Quantifying seagrass light requirements using an algorithm to spatially resolve depth of colonization

Marcus W. Beck1\*, James D. Hagy III2, Chengfeng Le3

1USEPA National Health and Environmental Effects Research Laboratory

Gulf Ecology Division, 1 Sabine Island Drive, Gulf Breeze, FL 32561

Phone: 850-934-2480, Fax: 850-934-2401, Email: [beck.marcus@epa.gov](mailto:beck.marcus@epa.gov)

2USEPA National Health and Environmental Effects Research Laboratory

Gulf Ecology Division, 1 Sabine Island Drive, Gulf Breeze, FL 32561

Phone: 850-934-2455, Fax: 850-934-2401, Email: [hagy.jim@epa.gov](mailto:hagy.jim@epa.gov)

3ORISE Research Participation Program

USEPA National Health and Environmental Effects Research Laboratory

Gulf Ecology Division, 1 Sabine Island Drive, Gulf Breeze, FL 32561

Current address:

Ocean College, Zhejiang University, Zhoushan, China

Email: [chengfengle@zju.edu.cn](mailto:chengfengle@zju.edu.cn)

\*Corresponding author

**Abstract**

Depth of colonization (*Zc*) is a useful seagrass growth metric that describes seagrass response to light attenuation. Similarly, percent surface irradiance (% SI) at *Zc* is a measure of seagrass light requirements with applications in seagrass ecology and management. Methods for estimating *Zc* and % SI, and the resulting estimates are highly variable making meaningful comparisons among estimates difficult. A new algorithm is presented to compute maps of median and maximum *Zc*, *Zc, med* and *Zc,max*, respectively, for four Florida coastal areas (Big Bend, Tampa Bay, Choctawhatchee Bay, Indian River Lagoon). Maps of light attenuation (*Kd*) based on SeaWiFS satellite imagery, PAR profiles, and Secchi depth measurements were combined to produce maps of % SI at *Zc,med* and *Zc,max*. Among estuary segments, mean *Zc,med* varied from (±s.e.) 0.86±0.08 m for Old Tampa Bay to 1.96±0.10 m for Western Choctawhatchee Bay. Coefficients of variation for *Zc,med* were 1-10%. Percent SI at *Zc,med* averaged 19% for Indian River Lagoon (range = 9-24%), 42% for Tampa Bay (37-49%) and 56% for Choctawhatchee Bay (51-67%). Estimated light requirements were significantly lower in Indian River Lagoon than in the other estuaries, while estimates for Tampa Bay and Choctawhatchee Bay were higher than the often cited estimate of 20%. Spatial gradients in depth of colonization and % SI were apparent in all estuaries. The analytical approach, implemented in R, could be applied easily to new data from these estuaries or to other estuaries and could be incorporated routinely in assessments of seagrass status and condition.

**Key words**: seagrass, depth of colonization, light requirements, remote sensing**Introduction**

Seagrasses are ecologically valuable components of aquatic ecosystems that have a critical role in shaping aquatic habitat. These ‘ecosystem engineers’ influence multiple characteristics of aquatic systems through interactions with many biological and abiotic components (Jones *et al*. 1994; Koch 2001). For example, seagrasses reduce wave action, stabilize sediments, and provide habitat and refuge for invertebrates and juvenile fish (Williams and Heck 2001; Hughes *et al*. 2009). Seagrasses also respond to changes in water clarity via physiological linkages with light availability. Seagrass coverage declines with water depth due to light attenuation, and declines more rapidly in productive aquatic systems where light attenuation is relatively high (Duarte 1995). The light-limited maximum depth to which seagrass grows is variously called “depth limits” or “depth of colonization.” Empirical relationships between nutrient loading, water clarity, light requirements, and depth of colonization have been identified (Duarte 1991; Kenworthy and Fonseca 1996; Choice *et al*. 2014) and have been used to characterize light regimes and other water quality requirements to maintain seagrass habitat (Janicki and Wade 1996; Steward *et al*. 2005). Seagrasses may be particularly useful in this respect because they respond to water quality over relatively long time scales, “integrating” their exposure to stress. Thus, time scales of seagrass response better match time scales for monitoring, assessment and nutrient management (Duarte 1995; Burkholder *et al*. 2007).

A variety of approaches have been used to estimate seagrass depth of colonization. A common *in situ* approach is to sample seagrass along depth transects until the maximum depth is adequately characterized (e.g., Spears *et al*. 2009; Choice *et al*. 2014). Alternative techniques include underwater photos or videos, aquascope identification, or hydroacoustic assessments (Zhu *et al*. 2007; Søndergaard *et al*. 2013). These are especially useful for site-specific evaluations where the analysis needs are driven by local questions (e.g., Iverson and Bittaker 1986; Hale *et al*. 2004). Availability of estuary-scale geospatial data for seagrass coverage, based on photo-interpretation of aerial imagery, suggests that standardized techniques can be applied at similarly large spatial scales and would be valuable for a variety of scientific and policy applications. For such large scale analysis, it is often useful to subdivide water bodies into segments for the purpose of analysis and policy development (e.g., Steward *et al*. 2005; Schaeffer *et al*. 2012; US EPA 2012). One challenge in doing so is that estuaries are often characterized by gradients in water quality, such that any segmentation scheme is likely to include within-segment gradients in water quality and associated seagrass depth of colonization.

An example from the Big Bend region of Florida illustrates the issue of scale in analyzing seagrass depth of colonization (Fig. 1a). In a segment from this region, the highest depth of colonization largely occurs around the outer perimeter of the mapped seagrass coverage (red line in Fig. 1a). However, depth-dependent seagrass growth patterns are also evident at smaller spatial scales within the segment, wherein the segment-scale depth of colonization overestimates the depth distribution near the outflow of the Steinhatchee River, where high concentrations of colored dissolved organic matter reduce water clarity locally (personal communication, N. Wellendorf, Florida Department of Environmental Protection). An improved method for estimating depth of colonization should have sufficient flexibility to characterize seagrass responses at a large scale, such as the segment average, while still resolving important patterns at smaller scales, such as the local impact of a river outflow. Developing and demonstrating this capability was one objective of this study.

Another objective of this study was to combine spatially-resolved estimates of depth of colonization with water clarity measures at the same spatial scales to characterize the pattern and range of seagrass light requirements in estuaries. Although not always the case, the spatial distribution of submersed aquatic plants is often associated with light availability (Barko *et al*. 1982; Hall *et al*. 1999; Dennison *et al*. 1993), wherein depth of colonization is controlled by light requirements needed and average water clarity. Published estimates of seagrass light requirements are quite variable. Duarte (1991) reported that seagrasses can extend to depths receiving an average of 11% of surface irradiance, while estimates of light requirements for seagrass in Chesapeake Bay were about 20% (Batiuk *et al*. 1992). Dennison *et al*. (1993) reported minimum light requirements, defined as the percent light at the maximum depth limit, ranging from less than 5% to greater than 30% depending on site conditions. Estimates of ~20% are common in the literature, approximating a value in the middle of published estimates (see also Kemp *et al*. 2004). An estimate of ~ 20% for seagrass in Florida estuaries has been applied for management purposes in Tampa Bay, Choctawhatchee Bay, and elsewhere in Florida (e.g., FDEP 2012; US EPA 2012) and can be traced to the estimate of 22.5% for lower Tampa Bay from Dixon and Leverone (1995).

Sources of variation in estimates of seagrass light requirements are numerous and include physiological differences among seagrass species, differences in attenuation of light on the surface of seagrass leaves, and variations in other physiological stressors such as salinity or water temperature (Kenworthy *et al*.1991; Kemp *et al*. 2004; Choice *et al*. 2014). Differences in operational definitions and method of estimation are also likely to contribute to differences in reported values. For example, Dennison *et al*. (1993) defined minimal light requirements as the percent light at the maximal depth limit for seagrass – where depth limit was defined variously by different included studies. Choice *et al*. (2014) applied a statistical method to data from individual stations seeking to find the percentage of surface irradiance linked to seagrass percent cover or shoot density of zero. In this study, we sought to generate more comparable estimates by broadly applying the same method to characterize seagrass depth of colonization and relating it to estimates of water clarity at similar scales. We defined light requirements following Dennison et al. (1993), except that we operationally defined depth of colonization in terms of our approach.

