We would like to thank all referees for their valuable comments. Moreover, we appreciate that all referees think the paper addresses an interesting topic and fit into the scope of HESS. We will consider all the comments from the referees for the revised version of the manuscript. Here is a detailed author response to all comments.

AUTHOR RESPONSE TO RC #1

General comments:

In general, the paper addresses an interesting topic, which would fit into the scope of HESS. Regional soil erosion assessment is still challenging due to the often-missing input data needed for such assessment. Therefore, an alternative approach to the more widespread – mostly USLE based approaches - would be welcome. However, I suggest rejecting the paper for the following reasons: I have general doubts if the produced regional assessment is valuable or if one could learn something regarding the methods presented. The authors use the erosion estimates form 3116 ‘points’ in the Shaanxi province and interpolate these data for a large region using different interpolation schemes. Mathematically the interpolation might be correct. However, from an erosion research perspective it just does not make any sense to interpolate erosion data from single locations (with specific land use, slope, slope length, soils, rainfall and soil management) into a large area without taking these important variables into account. The authors present the Chinese variant of the USLE, which identified all important parameters of erosion (Eq. 1, P. 6, line 23), why not using these parameters as co-variables in an interpolation or apply the model itself. From the different interpolation models presented it is obvious that those taking some of the important erosion drivers into account (models II-V) outperform model I, which solely use the erosion data for interpolation. So, concluding my comments I appreciate any efforts to regionalize soil erosion information but I do not think that the presented approach is a promising pathway to follow.

We understood the referee had three main concerns:

(1) *It just does not make any sense to interpolate erosion data from single locations (with specific land use, slope, slope length, soils, rainfall and soil management) into a large area without taking these important variables into account.*

Response: We actually did take these important variables into account to estimate regional soil loss whenever possible. One major point we want to make in the paper is that the simple interpolation without using any of the available factor information (Model I) is not good. Our recommended approach uses all the factor information that are available in the entire region (land use, rainfall, soils), and uses spatial interpolation to impute other factor information which are only available at the sampled PSU (slope degree, slope length, practice and management, aggregated as Q) to the entire region. The rational behind this approach is to exploit the spatial dependence among these factors to come up with better regional estimates. Since the reality in many countries is that we cannot have all factors measured in all areas in the foreseeable future, or the resolution of data for deriving the factors is limited, we believe our approach provide a viable alternative which is of practical importance.

(2) *The authors present the Chinese variant of the USLE, which identified all important parameters of erosion (Eq. 1, P. 6, line 23), why not using these parameters as co-variables in an interpolation or apply the model itself.*

Response: It seems that there is some misunderstanding here. We can only obtain the information for all seven erosion factors in the CSLE in the Primary Sample Unit (PSU), not for the entire region. Therefore, it is impossible to using all erosion parameters as co-variables in an interpolation or conduct a raster multiplication of all seven parameters in the CSLE. We will make this more clearly in the revision.

For the entire region, the information we can get at this stage is land use, rainfall erosivity (R) and soil erodibility (K). As explained in (1), we did apply the model itself by using parameters that are available in all area (land use, R and K) as covariates in our semi-parametric model (equation 5, 7 and 9), and interpolate the rest of the parameters aggregated as factor Q.

The other factors including the slope length, slope degree, biological, engineering and tillage practice factors are either impossible or very difficult to obtain for the entire region at this stage. We sampled small watersheds (PSUs) to collect detailed topography information and conducted field survey to collect soil and water conservation practice information. Previous research showed that topography factors should be derived from high resolution topography information (such as 1:10000 or larger scale topography contour map). Topography factors based on smaller scale of topography map (such as 1:50000 or 1:100000) in the mountainous and hilly area have large uncertainties. We can obtain 1:10000 topography contour map for the PSUs, but not for the entire region. For the forest land, the vegetation coverage derived from the remote sensing data was used as the canopy cover density, which was combined with the vegetation fraction and residue under the trees collected **during the field survey** to estimate the half-month biological practice factor. The vegetation fraction and residue under the trees is of great importance in protecting soil and it cannot be derived from satellite images. Engineering and tillage practice factors were **based on the sample field survey**. It is difficult to collect these factors from images with common resolution.

