Remote sensing and agent-based modelling for grazing management: a case study in Zeku, China

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Abstract

Monitoring grazing activities on grassland is crucial for ensuring sustainable grassland development and protecting it from grazing-led degradation. Leaf Area Index (LAI) is commonly used as a proxy for grassland condition. However, current studies all focus on the year round aggregated LAI change or seasonal variation rather than the specific grazing-led LAI defoliation for each pixel, which is the important indicator for quantifying grassland grazing activities. This paper presents a new exponential growth function under grazing with an estimation algorithm, with the purpose of extracting grazed LAI for every 8 days' satellite observations. All the analyses are based on the Moderate Resolution Imaging Spectroradiomete (MODIS) MOD15A2H products. The improved MODIS LAI and expected LAI are produced separately using grazing LAI estimation algorithm, considering both current and previous grazing defoliation effect. In addition, different grazing strategies and institutional arrangements would affect the grassland productivity and the local ecology (degraded land), especially under the government guided Ecological Economic Livestock Grazing Cooperative Group (group grazing) policy. How the performance of ecological indicators in response to grazing strategies? Which strategy is the most suitable one? This paper will explore all those related questions with an agent-based model, which would provide new view on precise and almost real-time grassland grazing monitoring and simulation under different grazing arrangement.

Key works:
Agent based modelling, Grassland grazing, Remote sensing, Leaf Area Index, Moderate Resolution Imaging Spectroradiomete (MODIS)

1 Introduction:

Remote sensing derived datasets are extensively employed in the field of grassland monitoring (Field, Randerson, & Malmström, 1995; Gao et al., 2013; Piñeiro, Oesterheld, & Paruelo, 2006; Potter et al., 1993). In this research, MODIS Leaf Area Index (LAI) is the commonly used measures to quantify the vegetation status of grassland (Fang, Wei, Jiang, & Scipal, 2012). It is widely used and extensively validated around the world (De Kauwe, Disney, Quaife, Lewis, & Williams, 2011). But the algorithm may fail and an empirical LAI would be filled for the pixels instead; in addition, the radiation is strongly affected by clouds, this is why MODIS LAI needs to be reprocessed before using. Current reprocessing methods are aimed at producing a smoother and spatiotemporally consistent products by taking spatial, temporal or hybrid combination of weighted LAI values (Fang, Liang, Townshend, & Dickinson, 2008; Hansen et al., 2003; Liu, Shang, Liu, & Lu, 2017; Xiao, Liang, Wang, Jiang, & Li, 2011; Yuan, Dai, Xiao, Ji, & Shangguan, 2011; Yuzhen Zhang, Qu, Wang, Liang, & Liu, 2012). Those improved LAI widely used in the broad view of pixel-specific vegetation dynamics at both regional level (Bobée et al., 2012; Jin et al., 2017) and global level (Yulong Zhang, Song, Band, Sun, & Li, 2017).

However, when looking into the vegetation dynamics for each time slice in grazing monitoring, those improved LAI dataset would demolish the original grazing information by spatiotemporal averaging. Ignorance of the effect of herbivore removers of vegetation is acceptable on a global scale of vegetation carbon assimilation or fixation, especially in some forest areas, where herbivores contribute little to the plant LAI fluctuation. However, in the context of grassland, especially in grazing intense areas (Gignoux, Fritz, Abbadie, & Loreau, 2001), the LAI consumption by livestock could have a significant effect on the quantity and quality of grass productivity. It could directly lead to the change from green land to bare land, and a consequent LAI change would be observed in the grass growth season (Miller-Goodman, Moser, Waller, Brummer, & Reece, 1999; Tsalyuk, Kelly, Koy, Getz, & Butterfield, 2015). In addition, different grazing strategies affect the grassland productivity and the local ecology (degraded land), especially under the government guided Ecological Economic Livestock Grazing Cooperative Group (group grazing) policy in Zeku. How to assess the effect of different grazing strategies on the grassland status? What would be the most suitable institutional arrangement for the local ecology?

Considering the problem, it is of great importance to identify the spatial distribution and quantity of LAI consumed by livestock on grassland. The aim of this paper is to estimate where and how much LAI has been consumed by livestock using a new integrated growth grazing exponential function with a grazed LAI estimation algorithm. In addition, agent based model would be employed to assess the different grazing straits and intuitional arrangement.

