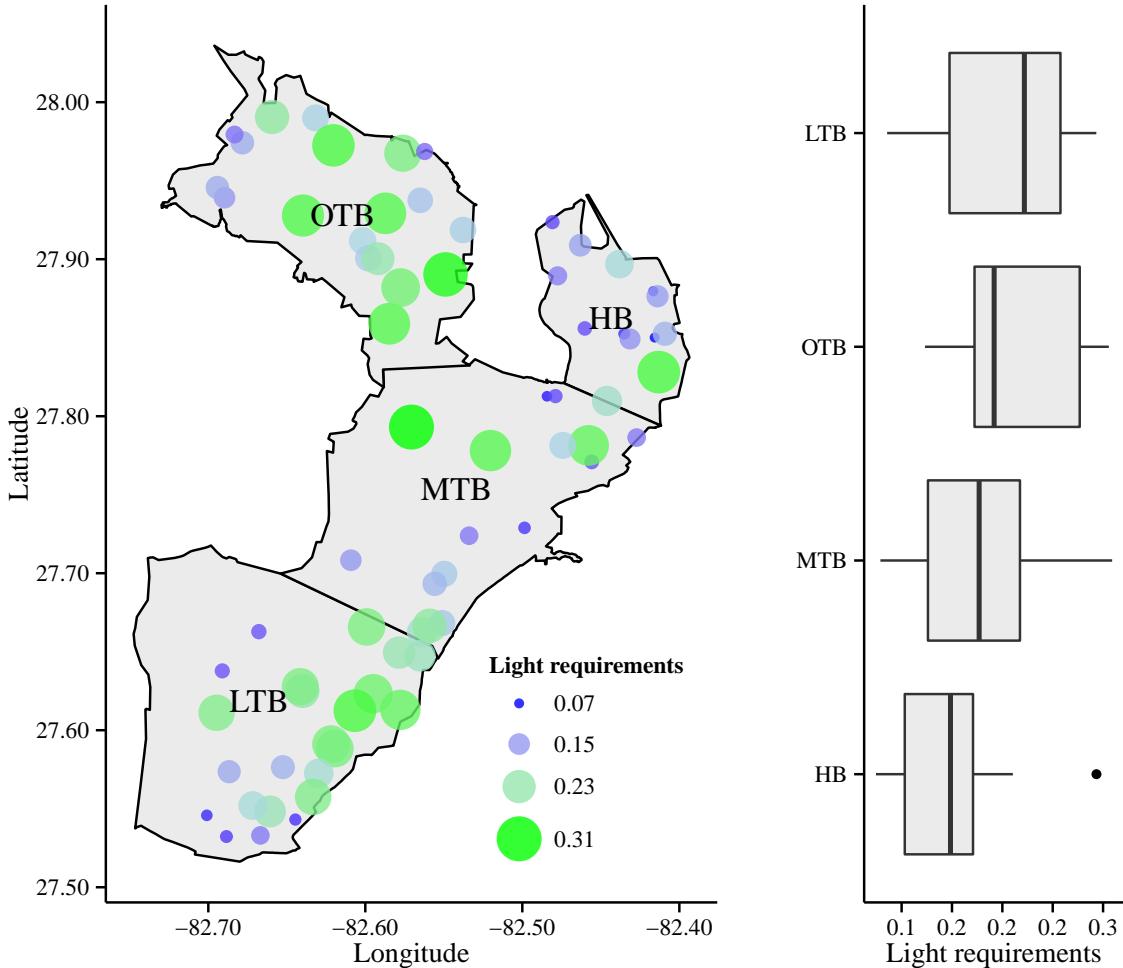


Fig. 7: Estimated light requirements of seagrass for multiple locations in Tampa Bay, Florida. Map locations are georeferenced observations of water clarity from secchi measurements in the Florida Impaired Waters Rule database, update 40. Data are also summarized by bay segment as boxplots where the 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 daily average secchi values for each location using all observations for Tampa Bay, estimated maximum depth of colonization using a radius of 0.7 decimal degrees for each secchi location to sample seagrass depth points for 2010 coverage data, and empirical relationships described by eq. (3). HB: Hillsborough Bay, LTB: Lower Tampa Bay, MTB: Middle Tampa Bay, OTB: Old Tampa Bay.

