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Title: Estimating aboveground biomass seasonal dynamics of a riparian pioneer plant community: an exploratory analysis by canopy structural data

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Keywords: Three Gorges Reservoir, non-destructive method, Cynodon dactylon, gap fraction, seasonal change, general model

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Abstract: The aboveground biomass (AGB) of vegetation is of central importance in providing ecosystem productivity. Models have already been developed to estimate AGB via canopy structural variables in both fundamental and applied ecological studies. However, the capabilities of canopy structural variables in indicating AGB dynamics throughout the growing season are still unclear. This study focuses on the AGB of the dominant pioneer species Cynodon dactylon (L.) Pers. (Bermuda grass) during early succession in newly formed riparian habitat of China's Three Gorges Reservoir (TGR). The aims are (1) to find the most important factor that impacts on AGB in different season, and (2) to develop a best model that can estimate the AGB throughout the growing season with multiple structural variables. We conducted six times of valid field sampling on the C. dactylon communities (from May to September in 2016) to develop AGB models. The models were developed based on the following five candidate canopy structural variables: canopy height (H), canopy cover (CC), leaf area index (LAI), the volume related variables VLAI (H × LAI) and VCC (H × CC), and one seasonal growth effect variable (SV). We conducted univariate linear regression analysis to reveal the most important estimator of AGB and the best subsets regression analysis to identify the best models for the estimation of AGB. Canopy structural characteristics of stand are key factors to determine the change of the most important estimators throughout the growth season. Cover was found to be the most important predictor during the early growing season, and VLAI was the most important one for mid and end of the growing season. The developed best models can explain an additional 11% in AGB variance on average throughout seasonal change and compared with those developed with the selected most important estimators. SV was found to be useful to develop a general model to estimate the seasonal AGB throughout the entire growing season. Since the studied structural variables could be obtained over large extent, it is recommended that the models for different growing stages are extend to regional scale. Such an extending application will be useful to provide both emprical and theoretical

explanations for riparian ecosystem functions against water level fluctuated disturbance.

Response to Reviewers: In case of any character and Table that cannot be shown properly in here, the response letter was uploaded as an attachment file.

Dear Dr. Petina Lesley Pert,
Associate Editor
Ecological Indicators

On behalf of my co-authors, we thank you very much for giving us the opportunity to revise the manuscript, and we appreciate the reviewer #3 very much for his/her kind comments and suggestions on our manuscript entitled "Estimating aboveground biomass seasonal dynamics of a riparian pioneer plant species: an exploratory analysis by canopy structural data" (Ms. Ref. No. ECOLIND-7907R2).

We have revised the manuscript according to the reviewer's comments. The revised parts were marked in red. In our point-by-point response letter attached below, the reviewer's comments were marked dark blue. We guess the reviewer's most concern is that the places of our sampling sites may have impacts on the modeling we conducted and should be verified first. In other words, some of the collected sampling quadrats may not be independent. In the response letter, we tested his/her concern and found that the all the sampling quadrats were independent and the places of the sampling sites have no significant impacts on the modeling. Attached please find the revised version, which we would like to submit for your kind consideration.

Looking forward to hearing from you.

Best regards,

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Responses to the Reviewer #3

Reviewer #3: The authors have improved the manuscript. However, the expression of study aims haven't been changed, and the statistic methods should be improved by adding place as a random factor to exclude the impact of place.

Response: Thanks. We have responded your comments point-by-point. Details are given below.

1. You have well explained your aims in the response letter, but you didn't change the expression in the manuscript. For my understanding, you used the univariate linear regression model to find the most important factor that impacts on AGB, while use multiple regression model to estimate AGB. Therefore, it is better to say "The aims are (1) to find the most important factor that impacts on AGB in different season, and (2) to develop a best model that can estimate the AGB throughout the growing season with multiple structural variables. Please correct it in the rest part of your manuscript.

Response: Thanks for your kindly suggestion. The relevant text in the manuscript have been revised in the light of your suggestion.

2. Since you collected samples from three places, you should use mixed-effects regression model, and include place as a random effect to check whether place has impact on results. If there is no difference between mixed effects regression results and regression results without random effect, you can use your present model.

Response: Thanks for your suggestion. We've tried to figure out how to respond this comment. However, we are afraid of not fully understanding the comment. The main confusion is on the term "three places". (1) Do you mean the "place" is "sampling quadrat"? If so, we collected samples not from three quadrats but more than 14 quadrats in a sampling date (Table 1). Moreover, we think the effects of sampling location have been considered. Because those effects can be represented by the different growth time and could be captured by the seasonal growth-effects variable (i.e., SV, **L222-228**) which has been involved in the modeling processing; (2) do you mean the "three places" are "three gorges"? If so, we are sorry for the confusion because the three gorges is a place name, not three different "places"; (3) or do you mean the "places" are sampling sites? If so, we collected samples from five sites (from A to E) as shown in Fig. 1. Follow your suggestion, for each sampling date, we considered the place (i.e., sites) as a random effect and developed a new linear mixed effects model by lme4 package in R, based on the selected variables in Table 2 and Table 3, respectively. We also developed a corresponding model without considering place as random effect. The difference between the two models was then tested by ANOVA analysis. The results are given here (Table R1). From Table R1, we can generally draw a conclusion that the selected sites did not have significant effects on the models we presented in the study. We added this information in the text, "The places of those sites have been tested (the results were not shown) having no significant effect on the modeling we conducted in the Section 2.3." **(L183-185).** Anyway, we would like very much to discuss with the reviewer, which can definitely help us in improving the manuscript. Thanks!

Table R1. Statistical test results of the difference between two linear models with and without considering place as random effect in model.

Sampling dates	Based on the selected variable in Table 2		Based on the selected variables in Table 3	
	Chi-Square value	*p*-value	Chi-Square value	*p*-value
May 30-31	0	1	0	1
Jun. 12-13	0.7371	0.3906	6.5239	0.01064
Jun. 21-22	0	1	0	1
Jul. 1-2	1.3209	0.2504	0.5946	0.4407
Jul. 10-11	0	1	0.0494	0.8241
Sep. 22-23	3.7916	0.05151	0.1526	0.6961

3. I also concern whether *Cynodon dactylon* community is mono-species community or multiple-species community. Please state this in the site description. For my understanding it is a mono-species community, but it is better to use "a riparian pioneer plant community" in the title. If it is not pure community, there is impact of other species on biomass as you listed in the introduction line 123-124.

Response: You are right. According to our field survey, the *Cynodon dactylon* community is mono community (see Appendices Fig. A.2) distributing at lowland of elevations roughly below 165 m. We have stated this in **L175-176** "In the lowland area, the *C. dactylon* communities are almost mono-species communities which were targeted in the study." The title also revised according to your suggestion "**Estimating aboveground biomass seasonal dynamics of a riparian pioneer plant community: an exploratory analysis by canopy structural data**".

Highlights (for review)

- Seasonal AGB of *C. dactylon* communities in riparian zone of the TGR were estimated
- Variations of canopy structural variables in estimating seasonal AGB were explored
- Canopy cover was detected as the best estimator of AGB in early growing season
- LAI-derived volume variable was found as the best indicator in late growing season
- Seasonal growth effect was useful for estimating AGB for the entire growing season

Estimating aboveground biomass seasonal dynamics of a riparian pioneer plant community: an exploratory analysis by canopy structural data

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Abstract: The aboveground biomass (AGB) of vegetation is of central importance in providing ecosystem productivity. Models have already been developed to estimate AGB via canopy structural variables in both fundamental and applied ecological studies. However, the capabilities of canopy structural variables in indicating AGB dynamics throughout the growing season are still unclear. This study focuses on the AGB of the dominant pioneer species *Cynodon dactylon* (L.) Pers. (Bermuda grass) during early succession in newly formed riparian habitat of China's Three Gorges Reservoir (TGR). The aims are (1) to find the most important factor that impacts on AGB in different season, and (2) to develop a best model that can estimate the AGB throughout the growing season with multiple structural variables. We conducted six times of valid field sampling on the *C. dactylon* communities (from May to September in 2016) to develop AGB models. The models were developed based on the following five candidate canopy structural variables: canopy height (H), canopy cover (CC), leaf area index (LAI), the volume related variables V_{LAI} (H × LAI) and V_{CC} (H × CC), and one seasonal growth effect variable (SV). We conducted univariate linear regression analysis to reveal the most important estimator of AGB and the best subsets regression analysis to identify the best models for the estimation of AGB. Canopy structural characteristics of stand are key factors to determine the change of the most important estimators throughout the growth season. Cover was found to be the most important predictor during the early growing season, and V_{LAI} was the most important one for mid and end of the growing season. The developed best models can explain an additional 11% in AGB variance on average throughout seasonal change and compared with those developed with the selected most important estimators. SV was found to be useful to develop a general model to estimate the seasonal AGB throughout the entire growing season. Since the studied structural variables could be obtained over large extent, it is recommended that the models for different growing stages are extend to regional scale. Such an extending application will be useful to provide both emprical and theoretical explanations for riparian ecosystem functions against water level fluctuated disturbance.

Keywords: Three Gorges Reservoir, non-destructive method, *Cynodon dactylon*, gap fraction, seasonal change, general model

Abbreviations

AGB: Vegetation aboveground biomass
CC: Canopy cover
H: Canopy height
LAI: Leaf area index
MS: May to September
SV: Seasonal growth effect variable
TGR: Three Gorges Reservoir
VIF: Variance inflation factor
V_{CC}: Volume related variable calculated via H×CC
V_{LAI}: Volume related variable calculated via H×LAI

1. Introduction

The riparian zone served as an ecotone between terrestrial and aquatic ecosystems and has often been suggested to play a central role in determining the vulnerability of natural and human systems to environmental changes (Capon et al., 2013; Nilsson et al., 1997). During the past decades, ecosystem functions of vegetation coverage in a riparian zone have been recognized, such as forming wildlife habitats and corridors, providing food for aquatic and riparian biota, stabilizing riverbanks, and improving water quality (Husson et al., 2014). As the main energy source of the riparian ecosystem, the aboveground biomass (AGB) of plant species is fundamental to other relevant resources (e.g., soil nutrients) and thus, can determine whether ecological processes are functioning appropriately (Raab et al., 2014).

In many ecosystematic studies, the most widely used biomass data is the seasonal maximum AGB, because it can partly indicate the productivity of an ecosystem (Raab et al., 2014; Sala and Austin, 2000; Thursby et al., 2002). It has been proposed that the seasonal maximum AGB is inadequate for the description of the dynamics of an ecosystem (Fernandez-Alaez et al., 2002). A collection of AGB dynamics throughout a growth season has been considered increasingly important for managing ecosystems (Fernandez-Alaez et al., 2002; Paillisson and Marion, 2006), modelling ecosystem processes (Hidy et al., 2012; Scurlock et al., 2002), monitoring plant-ecosystem functioning (Hooper et al., 2005), and evaluating vegetation life strategies against evironmental changes (Castelan-Estrada et al., 2002; Jagodzinski et al., 2016). Therefore, estimating the seasonal dynamics of AGB is of importance to enhance our knowledge of ecological functions and management for the restoration and protection of riparian zones.