2 Data and methods

The LAI datasets were gathered from the MODIS collection 6 LAI (MOD15A2H006). For each pixel (about463 $\times$463 m^2) during 2003-2012, there is a quality control (QC) value for each pixel stored as 8 bits of data (Table 1). The unit of the LAI is m^2/m^2 and the scale factor is 0.1 (meaning the real value is 10 times smaller than that of the MODIS LAI data recorded).

Table 1: MOD15A2 quality control (QC) definition

Bit Num	Parameter Name	Bit	FparLai_QC
0	MODLAND_QC bits	0	Good quality (main algorithm with or without saturation)
		1	Other Quality (back-up algorithm or fill values)
1	Sensor	0	Terra
		1	Aqua
2	DeadDetector	0	Detectors apparently fine for up to 50% of channels 1,2
		1	Dead detectors caused >50% adjacent detector retrieval
3–4	CloudState	0	0 Significant clouds NOT present (clear)
		1	1 Significant clouds WERE present

		10	2 Mixed cloud present on pixel
		11	3 Cloud state not defined, assumed clear
5–7	SCF_QC	0	0, Main (RT) method used, best result possible (no saturation)
		1	1, Main (RT) method used with saturation. Good,very usable
		10	2, Main (RT) method failed due to bad geometry, empirical algorithm used
		11	3, Main (RT) method failed due to problems other than geometry, empirical algorithm used
		100	4, Pixel not produced at all, value coudn't be retrieved (possible reasons: bad L1B data, unusable MODAGAGG data)

In this paper, only the data with QC=0 are used in order to avoid introducing any further uncertainties or errors to the model. In the MODIS LAI dataset, we have LAI observation every 8-days which in total is 46 observations each year; these are the snapshots values captured by satellite. The time range of the dataset is from 2003 to 2012. Figure 1 shows "a single pixel" example of a QC=0 LAI time series at row 54, column 123 (54, 123) in Zeku; we can see an obvious discontinuousness when the data with the condition QC=0 is used.

The land cover data is from the 30 meters Global Land Cover dataset (GlobalLand30). The overall classification accuracy reaches 83.51% (Kapaa= 0.78). Specifically, the accuracy for grassland is 76.88%. The coordinate system is WGS84 (UTM Projection) [1]. As it is organized in tiles, four of the tiles are downloaded to cover the extent of Zeku County (tile numbers are: N47_30_2010LC030, N47_35_2010LC030, N48_30_2010LC030 and N48_35_2010LC030).

The framework for identifying grazed LAI is shown in Figure 1:

[1] 30 meter global land cover dataset (GlobalLand30) Product Description, http://glc30.tianditu.com