To quantify water clarity at temporal and spatial scales relevant to understanding seagrass distributions in coastal ecosystems, we used estimates derived from satellite remote sensing along with more conventional water clarity observations (light profiles, Secchi depth). Ocean color data from satellite remote sensing can provide consistent estimates of water clarity across a large spatial extent, often with a high return frequency and sustained data collection, which is ideal for characterizing average water clarity (Woodruff *et al*. 1999; Chen *et al*. 2007). Since seagrass growth responds to relatively long-term seasonal and inter-annual patterns in water clarity, it is ideal for matching with data from satellite remote sensing. Secchi depth or other measures of water clarity can also be useful, either to validate remote sensing observations, or for direct use when remote sensing cannot be used. However, uneven sampling in space and time can make it harder to obtain sufficient long-term averages (Elsdon and Connell 2009). Moreover, Secchi depth measurements can be problematic in shallow, relatively clear waters, where the Secchi disk is likely to be visible on the bottom.

This study describes an algorithm for estimating seagrass depth of colonization and light requirements at a variety of spatial scales using geospatial datasets describing seagrass coverage and satellite remote sensing data of light attenuation in the water column. Study objectives were to 1) describe the method for estimating seagrass depth of colonization, 2) apply the technique to four target estuaries in Florida to illustrate quantification of seagrass growth patterns, and 3) develop a spatial description of relationships among depth limits and water clarity, characterizing patterns in light requirements in each case study. We then apply the estimates to characterize spatial variation in light requirements within and among regions.

**Methods**

*Study sites and data sources*

Study sites included four coastal areas in Florida: the Big Bend region (northeast Gulf coast), Choctawhatchee Bay (panhandle), Tampa Bay (central Gulf coast), and Indian River Lagoon (Atlantic coast; Table 1 and Fig. 2). Florida’s estuaries and coastal waters are partitioned into segments following a scheme developed by the US Environmental Protection Agency for numeric nutrient criteria. The method for estimating depth of colonization was evaluated initially using one segment in each of our 4 areas, chosen based on data availability and gradients in water clarity. These segments included Big Bend (BB), Western Choctawhatchee Bay (WCB), Old Tampa Bay (OTB), and Upper Indian River Lagoon (UIRL). The analysis was then expanded to quantify spatially-resolved seagrass depth limits and associated light requirements for all the segments in three of the estuaries, omitting the Big Bend from further analysis due to insufficient water clarity data.

Geospatial data describing seagrass coverage and bathymetry were used to estimate depth of colonization. These data are available for coastal regions of Florida from the US Geological Survey, Florida Department of Environmental Protection, Florida Fish and Wildlife Conservation Commission, and Florida’s watershed management districts. Seagrass coverage maps were obtained for a recent year in each of the study sites (Table 1). The original coverage maps were produced by photo-interpreting aerial images to categorize seagrass as absent, discontinuous (patchy), or continuous. We aggregated to two categories, present (continuous and patchy) and absent.

Bathymetry data were obtained from the National Oceanic and Atmospheric Administration’s (NOAA) National Geophysical Data Center (<http://www.ngdc.noaa.gov/>) as either Digital Elevation Models (DEMs) or as bathymetric sounding data from hydroacoustic or other surveys. Tampa Bay bathymetry provided by the Tampa Bay National Estuary Program are described in Tyler *et al*. (2007). Bathymetry for the Indian River Lagoon was obtained from the St. John’s Water Management District (CPE 1997). Because the vertical datum (i.e., MLLW, NAVD88, etc.) varied, all bathymetric data were vertically adjusted to local mean sea level using the NOAA VDatum tool (<http://vdatum.noaa.gov/>). Adjusted data were combined with seagrass coverage layers using standard union techniques for raster and vector layers in ArcMap 10.1 (ESRI 2012). To reduce computation time, bathymetry layers were first masked using a 1 km buffer of the seagrass coverage layer. Raster bathymetric layers were converted to point layers to combine with seagrass coverage maps, described below.

*Quantifying water clarity*

Satellite remote sensing imagery was used to create a gridded 1 km2 map of estimated water clarity for Tampa Bay and Choctawhatchee Bay. Secchi depth measurements were used to quantify water clarity for the Indian River Lagoon because light scattering from bottom reflectance and reflectance from shoreline areas prevented use of satellite remote sensing measurements.

For Tampa Bay and Choctawhatchee Bay, daily MODIS (Aqua level-2) satellite data were downloaded from the NASA website (<http://oceancolor.gsfc.nasa.gov/>) for the five years preceding the year the seagrass imagery was acquired. Images were reprocessed using the SeaWiFS Data Analysis System software (SeaDAS, Version 7.0). For Tampa Bay, water clarity was derived from daily MODIS images using a previously-developed algorithm that estimates Secchi depth based on satellite-derived estimates of the diffuse attenuation coefficient at 490 nm (*Kd* (490), Chen *et al*. 2007). Monthly and annual mean water clarity was calculated from the daily images and then averaged to create a single layer. Similarly, *Kd* for Choctawhatchee Bay was derived from MODIS using the QAA algorithm (Lee *et al*. 2005). Monthly field measurements of *Kd*obtained in 2010 at ten locations in Choctawhatchee Bay were used to correct annual means of the un-validated satellite values (*Kd, MODIS*) to match annual means of *in situ* measurements (model II regression: *Kd*=0.65*Kd,MODIS*, r2=0.93) Field *Kd* estimates were computed from regressions of underwater PAR (4 pi Biospherical PAR sensor on SBE25 CTD profiler) vs. depth. The regression based on 2010 data was applied to all five years of annual mean satellite-derived *Kd* data prior to averaging to create a single layer for further analysis.

For Indian River Lagoon, secchi depth data (meters, *ZSecchi*) collected within ten years prior to the seagrass coverage data (i.e., 1999–2009) were obtained from the state of Florida’s impaired waters rule (IWR) database, update 40. A 10-year averaging period was used for Indian River Lagoon to compensate for uneven temporal coverage, whereas 5-year averages were used for the other estuaries. Stations with less than five observations were removed as were observations flagged as a lower limit (i.e., Secchi disk visible on bottom). As an additional data quality screen, Secchi data were compared with bathymetry to ensure that the reported Secchi depth was less than water depth.

*Estimating seagrass depth of colonization*

Seagrass depth of colonization (*Zc*) was computed by overlaying seagrass coverage maps and bathymetry data to generate a point shapefile with attributes of location, depth (m), and seagrass presence or absence. The proportion of points with seagrass present was computed within discrete depth bins, spanning the full range of depths. Depth bins were dynamically selected, ensuring that bins were no larger than 0.5 m and contained no more than 50 bathymetric soundings. For whole segments using a large radius, these limits were changed to 0.1 m and 1000 points. If a very large number of soundings were present, this approach generated a larger number of narrower bins, while producing the opposite given a smaller number of observations. Three depth of colonization metrics were derived from the empirical pattern of seagrass presence vs. depth. These included minimum (*Zc,min*), median (*Zc,med*), and maximum (*Zc,max*) depth of colonization. These terms each describe meaningful points on the depth distribution of the seagrass coverage map. *Zc, max* is the deepest depth at which a significant coverage of mappable seagrasses occurred, excluding isolated patches (or outliers) at deeper depths. *Zc,med* is the median depth of the deep water edge of seagrass. Finally, *Zc,min* approximates the depth at which seagrass percent cover begins to decline with increasing depth, which may occur at *Z=*0 m.