So far, the most accurate estimation of AGB can be achieved with the direct destructive method (Marshall and Thenkabail, 2015; Redjadj et al., 2012). However, this method has two inherent drawbacks: (1) it is time consuming and labor intensive (Byrne et al., 2011), but most important, (2) it cannot be repeated in the same spatial location, which does not allow exact seasonal monitoring of growth trajectories. Thus, an array of alternative non-destructive methods has been developed over the past few decades (Redjadj et al., 2012). For example, indirectly estimating the AGB by modeling the relationships between biomass and some of the biometrics that are relevant to plant canopy structure (Martin et al., 2005; Pottier and Jabot, 2017). These biometrics including canopy height (Martin et al., 2005; Schmer et al., 2010), canopy cover (Flombaum and Sala, 2007; Zhang et al., 2016), leaf area index (LAI) (Liira et al., 2002; Rutten et al., 2015), and some canopy volume related indices such as the product of height and cover (Redjadj et al., 2012; Penderis and Kirkman, 2014; Pottier and Jabot, 2017).

Most of these studies for AGB estimation that utilize canopy structural variables focused on a specific growing stage (e.g., after reaching peak biomass) during a growing season. However, so far, the capabilities of those variables for estimating AGB in different growing stages along one growing season have not been fully explored. This poses two questions: (1) how will the performances of the corresponding AGB estimation models change along a growing season for a specific variable? Furthermore, (2) which of the variable(s) could be the most important estimator(s) for AGB throughout the growing season for a specific type of model (e.g., linear regression model)? For the first question, researchers have reported that the performance of models often depends on sampling dates (Ferraro et al., 2012; Virkajarvi, 1999). Martin et al. (2005) compared allometric equations relating canopy height to individual biomass using data that was collected on ten sampling dates in two distinct pastures and found that the estimating parameter varied with sampling occasions. The authors attributed this to seasonal changes in the species composition and structural characteristics of the stand (Martin et al., 2005). Using linear regression for AGB estimation via rising-plate meter measurements of canopy height, Nakagami and Itano (2014) found that the AGB slope against height decreased during the early season and then increased towards the end of the season. They furthermore developed a novel general model by incorporating sampling date variations. To the best of our knowledge however, little efforts have yet been undertaken to compare the capabilities among a group of variables for AGB estimation throughout an entire growing season. The question this raises is: which variable(s) are the most important estimator(s) of AGB throughout a growing season? The answer to this question will be helpful in guiding efficient sampling and modeling works in future.

The Three Gorges Reservoir (TGR) of China is a human-disturbed reservoir ecosystem. It was shaped by the Three Gorges Dam, which is one of the largest hydropower projects in the world to date (Fu et al., 2010). Since its first impound in 2003, the TGR has greatly altered the surrounding terrestrial environment with the largest range of annual water level fluctuations between 145 m to 175 m (after 2010), finally forming more than 300 km^2 of riparian zone (Zhang, 2008). Unlike other natural riparian ecosystems in the same climatic zone, the riparian zone that surrounds the TGR experiences low-water-level in summer but high-water-level in winter because of the artificial water level regulation. This type of dry-wet cycle causes heavy stress on the riparian ecosystem, resulting in severe habitat degradation (Su et al., 2013; Chen et al., 2015). For example, the vegetation (predominantly herbaceous plants) grown in summer will be submerged and died out in winter.

Cynodon dactylon (L.) Pers. (i.e., Bermuda grass) is an endemic grass within the riparian zone of the TGR that forms both aboveground stolons and belowground rhizomes (Dong and Kroon, 1994). Since the species has a strong capability to adapt to the dry-wet cycle disturbance of the degraded riparian habitat, it quickly bacame a pioneer and the most dominant plant species in the riparian ecosystem of the TGR (Chen et al., 2015; Liu et al., 2011). Consequently, *C. dactylon* plays a crucial role for ecosystem services by providing productivity, habitat, soil conservation, and riparian reinforcement, as well as protecting the water quality (Liu et al., 2011). Estimating the seasonal dynamic AGB of *C. dactylon* communities is thus, key for understanding riparian community succession, for monitoring riparian zone restoration processes, and for managing the reservoir ecosystems of the TGR (Byrne et al., 2011; Sala and Austin, 2000). Moreover, the evaluating of various canopy structural variables' capabilities in estimating seasonal AGB is also an urgent need as stated before. Therefore, this study targed on the *C. dactylon* communities and aimed to: (1) to find the most important factor that impacts on AGB in different season, and (2) to develop a best model that can estimate the AGB throughout the growing season with multiple structural variables. Results are expected to be helpful in conducting efficient seasonal AGB sampling and modeling works in the future for different research conditions and objects.

2. Methods

2.1 Study area

The study area is located in the upper-mid section of a primary tributary (named Pengxi River) of the Yangtze River, China (Fig. 1). The area has a humid subtropical monsoon climate, characterized by warm winters and hot summers. The mean annual temperature is 18.6 °C and the mean annual precipitation is 1300 mm. The slope in the area is low and the main soil type is purple soil. Prior to the formation of the TGR, it had a long history of agricultural reclamation with major land use types of paddy fields and dry farmland. After 2003, lands were abandoned and riparian zones formed due to the sharp water-level fluctuations of the TGR. Since then, the riparian zone entered a succession process. This area is suggested as a typical region that reflects the impact of the TGR, and various studies have covered the region related to different topics about the riparian zone in the TGR (Chen et al., 2012; Wang et al., 2014). Dominant plant species in the riparian zone are *Cynodon dactylon*, *Echinochloa colonum*, *Xanthium sibirium*, and *Setaria viridis*. Among these, *C. dactylon* and *E. colonum* are largely distributed throughout lowland area (147 – 165 m), and the rest are predominantly distributed throughout highland area (165 – 175 m) (Chen et al., 2012; Wang et al., 2014) (Fig .1). In the lowland area, the *C. dactylon* communities are almost mono-species communities which were targeted in the study.

Fig. 1 is about here

2.2 Field sampling methods and data processing

2.2.1 Field sampling

Based on earlier field investigations of species distribution and practical accessibility of sampling sites, five sampling sites (A-E in Fig. 1c) were selected. The places of those sites have been tested (the results were not shown) having no significant effect on the modeling we conducted in the Section 2.3. A maximum of four quadrats (1 × 1 m) per site were sampled for the *C. dactylon* community, while the number could be reduced to two in one site according to different field conditions and workloads during sampling time. During the growing season of *C. dactylon* (May to September) in 2016, we conducted nine field samplings on May 30-31, Jun. 12-13, Jun. 21-22, Jul. 1-2, Jul. 10-11, Jul. 20, Aug. 16-17, Sep. 6-7, and Sep. 22-23, respectively (Fig. 1d and Fig. 2). The locations of the quadrats at the different sampling dates were almost spatially identical, i.e., a quadrat collected on one sampling date was placed very close to that of the previously sampled within a distance less than10 m.

At each quadrat three sampling steps were conducted: Firstly, canopy heights at four corners were measured via meter stick and their mean value was recorded as the canopy height. Secondly, the ACCUPAR LP-80® ceptometer was utilized to measure the canopy gap fraction (a variable used to further calculate canopy cover) and LAI (Fig. 2c and 2d). The setting parameters of the instrument for each measurement were identical to maintain the consistency. In one measurement, the canopy gap fraction and LAI are automatically calculated by the instrument after measuring photosynthetically active radiation at both above and below (near ground) canopy in a same direction (Decagon, 2010). This measurement was repeated 2-4 times in different directions to reduce the directional uncertainties. For a specific quadrat, the mean values of recorded gap fraction and LAI were used in our study. Thirdly, one fourth of aboveground plants in a quadrat (0.5 × 0.5 m) were clipped and weighted. Thereafter, a part of the clipped plants (generally less than 300 g) were randomly chosen, weighted, and contained in a cloth bag for later drying. In lab, all collected plant samples were dried at 80 ºC for 48 hours, weighted, and the dry AGBs were retrieved in a unit of g/m^2.

2.2.2 Data processing

According to the field sampling as mentioned above, five canopy structural variables and a seasonal growth effect variable were used as candidate estimators to estimate AGB. The variables and their corresponding explanations are presented below:

- **Canopy height (H)**, a canopy structural variable with values > 0.
- **Canopy cover (CC)**, a canopy structural variable with a value ranging between 0 and 1. This could indicate the horizontal distribution of foliage in a canopy. It was calculated via one minus the gap fraction, which was directly measured with an ACCUPAR LP-80® ceptometer (see above). This was done because the gap fraction was often considered as a variant of the canopy cover and equal to the one minus vertically measured cover (Liu and Pattey, 2010).
- **LAI**, a canopy structural variable with a value > 0. This could indicate the inner distribution density of foliage in a canopy (Liira et al., 2002; Rutten et al., 2015).
- $\mathbf{V_{CC}}$, a canopy related variable derived from the equation: $V_{CC} = H \times CC$.
- $\mathbf{V_{LAI}}$, a further canopy volume related variable derived from the equation: $V_{LAI} = H \times LAI$.
- **SV**, a seasonal growth-effects variable. This was involved in this study to explore the seasonal growth effects on AGB estimation. SV of a quadrat is defined as the log-transformation (base 2) of growing days (i.e., the days after the first date on which a quadrat was exposed to the air due to declining water level (Fig. 1d)). The log-transformation process adopted here is mainly based on the understanding that *C. dactylon* could grow fast during the early growing season, while then slowing down during the mid and end of the growing season (see Appendices Fig. A.1).

The response variables of the developed models were the log-transformation (base 2) of the raw AGB. This is because the raw AGB have often been suggested as inherently non-linear and could thus be log-transformed to facilitate linear model construction (Thursby et al. 2002, Elzein et al. 2011, Marshall and Thenkabail 2015). We tested numerous different base values for log-transformation and found base 2 to be more suitable for our study. In addition, we also calculated the bulk density for each sample quadrat to explore the reasons of changing the most important variables in predicting the AGB. Similar to the definition by Zhang et al. (2016), the bulk density in this study is the ratio of $\log_2$(AGB) to volume related indexes (either V_{CC} or V_{LAI}).