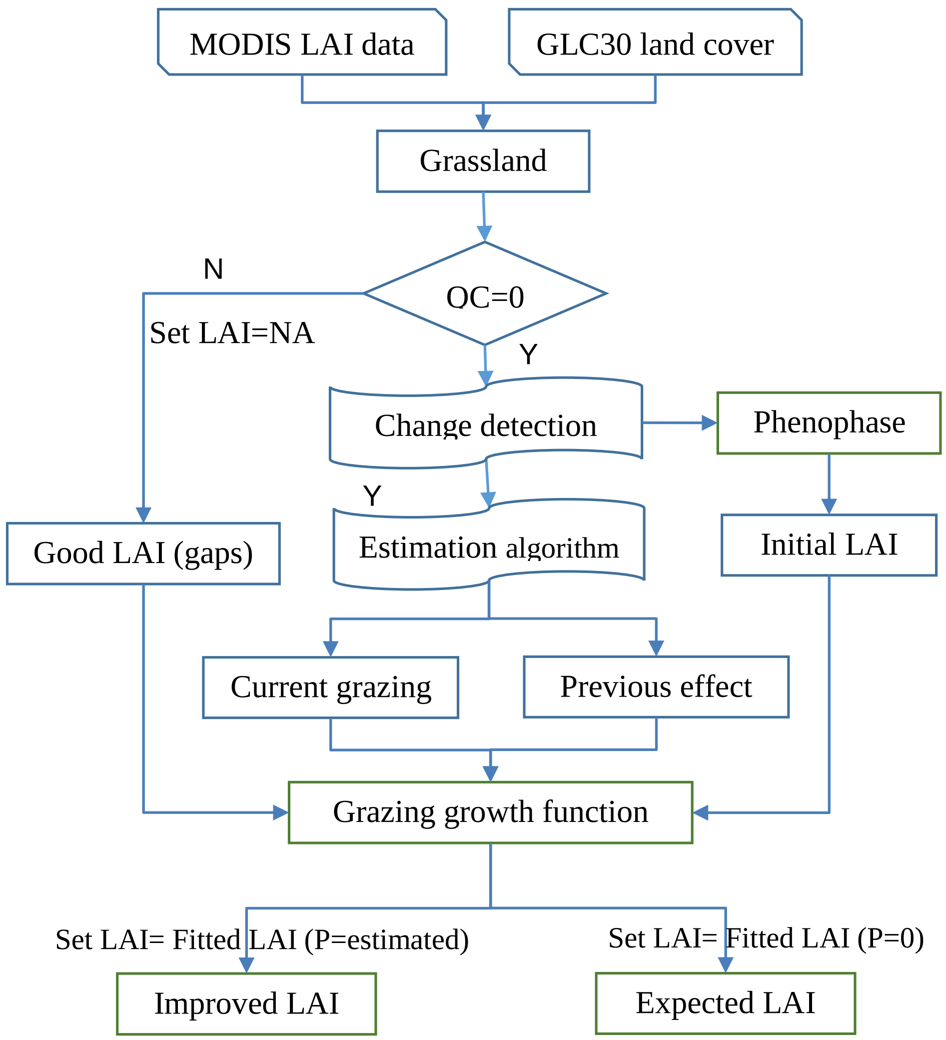


Figure 1: concept framework for quantifying grazing in Zeku, China

MODIS LAI data is the fundamental for this study, all the analysis is based on the time-series change of the LAI. In addition, the GlobalLand30 data is used to extract grassland information. Based on the GlobalLand30 classification, only the pixels classified as grassland are used in calculating the initial values of LAI from 2003 to 2012. A change detection technique was employed to estimate the starting date and end date of the grass growth season. An estimation algorithm was developed to estimate the grazing defoliation LAI. This was utilised with a curving fitting procedure to produce improved LAI and expected LAI. We will now outline their components.

The defects of conventional growth function when describing the live grass mass accumulation can be summarised as:

- Senescence or defoliation factors have been totally ignored
- The lack of parameters representing grazing effect

A feasible way to deal with those problem is to add a senescence or defoliation coefficient to the exponential growth function according to the nature of plant development. The ordinary exponential growth function are detailed in (Thornley & Johnson, 1990). When considering livestock grazing, the new function can be expressed as:

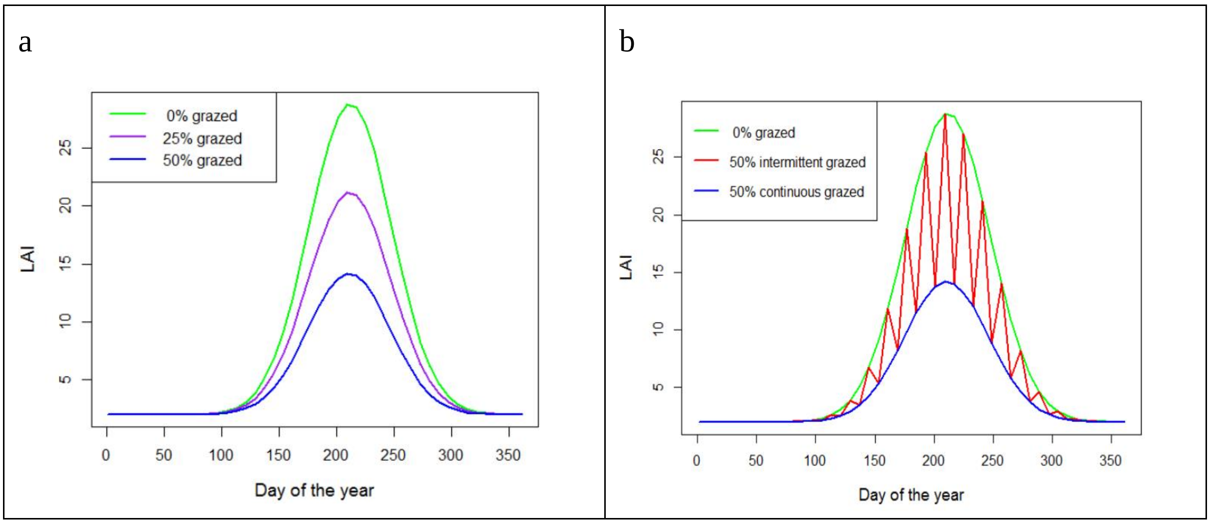
$$\frac{d(L_t+G_t+GB_t)}{dt} = k_1(L_t + G_t + GB_t) - k_2(L_t + G_t + GB_t)t \qquad \text{Eq. 1}$$