(3) *From the different interpolation models presented it is obvious that those taking some of the important erosion drivers into account (models II-V) outperform model I, which solely use the erosion data for interpolation. …I do not think that the presented approach is a promising pathway to follow.*

Response: Our contribution in this paper is twofold. First, our study quantified how important the knowledge of land use, rainfall erosivity and soil erodibility in all area are for estimating regional soil loss (*Land use is the key auxiliary information* *for the spatial model, which contributed much more information than R and K factors did. See* Page 11 Line 8-9). Second, we introduced a new regional soil erosion assessment method combining sample survey and geostatistics, which is valuable for regions with limited input data or limited data resolution. In the introduction part, we reviewed four methodologies for assessing regional soil erosion including a) fractional scoring, b) plot measurements, c) field-based approach, and d) model-based approach. Three kinds of (R)USLE-based approach include 1) area sample survey approach used by NRI in the USA, 2) raster multiplication used by Europe, Australia, and many other regions and 3) sample survey and geostatistics approach used in the fourth census on soil erosion in China, which was introduced in this study. All these methodologies have their suitability and limitations as discussed in the introduction part (Page 2 Line 21-28; Page 3, all lines; Page 4, Line 1-15). Raster multiplication is a popular model-based approach due to its lower cost, simpler procedures and easier explanation of result map. If the resolution of input data for the entire region is enough to derive all the erosion factors, raster multiplication approach is the best choice. However, there are several concerns about raster multiplication approach: (1) The information for the support practices factor (P) in the USLE is not easy to be collected given the common image resolution and was not included in some assessments (Lu et al., 2001; Rao et al., 2015), in which the resulting maps don't reflect the condition of soil loss but the risk of soil loss. Also, without the information of P factor, it is impossible to assess the benefit from the soil and water conservation practices. (2) The accuracy of soil erosion estimation for each cell is of concern if the resolution of database used to derive the erosion factors is limited. Thomas et al. (2015) showed that the range of LS factor values derived from four sources of DEM (20 m DEM generated from 1:50,000 topographic maps, 30 m DEM from ASTER, 90 m DEM from shuttle radar topography mapping mission (SRTM) and 250 m DEM from global multi-resolution terrain elevation data (GMTED)) were considerably different. As we mentioned in the supplement of SC2: 'Response to main comments by Referee #2' (Shuiqing Yin, 17 Oct 2016), a recent research by our group showed that the slope steepness based on the 30 m ASTER GDEM V1 is about 64% lower and the slope length on the other hand was 265% larger, compared with the reference value based on the topography map with a scale of 1:2000 for a mountainous watershed in Northern China. For many regions in the world, data used to derive erosion factor such as conservation practice factor is often not available for all area, or the resolution is not adequate for the assessment, as the referee has mentioned. Therefore, the assessment method combining sample survey and geostatistics proposed in this study is valuable.

AUTHOR RESPONSE TO RC #2

Main comments:

1. The authors present in the introduction a number of methodologies for assessing

soil erosion: a) factorial scoring b) plot measurements c) field-based approach d) Modelling (RUSLE). Then they analyse more in detail the application of RUSLE as 3 different options: 1) sample survey 2) raster multiplication 3) sample survey and geostatistics. The authors have followed the third option. Find below the most important remarks and issues that authors should address in their revision: First remark: I would appreciate if the authors have compared their results with the second option. This would give much more advanced knowledge in the manuscript. You mentioned that you have available K-factor, R-factor maps at 250m resolution plus a land use map at 100000 scale. So, it would have been excellent to compare your results with an estimated Soil loss by water erosion (simply multiplying the above mentioned high resolution grids).

Response: It is not difficult to conduct raster layer multiplication technically, however, we think the multiplication of R and K factors (assuming L=1, S=1, B=1, E=1, T=1) reflects the potential of soil erosion, which is different from the soil erosion estimated in this study.

2. As the 1st reviewer said (and I agree), the authors have presented an interpolation method which takes into account 5 different group of parameters. It is logical (and obvious that the IV and V would perform much better than the I. In a recent research (to be online soon), we identified cover management factor as the most sensitive for estimating soil loss by water erosion. The manuscript could be even more worthy if the authors have compared their findings with alternative methods (plot measurements, expert knowledge, field-based approach).