Fig. 2 is about here

2.3 Modeling process

To simplify analysis, this study considered linear regression modeling only. The modeling was conducted for individual sampling dates using their own respective collected samples and the whole growing season using all collected samples combined. According to the study objects, we conducted univariate linear regression modeling to explore the most important estimator of AGB for different sampling dates throughout one growing season of *C. dactylon* communities. This modeling means that only one variable was adopted in a linear regression. Therefore, for each sampling date, there were six established univariate linear regression models. However, only the variable that established the model with the maximum coefficient of determination (R^2) or the lowest mean squared error (MSE), was considered as the most important estimator (Zhang et al., 2016). It is worth to note that the selected most important estimator cannot guarantee that the corresponding univariate model is the optimal one (i.e., with the highest accuracy and robustness) for estimating the AGB, since joint effects of different variables were not taken into account in the modeling. Therefore, a best subsets regression method was adopted to select the best models to estimate AGB in different sampling dates throughout the growing season of *C. dactylon* communities. This method can automatically choose the "best subset" model from all the (linear regression) possible models, which contain a specific number of explanatory variables via criteria of Akaike Information Criterion (AIC) (Akaike, 1974). In our study, the number of variables ranges from one to five. Therefore, there were five output "best subset" models for a specific sampling date. The selected finial best model among all five candidate models was then manually selected by comparing both their ΔAIC and coefficients' variance inflation factor (VIF, identify collinearity among explanatory variables (Kutne et al., 2004) values. The smaller the ΔAIC (normally < 4) and VIF (normally < 5), the better the model (Burnham and Anderson, 2004). The goodness of fit in regression models was expressed as R^2, which can be interpreted as an explained variation. Moreover, leave-one-out cross validation was performed on these selected models to evaluate robustness of the models with regards to their prediction error (i.e., mean square error, MSE_{CV}) (Elzein et al., 2011). Plots and Pearson's linear correlations of observed and predicted AGB values further illustrate the accuracy of predictions. All regression analyses were conducted via linear regression function, using the XLStat add-in statistical software (Version 2014.5.03) for Microsoft Excel.

3. Results

3.1 Descriptive analysis of samples

Due to relatively small sample size or invalid measurements, three of nine sampling times during the growing season were eliminated in the regression analysis (i.e., on Jun. 20, Aug. 16-17, and Sep. 6-7) (Table 1). For the whole sampling season (MS in Table 1), the average AGB > 1000 g/m^2 and CC > 0.9 associated with a LAI around 4.45, indicated that *C. dactylon* communities within the study area were in high-density cover (Table 1). Generally, the AGB during the growing season followed an increasing trend from the lowest on May 30-31 (737 ± 429 g/m^2), up to half of the highest on Sep. 22-23 (1404 ± 481 g/m^2). The result means that the AGB of *C. dactylon* communities were accumulated throughout the entire growing season. A fast increase in AGB appeared before Jul. 10-11, indicating that the monthly net primary productivity during this period is the highest during the entire growing season. Apart from AGB, H, LAI, and CC generally followed increasing tendencies. All these measurements suggest that the cover of *C. dactylon* communities was getting increasingly higher (or thicker) from May to September in 2016.

Table 1 is about here

3.2 The most important estimators for AGB estimation throughout the growing season

Table 2 shows regression coefficients of models for estimating AGB (log-transformed) and using six explanatory variables. For a specific variable, different fitted parameters for different sampling dates were found. Taking slope (*a* in Table 2) as an example, the values for one variable varied considerably throughout the growing season. The slopes of most of the variables generally followed an increasing (or decreasing, depending on variable type) trend at the beginning (before Jun. 12-13 and Jun. 21-22), followed by a turnover. Furthermore, no variable was detected as the most important estimator of AGB for all sampling dates throughout the growing season. CC and V_{LAI} were selected as the most important estimators for more sampling dates compared to others. CC was considered as the most important estimator for May 30-31 and Jun. 12-13, because the models that were established with it have the highest R^2 and the lowest MSE_{CV} compared to all other variables for the same sampling date (R^2 = 0.83, MSE_{CV} = 0.24, and r = 0.91 for May 30-31; and R^2 = 0.63, MSE_{CV} = 0.34, r = 0.79 for Jun. 12-13, Table 2 and Fig. 3). During the mid and end of growing season (Jul. 10-11 and Sep. 22-23) however, V_{LAI} was detected as the most important estimator of AGB. The resulting models can provide the highest R^2 and lowest MSE_{CV} (R^2 = 0.78, MSE_{CV} = 0.06, and r = 0.81 for Jul. 10-11; and R^2 = 0.66, MSE_{CV} = 0.13, and r = 0.78 for Sep. 22-23, Table 2). On Jun. 21-22, V_{CC} was found the most important estimator of AGB. The performance of its established model was acceptable with R^2 = 0.58 and MSE_{CV} = 0.25. On Jul. 1-2, CC was also found as the most important estimator of AGB among all six studied variables; however, the regression model is at insignificance level (p-value = 0.14, not shown in Table 2) and its explanation power is low (R^2 = 0.17, Table 2). This indicated that the univariate linear regression is insufficient at such growing dates and more analysis might be required to improve AGB estimation.

Table 2 is about here

Fig. 3 is about here

3.3 Best model selection throughout the growing season

Table 3 is about here

Fig. 4 is about here

Table 3 lists the results of the best subsets regression analysis. As expected, the selected best models incorporated more variables and achieved higher accuracies and robustness compared to the corresponding selected univariate models for most of the growing season of *C. dactylon* communities (Tables 2 and 3; Figs. 3 and 4). During the early growing season, the models relied on the linear combination of CC and other variables for May 30-31 (LAI) and June 12-13 (H) have improved the capabilities in the AGB estimation, in contrast to the models where only CC was invovled (Table 2). These improvements can be measured in terms of improved R^2 (0.05 for May 30-31 and 0.10 for June 12-13) and reduced MSEcv (0.04 for May 30-31 and 0.07 for June 12-13). On Jun. 21-22, the selected best model was identical to using the single variable modeling. It means that variables other than V_{CC} added little value for the estimation of AGB for this sampling date. On July 1-2, although the selected best model had a great improvement compared to the corresponding univariate model, its R^2 still remained low (0.49). During the mid- and late growing season (July 10-11 and Sept. 22-23), the selected best models both incoroperated H and LAI (Table 3).

In addition, the selected best general model for the entire growing season (MS) had a much higher R^2 (0.72) and lower MSE_{CV} (0.21) than the corresponding single variable model (with R^2 = 0.61 and MSE_{CV} = 0.28, see Tables 2 and 3). Unlike the individual growing dates (except for July 10-11), the seasonal variable (SV) was selected by this general model (Table 3).

4. Discussion

4.1. Plant biomass and canopy structures: the most important estimator

Canopy structure is a key element for estimating plant AGB. For the entire sampling season, CC was found to be the most important estimator of AGB and the developed model had an acceptable performance (R^2 = 0.61 and MSE_{CV} = 0.28, Table 2). However, no variable was found to be the most important estimator in estimating AGB for all sampling dates. During the early growing season (from May 30-31 to June 11-12), CC was suggested as the most important estimator of AGB and enabled reliable estimating performance. During this period, the riparian grassland has a relatively low cover compared to the latter growing season (Table 1). This finding is consistent with previous studies (Axmanová et al., 2012; Flombaum and Sala, 2007; Zhang et al., 2016). For example, Axmanová et al. (2012) reported relatively tight correlations between cover and biomass when the cover is low in sparse vegetation communities; however, the authors reported poor correlations when vegetation cover was in high density. During the mid and late growing season (July 10-11 and Sep. 22-23), the V_{LAI} became the most important estimator of AGB (Table 2). Two of the key questions related to the above findings are: (1) why is CC rather than related variables the most important estimator of AGB during the early growing season of *C. dactylon* communities, as the volume related variables are always considered to contain more structural information of plant communities; and (2) why is the V_{LAI} rather than V_{CC} the most important estimator of AGB towards the end of the growing season, as both of them are volume related variables.

Theoretically, a volume related variable correlates linearly with AGB when the corresponding bulk density is constant (Zhang et al., 2016). In this study, however, the bulk density of the sampling quadrats variation largely during the early growing season, and decreased after that (Fig. 5). This may due to the large variation of community canopy structure in the early growing season, which decreased after that (Fig. 6 and Fig. 2). This suggests that in the early growing season, the large variation of bulk density resulted in less predictabilities of volume variables (both V_{LAI} and V_{CC}) in estimating AGB. Similar to the findings reported by other authors (e.g., Axmanová et al., 2012; Ni-Meister et al., 2010), the CC could be more suitable to estimate AGB during the early growing season since mean plant densities were relatively low (Fig. 2 and Table 1). Thus, this suggests that in data sets that are collected during the early growing season in a riparian environment, CC presents reasonably reliable estimates of biomass that are easy to obtain. At the end of the growing season in *C. dactylon* communities, the variation of bulk densities is relatively small, suggesting that a volume variable (V_{LAI} or V_{CC}) could correlate highly with AGB and be more suitable to be used for estimating AGB. Although two volume related variables exist (V_{CC} and V_{LAI}), our analysis suggests that V_{LAI} could be more suitable than V_{CC} for the AGB estimation. This may be due to the general understanding that LAI contains more inner structural information (such as layer density) than CC at the end of the growing season of *C. dactylon* communities, when the communities had become very dense (see Appendices Fig. A.2). As demonstrated in previous studies, *C. dactylon* is a stoloniferous and rhizomatous grass species with high growth rates when resources are available (Dong and Kroon, 1994). Its stolons extend to seek more radiance under the dense canopy cover (De Abelleyra et al., 2008). As a consequence, towards the end of the growing season, the canopy structure of *C. dactylon* communities often contains two distinct layers: a highly overlapping stolon layer on the ground surface and erect branches above the stolon layer (see Appendices Fig. A.2) (Ecoport, 2012). Since CC of a canopy has a fixed upper limit (i.e., 1), it moves toward saturation, while the community cover is getting higher during the growing season in September (Table 1). In this case, this could lead to misinterpretation in density and structurally diverse plant populations, and thus provide less useful information about canopy structural changes (Axmanová et al., 2012). However, the LAI is essentially a variable with no upper limit value, and thus can indicate more information of structural changes at the same condition (Fig. 6).

Fig. 5 is about here

Fig. 6 is about here

All this suggests that the canopy structural characteristics of a stand are important factors that determine the change of the most important AGB estimator (Martin et al., 2005). It is impractical to find a universal predictor that can be applied to all growing season of plants, given that the canopy structures constantly change like for the investigated *C. dactylon* in this study. Although the CC has been suggested as the universal most important estimator of AGB for the whole growing season in this study, the model on which this is based is not reliable enough to put it into practice due to its relatively low R^2 (0.61). Therefore, when other AGB estimation models are applied in practice, more attention needs to be paid on the sampling dates and plant structure characteristics on which these models were based (Martin et al., 2005; Zhang et al., 2016).

4.2. Optimal biomass estimated models along the growing season: the joint effects

Although most of the models that were established on selected the most important estimators can obtain reliable accuracies for estimating AGB (Table 2), they may not be optimal models since joint effects of the studied variables were not considered. After conducting best subsets regression, the overall performance of the newly built best models significantly improved, compared to the univariate models. For instance, the selected best models explained an additional 11% in AGB variance on average (Table 3). Consequently, the best-selected models in consideration of the joint effects of variables (except for June 21-22) could provide accurate estimations of AGB dynamics for different growing dates. Generally, higher accuracy could be achievable by incorporating more variables (but with less multicollinearity) to the univariate models (Fleming et al., 2014). Recently, many studies have found that some canopy properties such as the green index and the red edge reflectance could be easily measured via remote sensing techniques and can provide useful information for the estimation of grassland AGB (Byrne et al., 2011; Chen et al., 2009; Marshall and Thenkabail, 2015). Thus, these types of variables could be incorporated to develop non-destructive methods in estimating the AGB of grassland communities of riparian zones in the future. Moreover, the best model related variables could also be obtained via new generation remote sensing technology (Ni-Meister et al., 2010; Pueschel et al., 2014; Richter et al., 2012). Thus, the selected best model could be further developed and generalized into larger scale applications in the riparian zones of the TGR and for similar areas.