The algorithm for estimating *Zc* was implemented recursively for locations on a grid covering the study area, resulting in a map of depth of colonization. It was also implemented at a single central location in estuary segments with a radius large enough to encompass all observations in the segment. At each location, the seagrass-depth data (i.e., merged bathymetric and seagrass coverage data) was extracted within a radius from the chosen location (Fig. 1). Geospatial data were imported and processed using functions in the rgeos and sp packages in R (Bivand *et al*. 2008; Bivand and Rundel 2014). A *Zc* estimate for each location was then quantified by computing the proportions of points containing seagrass as a function of depth. The chosen radius depends on the information desired about a location. . In general, a sufficient radius will result in a plot illustrating a decreasing proportion of points with seagrass with increasing depth (Fig. 3). The radius should also change depending on whether an estimate at a single location is preferred or if a sampling grid is used. In the former, the radius depends on an expected area of influence given a priori knowledge of a location. As an example, the radius to characterize depth of colonization at the outflow of the Steinhatchee River in Fig. 1 should be large enough to describe variation in growth as affected by local conditions, while small enough to not over-sample beyond the expected influence of the river. In the latter, an appropriate radius will provide complete coverage of the grid while minimizing redundancy of information through overlap of the sampled area by each point.

At each location, a logistic function was fitted to the extracted depth points using non-linear regression, quantifying the decrease in seagrass cover with respect to depth (Equation 1; Fig. 3):

 (1)

where the proportion of points with seagrass present, *P*, within each depth bin, centered at *Z*, was defined by a logistic curve with an upper asymptote *α*, an inflection point *β*, and a scale parameter *γ*. The curve was fitted by minimizing the residual sums-of-squares with the Gauss-Newton algorithm (Bates and Chambers 1992). Initial parameter values for fitting were estimated as max(*P*), =median(*Z*) and =75th percentile(*Z*) - median(*Z*). The maximum rate of decrease in seagrass coverage respect to *Z* is and occurs at *Z*=. The tangent at *Z*= passes through the line P= at Z= and through P=0 at Z=The three seagrass depth of colonization metrics were defined in terms of these reference values as follows:

(2)

(3)

(4)

Several quality control measures were implemented to reduce spurious estimates. First, Zc parameters (i.e., depth of colonization) were estimated only if the number of seagrass depth points was sufficient for the logistic curve to be estimable. Second, estimates were provided only if the fitted value for , the inflection point on the logistic curve, was within the range of depth, Z, in the data. It was possible for -2 to be less than zero, and this was common when seagrass cover declined immediately as depth increased from zero (Fig. 3B). In these cases, *Zc,min*= 0 and *Zc,med* is half the depth from zero to *Zc,max* (Fig. 3B).

Estimates of parameter uncertainty from the logistic model were also used to evaluate the quality and variability associated with individual depth of colonization estimates. Elements of the model-estimated variance-covariance matrix for the model parameters ,  and  were used to estimate the variance of the depth of colonization parameters using equations for sums and differences of normal random variables (Ku 1966):

(5)

(6)

(7)

We then estimated 95% prediction intervals for each parameter as the estimate where 2 is the appropriate estimate from eq. 5, 6 or 7. The value of is not defined when - 2< 0 because *Zc,min* is fixed at zero (Fig. 3b). Given the estimated prediction intervals, we also considered depth of colonization to be inestimable if the 95% prediction interval for *Zc, max* included zero.

*Estimate of spatial distribution and mean depth of colonization*

Depth of colonization within estuary segments was estimated using (1) a single central point in the segment and a large sampling radius, and (2) a grid of sample points. For the first approach, a segment mean was generated using all the depth vs. seagrass observations within the segment. The variance of *Zc* was computed using eqs. 5, 6 and 7. For the second approach, *Zc* was estimated at each node on a regular grid of sample points distributed throughout each estuary segment (Fig. 4). Nodes were spaced at an interval of 0.01 degrees latitude and longitude (≈ 0.6 x 0.5 km at 30° N) and the sampling radius for each location was set to 0.02 degrees. To account for spatial correlation among the estimates, segment means and standard errors were computed from the gridded estimates using an intercept-only spatial mixed model, implemented using the nlme package in R. An isotropic Gaussian correlation structure with a nugget effect was selected from among other options based on the Akaike Information Criterion.

*Seagrass Light Requirements*

Seagrass light requirements were computed as the average fraction of surface irradiance (PAR) reaching the depth of colonization, which was quantified for this purpose as *Zc,med*. The same calculations using *Zc,max* are included as online supplemental information. Depth of colonization and water clarity were each quantified on identical grids. Grid size was selected to maximize the number of matches between depth of colonization and water clarity measurements, resulting in grid radii of 0.04 degrees for Choctawhatchee Bay, 0.1 degrees for Tampa Bay and 0.15 degrees for Indian River Lagoon. Grid cells centered more than 1 km from seagrass were not included, preventing spurious comparison of seagrass depth of colonization with water clarity far from shorelines. The percentage of surface irradiance (% SI) at the median depth of colonization was computed using

 (8)

where the light extinction coefficient (*Kd*) was obtained as a remote sensing product (Choctawhatchee Bay), was computed from a remote sensing-derived estimate of Secchi depth (Tampa Bay), or from field-based Secchi depth measurements (Indian River Lagoon). Where *Kd* was derived from Secchi depth (*ZSecchi*), it was computed using (Poole and Atkins 1929; Idso and Gilbert 1974). The % SI at the maximum depth of colonization (*Zc,max*) was also estimated and is reported as supplemental information.

Segment means and standard errors for light requirements were computed from the spatially-correlated gridded estimates using an intercept-only spatial mixed model, as for depth of colonization. Tests for differences in mean light requirements among estuaries and estuary segments were also implemented using a spatial mixed model implemented in R using nlme, in this case with a single categorical fixed effect (estuary or estuary segment) and a Gaussian spatial correlation structure with a nugget effect.

**Results**

*Segment characteristics and seagrass depth estimates*

The study areas varied in size and depth (Table 1). Area ranged from 59 km2 for Western Choctawhatchee Bay (WCB) to 271 km2 for the Big Bend (BB). Mean depth was less than 5 meters in each segment, except for WCB, which was slightly deeper (5.3 m). Maximum depth was greater in WCB (11.9 m) and Old Tampa Bay (OTB, 10.4 m) compared to BB (3.6 m) and Upper Indian River Lagoon (UIRL, 3.7 m) segments. Seagrass coverage was extensive in BB (74.8 % of total segment area), less in UIRL (32.8 %) and OTB (11.9 %), and very sparse in WCB (5.9 %), where most seagrass was in a large patch located just west of the inlet to the Gulf of Mexico (Fig. 2). Seagrasses were distributed throughout BB except for a noticeable area of decreased coverage near the outflow of the Steinhatchee River (Fig. 2, upper left). Seagrasses in OTB and UIRL were distributed narrowly along the shorelines, consistent with strong depth-dependence. Seagrass coverage declined toward the northern ends of both OTB and UIRL.

Whole segment estimates (± prediction interval) for *Zc,med* varied from 0.95±0.07 m in OTB to 2.29±0.19 in BB, with 95% prediction intervals equal to ±1% to 10% of the estimate (Table 2). Estimates of *Zc,max* varied from 1.1 m to 3.8 m and were somewhat less precise, with 95% prediction intervals equal to 3 to 20% of the estimate (Table 2). Means of spatially-resolved estimates of *Zc,med* varied from 2% more than to 15% less than the whole-segment estimates (Table 2), within the margin of uncertainty for each, suggesting that the two approaches gave comparable results. The difference was largest for BB, where the gridded estimates of depth of colonization had a bi-modal distribution (i.e., lower estimates near the Steinhatchee outflow vs. higher values distant from the river outflow (Fig. 4, upper left). The whole segment estimate of *Zc,max* for BB was 3.8 m, 65% more than the 2.3 m average of the gridded estimates, reflecting a greater influence of the deeper-distributed seagrass on the whole segment calculation (Table 2; Fig. 4). Estimates for *Zc,min* were as low as zero in BB and OTB (Table 2), indicating that seagrass coverage decreased immediately with any increase in depth. The highest values for *Zc,min* were associated with relatively deep seagrass distributions, as in WCB. In these cases, coverage did not decrease initially with depth. Seagrass percent cover often increased initially with increasing depth, likely reflecting stressors such as wave energy or desiccation during extreme low tides affecting the shallow margin of the seagrass bed.