   Response: In the original manuscript, we did some comparison with the plot measurements (Guo et al., 2015). We will add more comparison with the result of the first three nationwide soil erosion investigations over China. Ministry of Water Resources of the People's Republic of China (MWR) has organized four nationwide soil erosion investigations. The first three (in mid-1980s, 1999 and 2000) were mainly based on field survey, visual interpretation by experts and factorial scoring method (Wang et al., 2016). The fourth (2010-2012) was based on sample survey and geostatistics method. The third investigation used 30 m resolution of Landsat TM images and 1:50000 topography map. Six soil erosion intensities were classified mainly based on the slope for the arable land and a combination of slope and vegetation coverage for the non-arable land. The limitations for the first three investigations include the limited resolution of satellite images and topography maps, limited soil erosion factors considered (rainfall erosivity factor, soil erodibility factor, practice factor were not considered), incapability of generating the soil erosion rate, incapability of assessing the benefit from the soil and water conservation practices.

   The spatial pattern of soil erosion in Shaanxi province in this study is similar with the result of the third national investigation. Since the expert factorial scoring method didn't generate the erosion rate for each land use, we compared the percentage of soil erosion area for ten prefecture cities in Shaanxi province between the third and the fourth investigations. Both investigations showed that

Yan’an, Yulin and Tongchuan in the northern part and Ankang in the southern part had the most serious soil erosion. The difference is that Hanzhong was underestimated and Shangluo was overestimated in the third investigation, comparing with the fourth investigation.

3. The findings regarding the forests are much too high. Erosion of > 3 t ha-1 in forest is not at all acceptable. Even there can be very steep slopes, the forestland experience erosion of much less than 1 t ha-1 annually. Their comparison with the findings of Guo (2015) and the findings in Europe (2015) show that erosion in forests is much less. The same applies for grasslands. Please consider also a comparison of your findings with the paper of Wang et al (2016) “Assessment of soil erosion change and its relationships with land use/cover change in China from the end of the 1980s to 2010”.
   Response: Wang et al. (2016) used a factorial scoring method to assess soil erosion risk and change in China from the end of the 1980s to 2010. As it was discussed in the introduction of this study, the resulting map by the factorial scoring method depicts classes ranging from very low to very high erosion or erosion risk. However, it can’t generate soil erosion rates. We are also concerned about the relatively high erosion rates of forest and grassland in the Shaanxi province compared with some previous research. Our analyse showed that they came from the Primary Sampling Units, and was not introduced by the spatial interpolation process. Possible reasons include: the different definitions of forest and grassland, concentrated storms with intense rainfall, the unique topography in Loess plateau and the sparse vegetation cover due to intensive human activities (Zheng and Wang, 2014). The minimum canopy density (crown cover) threshold for the forest across the world vary from 10-30% (Lambrechts et al., 2009) and a threshold of 10% was used in this study, which suggests on average a lower cover coverage and higher B factor. Annual average precipitation varies between 328-1280 mm in Shaanxi, with 64% concentrating in June through September. Most rainfall comes from heavy storms of short duration, which suggests the erosivity density (rainfall erosivity per unit rainfall amount) is high. The slope degree and slope length for the forest and grassland in Shaanxi province have been discussion in the original manuscript (Page 13 Line 7-13). The grassland includes the native and artificial grassland, with more intensive livestock and human activities. We will add such discussion in the revision for clarification.

4. Authors should explain and justify the selection of their statistical model BPST and not the selection of Cubist or GPR or regression krigining? Moreover, In your geo-statistical model, the topography is ignored. Why?
   Response: In spatial data analysis, there are mainly two approaches to make the prediction of a target variable. One approach (e.g., kriging) treats the value of a target variable at each location as a random variable and uses the covariance function between these random variables or a variogram to represent the correlation; another approach (e.g., spline or wavelet smoothing) uses a