The selected best general model for an entire growing season provides a relatively good performance in estimating the AGB (R^2 = 0.72 and MSE_{CV} = 0.21, Table 3). It would be very useful to estimating AGB via model interpolation during some other sampling dates, in which samples were not collected or in which the established individual models lacked reliability, such as for June 21-22 and July 1-2 in this study. In the model, CC, H, and SV were selected. These variables represent the horizontial canopy structure (CC), the vertical canopy structre (H), and seasonal growth effects (SV) of *C. dactylon* communities. In many previous studies, canopy structural variables were often considered to be important estimators of AGB; however, the seasonal growth effects were considered less in these models (Hidy et al., 2012; Martin et al., 2005; Redjadj et al., 2012). In this study, the SV was found to be helpful in improving AGB estimation. This result is in accordance with the work conducted by Nakagami and Itano (2014), in which they suggested that a general model considering the sampling date effect in an appropriate way could be useful to improve the performance of an AGB estimation model. Although our developed general models are specific for one dominant species in a riparian environment, the methods we developed for the general model should be applicable to herbaceous species in other environments, where plant growth follows distinct canopy structures throughout the growing season.

Both the univariate and the multivariate models for July 1-2 have rather low R^2 compared to models for other growing season (R^2 = 0.17 and 0.49, respectively, Tables 2 and 3). Two possible reasons could explain this result: Firstly, the difference of sampling condition, in terms of the distinction of water and soil attached to plants, between quadrats was distinct. Heavy rain preceded the field sampling of July 1st. It resulted in considerable amounts of mud attached to the plants (when clipping), thus causing some uncertainties in measuring AGB, CC, and LAI for the quadrats on that day, given that the ACCUPAR LP-80 equipment is easily affected by the water content (Decagon, 2010). On July 2, however, some water on plants and ground had dried due to sunny weather. Secondly, the values of collected samples on June 1-2 were convergent as their standard deviations were relatively low, e.g., AGB of 273 g/m^2, H of 8 cm, LAI of 0.39, and CC of 0.04 (Table 1). Those concentrated sampling data can undermine the predictability of the regression model. This might be caused by a new sampler (a postgraduate student with less training) on that sampling date, who tended to select quadrats with high density cover and omitted to take the gradient effects into account during sampling.

4.3. Limitations

The *C. dactylon* communities investigated in the riparian zone of the TGR were focused. They are mainly distributed in lowland with elevations roughly below 165 m (Chen et al., 2012). However, other communities (e.g., *Xanthium sibiricum Patr*, and *Setaria viridis (L.) Beauv*) were mainly found between 165 m to 175 m and were not considered here due to their relative low eveness along the TGR drawdown zone and the limited number of sampling quardrants (not shown in this study). More field work is required to estimate the AGB of those communites by obtaining a sufficient number of samples over the next few years. Moreover, although an aproximate 10-day interval field samping was tried to be conducted throughout the growing season, they were still unable to be guaranteed after July 20 due to some unforeseen factors such as rising water level and intolerable hot weather during August (see Fig. 1d). Nevertheless, the valid sampling dates still covered the early (May and June), middle (July), and end (September) of the growing season of *C. dactylon* communities. Therefore, the findings of this study are also expected to be helpful for sampling work, aimed at understanding seasonal AGB dynamics in future.

5. Conclusion

Seasonal AGB dynamics of pioneer plant species during early succession is a key indicator for both planning and monitoring of ecosystem restorations. This study focused on one dominant plant pioneer species in the TGR riparian zone: *C. dactylon*. We explored the capabilities of five canopy structure variables and one seasonal growth effects variable to estimate the AGB of the species along different dates throughout the growing season. Our results indicate that the studied canopy structural variables can be applied for estimating the AGB with reasonable accuracy and robustness. However, the seasonal change of canopy structure indicates that there is no variable that can be the most important AGB estimator throughout the entire growing season. CC was found as the best estimator during the early growing season, and V_{LAI} became the most important for the middle and the end of the growing season. The joint effects of multiple structural variables were also demonstrated to be helpful in improving AGB estimation of different sampling dates. A reliable general model for estimating AGB during the entire growing season was also developed with the contribution of SV. The selected most important estimators and models of AGB estimating can be used as indicators for monitoring ecosystem productivity, succession, and restoration processes of riparian ecosystems. Given that the structural variables can be obtained via current remote sensing techniques, it is recommended that the developed models can also be applied for the rapid estimation of biomass in riparian zones, using remotely sensed data and that they can be extended to regional scales. Furthermore, the models developed at different growing dates enable time-series analysis of biomass dynamics, which is essential for assessing the temporal response patterns of seasonal changes, and might provide both emperical and therotical explanations of riparian zone ecosystem functions in response to water level fluctuations in the TGR. Finally, we suggest that the development of estimating models via our approach could expand upon, rather than replace, the other modeling methods.

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Figures with captions

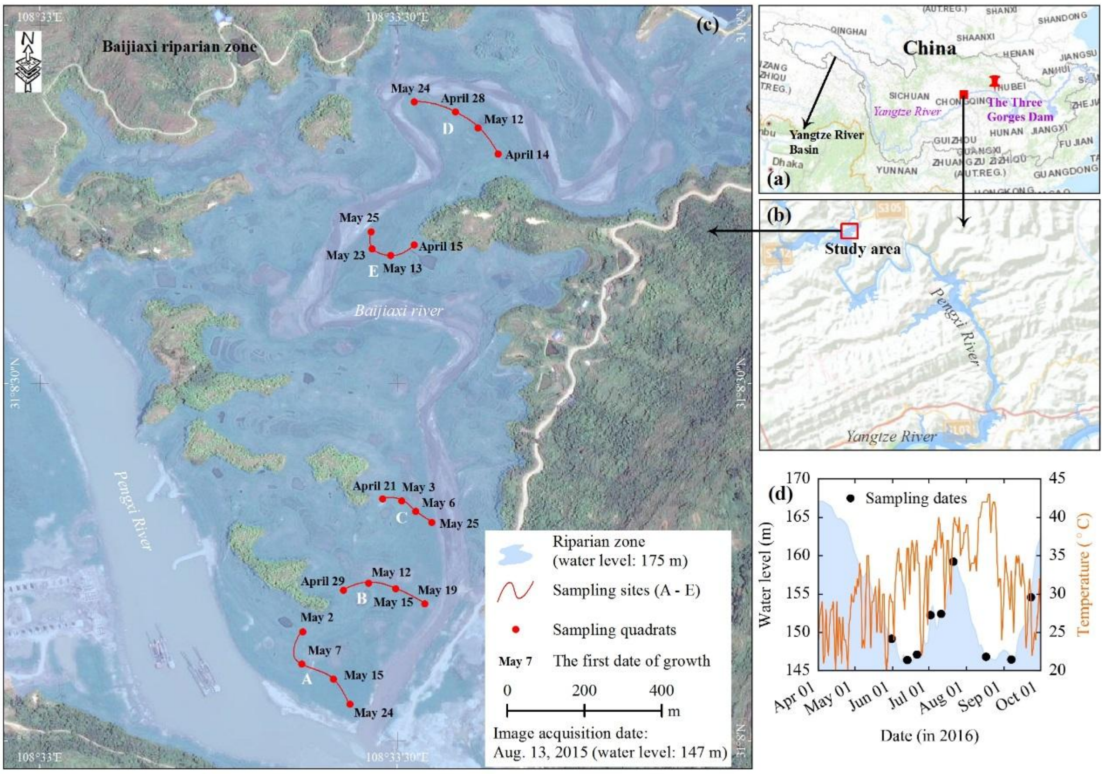


Fig. 1. Location of study area (a-b), (c) satellite image of the study area with the distribution of sampling sites, and (d) daily water level fluctuations at the Wanzhou hydrological station near the study area (data from http://www.cxfww.cn/), daily average temperatures, and sampling dates.

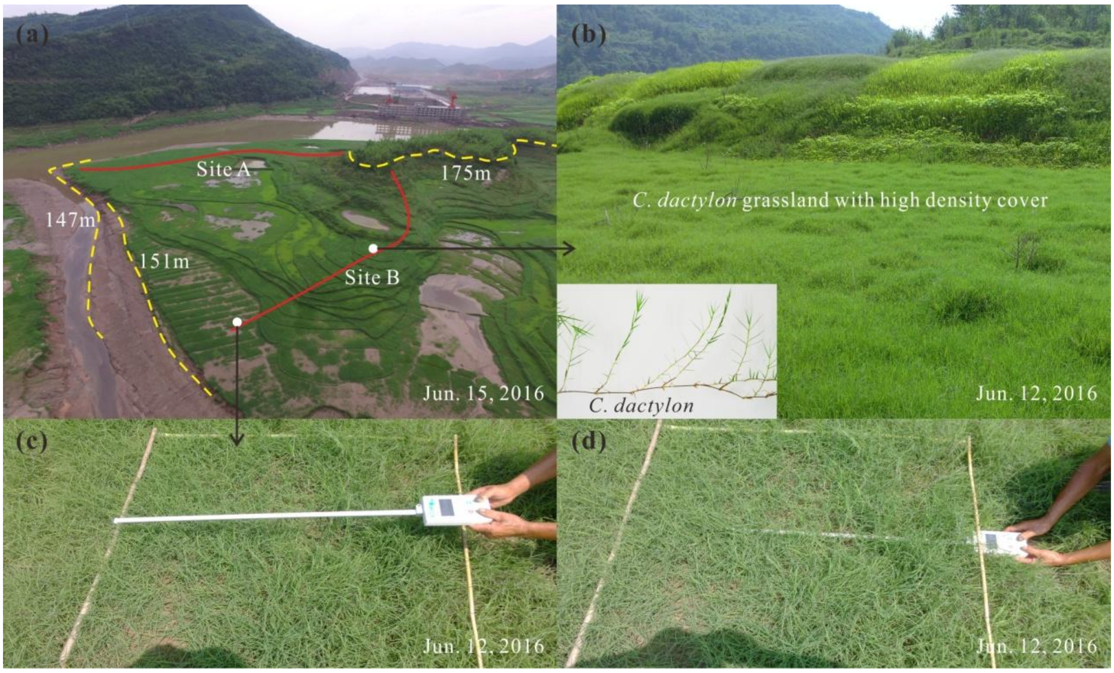


Fig. 2. Images depicting our sampling methods: (a) an overview of the sampling sites A and B (See Fig.1), (b) representative picture for a *C. dactylon* community with high density cover, (c) and (d) measuring photosynthetically active radiation both above (c) and below the canopy (d) via ACCUPAR LP-80 ceptometer.