Gridded estimates provided further information on the distribution of seagrasses in each segment (Table 3; Fig. 4) and on the average depth of colonization in the entire estuary. Seagrass *Zc* estimates were computed for 255 locations in Choctawhatchee Bay, 218 locations in Tampa Bay, and 45 locations in the Indian River Lagoon (Table 3 and Figs. 7, 8, 9). Mean *Zc,med* (±s.e.) for the bays were 2.03±0.12, 1.16±0.10, and 1.10±0.11 m for Choctawhatchee Bay, Tampa Bay, and Indian River Lagoon, respectively. Mean *Zc,med* for Tampa Bay and Indian River Lagoon were not significantly different, while *Zc,med* was significantly higher in Choctawhatchee Bay than either other bay (p<0.01; Table 3).

Spatial heterogeneity in depth of colonization was particularly apparent for BB and UIRL (Fig. 4). As previously mentioned, depth of colonization in the Big Bend segment was reduced in the vicinity of the Steinhatchee River discharge. Seagrasses were also limited to shallower depths at the north end of the Upper Indian River Lagoon segment, but grew at maximum depths up to 2.2 m on the eastern portion of the Upper Indian River Lagoon segment near the Merritt Island National Wildlife Refuge (Fig. 2). Seagrasses in Old Tampa Bay grew slightly deeper in the eastern and southern portion of the segment and declined to shallower depths near freshwater inflow channels on the northern margin (Fig. 4, Fig. 8). The deepest growing seagrass in western Choctawhatchee Bay was closest to Destin Pass, where regular tidal exchange with Gulf of Mexico waters maintains increased water clarity (Fig. 4). *Zc* could not be estimated where seagrasses were sparse or absent as in the center of Old Tampa Bay and western Choctawhatchee Bay, or where there was an insufficient gradient in water depth, as in several areas of the Big Bend segment (Fig. 4). Conversely, individual points absent of seagrass can be assigned a depth estimate if the radius of the sample area satisfies the above criteria. This can produce gridded maps that may not resemble the original coverage maps because they do not describe the same information.

Despite apparent gradients in depth of colonization aligned with the major axis of each estuary (Fig. 4, 7, 8, 9), segment means for *Zc,med* were mostly not statistically different (Table 3). In Tampa Bay, *Zc,med* was ~0.5 m less (p<0.05) in Old Tampa Bay than in the Lower or Middle Tampa Bay (p<0.05) segments. Differences among the other segments were not statistically significant. For Choctawhatchee Bay, *Zc,med* in the eastern segment was 1.1 m and 1.5 m less than in the central and western bay, respectively. Similarly, the apparent differences in *Zc,med* in lower Indian River Lagoon vs. elsewhere in the lagoon (Fig. 9) were also not statistically significant.

*Seagrass light requirements*

Estimates of water clarity, seagrass depth of colonization, and corresponding light requirements for all locations in Choctawhatchee Bay, Tampa Bay, and the Indian River Lagoon indicated substantial variation, both between and within the different bays. Satellite-derived estimates of light attenuation for Choctawhatchee Bay (as *Kd*) and Tampa Bay (as clarity) resolved spatial variation in average water clarity (Figs. 5 and 6). For Choctawhatchee Bay, *Kd* increased from the western and central segments toward the eastern segment, which is adjacent to the Choctawhatchee River discharge (Fig. 5). Similarly, water clarity decreased from lower and central Tampa Bay into Old Tampa Bay and Hillsborough Bay. Although it would most likely not affect the seagrass distribution near shore, water clarity was also greater in the central area of the lower bay segments (Fig. 6). Secchi depth was highest in the southern Indian River Lagoon and decreased to the north. Relatively few Secchi depth measurements were available for the Upper Indian River Lagoon and Banana River segments, likely because water clarity exceeded the maximum depth in shallow areas, resulting in right-censored measurements.

Whole-estuary means for percent surface irradiance (% SI) at *Zc,med* (i.e., seagrass light requirement) was (mean±s.e.) 50±3.0 % SI for Choctawhatchee Bay, 41±2.5 % SI for Tampa Bay, and 18±2.9 % SI for Indian River Lagoon. Based on Tukey contrasts, light requirements for seagrass in Indian River Lagoon were lower (p<0.01) than for either of the other estuaries, whereas Choctawhatchee Bay and Tampa Bay light requirements were similar (Table 3). Despite some apparent spatial patterns in seagrass light requirements (Fig. 7, 8, 9), no significant differences were found among segments within a single estuary. In Tampa Bay, the segment mean (±s.e.) % SI at *Zc,med* ranged from 34±11.2% to 49±8.7 % (Table 3, Fig. 8). For Choctawhatchee Bay, segment means were 46±6.4 % SI to 64±8.9 % SI, with the apparently higher values in eastern Choctawhatchee Bay (Table 3, Fig. 7). A larger range was observed for Indian River Lagoon: 9.2±2.8 % SI to 24±6.4 % SI (Table 3, Fig. 9). Either small sample sizes, as for Indian River Lagoon, or a small number of effectively independent samples given the spatial correlation of residuals, reduced the statistical significance of apparent spatial differences in light requirements.

**Discussion**

Seagrass depth of colonization is an important measure of the status and condition of seagrass communities in estuaries because it relates to water clarity and related anthropogenic water quality changes, especially eutrophication caused by excess nutrient loading (Dennison *et al*. 1993; Short and Wyllie-Echeverria 1996; Burkholder *et al*. 2007). Because seagrasses are ecologically important and sensitive to water quality changes, both seagrass coverage and depth of colonization have been used to define water quality management objectives (Steward *et al*. 2005; Environmental Protection Agency 2012; Greening *et al*. 2014). The methods developed and demonstrated in this study are a rigorous, yet efficient and practical approach for computing seagrass depth of colonization at a large scale using widely-available geospatial data sets describing seagrass areal extent and bathymetry. The method is automated via R code, and thus not especially labor-intensive. Because it is automated, it is reproducible and could be applied to new data from the studied estuaries or other estuaries with appropriate data. The method provides maps of depth of colonization, resolving both means and spatial gradients at a range of scales from an individual measurement to the whole estuary. Uncertainty is estimated for individual estimates of depth of colonization, while both variability (s.d.) and uncertainty (s.e.) are quantified for segments of estuaries and whole estuaries. Given these characteristics, our approach is a useful tool for large scale assessment of seagrass distribution with respect to water depth wherever the required data are available. Moreover, resolving spatial differences in depth of colonization and light requirements provides valuable information to support further investigation of the causes and mechanisms affecting the extent and spatial distribution of seagrass habitats.

Maps illustrating spatial patterns in depth of colonization quantified expected patterns in depth of colonization, wherein seagrasses grew to greater depth when closer to ocean passes, where water was clearer (Figs. 7, 8, 9). Differences among segment means were mostly not statistically different, reflecting both variability in estimates at the scale of estuary segments and spatial correlation of residuals, which reduced the effective number of degrees of freedom. For example, if the seagrass distribution within a segment includes two areas with homogeneous depth of colonization within but differences among them, this will tend to inflate uncertainty regarding the segment means, leading to poor resolution of differences among segments. Possible solutions could include a different segmentation approach or analysis of pattern without segmentation. If the objective was to resolve changes in average depth of colonization over time, which would be of interest ecologically, a statistically powerful approach could be an evaluation of pairwise changes at each grid node. While we have not yet evaluated a time series of coverages in this way it would be a useful extension of our research.

