Response to Referee #1

The authors thank the referee #1 for his/her very valuable review of the manuscript. Our responses to referee's comments are in a regular form while referee's comments are in the italic form.

Q: Zhang et al. compare different methods to reduce the impact of systematic errors of observational data on the inversion of ecosystem model parameters. They apply these methods to the inversion of photosynthetic capacity in a process based ecosystem model against artificial observations of Leaf Area Index (LAI). The artificial LAI data were created by adding different types of systematic error (fixed, proportional, fixed+proportional and binomial) and random error (Gaussian with mean zero and standard deviation proportional to true value) to LAI output of the vegetation model. Of the three method which are compared, the z-score normalization (normalization of observations by mean and standard deviation) provides posterior estimates for photosynthetic capacity that are close to the true values, which had been used to produce the artificial data. Therefore the authors conclude that the z-score normalisation should generally be applied to observations in the context of model parameter inversion. While the authors successfully demonstrate the effectiveness of the z-score normalization to minimize the impact of systematic errors of observations on inverted parameter values in the presented cases of artificial data, they fail to sufficiently analyse the normalization method and to discuss prerequisites, implicit assumptions and disadvantages. Additionally the presented artificial data account for only a part of probable kinds of errors, which influence an inversion against real world data.

A: Thanks for the summary and comments. We agree with the referee in the necessary of discussing the prerequisites, implicit assumptions and disadvantages of normalization method in the context of model parameter inversion and considering other kinds of errors. We did consider the application of the normalization method against real world data. In fact, we originally designed to discuss it in the second manuscript. Taking the referee's comments, we further analyzed why and when the normalization methods work, added sentences to discuss the prerequisites, implicit assumptions and disadvantages of normalization method, revised the expression in the section of conclusion, and gave an example of the application of the z-score normalization method to the real MODIS LAI data in the revised manuscript.

Q: An inversion of model parameter values against real observational data is simultaneously influenced by random and systematic errors of observations and by model error. The systematic error does not need to be similar or follow similar rules for all parts of the dataset: some data may be differently biased than others; even the direction of the bias may be different in different parts of the dataset. The examples of artificial data that are presented here, account for only one kind of systematic error *in each set of data. It would be useful to analyse the impact of the normalization if different parts of the dataset are differently biased, and in combination with model error. Could the combination of different error types lead to spurious results? To which extend would these be due to model error or data error?*

A: Thanks for the good suggestion. We agree with the referee that systematic errors may be different in different parts of the data. As suggested by the referee, we conducted new experiments where different systematic errors were added to two different parts of the LAI data. We divided all model points into two groups randomly using bootstrap sampling. The result showed that the z-score normalization method still worked well when the two parts of the data had a similar magnitude. For example, when one part of the LAI data were added a systematic error of C4 and the other part were added a system error of D4, the relative errors of estimated three parameters were reduced from 17.9%, 6.7%, 18.2% with taking no normalization to 3.6%, 3.3%, 0% with taking z-score normalization. On the other hand, the effect of the z-score normalization was weakened when the two parts of the data had a big difference in magnitude. For example, when the two parts of the LAI data were added respective systematic errors of A1 and B1, the relative errors of estimated three parameters without normalization were 17.9%, 10.0%, and 27.3%, while those with z-score normalization were 17.9%, 6.7%, and 9.1%, respectively. Compared with the estimation without normalization, the z-score normalization had a limited effect on reducing the error of estimated $v_{cmax,25}$, but still greatly improved the estimation of parameters a_1 and $t_{opt.}$

It is still difficult to quantify the model error stemming from model structure due to imperfect assumptions, simplification, formulations and understanding of underlying processes. In our manuscript, we calculated the cost function based on normalized model output and normalized observation. The normalization of observations successfully reduced the impact of systematic errors when using the synthetic data. We inferred that the impact of model error might be reduced by the normalization either. We would further quantify the impact of model error when the model structural uncertainty analysis method is available.

Q: The model would not be optimized to reproduce the observed data values, but the observed data pattern, while the reproduced values could be quite different. The results of an inversion of model parameters against normalised observational data can no longer be directly validated against the given kind of observations, as the normalization assumes/accounts for a bias in the data.

A: In the original manuscript, we generated the synthetic data on the basis of model output with assigned values of parameters and different types of errors, which provided the known true value and error. When we searched the optimized parameters, we did not compare the absolute values but the pattern between “observed” data and modeled output, as the referee suggested. Moreover, we calculated the relative errors of estimated parameters compared with the assigned values to examine the performance of parameter estimation.

Q: The approach is based on a cost function in which the square difference of observations is divided by the variance of observed data (sigmaˆ2, equ. 1 and 2). The normalization (eqn. 5) is based on the same sigma (standard deviation of observations). On the other hand, the examples cited (Rayner et al. 2005 and Kaminski et al. 2002) are based on an error covariance matrix, which provides the opportunity to address a specific variance term to each single observation (sigmaˆ2_i). Lasslop et al. (2008) have shown that deriving individual estimates for the random error component may improve parameter retrieval in the inversion. Additionally they derive the random error component with respect to deviation from a model, not based on the variance of observations.

A: There are different choices of weights in the cost function for parameter estimation. Some use the variance of observations (Wang et al, 2001; Luo et al., 2003) or the error covariance of observations (Knorr & Kattge, 2005); some of the others use the standard deviation of residuals (Braswell et al., 2005; Sacks et al., 2006). Lasslop et al. (2008) pointed out that standard deviation of the observations with similar meteorological conditions is better than the standard deviation of residuals of the gapfilling algorithm in describing the error standard deviation. However, Trudinger et al (2007) compared the choice of weights in the cost function, including constant weights and changing weights varied for each observation, and found that weighting by noisy observations was not particularly successful. Here we compared two different weights. One was the standard deviation of observations as used in the original manuscript; the other was the standard deviation of residuals that varied with observations. We found that the difference in weight did not influence the optimization of model parameters in our study. Considering spatial heterogeneity of remote sensing data in different pixels, we used the standard deviation of MODIS LAI observations varied for each pixel as the weight in the cost function.

