Assessment of *Thalassia hemprichii* seagrass metrics for biomonitoring of environmental status

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Abstract. Seagrass has long been known to be very sensitive to environmental changes, especially caused by human activities and has been used as a bioindicator for environmental condition of ecosystems. This research aimed to study 19 *Thalassia hemprichii* metrics (10 measured and 9 derived metrics) at two organizational levels (individual and population), to explore and confirm these metrics for development of a multimetric index of environmental quality. Seagrass meadows was selected along a gradient of an anthropogenic disturbance at Kepulauan Seribu (inhabited and uninhabited locations, fixed effect, namely Status), 4 sites for each location (random effect nested in status) within intertidal and subtidal zones (random effect across Sites). We also briefly described about social-ecological system of seagrass being studied using a qualitative network model, for an understanding of interaction that affects the exploited seagrass ecosystems. The significance of variability between states, sites, and zones were examined using linear mixed effect model followed by exploratory factor analysis in the confirmatory factor analysis (CFA) framework (E/CFA strategy) to explore and confirm adequacy of the metrics as indicators for two-factor organizational levels (individual and population). Based on the analysis, leaf surface area, leaf wide, leaf area index, density, rhizome diameter, and *Thalassia hemprichii* cover differed significantly at the scale of interest and represented two levels of organizational levels (individual and population).

1. Introduction

Seagrass ecosystem is commonly found in shallow coastal water close to settlements with high anthropogenic disturbances (house construction, beach reclamation, traditional ports, boating, boat landing area, dredging, aquaculture, ecotourism, and wastewater discharge area). Seagrass beds are sensitive to these human disturbances and can be used as bioindicators of environmental condition [1, 2], because their integration in ecological processes occurred in the sediment and water column [3].

Studies using seagrasses as bioindicators of environmental quality (in the form of multimetric indices) related to anthropogenic influences have been carried out, mostly in temperate European waters, including; [4] using *Posedonia oceanica* with 5 metrics (PoSte index), [5] using *Posedonia oceanica* with 14 metrics (POMI index), [6] examined 59 attributes as candidates for seagrass indicators; [7] used *Posedonia oceanica* with 5 metrics (PREI index), [8] using *Posedonia oceanica* with 5 metrics (BiPo index), [9] using *Cymodocea nodosa* with 37 metrics (CYMIX index) and [10]...
using Zostera noltii with 9 metrics (ZONI index). These studies showed promising results to use seagrass species as bioindicators for anthropogenic disturbances and the metrics as indicators should represent more than one level of biological organization [11].

Thalassia hemprichii (T. hemprichii) is one of seagrass species with the widest distribution and high abundance in Indonesian waters [12, 13], and commonly found in Kepulauan Seribu Marine National Park area [14-16]. T. hemprichii is the most sensitive tropical seagrass species to environmental stress [17] and the main primary producer on tropical beaches [18]. This species has the potential to be a bioindicator for anthropogenic disturbances.

This preliminary study examined 19 (measured and derived) T. hemprichii metrics which theoretically represent two levels of biological organization of seagrass (individual and population), to search and validate the metrics as indicators that having sensitivity to anthropogenic disturbances. The metrics were chosen from the previous studies that showed sensitivity to diverse disturbances at the two biological organization levels and the metrics also relatively simple and easy to measure with low cost and not required sophisticated equipment. In addition to searching indicators as tools for monitoring purposes, we also carried out a brief analysis of seagrass social-ecological systems (SES) being studied to identify the feedbacks between seagrass ecosystems and humans that affect the seagrass ecosystems for management purposes.

2. Method

2.1. Study site

The field study was conducted on July-October 2018 at Kepulauan Seribu Marine National Park (TnLKs) at North Jakarta Bay Indonesia (Figure 1), in eight islands spread from the southern to the northern parts of TnLKs, purposively chose to encompass anthropogenic gradient pressure of the region. Four locations are very densely populated islands (Panggang, Pramuka, Harapan and Kelapa Dua) with a population ranging from 3000-7000 people and considered area with high anthropogenic disturbances. These four islands are the main islands that are populated and are domestic recreation islands with a very dense population, massive development, and reclamation. The other three islands are uninhabited islands (private property), two of which are islands with limited access (Semut Kecil and Kotok), one island is a tourist island with a camp site (Semak Daun). One location (Karang Lebar) is a reef flat area with small lagoons and no island exists. These locations represent area with low anthropogenic disturbances. The distance between the southernmost and northernmost locations was 21 km.