For the first time, we also combined estimates of water clarity for estuaries based on satellite remote sensing and Secchi depth measurements to resolve spatial patterns in seagrass light requirements. Like depth of colonization, maps of these values quantify gradients in light requirements, even if “segments” delineated for management purposes did not clearly identify regions that differed by light requirements. We would expect light requirements, as we defined them, to be higher at locations closer to freshwater and nutrient sources because epiphytic algal growth, salinity variations, color, or other factors such as sediment geochemistry could impose constraints on seagrass growth beyond those imposed by light attenuation in the water column (Hemminga 1998; Kemp *et al*. 2004). The results neither conflicted with nor definitively supported this expectation. For example, the highest light requirements in each of the estuaries were furthest from tidal exchange and closest to sources of freshwater and nutrients (Fig. 7, 8, 9). But, the differences were subtle and, given variations within segments, did not emerge as significant differences among segment means. On the other hand, light requirements for seagrass in Indian River Lagoon (IRL) was significantly less than for seagrass in Choctawhatchee Bay and Tampa Bay. Light requirements for Choctawhatchee Bay and Tampa Bay were both more than the 20% estimate that has been referenced broadly in water quality management (Batiuk *et al*. 1992; Dennison *et al*. 1993; Kemp *et al*. 2004) and locally within Florida (Dixon and Leverone 1995; US EPA 2012). Light requirements for Tampa Bay were similar to 20% in only a few areas of the Bay. Given the broad range in published estimates of seagrass light requirements (Dennison *et al.* 1993), our estimates are not outside the norm. Nonetheless, it is useful to consider possible explanations and implications associated with these results, especially with respect to the range within our own estimates.

Some of the differences in light requirements that we observed may relate to species composition, since the physiology of seagrass species is far from invariant. For example, *Halodule wrightii* is the most abundant seagrass in western Choctawhatchee Bay (Yarbro and Carlson 2015) andhas higher light requirements than several other abundant species in Florida (Choice *et al*. 2014) including *Thalassia testudinum*, which dominates the more oceanic areas of Tampa Bay. Choice *et al*. (2014) found that light requirements for *Syringodium filiforme* were much less, as low as 8-15 % SI, although Kenworthy (1993) found that the depth distribution of *H. wrightii* and *S. filiforme* were similar in the lower Indian River Lagoon, implying their light requirements may be similar. Estimates of light requirements for several species of *Halophila* indicate a potential to grow at 5% SI or less (Kenworthy and Haunert 1991), consistent with some of our lowest estimates from Lower Indian River Lagoon (Fig. 9). Neither *S. filiforme* nor any of the *Halophila* spp. appear to be dominant species in Tampa Bay or Choctawhatchee Bay, perhaps limiting seagrass distributions in those estuaries to higher light environments compared with lower Indian River Lagoon. Although we cannot be certain the extent to which species composition can explain the differences that we observed in %SI at the depth of colonization, the key observation is that differences were observed, that seagrass species vary in their physiology and responses to a range of factors, and therefore, that it may be useful to understand and manage seagrass habitats utilizing local information where possible. Another consideration related to species composition is that our estimates are likely to be driven by the deepest growing species. Water clarity changes could alter competitive relationships among species within the mappable seagrass area, which would not be apparent in our analysis.

Our estimates of % SI at the depth of colonization necessarily also depend on our approach to estimating depth of colonization, as do others in the literature. Depth of colonization is a reference point along a gradient of decreasing seagrass cover (presumably) associated with increasing light limitation and related physiological stress (e.g., Fig. 3 in Hemminga 1998). In some studies, percent cover was estimated by diver observation (Choice *et al*. 2014), enabling a statistical approach (e.g., moving split window) that directly resolves a threshold for rapid decline in percent cover with respect to % SI at the scale of a single quadrat. To scale up the analysis, we needed to use seagrass coverage maps based on photointerpretation which necessarily imposes a binary classification (present/absent). By inferring the probability of seagrass presence conditional on depth, however, we obtained an estimate analogous to that of Choice *et al*. (2014), with the parameter β (Fig. 3) estimating the threshold for most rapid decline in seagrass presence. However, it is still unavoidable that seagrass will be both present at greater depths and stressed by light limitation at lesser depths. In this regard, a strength of our approach is that we can estimate the % SI associated with both the local extremes of the mappable seagrass distribution (i.e., *Zc,max*; Figs. S1, S2, S3) and the center of that depth distribution (i.e., *Zc,med*). Moreover, by being linked to aerial coverage data, the estimates are available for a range of spatial scales, are comparable across all those scales, and can be quickly re-computed when new surveys are completed.

Our estimates also depend on an accurate characterization of average water clarity, something that will always be challenging in the context of seagrass ecology. For example, since and and *ksd* ~1.4 to 1.7, Secchi depth in seagrass habitats is often similar to the depth of colonization, potentially leading to right censoring of Secchi measurements when the disk would be visible on the bottom. Accurate light profiling is possible but also more difficult in shallow water than in deeper water. Limitations on boat operations also favor sampling during periods of calm winds, perhaps leading to under-sampling of periods when sediment resuspension is above average. Quantifying water clarity via satellite remote sensing has advantages but also presents both similar and new challenges. For example, concern regarding bottom reflectance led Chen *et al*. (2007) to exclude data if water depth was <2 m, excluding nearly all seagrass areas. Water clarity estimates are therefore based on nearby, but deeper waters. If attenuation is lower in open water, this will tend to increase the estimate of % SI at the depth of colonization. On the other hand, the uniform and sustained spatial and temporal coverage provided by satellite remote sensing is an advantage. Such uniform coverage may reduce spurious small-scale variability.

Sustained trends in water quality are another factor that can affect estimates of light requirements because seagrasses can be both slow to recover following disturbance and resistant to stress in the first place. In particular, species such as *Thalassia testudinum* display a phalanx growth strategy and buffer against periods of low light by tapping into below ground reserves, making them slow to achieve a light-limited equilibrium distribution in the presence of water quality trends. Improving trends in water clarity could lead to higher estimates of light requirements, whereas the opposite may be true with declining trends in clarity. As a result, considering both depth of colonization and changes in the apparent light requirements may be useful for understanding the status and trends related to seagrass habitats.

This study has implications for both seagrass ecology and environmental management. Scientifically, the ability to resolve patterns in several parameters related to depth of colonization as well as % SI at the depth of colonization could be a useful tool for generating testable hypotheses. For example, persistent differences in spatial patterns of depth distributions may suggest hypotheses regarding the causes and could stimulate research to identify local drivers. Similarly, we could seek to better understand temporal changes in depth of colonization, but without a consistent approach to quantifying it, we may not be aware of such changes. For example, despite extensive documentation of changes in the area of seagrass habitat in Tampa Bay since 1950 (Greening *et al*. 2014), little attention has been given to trends in the depth distribution during the same period. Simultaneous analysis of each could provide additional insights into patterns and processes associated with seagrass recovery from eutrophication impacts.

There are several important management implications related to our method and results. Localized patterns in depth of colonization, such as in the case of the Steinhatchee River outflow, illustrate that management goals related to seagrass depth distribution and water clarity may not be applicable throughout water quality segments drawn without considering local drivers. At a slightly larger scale, differences among segments and among entire estuaries show that it can be both important and (fortunately) possible to consider local differences in the water quality requirements for seagrasses when developing and evaluating water quality goals over time. Even though seagrasses are affected by factors other than water clarity, resistance and resilience in the face of multiple stressors can be influenced by the physiological and energetic changes affected by light availability (Burkholder *et al*. 2007). In the case of Tampa Bay, light availability generally exceeds seagrass light requirements estimated in the early 1990s. This may have sustained the seagrass recovery, which accelerated following a brief ENSO-related period of increased river flow and decreased water clarity in the late 1990s (Greening *et al*. 2014).

**Acknowledgments**

We thank Dr. Peter Tango for comments on an early draft of the manuscript. The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the U.S. Environmental Protection Agency.