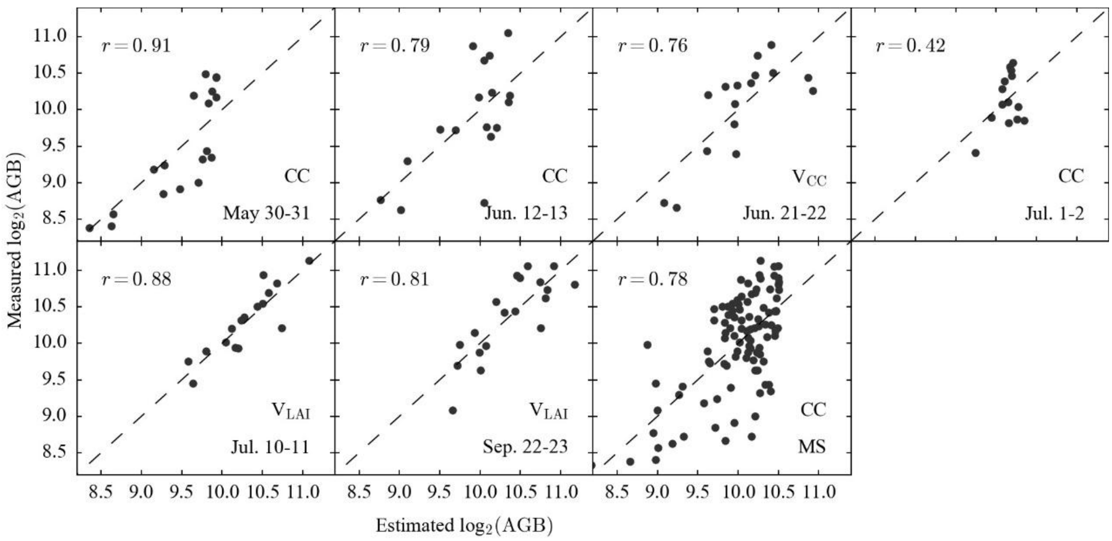


Fig. 3. Correlation coefficients (r) between the measured $\log_2$(AGB) and the estimated values via the selected best variable (i.e., the labeled variable) for different sampling dates. The dashed line marks a 1:1 ratio. MS = May 30 to Sep. 23 in 2016.

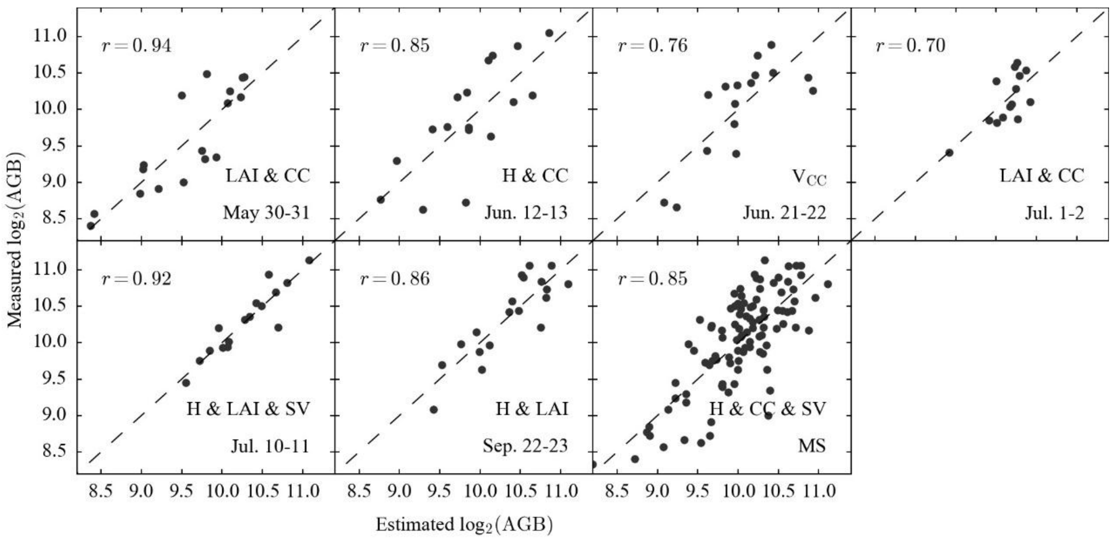


Fig. 4. Correlation coefficients (r) between the measured $\log_2$(AGB) and the estimated values via the selected best model (the involved variables were labeled) for different sampling dates. The dashed line marks a 1:1 ratio. MS = May 30 to Sep. 23 in 2016.

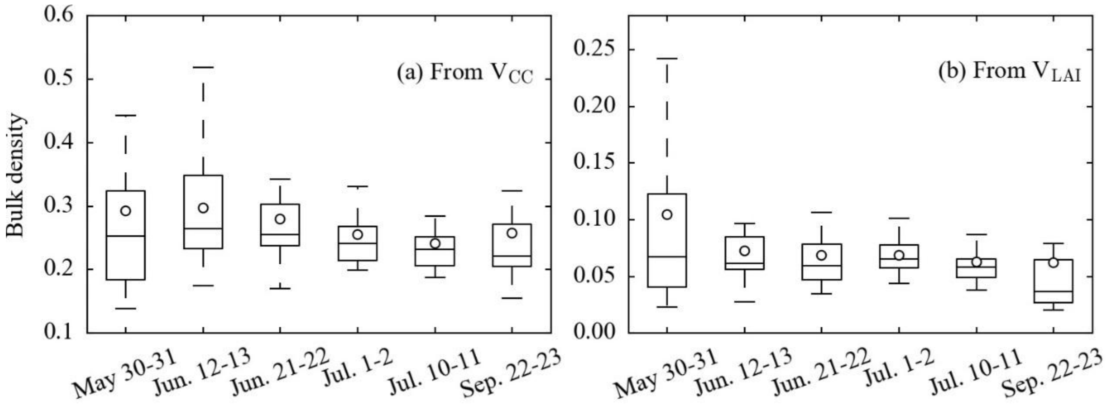


Fig. 5. Statistical distributions of the bulk densities of samples at different sampling dates. (a) Bulk density calculated from V_C and (b) from V_{LAI}. The small circle (◦) is the mean value.

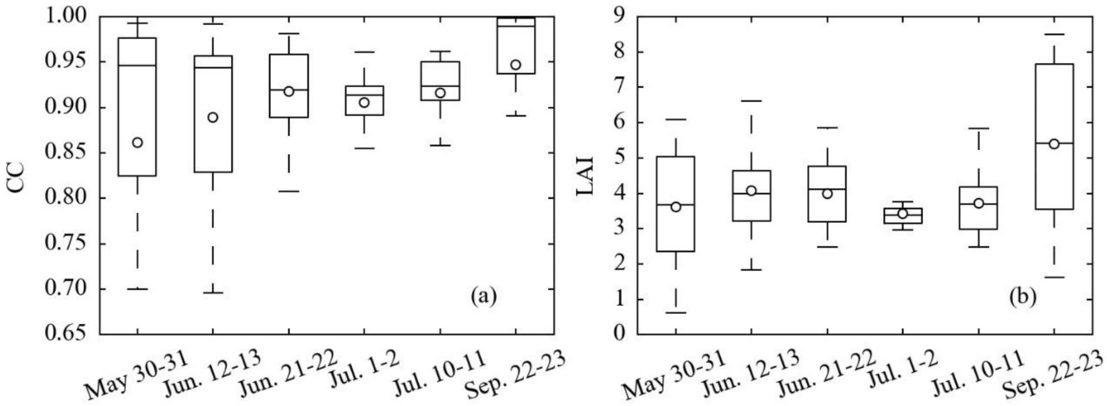


Fig. 6. Statistical distributions of the canopy cover of samples (a) and the LAI (b) at different sampling dates. The small circle (◦) is the mean value.

Table

Table 1. Basic statistics of *C. dactylon* community samples at different sampling dates in 2016. Sample values are shown as mean ± standard deviation. SPD: sampling dates, NS = number of samples, AGB = aboveground biomass, H = height, LAI = leaf area index, CC = canopy cover, V_{LAI} is a canopy volume-like variable calculated via H × LAI, and V_{CC} is a further volume-like variable calculated via H × CC. MS = May to Sep. (i.e., all samples collected during valid sampling dates). Light gray shaded data were not applied in the regression modeling due to the relatively small number of samples or invalidity of measurements.

SPD	NS	AGB (g/m^2)	H (cm)	LAI	CC	V_{LAI}	V_{CC}
May 30-31	20	737±429	44±15	3.60±1.79	0.86±0.18	176±130	39±18
Jun. 12-13	19	979±544	40±12	4.06±1.32	0.89±0.11	171±94	36±13
Jun. 21-22	16	1144±428	43±12	3.99±0.98	0.92±0.05	172±70	39±12
Jul. 1-2	14	1171±273	46±8	3.40±0.39	0.91±0.04	156±36	41±8
Jul. 10-11	16	1314±427	48±8	3.72±0.90	0.92±0.05	176±56	44±9
Jul. 20	4	874±240	37±5	4.31±1.00	0.87±0.07	157±36	32±5
Aug. 16-17	19	1347±408	45±11	invalid	invalid	invalid	invalid
Sep. 6-7	20	1352±676	45±14	invalid	invalid	invalid	invalid
Sep. 22-23	19	1404±481	47±12	5.39±2.32	0.95±0.07	267±145	45±13
MS	104	1189±497	46±12	4.45±1.72	0.92±0.10	213±122	42±14

Table 2. Regression coefficients of models that estimate dry aboveground biomass (*Y*), using variables (*X*) of canopy height (H), canopy cover (CC), leaf area index (LAI), V_{CC}, V_{LAI}, and seasonal growth effects variable (SV) via the univariate linear model of $\log_2(Y) = aX+b$. For each sampling date, the numbers in bold depict the highest R^2 or the lowest MSE_{CV} among all six variables. Light grayed values indicate that the corresponding fitted model is insignificant with *p*-values > 0.05. MS = May 30 to Sep. 23 in 2016.