2.2. Sampling design and data acquisition

The eight islands were grouped in two Status (inhabited islands/high anthropogenic disturbances and uninhabited islands/ low anthropogenic disturbances, as fixed effect) with four island each (namedly Sites, as random effect) nested in Status. Our analysis of the metrics will focus on these two Status which represent two different level of human activities. Total 121 quadrats (0.25 m²) were spread on seagrass meadow in intertidal and subtidal zone (random effect), except Karang Lebar site which only consist of subtidal zone, of the eight islands using systematic random pattern of points using R software v.3.6.0 [19] and its package spatstat [20]. Distance between sampling points ranging from 30 to 34 m. In every quadrat, T. hemprichii coverage was estimated visually and all individual shoots were counted (shoot density). All of T. hemprichii within quadrats were removed using shovel for further measurement of morphological descriptors.

Morphological descriptors were measured manually using caliper. Leaf length (cm) were measured from 5-10 leaves (length of green part of leaves), leaf width (cm) was averaged from three part of leaf (top, mid and base). Rhizome diameter (cm) and vertical rhizome (cm) measured from 3-5 individual shoot. Leaf surface area (cm²) derived from multiplying leaf length and width, and leaf area index (m²·m⁻²) was calculated by multiplying the mean surface area by shoot density. Leaf, shoot and
rhizome biomass were measured in dry weight. The methods and references used to measure *T. hemprichii* metrics are presented in Table 1.

![Figure 1](image.png)

**Figure 1.** Eight sampling locations at Kepulauan Seribu Marine National Park Jakarta Indonesia.

2.3. *Data analysis*

All data were tested for multivariate normality test before the analysis, using R package MVN [21]. The partitioned of variance of each metric were examined using linear mixed-effect models in R package lme4 [22] to test the variability between scale of interest (Status, Sites, and Zones). The metrics that showed significant between Status (fixed effect) will further be included in exploratory factor analysis (EFA) in the confirmatory factor analysis (CFA) framework (E/CFA strategy) to confirm two levels of biological organization (factors) dimensionality of 19 *T. hemprichii* descriptors.

According to Brown [23] EFA and CFA are common factor models both aim to describe and confirm the pattern of relationship between observed measures or indicators with its latent structures or factors (unobservable variable) that account for the variation and covariation among a set of observed measures. CFA is a type of structural equation modeling (SEM) that confirms the relationships between observed measures or indicators (here is *T. hemprichii* metrics) and latent variables or factors (here is two levels of biological organization). CFA is a hypothesis-driven process, meanwhile, EFA is an exploratory fashion of a data-driven process. E/CFA strategy is a method to produce more viable CFA measurement models based on EFA findings. E/CFA strategy was done by selecting an anchor item for each factor whose cross-loadings are fixed to zero (selected from the highest primary loading on the factor based on EFA result), meanwhile the non-anchor items factor loadings are freely estimated on each factor and fixing the factor variances to 1.0 (completely standardized factor loadings). The E/CFA result then confirmed by a more restrictive pure confirmatory framework (CFA).
Table 1. *Thalassia hemprichii* seagrass variables (metrics), methods and reference.