Where L_t is the current LAI or live mass observed, G_t is the livestock grazed LAI or live mass, GB_t is the previous grazing effect on current growth. $k_1(L_t + G_t + GB_t)$ represents the current total growth rate, which is proportional to the current total LAI or live mass. While $k_2(L_t + G_t + GB_t)t$ represents the current total senescence or defoliation rate, and is proportional to the current total LAI or live mass. Notice that it takes the time as a weightf$(t) = t$, is calculated in a is a time-dependent manner, which means the senescence rate is linear to time t;

3 Results

3.1 Grass growth under different defoliation severity

The indicator used in this paper is LAI, which will be used to extract grazing information according to the time series change. LAI is based on the greenness of vegetation, therefore, it can only provide the grazing information during the summer growth season. Though as some grass is harvested for winter stocks, but the amount is really small and the local herders tend to keep one spare grassland un-grazed for winter according to the field survey in 2012. No matter how much grass have been consumed by livestock during winter, the grass would be able to recover next year as long as the soil condition and grass root have not been severely affected by livestock browsing or trampling. Here, the results generated by Eq.1 under three different grazing defoliation severities are shown in Figure 2:



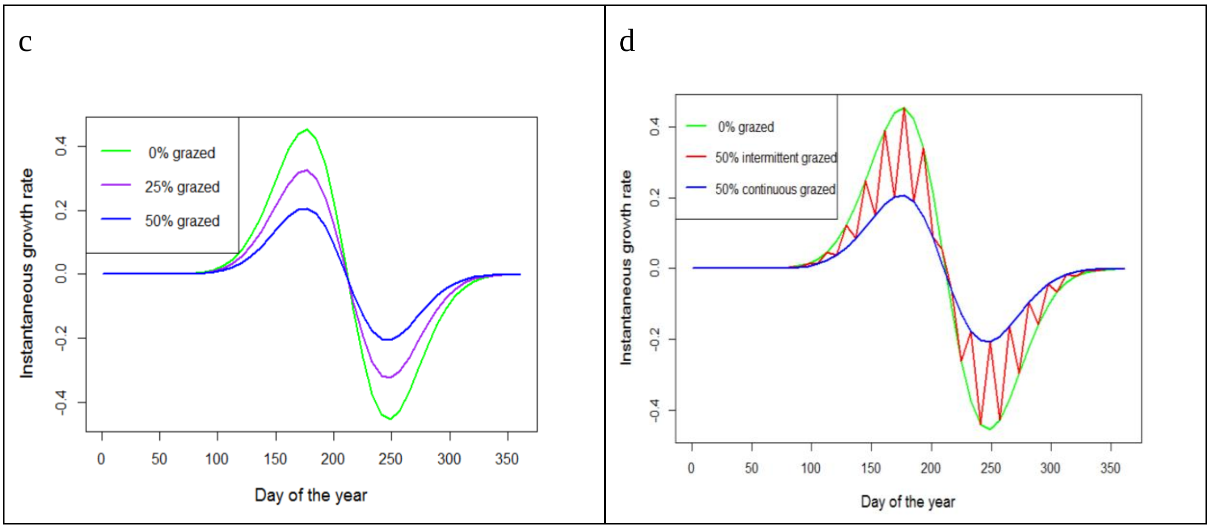


Figure 2: the effect of grazing severity on the observed LAI and instantaneous net growth rate of LAI, with for example: k1= 0.16, k2=0.0003, a=-14. c and d are $L_t{}'$

The model verification shows that the agent based modelling of grassland grazing can matches well with the remote sensing derived results well in terms of grazed LAI distribution (Figure 3).