Q: How should the posterior uncertainty ranges of the parameter values be interpreted if the observations have been normalized (fig 5, 6 and 7)? Do posterior parameter estimates have the same uncertainty ranges if they are derived without normalization, in cases where no systematic error has been added to the observations? This aspect should be analyzed. Figure 2 should be added to Figure 6 and 7, including uncertainty ranges of posterior parameter estimates based on not normalized observations.

A: Fig. 5-7 did not present the posterior uncertainty of the parameter values but the uncertainty due to random errors added to the "true" values. The optimization method used in our study was not based on the Bayesian theory and therefore could not obtain the posterior uncertainty. Optimized parameter values were searched within the same range whether the observation and model output were normalized or not. As suggested by the referee, we added the interpretation on different uncertainty ranges of the parameter values when the observations have normalized in the revised manuscript. In fact, we included the standard deviation of parameter v_{cmax} based on no normalized observations in Figure 2, but the values were very small and even can not be seen. The results indicated that the estimation of parameters without normalization is influenced more strongly by systematic errors than random errors.

Q: Often different kinds of observations are used for parameter inversion. Is the normalization of observations applicable in these cases (e.g. Knorr and Kattge, 2005 or Santaren et al. 2007)?

A: The aim of this manuscript is to find a way to take into systematic errors account and utilize the spatial information for parameter estimation against remotely-sensed observations with similar systematic errors. The normalization of observations is not suitable for observations of carbon and water fluxes measured by eddy covariance techniques, because flux data measured in different sites have different error properties. To clarify the purpose of using normalization methods, we revised the title and corresponding text in introduction, discussion, and conclusion. We adjusted the title to "Reducing impacts of systematic errors in LAI observation on inversing ecosystem model parameters using different normalization methods".

Q: The inversion of model parameters against observational data is often based on a Bayesian approach, including prior information of parameter estimates (e.g. Rayner et al. 2005). Is the normalization consistently applicable in a Bayesian context?

A: We agree with the reviewer in that the Bayesian approach (for example, the Markov-chain Monte Carlo method) has been widely used in estimating model parameters against observation data in recent years. To inverse target model parameters, the cost function for measuring the distance between data and model and the search strategy for finding the optimum values are two basic choices. The Bayesian approach is more efficient in estimating many parameters simultaneously and can provide the posterior probability distributions for parameters to be estimated. There are many other approaches can be used to find the optimum values, such as the Levenberg-Marquardt algorithm, the Kalman filter algorithm, simulated annealing and genetic algorithms (Rayner et al. 2005). Different optimization techniques were found equally successful at estimating parameters in the Optimisation InterComparison (OptIC) project (Trudinger et al. 2007). In our manuscript, the normalization methods affect not the search strategy but the cost function. We think if the normalization method can be applicable in a simple search method, then it should have the potential to be applicable in a Bayesian context.

Q: These are some aspects that would need to be analyzed or discussed before the *zscore normalization might be applied to invert ecosystem model parameters against real world data. Other aspects to be analyzed may still be missing. Although the normalization of observations successfully reduced the impact of systematic errors in the presented cases of artificial data, I would therfore conclude that the manuscript does not yet provide sufficient background to apply the method in the context of real world data. The analysis of the z-score normalization method is too simplistic.*

A: As suggested by the referee, we conducted additional model experiments and analysis on the z-score normalization method. Furthermore, we used the real MODIS LAI product data to estimate the three model parameters related to LAI, and compared the results of estimated parameters between the z-score normalization and no normalization. As stated above, we took the standard deviation of MODIS LAI values in a 10 km grid as the weight in the cost function. According the cost distribution as showed in Fig. 10 in the revised manuscript, the optimized values of $V_{cmax,25}$, a_1, and t_{opt} with the estimation taking z-scored normalization were 33.6 μmol m^{-2} s^{-1}, 5.6, 22°C. While those with the estimation taking no normalization were 31.9 μmol m^{-2} s^{-1}, 5.64, and 26°C, respectively. Compared with the estimation using z-scored normalization, the estimate from absolute values of MODIS LAI observation underestimated the parameter $V_{cmax,25}$ by 5% and overestimated the parameter t_{opt} by 18%. Taking the parameter t_{opt} as an example, the estimation with taking z-score normalization was more reasonable. The optimum temperature of photosynthesis is one of vegetation properties, ranges between 15 and 30°C for most C_3 plants, among which the optimum temperature of photosynthesis for deciduous trees of the temperate zone ranges between 20 and 25°C (Larcher, 2001, Physiological Plant Ecology). As for the deciduous needle-leaf forest in the cool temperate zone in this study, the estimated t_{opt} taking no normalization overestimated the optimum temperature of photosynthesis.

Q: One question with respect to the description of the method: Page 10453 ": : : xmax and xmin are the maximum and minimum of observation or simulation respectively, xmean and sigma are the mean and standard deviation of observation respectively." According to this description simulated xi would be normalized by observation xmean and sigma? I would guess simulated xi should be normalized by simulated xmean and sigma?

A: Thanks for the question. As mentioned by the referee, simulated x_i was normalized by simulated x_{mean} and sigma in our study. To clarify it, we revised the sentence in the revised manuscript.