| Level     | Metric (units)                              | Code | Method                                                                 | Reference |
|-----------|---------------------------------------------|------|------------------------------------------------------------------------|-----------|
| Individual| Measured                                    |      |                                                                        |           |
|           | Leaf length (cm)                            | LL   | Length average of green leaf area                                      | [32]      |
|           | Maximal leaf length (cm)                    | MLL  | The longest leaf                                                       |           |
|           | Leaf width (cm)                             | LW   | Width average of green leaf area                                       |           |
|           | Vertical rhizome (cm)                       | VR   | Length of shoot vertical rhizome                                       |           |
|           | Rhizome diameter (cm)                       | RD   | Diameter of shoot rhizome                                              |           |
|           | Rhizome biomass (g DW)                      | RB   | Weight after drying at 60°C for 48 h                                  | [33]      |
|           | Leaf biomass (g DW)                         | LB.1 | Sum of LB.1 and ShB.1 biomass                                          |           |
|           | Sheath biomass (g DW)                       | ShB.1|                                                                       |           |
|           | Shoot biomass (g DW)                        | SB   |                                                                       |           |
|           | Leaf surface area (cm²)                     | LSA  | Leaf length multiplied by leaf width                                  | [32]      |
|           |                                        |      |                                                                        |           |
| Population| T. hemprichii cover (%)                     | Th_cov | Visual estimation of the area covered by *T. hemprichii* within 50 x 50 cm quadrates | [33]      |
|           | Density (no. of shoots m⁻²)                 | D    | Count of the number of shoots present in a 50 x 50 cm quadrates        |           |
|           | Leaf area index (m²m⁻²)                     | LAI  | Multiplying the mean surface area by D                                 | [32]      |
|           | Below ground biomass (g DW m⁻²)             | BG   | RB extrapolated to m²                                                  |           |
|           | Leaf biomass (g DW m⁻²)                     | LB.2 | LB.1 extrapolated to m²                                               |           |
|           | Above ground biomass (g DW m⁻²)             | AG   | Sum of LB.1 and ShB.1 extrapolated to m²                              |           |
|           | Sheath biomass (g DW m⁻²)                   | ShB.2| ShB.1 extrapolated to m²                                              |           |
|           | Biomass total (g DW m⁻²)                    | BT   | Sum of above and below ground biomass extrapolated to m²              |           |
|           | Biomass ratio of AG and BG (g DW m⁻²)       | BR   | Ratio of above and below ground biomass                               |           |

Visualization of E/CFA and CFA models were displayed as follows [24, 25]: a square box signifies observed, measured, manifest or indicator variable; circles signifies latent, unmeasured, construct or factor variable; straight arrow indicated assumption that variable at head of arrow "caused by" variable at base of arrow; curved two-headed arrow signifies association (covariance in unstandardized or correlation in standardized variable) between two variables. Variable without arrow pointing at it is called exogenous variable (independent variable) and vice versa are called endogenous variable (dependent variable). An arrow pointing at square box indicated unexplained variance (error) and double head arrow at square box indicated variance. E/CFA and CFA analysis were conducted using R.
package lavaan [26] and R package semPlot [27]. Visualization of E/CFA and CFA analysis used Önyx software v.1.0-1010 [28].

Maximum likelihood estimation was used to all model and model fit was evaluated based on the fit indices for a single path coefficient (p-value at significant level 0.05) and the overall goodness of fit indices: chi-square value (χ²) not significantly different with null model, standardized root mean square residual (SRMR) are close to 0.08 or below, root mean square error of approximation (RMSEA) are close to 0.06 or below, comparative fit index (CFI) and Tucker Lewis Index (TLI) close to 0.95 or greater [29].

SES analysis was based on conceptual model of SES by McGinnis and Ostrom [30] and qualitative network model followed [31] framework. In the [31] framework, the conceptual model first translated into the community matrix defined by pairwise links (+1, -1, or 0) represent of bivariate interactions between the SES components (signed digraph) and randomly drawing values for each the pairwise links. The quantitative response of the community to a press perturbation is predicted and summarized through simulation to generate probabilities of sign outcomes.

3. Results and discussion

Mardia test for multivariate normality showed a departure from normality of two sites (Karang Lebar and Semak Daun) with Mardia kurtosis statistics -2.19 (p-value 0.03 at α 0.05) and -2.24 (p-value 0.03 at α 0.05) respectively (Table 2). We included these two sites in analysis considering that the nonnormality is not too severe.

| Site          | Statistics skewness | p value | Statistic kurtosis | p value |
|---------------|---------------------|---------|--------------------|---------|
| Harapan       | 282.89              | 0.54    | -2.00              | 0.05    |
| Karang Lebar  | 274.12              | 0.68    | -2.19              | 0.03    |
| Kelapa Dua    | 303.59              | 0.23    | -1.75              | 0.08    |
| Kotok         | 302.51              | 0.24    | -1.74              | 0.08    |
| Panggang      | 303.51              | 0.23    | -1.73              | 0.08    |
| Pramuka       | 302.72              | 0.24    | -1.88              | 0.06    |
| Semak Daun    | 277.21              | 0.63    | -2.24              | 0.03    |
| Semut Kecil   | 316.89              | 0.10    | -1.67              | 0.09    |

Figure 2. Comparison of T. hemprichii cover between inhabited and uninhabited areas.
Based on field observation, dense *T. hemprichii* was commonly found in shallow water near islands and dominated the area (in many sampling plots near inhabited islands *T. hemprichii* was the only species found), the farther away from the land the more rarely *T. hemprichii* found. Figure 2 shows that very dense *T. hemprichii* cover only found in the inhabited area and dense *T. hemprichii* cover was more common in the inhabited area than in the uninhabited area. The uninhabited area was dominated by sparse and moderate cover of *T. hemprichii*. Five years observation of seagrass meadows by [14] in 36 locations at TnLKS also reported that *T. hemprichii* was the most commonly found species and its cover was higher in inhabited area than in uninhabited area.