deterministic smooth surface function to describe the variations and connections among values at different locations. Our work (Bivariate Penalized Spline over Triangulation, BPST) takes the second approach. The relationship between the traditional spatial statistics, and splines have been discussed in the literature, e.g. Matheron (1981) and Wahba (1990). A brief comment is presented in the following. Specifically, as discussed in Mitas and Mitasova (1999), “Kriging assumes that the spatial distribution of a geographical phenomenon can be modeled by a realization of a random function and uses statistical techniques to analyze the data and statistical criteria for predictions. However, subjective decisions are necessary such as judgement about stationarity, choice of function for theoretical variogram, etc. In addition, often the data simply lack information about important features of the modelled phenomenon, such as surface analytical properties or physically acceptable local geometries.” In contrast, “Splines rely on a physical model with flexibility provided by change of elastic properties of the interpolation function. Often, physical phenomena result from processes which minimize energy, with a typical example of terrain with its balance between gravitation force, soil cohesion, and impact of climate. For these cases, splines have proven to be rather successful.” For our problem, we also pay special attention to the following two practical issues: (1) the data are not necessarily evenly distributed; observations can be dense at some locations while sparse at others. (2) the domain for the data can take non-rectangular shapes.

In this work we introduce bivariate splines on triangulations to handle irregular domains and propose to extend the idea of univariate penalized splines (Eilers and Marx, 1996) to the two-dimensional case. The BPST method we consider have several advantages. First, it provides good approximations of smooth functions over complicated domains. Second, the computational cost for spline evaluation and parameter estimation are manageable. Third, the BPST doesn’t require the data to be evenly distributed or on regular-spaced grid.

Topography factors based on smaller scale of topography map in the mountainous and hilly area have large uncertainties. A recent research by our group showed that the slope steepness based on the 30 m ASTER GDEM V1 is about 64% lower and the slope length on the other hand was increased by 265%, compared with the reference value based on the topography map with a scale of 1:2000 for a mountainous watershed in Northern China. We haven’t obtained topography map with such high resolution yet. If larger scale topography map could be collected, it is not difficult to incorporate topography factors into our model by adding L and S factors in the equations (8) and (9).

5. The filed survey (section 2.1) indicates that the sampling of erosion points was not so dense. Please give some levels of uncertainty taking into account that you sampled on PSU every 25 km2 even less. Moreover, you mentioned that “PSU points were surveyed” : you don’t describe how you estimate the R, K, LS, B, E, T factors in each point? Did you sample and analyse the soil for estimating K-factor? Did you install a high temporal resolution rainfall station for measuring

R-factor? Etc. Maybe this is somehow written in section 2.3 but it is not clear as you don't provide detailed information on how the R-factor, K-factor was calculated. In the same way that you criticize the non-availability of all input layers when multiplying the grids (factors), somebody can criticize your methodology that non all information (K-factor, R-factor, ect) is available at point level. How you respond to this?

Response: The density of sample units in our survey depends on the level of uncertainty and the budget of the survey. We sampled a density of 4% in four experimental counties in different regions over China and found a density of 1% was acceptable given the current financial condition. Lai and Wang (2013) provided the asymptotic properties of the BPST method, For example, they investigated how the bias and variance of the BPST estimator change with respect to the sample size and the number of the triangulations. Since our data are a little sparse in some area, we employed the roughness penalties to regularize the spline fit; see the energy functional defined in equation (12). When the sampling is sparse in certain area, the direct BPST method may not be effective since the results may have high variability due to the small sample size. The penalized BPST is more suitable for this type of data because it can help to regularize the fit. We will add more information about how we estimated the R, K, LS, B, E, T factors in each point (PSU). We didn't install a rainfall station or collect soil samples for measuring R or K factor for each PSU. Instead, we collected 2678 weather and hydrologic stations with erosive daily rainfall from 1981 through 2010 and generated the R factor raster map over the entire China (Xie et al., 2016). And for the K factor, the physicochemical data of 16 493 soil samples (belong to 7764 soil series, 3366 soil families, 1597 soil subgroups and 670 soil groups according to Chinese Soil Taxonomy) from the Second National Soil Survey in 1980s and the latest soil physicochemical data of 1065 samples through the ways of field sampling, data sharing and consulting literatures were collected to generate the K factor for the entire country (Liang et al., 2013; Liu et al., 2013). **The R and K factors for each PSU were clipped from the map of the entire country.** A topography contour map with a scale of 1:10000 for each PSU was collected to derive the slope length and slope degree and to calculate the slope length factor and slope steepness factor (Fu et al., 2013). The calculation of B, E and T was based on the field survey of each PSU. As we know that R factor in USLE requires the breakpoint rainfall data more than 20 years, which is not feasible if a rainfall station was set up in each PSU. We assumed that the variation of R factor could be captured by more than 2000 stations over China, which were the most stations we could collect at present. Soil maps with scales of 1:500,000 to 1:200,000 (for different provinces) generated more than 0.18 million polygons of soil attributes over mainland China, which was the best available spatial resolution of soil information we could collect at present. We assumed the result of the soil survey could be used to estimate the K factor in our soil erosion survey. R factor and K factor in the sample point of NRI USA was also from the interpolation result of weather stations and soil survey map, respectively.