**References**

Barko, J.W., D.G. Hardin, and M.S. Matthews. 1982. Growth and morphology of submersed freshwater macrophytes in relation to light and temperature. *Canadian Journal of Botany* 60: 877–887.

Bates, D.M., and J.M. Chambers. 1992. Nonlinear models, p. 421–454. In: Statistical models in S, J.M. Chambers and T.J. Hastie (eds.), pp. 421-454. Pacific Grove, California: Wadsworth and Brooks/Cole.

Batiuk, R. A., R. J. Orth, K. Moore, W. C. Dennison, J. C. Stevenson, L. W. Staver, V. Carter, N. B. Rybicki, R. E. Hickman, S. Kollar, S. Bieber and P. Heasly. 1992. Chesapeake Bay Submerged Aquatic Vegetation Habitat Requirements and Restoration Targets: A Technical Synthesis. Annapolis, MD, US Environmental Protection Agency, Chesapeake Bay Program Office: 190 pp.

Bivand, R.S., E.J. Pebesma, and V. Gómez-Rubio. 2008. Applied spatial data analysis with R. New York: Springer.

Bivand, R., and C. Rundel. 2014. rgeos: Interface to geometry engine - open source (gEOS), R package version 0.3-8. <http://CRAN.R-project.org/package=rgeos>. Accessed July 1, 2015.

Burkholder, J. M., D. A. Tomasko and B. W. Touchette 2007. Seagrasses and eutrophication. *Journal of Experimental Marine Biology and Ecology* 350(1-2): 46-72.

Caffrey, J.M., M.C. Murrell, K.S. Amacker, J. Harper, S. Phipps, and M. Woodrey. 2013. Seasonal and inter-annual patterns in primary production, respiration and net ecosystem metabolism in 3 estuaries in the northeast Gulf of Mexico. *Estuaries and Coasts* 37(Suppl 1): S222–S241.

Chen, Z., F.E. Muller-Karger, and C. Hu. 2007. Remote sensing of water clarity in Tampa Bay. *Remote Sensing of Environment* 109: 249–259.

Choice, Z. D., T. K. Frazer, and C. A. Jacoby. 2014. Light requirements of seagrasses determined from historical records of light attenuation along the Gulf coast of peninsular Florida. *Marine Pollution Bulletin* 81: 94–102.

CPE (Coastal Planning and Engineering). 1997. Indian River Lagoon bathymetric survey. A final report to St. John’s River Water Management District. Contract 95W142, Palatka, Florida, Coastal Planning and Engineering.

Dawes, C., and W. Avery. 2010. Epiphytes of the seagrass *Halodule wrightii* in Hillsborough Bay, Florida, a 14 year study in an estuary recovering from eutrophication. *Florida Scientist* 73: 185–195.

Dennison, W.C., R.J. Orth, K.A. Moore, J.C. Stevenson, V. Carter, S. Kollar, P.W. Bergstrom, and R.A. Batiuk. 1993. Assessing water quality with submersed aquatic vegetation. *Bioscience* 43: 86–94.

Dixon, L.K., and J.R. Leverone. 1995. Light requirements of *Thalassia testudinum* in Tampa Bay, Florida. Technical Report Number 425, Sarasota, Florida, Mote Marine Lab, Sarasota, Florida.

Duarte, C.M. 1991. Seagrass depth limits. *Aquatic Botany* 40: 363–377.

Duarte, C.M. 1995. Submerged aquatic vegetation in relation to different nutrient regimes. *Ophelia* 41: 87–112.

Elsdon, T.S., and S.D. Connell. 2009. Spatial and temporal monitoring of coastal water quality: refining the way we consider, gather, and interpret patterns. *Aquatic Biology* 5: 157–166.

ESRI (Environmental Systems Research Institute). 2012. ArcGIS v10.1. Redlands, California, Environmental Systems Research Institute.

FDEP (Florida Department of Environmental Protection). 2012. Site-specific information in support of establishing numeric nutrient criteria for Choctawhatchee Bay. Tallahassee, Florida, Florida Department of Environmental Protection: 121 pp.

Hale, J.A., T.K. Frazer, D.A. Tomasko, and M.O. Hall. 2004. Changes in the distribution of seagrass species along Florida’s central gulf coast: Iverson and Bittaker revisited. *Estuaries* 27: 36–43.

Hall, M.O., M.J. Durako, J.W. Fourqurean, and J.C. Zieman. 1999. Decadal changes in seagrass distribution and abundance in Florida Bay. *Estuaries* 22(2B): 445–459.

Hemminga, M. A. 1998. The root/rhizome system of seagrasses: an asset and a burden. *Journal of Sea Research* 39(3-4): 183-196.

Hilborn, R., and M. Mangel. 1997. The ecological detective: Confronting models with data. Princeton, New Jersey: Princeton University Press.

Hughes, A.R., S.L. Williams, C.M. Duarte, K.L. Heck, and M. Waycott. 2009. Associations of concern: declining seagrasses and threatened dependent species. *Frontiers in Ecology and the Environment* 7: 242–246.

Idso, S.B., and R.G. Gilbert. 1974. On the universality of the Poole and Atkins Secchi disk-light extinction equation. *Journal of Applied Ecology* 11: 399–401.

Iverson, R.L., and H.F. Bittaker. 1986. Seagrass distribution and abundance in eastern Gulf of Mexico coastal waters. *Estuarine, Coastal and Shelf Science* 22: 577–602.

Janicki, A., and D. Wade. 1996. Estimating critical external nitrogen loads for the Tampa Bay estuary: An empirically based approach to setting management targets. Technical Report 06-96, St. Petersburg, Florida, Tampa Bay National Estuary Program. 200 pp.

Jones, C.G., J. H. Lawton, and M. Shachak. 1994. Organisms as ecosystem engineers. *OIKOS* 69: 373–386.

Kemp, W.C., R. Batiuk, R. Bartleson, P. Bergstrom, V. Carter, C.L. Gallegos, W. Hunley, L. Karrh, E.W. Koch, J.M. Landwehr, K.A. Moore, L. Murray, M. Naylor, N.B. Rybicki, J.C. Stevenson, and D.J. Wilcox. 2004. Habitat requirements for submerged aquatic vegetation in Chesapeake Bay: Water quality, light regime, and physical-chemical factors. *Estuaries* 27: 363–377.

Kenworthy, W. J. and D. E. Haunert (eds.). 1991. The light requirements of seagrasses: proceedings of a workshop to examine the capability of water quality criteria, standards and monitoring programs to protect seagrasses. NOAA Technical Memorandum NMFS-SEFC-287. Beaufort, NC: 181 pp.

Kenworthy, W.J., and M.S. Fonseca. 1996. Light requirements of seagrasses *Halodule wrightii* and *Syringodium filiforme* derived from the relationship between diffuse light attenuation and maximum depth distribution. *Estuaries* 19: 740–750.

Koch, E.W. 2001. Beyond light: Physical, geological, and geochemical parameters as possible submersed aquatic vegetation habitat requirements. *Estuaries* 24: 1–17.

Ku, H. H. 1966. Notes on the use of propagation of error formulas. *Journal of Research of the National Bureau of Standards - C. Engineering and instrumentation*. 70C(4): 263-273.

Lee, Z P., K.P. Du, and R. Arnone. 2005. A model for the diffuse attenuation of downwelling irradiance. *Journal of Geophysical Research* 110: 1-15.

Lottig, N.R., T. Wagner, E.N. Henry, K.S. Cheruvelil, K.E. Webster, J.A. Downing, and C.A. Stow. 2014. Long-term citizen-collected data reveal geographical patterns and temporal trends in water clarity. *PLoS ONE* 9: 1-8.

Poole, H.H., and W.R.G. Atkins. 1929. Photo-electric measurements of submarine illumination throughout the year. *Journal of the Marine Biological Association of the United* *Kingdom* 16: 297–324.