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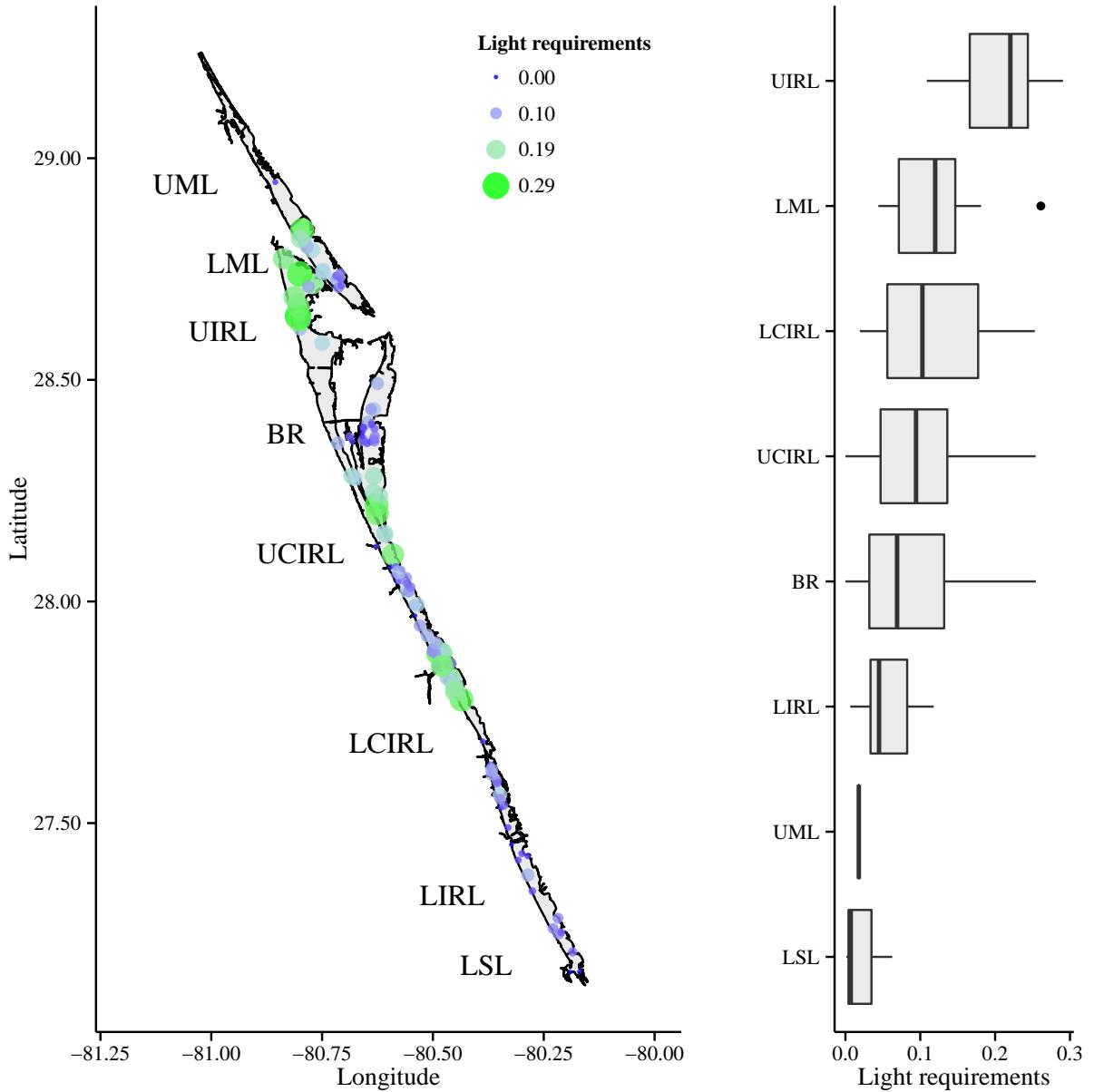


Fig. 8: Estimated light requirements of seagrass for multiple locations in Indian River Lagoon, Florida. Map locations are georeferenced observations of water clarity from secchi measurements in the Florida Impaired Waters Rule database, update 40. Data are also summarized by bay segment as boxplots as in Fig. 7. Light requirements are based on daily average secchi values for each location using all observations for Tampa Bay, estimated maximum depth of colonization using a radius of 0.02 decimal degrees for each secchi location to sample seagrass depth points for 2009 coverage data, and empirical relationships described by eq. (3). 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.

{fig:light}