Variables	Models	Sampling dates						
		May 30-31	Jun. 12-13	Jun. 21-22	Jul. 1-2	Jul. 10-11	Sep. 22-23	MS
H	*a*	0.039	0.051	0.040	0.008	0.033	0.032	0.040
	b	7.500	7.640	8.320	9.790	8.720	8.850	8.150
	R^2	0.288	0.461	0.561	0.035	0.372	0.512	0.331
	MSE_{CV}	0.902	0.487	0.254	0.155	0.153	0.178	0.467
	p-value	0.015	0.001	0.001	0.523	0.012	0.001	<0.001
CC	*a*	**5.390**	**6.510**	6.000	**3.880**	5.550	5.000	**6.170**
	b	**4.580**	**3.890**	4.500	**6.620**	5.250	5.600	**4.330**
	R^2	**0.831**	**0.630**	0.187	**0.175**	0.394	0.517	**0.606**
	MSE_{CV}	**0.238**	**0.340**	0.471	**0.167**	0.151	0.221	**0.275**
	p-value	<0.001	<0.001	0.094	0.137	0.009	0.001	<0.001
LAI	*a*	0.532	0.456	0.214	-0.314	0.395	0.186	0.325
	b	7.310	7.840	9.180	11.200	8.820	9.360	8.610
	R^2	0.804	0.457	0.100	0.117	0.596	0.613	0.396
	MSE_{CV}	0.271	0.512	0.473	0.129	0.100	0.143	0.428
	p-value	<0.001	<0.001	0.232	0.232	<0.001	<0.001	<0.001
V_{CC}	*a*	0.046	0.053	**0.043**	0.014	0.035	0.032	0.045
	b	7.430	7.800	**8.360**	9.580	8.730	8.950	8.110
	R^2	0.583	0.603	**0.581**	0.087	0.467	0.590	0.497
	MSE_{CV}	0.570	0.357	**0.248**	0.134	0.129	0.149	0.357
	p-value	<0.001	<0.001	0.001	0.305	0.004	<0.001	<0.001
V_{LAI}	*a*	0.006	0.007	0.007	0.007	**0.007**	**0.003**	0.005
	b	8.100	8.550	8.910	10.200	**8.990**	**9.540**	8.960
	R^2	0.607	0.503	0.479	0.001	**0.776**	**0.658**	0.426
	MSE_{CV}	0.532	0.477	0.297	0.168	**0.058**	**0.127**	0.407
	p-value	<0.001	0.001	0.003	0.924	<0.001	<0.001	<0.001
SV	*a*	0.457	0.074	0.868	-0.135	-0.312	-1.410	0.398
	b	7.240	9.310	5.380	10.900	12.200	20.400	7.700
	R^2	0.301	0.003	0.273	0.015	0.058	0.062	0.286
	MSE_{CV}	0.967	0.950	0.399	0.163	0.242	0.338	0.509
	p-value	0.012	0.819	0.038	0.682	0.368	0.304	<0.001

Table 3. Output of the best subsets regression. The finial selected best model for an individual sampling date is marked in bold. SPD = sampling dates and NV = number of variables. MSE_{CV} = mean MSE value from the leave-one-out cross validation. "-" = no data.

SPD	NV	Selected variables (corresponding VIF value)	MSE_{CV}	MSE	R^2	AIC	ΔAIC	*p*-value
May 30-31	1	CC(-)	0.238	0.201	0.831	-30.161	4.842	<0.001
	2	**LAI(3.92); CC(3.92)**	**0.199**	**0.153**	**0.879**	**-34.777**	**0.226**	**<0.001**
	3	H(6.08); CC(2.44); V_{LAI}(9.16)	0.167	0.146	0.891	-35.003	0.000	<0.001
	4	H(57.11); LAI(8.61); CC(13.20); V_{CC}(108.95)	0.263	0.153	0.893	-33.288	1.715	<0.001
	5	H(57.12); LAI(8.68); CC(13.74); V_{CC}(109.05); SV(1.61)	0.278	0.163	0.893	-31.393	3.61	<0.001
Jun. 12-13	1	CC(-)	0.340	0.310	0.630	-20.343	3.952	<0.001
	2	**H(1.36); CC(1.36)**	**0.269**	**0.241**	**0.729**	**-24.295**	**0.000**	<0.001
	3	LAI(7.29); V_{LAI}(21.09); V_{CC}(8.40)	0.287	0.245	0.742	-23.189	1.106	<0.001
	4	H(80.44); LAI(26.05); V_{LAI}(39.38); V_{CC}(69.07)	0.338	0.259	0.746	-21.480	2.815	<0.001
	5	H(366.60); LAI(109.22); CC(92.97); V_{LAI}(221.93);V_{CC}(918.45)	0.445	0.273	0.751	-19.856	4.439	0.001
Jun. 21-22	**1**	**V_{CC}(-)**	**0.248**	**0.198**	**0.581**	**-24.084**	**0.000**	0.001
	2	V_{CC}(1.27); SV(1.27)	0.245	0.194	0.619	-23.590	0.494	0.002
	3	H(1.26); CC(1.21); SV(1.34)	0.254	0.202	0.634	-22.228	1.856	0.006
	4	H(320.27); CC(9.28); V_{CC}(360.45); SV(1.34)	0.297	0.207	0.655	-21.195	2.889	0.013
	5	H(529.62); LAI(53.98); CC(21.08); V_{LAI}(140.55);V_{CC}(888.40)	0.372	0.177	0.732	-23.260	0.824	0.011
Jul. 1-2	1	CC(-)	0.167	0.115	0.175	-28.481	5.515	0.137
	2	**LAI(1.20); CC(1.20)**	**0.081**	**0.077**	**0.493**	**-33.310**	**0.686**	**0.024**
	3	H(16.64);V_{LAI}(4.40);V_{CC}(18.98)	0.096	0.070	0.582	-33.996	0.000	0.028
	4	H(21.28); LAI(1.18); V_{CC}(22.00); SV(1.15)	0.110	0.076	0.590	-32.280	1.716	0.066
	5	H(195.11); LAI(55.35); V_{LAI}(206.24);V_{CC}(23.93); SV(1.55)	0.152	0.085	0.590	-30.286	3.71	0.141
Jul. 10-11	1	V_{LAI}(-)	0.058	0.051	0.776	-45.792	4.677	<0.001
	2	V_{LAI}(1.27); SV(1.27)	0.053	0.046	0.811	-46.562	3.907	<0.001
	3	**H(1.26); LAI(1.17); SV(1.38)**	**0.050**	**0.041**	**0.847**	**-47.898**	**2.571**	**<0.001**
	4	H(50.99); LAI(114.55); V_{LAI}(189.98); SV(1.99)	0.052	0.033	0.885	-50.469	0.000	<0.001
	5	H(76.41); LAI(176.34); CC(2.93); V_{LAI}(270.58); SV(2.09)	0.060	0.034	0.892	-49.561	0.908	<0.001
Sep. 22-23	1	V_{LAI}(-)	0.127	0.110	0.658	-39.976	4.885	<0.001
	2	**H(1.37); LAI(1.37)**	**0.105**	**0.088**	**0.743**	**-43.386**	**1.475**	<0.001
	3	H(6.44); LAI(21.48); V_{LAI}(36.71)	0.087	0.078	0.786	-44.861	0.000	<0.001
	4	H(6.50); LAI(24.56); V_{LAI}(39.61); SV(1.28)	0.091	0.077	0.803	-44.446	0.415	<0.001
	5	H(8.59); LAI(38.98); CC(4.13); V_{LAI}(48.79); SV(1.32)	0.105	0.083	0.804	-42.562	2.299	<0.001
MS	1	CC(-)	0.275	0.270	0.606	-134.060	32.126	<0.001
	2	H(1.24); CC(1.24)	0.238	0.227	0.673	-151.430	14.756	<0.001
	3	**H(1.24); CC(1.45); SV(1.22)**	**0.205**	**0.195**	**0.722**	**-166.186**	**0.000**	**<0.001**
	4	CC(2.06); V_{LAI}(3.73);V_{CC}(3.71); SV(1.23)	0.207	0.197	0.722	-164.211	1.975	<0.001
	5	H(33.94); LAI(23.58); V_{LAI}(36.68);V_{CC}(29.62); SV(1.23)	0.209	0.194	0.728	-164.598	1.588	<0.001

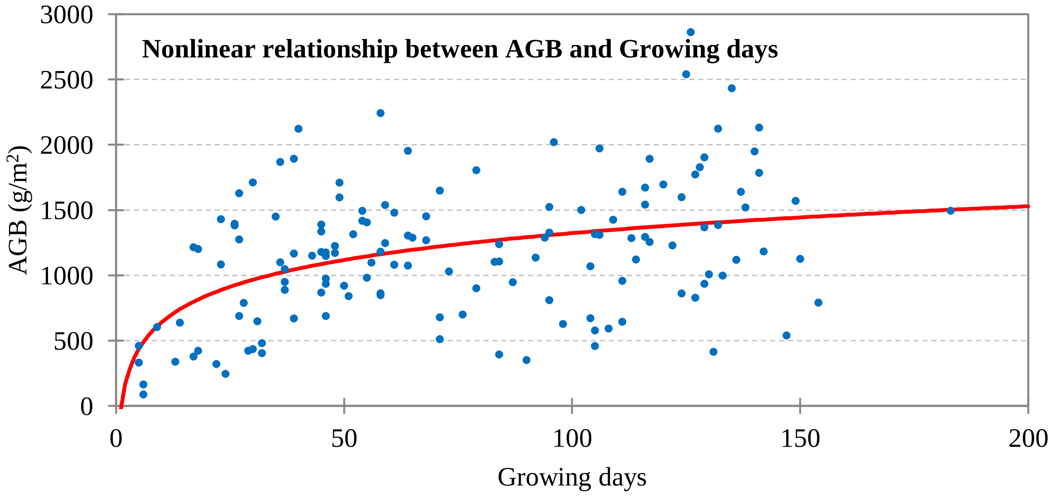


Figure A.1. Scatter plot of AGB against growing days (i.e., days after first date emerging from water in 2016) for all collected samples of *C. dactylon* communities in the growing seasons (see Table 1). It shows that the AGB was accumulated fast in the early growing seasons and then slowed down in the mid- and end- growing season. This nonlinear growing process was thus could be characterized by a logarithmic function (the red solid line). Based on this observation, the seasonal growing effect variable was defined as log-transformed (base 2) of growing days to facilitate linear AGB estimation model in this study.