RCT (R Core Team). 2015. R: A language and environment for statistical computing. Vienna, Austria, R Foundation for Statistical Computing.

Schaeffer, B., J. Hagy, R. Conmy, J. Lehrter and R. Stumpf. 2012. An approach to developing numeric water quality criteria for coastal waters using the SeaWiFS satellite data record. *Environmental Science & Technology* 46: 916-22.

Spears, B.M., I.D.M. Gunn, L. Carvalho, I.J. Winfield, B. Dudley, K. Murphy, and L. May. 2009. An evaluation of methods for sampling macrophyte maximum colonisation depth in Loch Leven, Scotland. *Aquatic Botany* 91: 75–81.

Steward, J.S., R.W. Virnstein, L.J. Morris, and E.F. Lowe. 2005. Setting seagrass depth, coverage, and light targets for the Indian River Lagoon system, Florida. *Estuaries* 28: 923–935.

Søndergaard, M., G. Phillips, S. Hellsten, A. Kolada, F. Ecke, H. Mäemets, M. Mjelde, M.M. Azzella, and A. Oggioni. 2013. Maximum growing depth of submerged macrophytes in European lakes. *Hydrobiologia* 704: 165–177.

Thompson, M. J. 1978. Species composition and distribution of seagrass beds in the Indian River Lagoon, Florida. *Florida Science* 41(2): 90-96.

Tyler, D., D.G. Zawada, A. Nayegandhi, J.C. Brock, M.P. Crane, K.K. Yates, and K.E.L. Smith. 2007. Topobathymetric data for Tampa Bay, Florida. Open-File Report 2007-1051 (revised), St. Petersburg, Florida, US Geological Survey, US Department of the Interior. (poster)

US EPA (US Environmental Protection Agency) 2012. Technical support document for U.S. EPA's proposed rule for numeric nutrient criteria for Florida's estuaries, coastal waters, and south Florida inland flowing waters. Volume 1: Estuaries. November 30, 2012. EPA-HQ-OW-2010-0222-0002. 365 pp.

Venables, W.N., and B.D. Ripley. 2002. Modern applied statistics with S, 4th edition. New York: Springer.

Virnstein, R. W. 2000. Seagrass management in Indian River Lagoon, Florida: Dealing with issues of scale. *Pacific Conservation Biology* 5:299-305.

Williams, S.L., and K.L. Heck. 2001. Seagrass community ecology. In: Marine Community Ecology. M.D. Bertness, S.D. Gaines, and M.E. Hay (eds.). Sunderland, Massachusetts: Sinauer Associates.

Woodruff, D.L., R.P. Stumpf, J.A. Scope, and H.W. Paerl. 1999. Remote estimation of water clarity in optically complex estuarine waters. *Remote Sensing of Environment* 68: 41–52.

Yarbro, L. A. and P. R. Carlson, Jr. 2015. Seagrass Integrated Mapping and Monitoring Program, Mapping and Monitoring Report No. 1.1. FWRI Technical Report TR-17. St. Petersburg, FL, Florida Fish and Wildlife Conservation Commission: 10 pp.

Zhu, B., D.G. Fitzgerald, S.B. Hoskins, L.G. Rudstam, C.M. Mayer, and E.L. Mills. 2007. Quantification of historical changes of submerged aquatic vegetation cover in two bays of Lake Ontario with three complementary methods. *Journal of Great Lakes Research* 33: 122–135.

Figure Captions

**Fig.1** Examples of data and grid locations for estimating seagrass depth of colonization for a region of the Big Bend, Florida. (a) seagrass coverage and depth contours at 2 meter intervals, including the whole segment estimate for depth of colonization; (b) a grid of sampling locations with sampling radii for estimating *Zc* and seagrass depth points derived from bathymetry and seagrass coverage layers; (c) an example of sampled seagrass depth points for a test location. Estimates in Fig. 3 were obtained from the test location in (c)

**Fig. 2** Locations and seagrass coverage of estuary segments used to evaluate depth of colonization estimates. Seagrass coverage layers are from 2006 (BB: Big Bend), 2010 (OTB: Old Tampa Bay), 2009 (UIRL: Upper Indian R. Lagoon), and 2007 (WCB: Western Choctawhatchee Bay). SR= Steinhatchee River outflow; MI= Merritt Island National Wildlife Refuge

**Fig. 3** Methods for estimating seagrass depth of colonization using sampled seagrass depth points around a single location. Three depth estimates (*Zc,min*, *Zc,med*, *Zc,max*) are based on a linear curve through the inflection point of a logistic growth curve. The logistic curve is defined by the parameters α, β, and γ and describes the decrease in the proportion of sample points with seagrass as a function of depth below mean tide level (MTL). (A) The estimation method when the linear curve intercepts α at a depth greater than zero. (B) The alternative method when the linear curve intercepts α at depth less than zero

**Fig. 4** Spatially-resolved estimates of maximum seagrass depth of colonization (m) for four coastal segments of Florida. Estimates are assigned to grid locations for each segment, where grid spacing was fixed at 0.01 decimal degrees. Radii for sampling seagrass bathymetric data around each grid location were fixed at 0.02 decimal degrees. From left to right, top to bottom: Big Bend, Old Tampa Bay, Upper Indian R. Lagoon, Western Choctawhatchee Bay

**Fig. 5** Satellite estimated light attenuation for Choctawhatchee Bay as an average of all years from 2003 to 2007. See Fig. 7 for segment identification

**Fig. 6** Satellite estimated water clarity for Tampa Bay as an average of all years from 2006 to 2010. See Fig. 8 for segment identification

**Fig. 7** Median depth of seagrass colonization (*Zc,med*, m) and light requirements (% surface irradiance at *Zc,med*) for multiple locations in Choctawhatchee Bay, Florida. Each location has both water clarity estimates from satellite observations and an estimate of seagrass depth of colonization with a search radius of 0.04 degrees. At right: Estimates summarized by bay segment where the dimensions are the 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. CCB: Central Choctawhatchee Bay, ECB: East Choctawhatchee Bay, WCB: West Choctawhatchee Bay

**Fig. 8** Median depth of seagrass colonization (*Zc,med*, m) and light requirements (% surface irradiance at *Zc,med*) for multiple locations in Tampa Bay, Florida. Each location has both a water clarity estimate from satellite observations and an estimate of seagrass depth of colonization with a search radius of 0.1 degrees. Box plots show 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. HB: Hillsborough Bay, LTB: Lower Tampa Bay, MTB: Middle Tampa Bay, OTB: Old Tampa Bay

**Fig. 9** Median depth of seagrass colonization (*Zc,med*, m) and light requirements (% surface irradiance at *Zc,med*) for multiple locations in Indian River Lagoon, Florida. Each location has both an average Secchi depth observation and an estimate of seagrass depth of colonization with a search radius of 0.15 degrees. Map locations are georeferenced observations of Secchi depth. Box plots show 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. 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

Supplementary figures

**Fig. S1** Maximum depth of seagrass colonization (*Zc,max*, m) and light requirements (% surface irradiance at *Zc,max*) for multiple locations in Choctawhatchee Bay, Florida. Each location has both water clarity estimates from satellite observations and an estimate of seagrass depth of colonization with a search radius of 0.04 degrees. At right: Estimates summarized by bay segment where the dimensions are the 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. CCB: Central Choctawhatchee Bay, ECB: East Choctawhatchee Bay, WCB: West Choctawhatchee Bay

**Fig. S2** Maximum depth of seagrass colonization (*Zc,max*, m) and light requirements (% surface irradiance at *Zc,max*) for multiple locations in Tampa Bay, Florida. Each location has both a water clarity estimate from satellite observations and an estimate of seagrass depth of colonization with a search radius of 0.1 degrees. Box plots show 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. HB: Hillsborough Bay, LTB: Lower Tampa Bay, MTB: Middle Tampa Bay, OTB: Old Tampa Bay