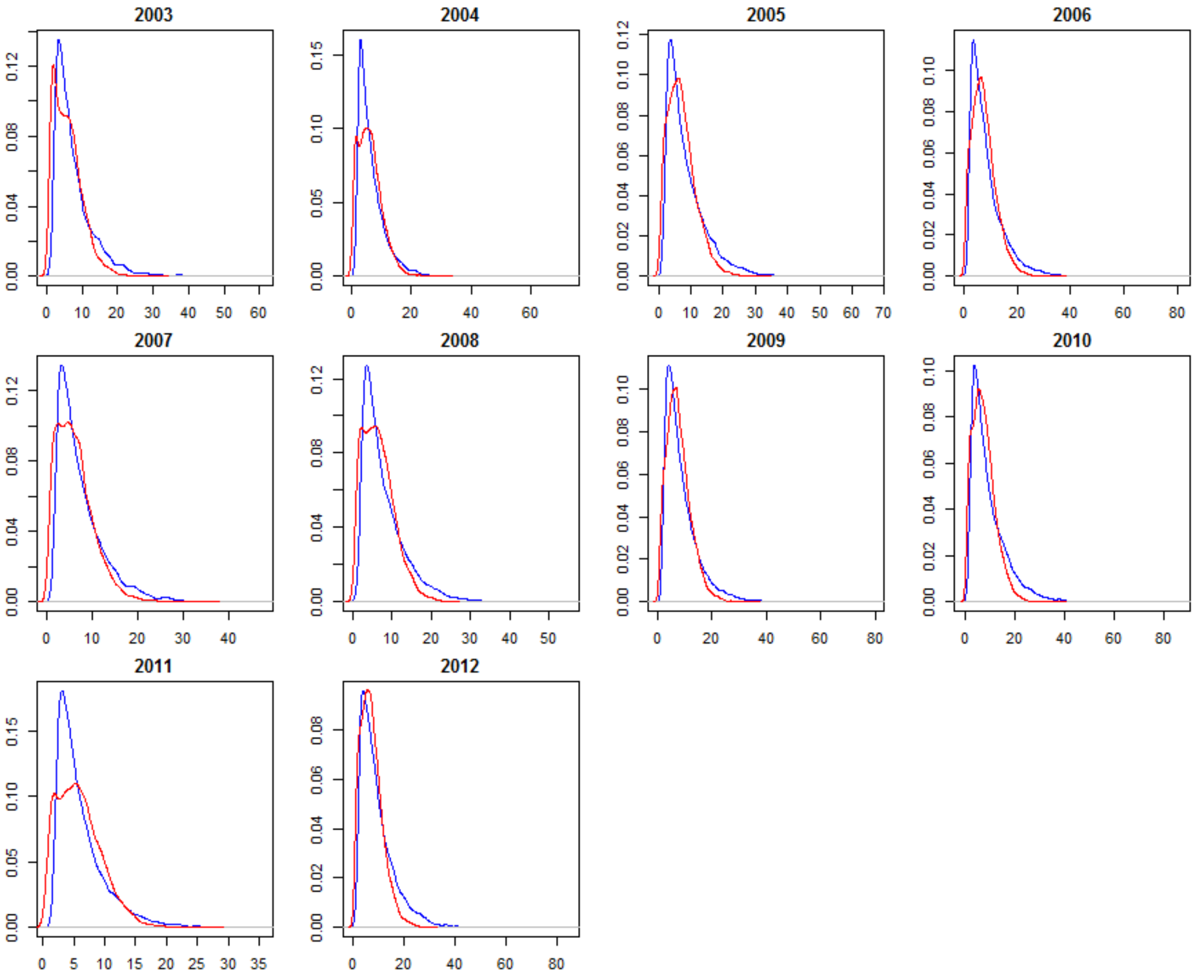


Figure 3: grazed LAI distribution of simulated and remote sensing derived

3.2 Comparison of different grazing strategies and institutional arrangements

It is interesting to see almost all the scenario have a bigger number of severe degraded patches except some points of TTF and TTT (Figure-D), as any grazing strategies or institutional arrangement would in essence lead to the less amount of grazed LAI for some patches while greater amount of grazed LAI for the others. TFT and FFT have a stable and relative smaller number of severe degraded patches for all the steps during the simulation. Not like TTT and TTF, where group moving behaviours have an opposite effect on the number of severe degraded patches depends on the number of degraded patches, the number of severe degraded patches of FTF and FTT were stably bigger than that of sedentary grazing scenario (FFF).