More specific comments related to text:

- P2L25-26: Rephrase the sentence.
Response: Followed the suggestion and revised it.

- P2L3: The reference should be Panagos et al, 2016a. The paper of Panagos et al, 2015a in your reference list does not feature in the literature. Please check carefully your literature. The same in P2L6 (it should be Panagos et al 2015; Panagos et al., 2016a).
Response: We supposed the referee refers P3L3 and P3L6. They were corrected and one reference missing in the old version was added. (Evans, R., and Boardman, J.: The new assessment of soil loss by water erosion in Europe. Panagos P. et al., 2015 Environ. Sci. Policy 54, 438–447—A response. Environ. Sci. Policy, 58, 11-15, 2016.)

- P3L16-17: You cannot put in the same importance the papers of Bosco (2015) and Panagos (2015) regarding the European soil erosion assessments. The second one is much more advanced with new knowledge. For more info about the model evolution in Europe, please consider the paper of Borrelli et al (2016), Land Use policy.
Response: Thanks for your information. We reviewed the paper of Borrelli et al. (2016), Effect of good agricultural and environmental conditions on erosion and soil organic carbon balance: A national case study, land use policy, 2016(50): 408-421) and the information provided in the paper will be added in the revision

- P3L23-25: some references to NRI methodology and the outcome results are missing here. I would also appreciate some applications and datasets derived (With references) from this methodology.
Response: The 2012 NRI is the current NRI data, which provides nationally consistent data on the status, condition, and trends of land, soil, water, and related resources on the Nation's non-Federal lands for the 30-year period 1982-2012. USDA-NRCS (2015) summarized the results from the 2012 NRI, which also include a description of the NRI methodology and use. A summary of NRI results on rangeland is presented in Herrick et al. (2010). See for example Brejda et al. (2001), Hernandez, M., et al. (2013) for some applications using NRI data.

- P4L6-9: The European assessments was commented by 2 papers (you have put the 3 comments here) but you ignore the response of Panagos et al (2016a, 2016b) to those 3 critiques.
Response: Panagos et al. (2006a, 2016b) argued that field survey proposed by Evans et al. (2015) is not suitable for the application at the European scale mainly due to work force and time requirements. They emphasized that the focus of their work is on the differences and similarities between regions and countries across the Europe and RUSLE model with the simple transparent structure can achieve their goal if

harmonized datasets were inputted. We will add this in the revision.

- Section 2.2 and elsewhere: R-factor, K-factor and land use map. Please give some citations and source of this dada.
Response: Thanks for your suggestion. We will introduce the source of the data and give the Citations. The data for the R-factor was based on 2678 weather and hydrologic stations with erosive daily rainfall from 1981 through 2010. The daily model used to generate at-site R factor was Model I in **Xie et al. (2016)**. The data of K-factor was based on the physicochemical data of 16 493 soil samples from the Second National Soil Survey in 1980s and latest soil physicochemical data of 1065 samples through the ways of field sampling, data sharing and consulting literatures (**Liang et al., 2013; Liu et al., 2013**). Land use map with a scale of 1:100000 was from China's Land Use/cover Datasets (CLUD), which were updated regularly at a five-year interval from the late 1980s through the year of 2010 with standard procedures based on Landsat TM/ETM images (**Liu et al., 2014**). Land use map used in this study was the version of 2010.

- You may be familiar with CSLE but for some non-Chinese, it would be better to write 2 lines about the biological and engineering factor.
Response: Good suggestion. We will revise it. Biological (B), Engineering (E) and Tillage (T) factor was defined as the ratio of soil loss from the actual plot with biological, engineering or tillage practices to the unit plot. Biological practices are the measures to increase the vegetation coverage for reducing runoff and soil loss such as trees, shrubs and grass plantation and natural rehabilitation of vegetation. Engineering practices refer to the changes of topography by engineering construction on both arable and non-arable land using non-normal farming equipment (such as earth mover) for reducing runoff and soil loss such as terrace, check dam and so on. Tillage practices are the measures taken on the arable land during ploughing, harrowing and cultivation processes using normal farming operations for reducing runoff and soil loss such as crop rotation, strip cropping and so on (Liu et al., 2002).