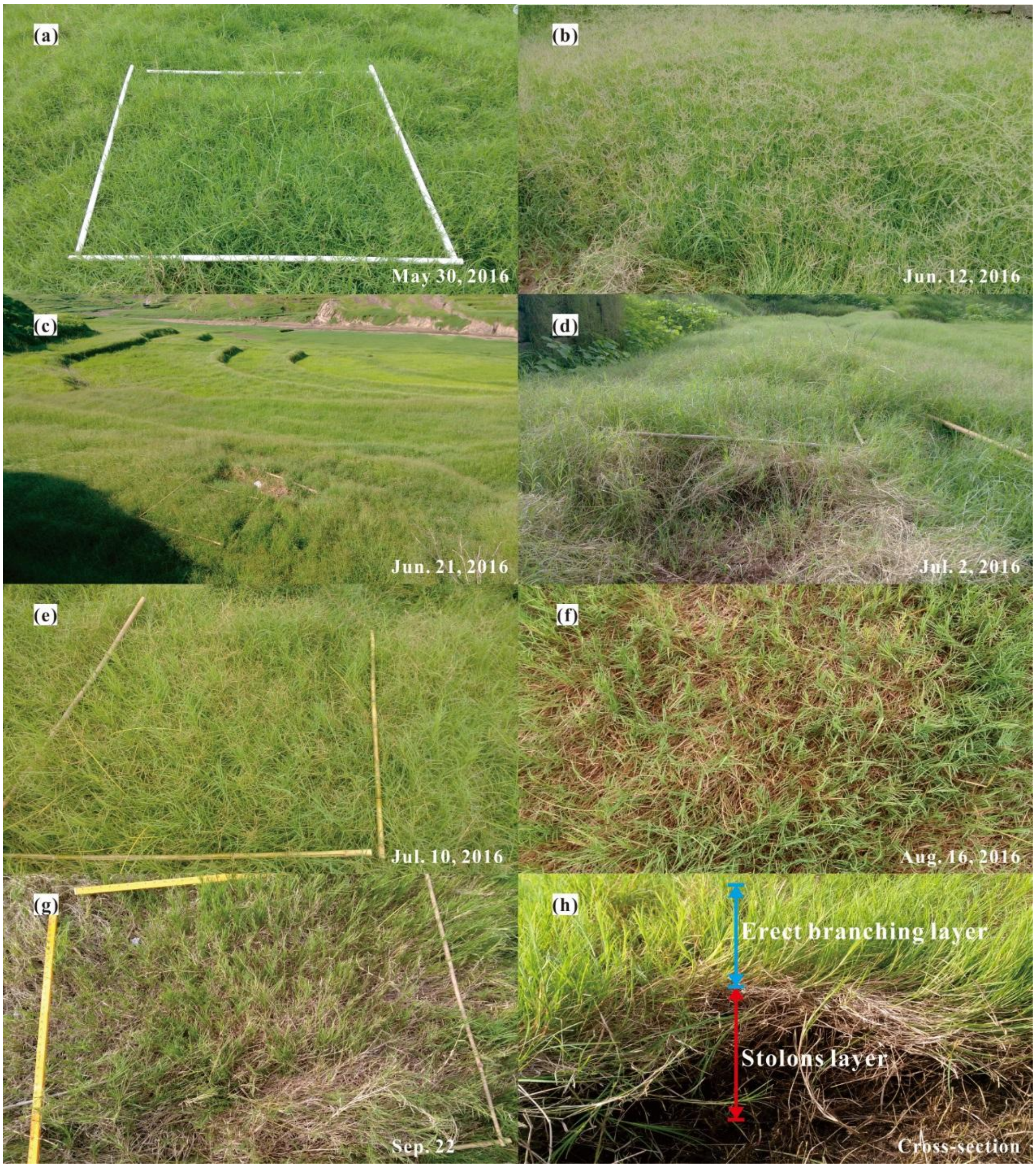
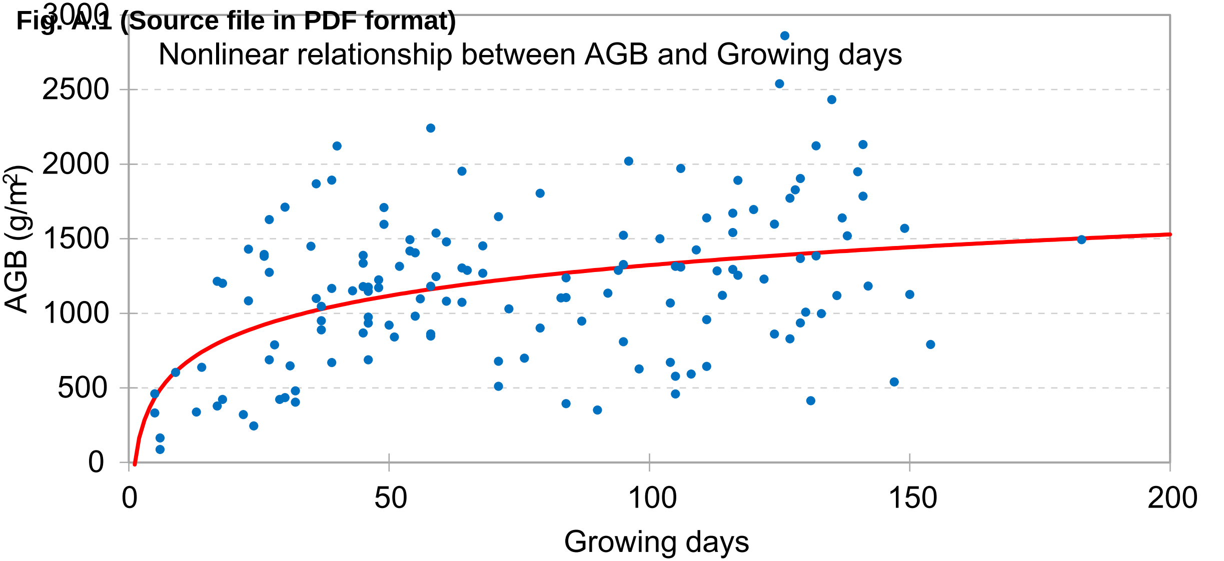


Figure A.2. (a)-(g): Growing statue dynamics of *C. dactylon* community sampling quadrats in different growing seasons (from May to September). The spatial locations of these quadrats were close to each other within distance less than 10 m. (h) A cross-section view of two distinct layers of *C. dactylon* community in the end of growing season.

Fig. A.1 (Source file in PDF format)



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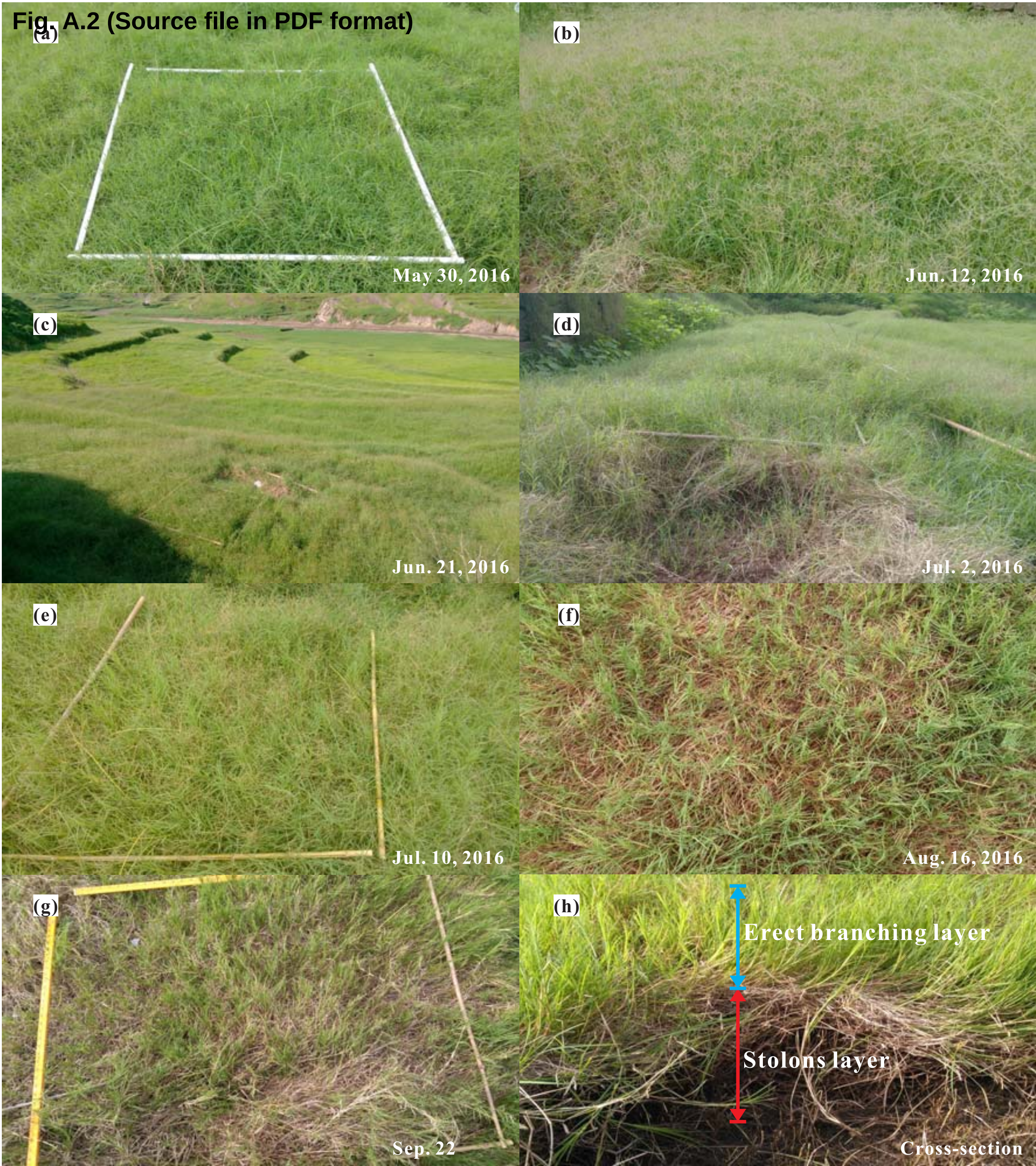

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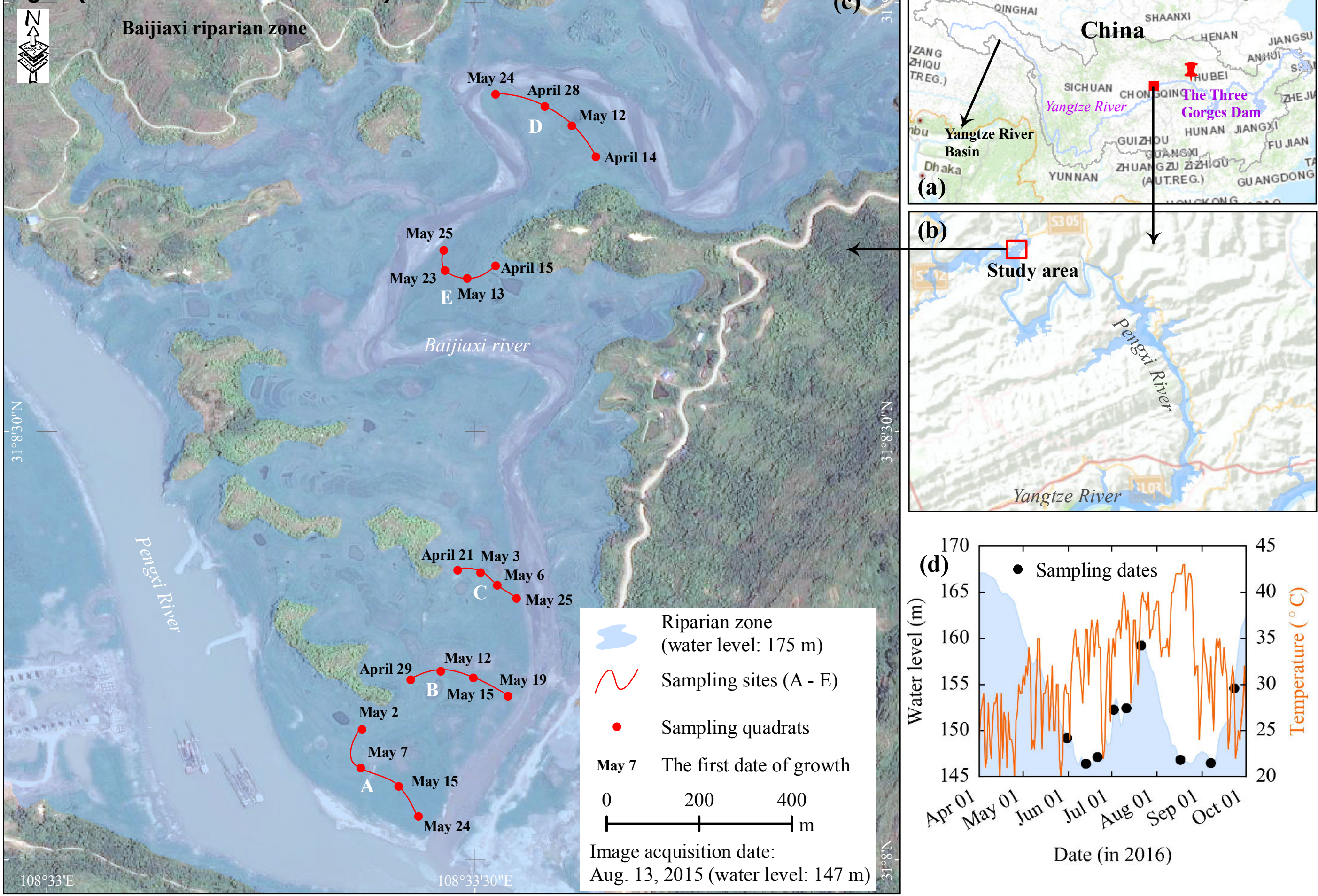