Summary statistics (Table 3 and 4) revealed that in average, the uninhabited area only exceeded the inhabited area in four metrics (vertical rhizome, rhizome biomass, sheet biomass per shoot and shoot biomass). Shoot density (no. of shoot m\(^{-2}\)), biomass total (g DW m\(^{-2}\)) and above ground biomass (g DW m\(^{-2}\)) showed high variation compared to the other metrics in both statuses. *T. hemprichii* shoot density high variation also indicated by Savurirajan et al. [34] at Andaman Island India. The inhabited area which is much higher in human activities and anthropogenic disturbances showed more longest, heaviest leaves and more dense shoots, meanwhile in the uninhabited area showed higher values in the lower part of individual plants. *T. hemprichii* in the area proximal to industrial and maritime activities with high nutrient availability in Singapore waters reported by Ali et al. [35] also have the longest and heaviest leaves. The four inhabited areas are very densely populated islands and certainly with high organic or nutrient waste disposal from crowded houses to surrounding waters, and seemed to influence the upper part of *T. hemprichii*.

### Table 3. Summary statistics of *T. hemprichii* metrics in Inhabited area.

| Status  | Attribute | Min | max | mean | median | sd |
|---------|-----------|-----|-----|------|--------|----|
| Inhabited | LL (cm) | 5.56 | 15.54 | 9.25 | 8.77 | 2.51 |
|         | MLL (cm) | 6.35 | 18.75 | 10.99 | 10.16 | 2.89 |
|         | LW (cm) | 0.56 | 0.93 | 0.75 | 0.75 | 0.09 |
|         | LSA (cm\(^2\)) | 3.57 | 15.67 | 7.21 | 6.73 | 2.73 |
|         | VR (cm) | 0.54 | 6.52 | 2.06 | 1.84 | 1.06 |
|         | RD (cm) | 0.30 | 0.62 | 0.39 | 0.38 | 0.04 |
|         | Th\(\text{cov}\)% | 10.00 | 90.00 | 42.06 | 38.25 | 21.34 |
|         | D (no.of shoot m\(^{-2}\)) | 24.00 | 640.00 | 215.67 | 200.00 | 127.69 |
|         | LAl (m\(^2\)m\(^{-2}\)) | 0.03 | 0.82 | 0.15 | 0.11 | 0.12 |
|         | RB (g DW) | 0.08 | 0.24 | 0.16 | 0.16 | 0.03 |
|         | LB.1 (g DW) | 0.01 | 0.21 | 0.05 | 0.04 | 0.03 |
|         | ShB.1 (g DW) | 0.12 | 0.49 | 0.28 | 0.28 | 0.09 |
|         | BG (g DW m\(^2\)) | 3.32 | 125.90 | 36.12 | 28.69 | 25.74 |
|         | LB.2 (g DW m\(^2\)) | 3.22 | 202.24 | 49.04 | 29.02 | 35.39 |
|         | ShB.2 (g DW m\(^2\)) | 5.18 | 231.25 | 60.58 | 50.87 | 41.42 |
|         | SB (g DW) | 0.16 | 0.54 | 0.33 | 0.32 | 0.09 |
|         | AG (g DW m\(^2\)) | 8.39 | 378.20 | 101.52 | 79.27 | 71.13 |
|         | BT (g DW m\(^2\)) | 11.71 | 504.10 | 137.64 | 107.45 | 94.62 |
|         | BR (g DW m\(^2\)) | 1.42 | 13.13 | 3.00 | 2.88 | 1.54 |

#### 3.1. Variance components and E-CFA/CFA analysis

The metrics that were significant between statuses are showed in Table 5 and retained for further analysis. Intra-class correlation (ICC) is a measure of degree of dependence among data and interpreted as the percentage of variance of the metrics in status that can be explained by the random effect. Meanwhile, \(\sigma^2\) is residual variance and \(\tau_{00}\) is variance of random effect. The highest ICC was 44\% in LL metric, meaning that about 44 \% of the variance in leaf length (LL) achievement can be accounted for by site and zone effects. In overall indicated from the data and analysis, *T. hemprichii*
metrics from the deeper subtidal zone were higher than those from the intertidal zone, and zone generated more variation in the metrics compared to Site. These results confirmed the findings by Martinez-crego et al. [6] who stated that the depth factor influenced seagrass metrics and gave clearer response to the quality gradient of anthropogenic disturbances.