**Fig. S3** Maximum depth of seagrass colonization (*Zc,max*, m) and light requirements (% surface irradiance at *Zc,max*) for multiple locations in Indian River Lagoon, Florida. Each location has both an average Secchi depth observation and an estimate of seagrass depth of colonization with a search radius of 0.15 degrees. Map locations are georeferenced observations of Secchi depth. Box plots show 25th percentile, median, and 75th percentile. Whiskers extend to the 5th and 95th percentiles with outliers beyond. 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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Table 1** Characteristics of coastal segments used to evaluate seagrass depth of colonization estimates (see Fig. 2 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 square kilometers and meters, respectively. Secchi measurements (m) were obtained from the Florida Department of Environmental Protection's Impaired Waters Rule (IWR) database, update number 40. Secchi mean and standard errors are based on all observations within the ten years preceding each seagrass survey | | | | |
|  | BB*a* | OTB | UIRL | WCB |
| Year*b* | 2006 | 2010 | 2009 | 2007 |
| Latitude | 29.61 | 27.94 | 28.61 | 30.43 |
| Longitude | -83.48 | -82.62 | -80.77 | -86.54 |
| Surface area | 271.37 | 205.5 | 228.52 | 59.41 |
| Seagrass area | 203.02 | 24.48 | 74.89 | 3.51 |
| Depth (mean) | 1.41 | 2.56 | 1.4 | 5.31 |
| Depth (max) | 3.6 | 10.4 | 3.7 | 11.9 |
| Secchi (mean) | 1.34 | 1.41 | 1.3 | 2.14 |
| Secchi (se) | 0.19 | 0.02 | 0.02 | 0.08 |
| *a*BB: Big Bend, OTB: Old Tampa Bay, UIRL: Upper Indian River Lagoon, WCB: Western Choctawhatchee Bay | | | | |
| *b*Seagrass coverage data sources, see methods for bathymetry data sources | | | | |
| BB: http://atoll.floridamarine.org/Data/metadata/SDE Current/seagrass bigbend 2006 poly.htm | | | | |
| OTB: http://www.swfwmd.state.fl.us/data/gis/layer library/category/swim | | | | |
| UIRL: http://www.sjrwmd.com/gisdevelopment/docs/themes.html | | | | |
| WCB: http://atoll.floridamarine.org/data/metadata/SDE Current/seagrass chotawhatchee 2007 poly.htm | | | | |

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2** Summary of seagrass depth estimates (m) for each segment in Fig. 4. Whole segment estimates and prediction intervals were obtained from a single point estimate that included all seagrass depth data for the segment. Mean, standard error, standard deviation, minimum, and maximum values are for multiple grid points within each segment in Fig. 4. Mean and standard error estimates were from intercept-only models that included Gaussian correlation structures to account for spatial dependencies between points | | | | | | | |
| Segment*a* | Whole segment | Pred. Int. (+/-) | Mean | St. Err. | St. Dev. | Min | Max |
| BB |  |  |  |  |  |  |  |
| *Zc,min* | 0.75 | 0.25 | 1.56 | 0.18 | 0.79 | 0 | 2.72 |
| *Zc,med* | 2.29 | 0.19 | 1.94 | 0.17 | 0.76 | 0.55 | 2.97 |
| *Zc,max* | 3.84 | 0.43 | 2.29 | 0.19 | 0.81 | 0.74 | 3.48 |
| OTB |  |  |  |  |  |  |  |
| *Zc,min* | 0.83 | 0.16 | 0.58 | 0.07 | 0.28 | 0.05 | 1.48 |
| *Zc,med* | 0.95 | 0.07 | 0.86 | 0.08 | 0.3 | 0.33 | 1.74 |
| *Zc,max* | 1.07 | 0.21 | 1.17 | 0.12 | 0.4 | 0.34 | 2.04 |
| UIRL |  |  |  |  |  |  |  |
| *Zc,min* | 1.19 | 0.04 | 1.36 | 0.06 | 0.27 | 0.75 | 2.01 |
| *Zc,med* | 1.48 | 0.02 | 1.51 | 0.08 | 0.23 | 0.98 | 2.08 |
| *Zc,max* | 1.77 | 0.05 | 1.63 | 0.08 | 0.23 | 1.11 | 2.16 |
| WCB |  |  |  |  |  |  |  |
| *Zc,min* | 1.84 | 0.42 | 1.58 | 0.11 | 0.34 | 0.78 | 2.29 |
| *Zc,med* | 2.17 | 0.22 | 1.96 | 0.1 | 0.31 | 1.51 | 2.51 |
| *Zc,max* | 2.5 | 0.47 | 2.36 | 0.14 | 0.39 | 1.75 | 3.1 |
| *a*BB: Big Bend, OTB: Old Tampa Bay, UIRL: Upper Indian R. Lagoon, WCB: Western Choctawhatchee Bay | | | | | | | |

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 3** Summary of median depth of colonization (*Zc,med*, m) and light requirements (%) for all bay segments of Choctawhatchee Bay, Indian River Lagoon, and Tampa Bay. Superscripts for mean *Zc,med* denote significant differences among segments within estuaries (letters) or among estuaries (numbers). See Figs. 7 to 9 for spatial distribution of the results | | | | | | | | | | |
| **Segment*a*** |  | *Zc,med* | | | |  | % light | | | |
|  | *n* | Mean | St. Err. | Min | Max |  | Mean | St. Err. | Min | Max |
| Choctawhatchee Bay | 255 | 2.01 | 0.1 | 0.6 | 2.8 |  | 501 | 3.0 | 20 | 87 |
| CCB | 111 | 2.0b | 0.6 | 0.6 | 4.2 |  | 51 | 13.2 | 20 | 87 |
| ECB | 4 | 0.9a | 0.1 | 0.7 | 0.9 |  | 64 | 8.9 | 55 | 75 |
| WCB | 140 | 2.3b | 0.3 | 1.7 | 2.8 |  | 46 | 6.4 | 22 | 70 |
| Indian River Lagoon | 45 | 1.12 | 0.1 | 0.8 | 1.6 |  | 182 | 2.9 | 7.5 | 31 |
| BR | 2 | 1.0a | 0.1 | 1 | 1.1 |  | 21 | 0.8 | 20 | 21 |
| LCIRL | 14 | 1.2a | 0.3 | 0.9 | 1.6 |  | 14 | 6.3 | 5.8 | 25 |
| LIRL | 3 | 1.5a | 0 | 1.5 | 1.6 |  | 9.2 | 2.8 | 6.0 | 11 |
| LML | 4 | 1.0a | 0 | 1 | 1 |  | 22 | 2.2 | 19 | 24 |
| UCIRL | 17 | 0.9a | 0.1 | 0.8 | 1.1 |  | 20 | 7 | 7.5 | 31 |
| UIRL | 1 | 1.0a | - | 1 | 1 |  | 24 | - | 24 | 24 |
| UML | 4 | 0.8a | 0.1 | 0.8 | 1 |  | 24 | 6.4 | 15 | 31 |
| Tampa Bay | 218 | 1.22 | 0.1 | 0.6 | 1.6 |  | 411 | 2.5 | 13 | 66 |
| HB | 20 | 1.1ab | 0.2 | 0.8 | 1.3 |  | 34 | 11.2 | 13 | 56 |
| LTB | 60 | 1.3b | 0.1 | 1.1 | 1.5 |  | 40 | 7.5 | 24 | 56 |
| MTB | 74 | 1.4b | 0.1 | 1.1 | 1.6 |  | 36 | 7.6 | 17 | 58 |
| OTB | 64 | 0.8a | 0.2 | 0.6 | 1.1 |  | 49 | 8.7 | 30 | 66 |
| *a*CCB: Central Choctawhatchee Bay, ECB: Eastern Choctawhatchee Bay, WCB: Western Choctawhatchee Bay, BR: Banana R., LCIRL: Lower Central Indian R. Lagoon, LIRL: Lower Indian R. Lagoon, LML: Lower Mosquito Lagoon, 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. | | | | | | | | | | |