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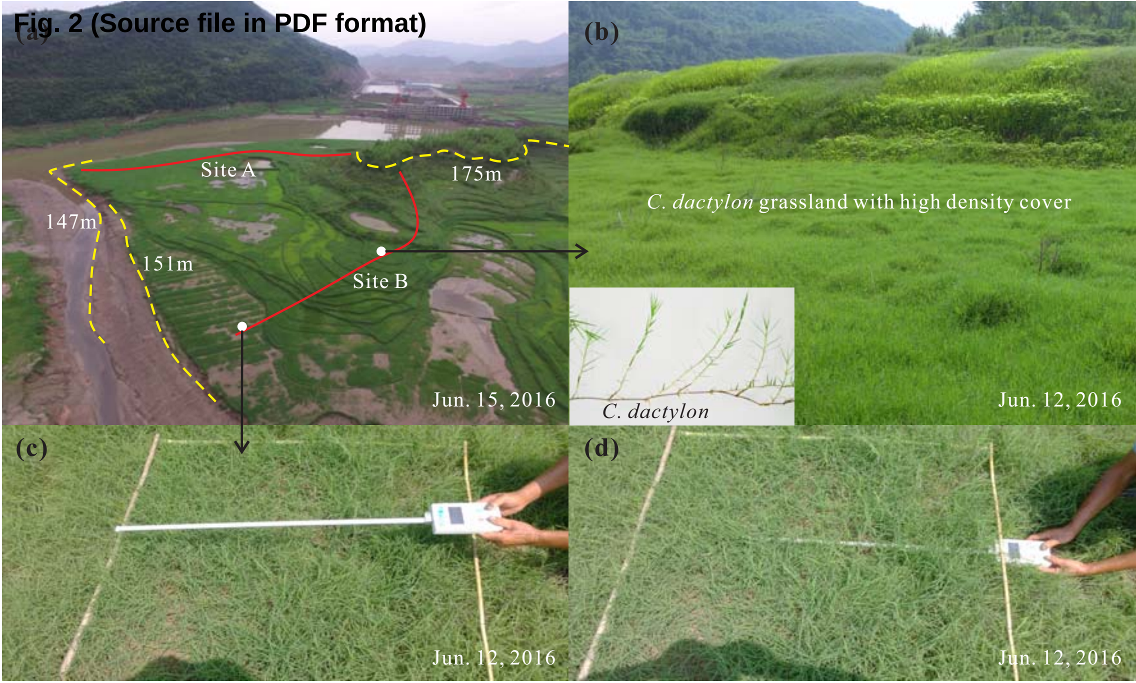

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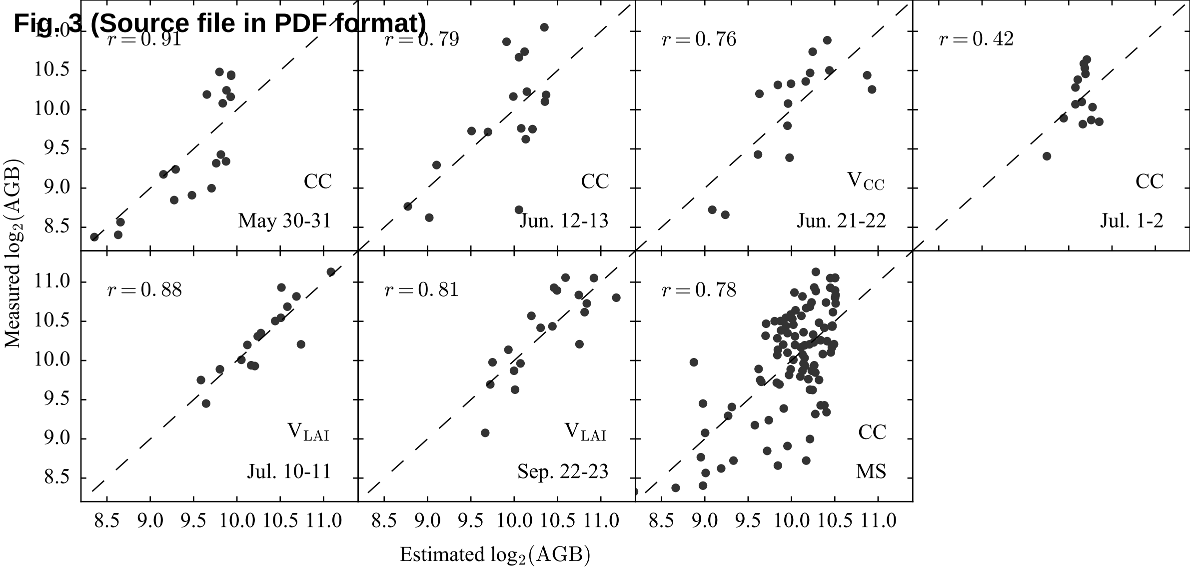

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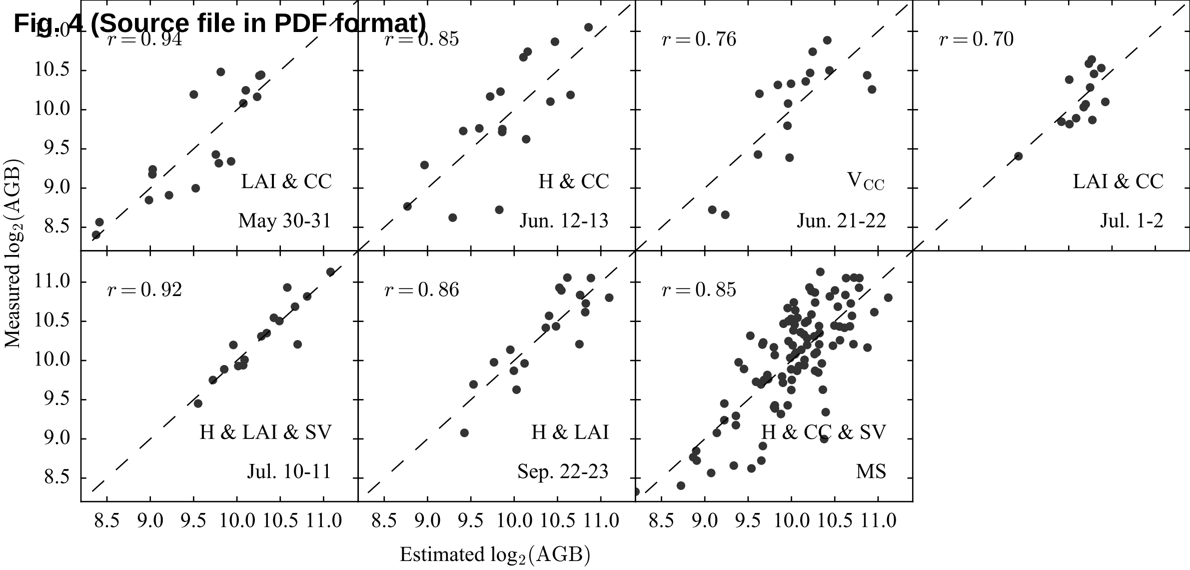

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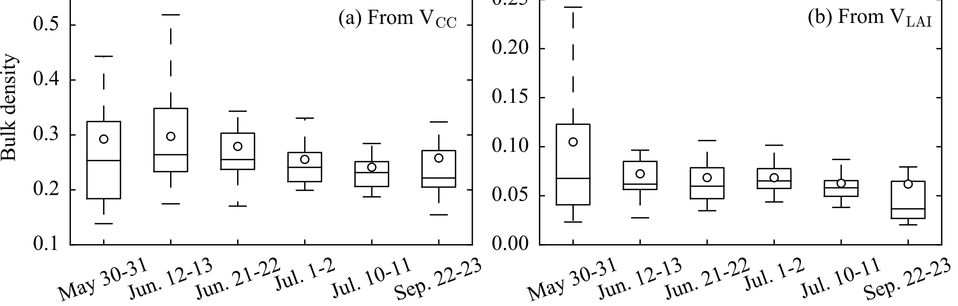

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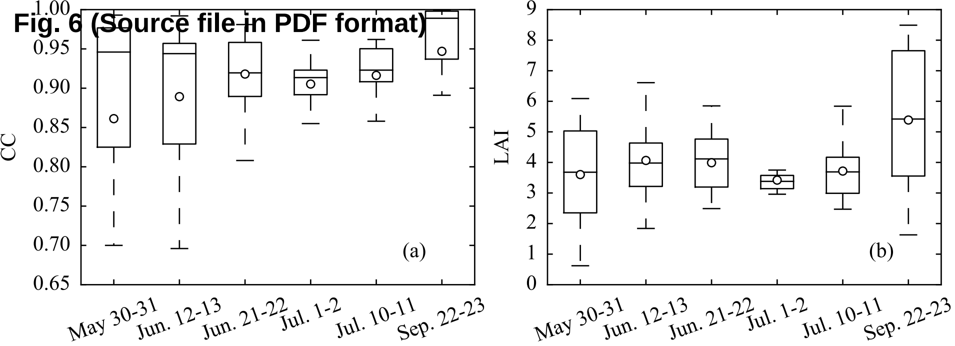

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