Table 4. Summary statistics of *T. hemprichii* metrics in Uninhabited area.

| Status              | Attribute | min  | max  | mean | median | sd  |
|---------------------|-----------|------|------|------|--------|-----|
| Uninhabited         | LL (cm)   | 5.71 | 12.27| 8.03 | 7.58   | 1.57|
|                     | MLL (cm)  | 6.57 | 16.03| 10.00| 9.85   | 2.08|
|                     | LW (cm)   | 0.51 | 1.01 | 0.67 | 0.66   | 0.09|
|                     | LSA (cm²) | 3.13 | 11.83| 5.51 | 5.07   | 1.74|
|                     | VR (cm)   | 0.95 | 7.46 | 3.22 | 3.08   | 1.44|
|                     | RD (cm)   | 0.29 | 0.46 | 0.36 | 0.36   | 0.04|
|                     | Th_cov (%)| 8.00 | 70.00| 29.78| 30.00  | 15.14|
|                     | D (no. of shoot m⁻²)| 10.00 | 320.00 | 109.95 | 112.00 | 69.48|
|                     | LAI (m²m⁻²)| 0.01 | 0.20 | 0.06 | 0.06   | 0.04|
|                     | RB (g DW) | 0.10 | 0.31 | 0.20 | 0.19   | 0.05|
|                     | LB.1 (g DW)| 0.01 | 0.13 | 0.04 | 0.04   | 0.02|
|                     | ShB.1 (g DW)| 0.15 | 1.11 | 0.37 | 0.34   | 0.17|
|                     | BG (g DW m⁻²)| 1.78 | 58.46 | 20.95 | 18.85 | 13.42|
|                     | LB.2 (g DW m⁻²)| 0.74 | 59.83 | 17.94 | 15.47 | 13.31|
|                     | ShB.2 (g DW m⁻²)| 2.81 | 187.85 | 38.85 | 27.64 | 31.58|
|                     | SB (g DW) | 0.18 | 1.15 | 0.41 | 0.38   | 0.17|
|                     | AG (g DW m⁻²)| 4.93 | 208.34 | 56.80 | 49.71 | 39.32|
|                     | BT (g DW m⁻²)| 7.53 | 266.80 | 77.74 | 70.24 | 51.29|
|                     | BR (g DW m⁻²)| 1.20 | 8.00 | 2.88 | 2.60   | 1.28|

Figure 3. Pairs correlation matrix after excluded the derived metrics (the size of the font numbers indicate the magnitude of the relationship between variables).
The derived metrics as expected had a strong correlation with their measured metrics from which they were derived, except LAI only showed moderate correlation to LL and LW. This multicollinearity can cause problematic consequences in the E/CFA and CFA models such as inflated standard error, Heywood cases (communalities > 1.00, negative error variances) and in convergence model [23]. Figure 3 displays correlation matrix after excluded the derived metrics (except for LAI), and further analysis (E/CFA and CFA) only included these nine metrics (LL, LW, VR, RD, Th cov, D, LAI, RB, and ShB.1).

Table 5. The partition of total variance from mixed effect model analysis (only shows the metrics that were significant between statuses).

| Predictors | LL Estimates | P value | LW Estimates | P value | RB Estimates | P value |
|------------|--------------|---------|--------------|---------|--------------|---------|
| (Intercept) | 8.72         |         | 0.71         |         | 6.42         |         |
| Confidence interval | (7.76 – 9.68) | <0.001 | (5.36 – 7.47) | <0.001 |
| Random Effects | | | | |
| $\sigma^2$ | 1.98         | 0.01    | 2.51         |         |
| $\tau_{00}$ | 2.82 ZoneID | 0.00 ZoneID | 3.65 ZoneID |         |
| Site       | 0.24 Site    | 0.15 Site |
| ICC        | 0.61         | 0.45    | 0.6          |         |