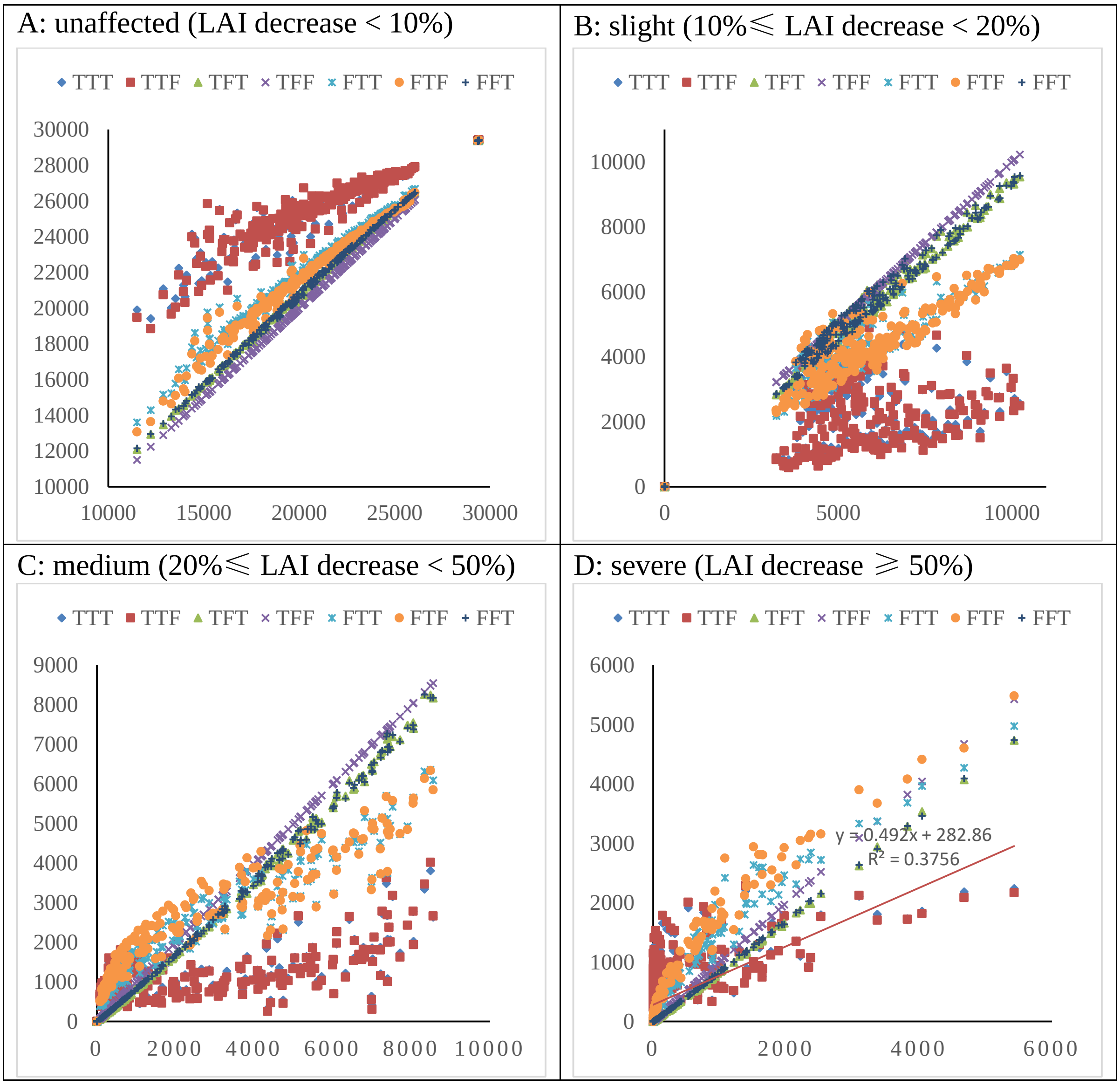


Figure 4: number of degraded patches simulated by ABMGG under different combination of grazing strategies and institutional arrangements

Overall, group grazing scenario can produce the smallest average number of severe degraded patches and the largest number of unaffected patches; Although the majority of the numbers of severe degraded patches concentrated around the low value area (about 0~1000 from x-axis), the numbers of severe degraded patches are much smaller than that of the other scenarios in the high value area (>1000 from x-axis), the overall trend of those two effect is shown by the red regression line in Figure 4, panel D. Land market could have a negative effect on the number of unaffected, slight and medium degraded patches, but a positive effect on the number of severe degraded patches. Sedentary grazing can produce a stable and smaller number of slight, medium and severe degraded patches compared with random moving grazing, but it lead to the higher number of unaffected patches. Therefore, in Zeku, the combination of group grazing and land market is highly recommend for the grassland management.

4 Summary and conclusion

Remote sensing provided a near real time information of grass status under grazing. This paper has developed a novel growth function under livestock grazing and has designed an estimation algorithm to derive grazing information for each pixels. By agent-based modelling, different grazing strategies and institutional arrangements were simulated to explore their impact on the performance of grassland grazing system, which is helpful to understand the dynamics of grassland grazing system under different managements.

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