| Predictors | VR Estimates | P value | RD Estimates | P value | Th cov Estimates | P value |
|------------|--------------|---------|--------------|---------|-----------------|---------|
| (Intercept) | 2.63         | 0.38    | 36.79        |         |                 |         |
| Confidence interval | (2.04 – 3.22) | <0.001 | (28.93 – 44.66) | <0.001 |
| Random Effects | | | | |
| $\sigma^2$ | 1.36         | 0       | 265.96       |         |
| $\tau_{00}$ | 0.64 Site    | 0.00 ZoneID | 52.26 ZoneID |         |
| Site       | 0.32 Site    | 0.25    | 0.33         |         |

| Predictors | D Estimates | P value | LAI Estimates | P value | ShB.1 Estimates | P value |
|------------|-------------|---------|---------------|---------|-----------------|---------|
| (Intercept) | 165.99      | 0.11    | 0.32          |         |                 |         |
| Confidence interval | 213.72 | <0.001 | (0.27 – 0.38) | <0.001 |
| Random Effects | | | | |
| $\sigma^2$ | 8972.51     | 0.01    | 0.01          |         |
| $\tau_{00}$ | 1564.87 ZoneID | 0.00 ZoneID | 0.01 Site |
| Site       | 3207.14 Site | 0.00 Site |
| ICC        | 0.35         | 0.5     | 0.27         |         |

Initial EFA analysis supported the viability of a 2 factor model ($\chi^2(19)=101.28$, $p$-value < 0.01), LL had the highest factor loading on factor 1 (F1), Th cov on factor 2 (F2) and correlation between F1 and F2 was -0.24. Hence LL will be the anchor variable for F1 and Th cov for F2. EFA results also revealed that VR, RB, and ShB.1 had low or negative factor loadings on both factors (had no salient relationship to any factor). E/CFA results confirmed these findings, the E/CFA model that fitted the data well ($\chi^2 (4)=7.84$, $p$ value=0.098, SRMR=0.034, RMSEA=0.09 (CI=0.00–0.181, $p$ value=0.197),
TLI=0.942, CFI=0.985) not included VR, RB and ShB.1 metrics (Figure 4). Including these 3 metrics in the E/CFA model produced poor model fit to the data. Compare to EFA analysis, the E/CFA produced quite a lot of information about the suitability of the model to the data, including the statistical significance of cross-loadings and the potential presence of salient error covariances [23].

As shown in Figure 4, from factor loading values of the E/CFA results suggested that F1 represented individual level with LL, LW, RD, and LAI as its indicators, meanwhile, F2 represented population level with Th_cov, D and also LAI as its indicators. LAI was derived from multiplying D (population indicator) and LAS (individual indicator derived from multiplied LL and LW) and turned out its variance can be explained by the two factors. E/CFA suggested a non-congeneric indicator CFA model i.e., a model with double loading items [23].

Table 6. Fit indices of two CFA model.

|                | RD included | RD not included |
|----------------|-------------|-----------------|
| n parameters   | 20          | 17              |
| $\chi^2$       | 16.200      | 6.204           |
| df             | 7           | 3               |
| p-value        | 0.023       | 0.102           |
| CFI            | 0.963       | 0.986           |
| TLI            | 0.921       | 0.954           |
| AIC            | 2016.125    | 2442.499        |
| BIC            | 2072.041    | 2490.028        |
| n total        | 121         | 121             |
| RMSEA          | 0.104       | 0.094           |
| RMSEA.ci.lower | 0.036       | 0.000           |
| RMSEA.ci.upper | 0.172       | 0.200           |
| RMSEA.p value  | 0.083       | 0.189           |
| SRMR           | 0.075       | 0.052           |

Pure confirmative analysis (CFA) based on the E/CFA results can be developed with or without RD in the individual level (Figure 5), but left out LAI metric in the CFA model (RD was included) caused model failed to converge (no solution found in maximum likelihood iterations). Dropping RD and LAI all together were not an option because two factors with indicator less than six indicators (three indicators per factor) prone to produce an unidentified model [23, 25]. Excluding RD without
related LAI to both factors or only related to one factor made one of the factors in the model only have two indicators, the models will not identified also one relationship in the data was not represented by the model. Model fit indices of two noncongeneric CFA model are presented in Table 6.

Table 6 shows that RMSEA values of two model CFA range between 0.094-0.104 suggested mediocre fit [36], $\chi^2$ value for CFA model with included RD indicated discrepancy between the model and the data covariance matrix [37], but it is affected by sample size and rarely used as a sole index of model fit in applied research [23]. Akaike information criterion (AIC) and Bayesian information criterion (BIC) can be used to compare the two models. The overall goodness of fit indices of two models showed acceptable fit, but CFA model with included RD produced least information lost (AIC) and more parsimonious (BIC) model than CFA model with included RD and the fact that RD metric had moderate path coefficient loading ($p$-value < 0.01, standard error 0.004). CFA models confirmed that LL, LW, RD as indicators of individual level and Th_cov, D as indicators of population level as suggested by previous studies [6, 9, 38].

3.2. SES analysis

The SES analysis of seagrass under study was carried out based on field interviews, literature studies and official reports from Kepulauan Seribu District Government. In this area, many studies have been carried out relating to social, economic and environmental issues, especially at the beginning of the change in the status of the Thousand Islands from a sub-district to an administrative district. We only examined the basic components of SES of seagrass and traditional daily fisherman as main actor at small islands, as a reference and preliminary assessment for subsequent in-depth study.

![Diagram](image_url)

**Figure 5.** Two CFA model with RD (top) and without RD (bottom) in the individual level. Unstandardized and standardized factor loadings of LL and Th_cov were slightly different in both models (LL 1.815/0.841 respectively for CFA model with RD and 1.817/0.842 respectively for CFA model without RD; Th_cov 16.933/0.876 respectively for CFA model with RD and 1.817/0.842 respectively for CFA model without RD).
Figure 6 shows pictorial representation of conceptual interactions between SES components: SE (seagrass ecosystem), FS (fish stock), MoS (mollusc stock), FTP (fisherman population), Reg (regulation by governmental agency), FE (fishing effort), FiA (fishing activity), Ca (catch), FCo (fishing cost), Prc (price) and FsI (fisherman income). Biological interactions in the SES were represented by the intercorrelated relations between two main targets (FS and MoS) and the seagrass meadow (SE). Traditional small scale daily fisherman population (FsP) affected negatively to the seagrass through fishing activities (FiA) and direct negative impact such as use seagrass meadow as landing, docking and reclamation for house construction area and discharge wastewater household directly to seagrass meadow. Traditional fishermen in the study area are affected by the demand-price relationship (high catches not accompanied by additional profits, negative link from Ca to Prc) also price mechanism is determined by local traders. The good price occurs when FS or MoS decrease but this cause fishing effort (FE) more difficult (rare availability of FS and/or MoS) hence the larger the stock, the lower the effort (negative link from FS and MoS to FE) and make fishing cost higher (positive link from FE to FCo) and in turn affect overall fisherman income (FsI). Reg without self-loop/self-damping represent government management and/or controlling action that only responds to FsP (eg., by controlling reclamation expansions in seagrass meadow or by protected area), FiA and FE also protect FsP, FiA, and FE from other influences. We ran 10000 simulation of five scenarios (without controlling action from Reg to the system, controlling action from Reg to one of FsP, FiA and FE and Reg to all of the three).

Based on simulation results (Figure 7), higher positive response of SE (~67% positive responses) was gained in scenario where Reg simultaneously controlled the three main sources of seagrass disturbance (FsP, FiA, and FE), controlling only one of them did not produce much positive response of SE. By controlling these three Reg also affect FsI implied that the control action must be accompanied by providing programs or policies to stimulate alternative livelihood for fisherman to minimize conflict (eg., mariculture and/or ecotourism). The most influential component on seagrass was FiA followed by FsP. The results emphasized that in the studied area (overpopulated small island environment) the dependency of small fishermen on nature (seagrass) and their surrounding socio economic aspects was very strong and the negative effects of human activities on seagrass ecosystem can only be reduced through government interventions. Expecting fisherman awareness to maintain the sustainability of seagrass meadows without minimizing their dependence on it, possibly only produce failed seagrass mitigation projects.
4. Conclusion

*T. hemprichii* implied different structural and functional characteristics related to their environmental conditions. These characteristics referred as metrics had the potential to be used as indicators for anthropogenic disturbances, using leaf length (LL), leaf width (LW), *T. hemprichii* cover (Th_cov), shoot density (D) and leaf area index (LAI) as indicators that represented response of two levels of biological organization to anthropogenic disturbances. Small scale daily fisherman dependency on seagrass ecosystem was very strong and required government intervention to mitigate both fisherman and seagrass conditions.

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