- P7L11-13: Your method has many similarities with the estimation of C-factor in Europe based on vegetation density and land use (Panagos et al., 2015 Land use policy).
Response: Yes. Both C-factor in Panagos et al. (2015) and B-factor in this study for forest, shrub land and grassland were estimated based on the vegetation density derived from satellite images. The difference is that C factor in Panagos et al. (2015) for arable land and non-arable land was estimated separately based on different methodologies, whereas in this study, the biological factor (B factor) was used to reflect biological practices on the forest, shrub land or grassland for reducing runoff and soil loss and the tillage factor (T factor) was used to reflect tillage practices on the farmland for reducing runoff and soil loss. For the farmland, biological factor equals 1 and for the other land uses, tillage factor equals 1.

- P7 Equations 2 and 3: they seem to be very similar. Which is the difference, please explain.

Response: Yes, they were similar because both of them used weight-averaged method by the area of plots. The difference is Equation 2 is for the estimation of soil loss for each land use in the PSU and Equation 3 is for the estimation of soil loss for the entire PSU.

- Model I has no sense as it is obvious to be so poor!!!

Response: Model I was a naive method which was used as a comparison.

- Section 2.4.2: you start without any introduction about BPST model. Please add an introductory paragraph

Response: Good suggestion. We will add an introduction paragraph about Bivariate Penalized Spline over Triangulation (BPST) method as follows in the revision: "*In spatial data analysis, there are mainly two approaches to make the prediction of a target variable. One approach (e.g., kriging) treats the value of a target variable at each location as a random variable and uses the covariance function between these random variables or a variogram to represent the correlation; another approach (e.g., spline or wavelet smoothing) uses a deterministic smooth surface function to describe the variations and connections among values at different locations. In this study, Bivariate Penalized Spline over Triangulation (BPST), which belongs to the second approach, was used to explore the relationship between location information in a two-dimensional (2-D) domain and the response variable. Given the complexity of the boundary in our data, traditional methods of smoothing which rely on the Euclidean metric or which measures smoothness over the entire real plane may then be inappropriate; see excellent discussions in Ramsay (2002) and Wood et al (2008). Here we present a method using bivariate splines over triangulations to smooth scattered bivariate data over domains with complex boundaries. The smoothing function is the minimum of a penalized sum-of-squares error functional. To be more specific, Let* $(x_i, y_i) \in \Omega$ *be the latitude and longitude of unit i for* $i = 1, 2, \dots, n$*....*"

- P11L13-15: it is obvious that model I and II will have no extreme erosion levels (as the land use is ignored). The smoothening effect is obvious!

Response: It is true that when the land use is ignored, the extreme erosion levels, mostly in farmland and bare land, were smoothed by the surrounding low erosion levels, mostly in forest, shrub land, grassland and construction land.

- Conclusions: P14L5-6: it is better somewhere in the introduction. In general the conclusions should highlight the important findings of this study.

Response: Good suggestion. We will revise it. Many studies indicated that land use is one of the most important factors in soil erosion estimation. Our study quantified how important the knowledge of land use, rainfall erosivity and soil erodibility are for estimating regional soil loss by comparing five different spatial models. Besides, we introduced a new model-based regional soil erosion assessment method, which is valuable when input data used to derive soil erosion factors is not available for the entire region, or the resolution is not adequate.

- The way forward: The authors should conclude about the usefulness of their methodology. How this can be used? How it can be complementary to the traditional multiplication of grids.
Response: Good suggestion! We will add more information in the revision. When the input data used to derive soil erosion factors is not available or the resolution is not adequate, and the budget is limited, our suggestion is sampling a certain amount of small watersheds as primary sampling units and put the limited money into these sampling units to ensure the accuracy of soil erosion estimation in these sampling units. Limited money could be used to collect high resolution of data such as satellite images and topography maps and conduct field survey to collect information such as conservation practices for these small watersheds. Then use the best available raster layers for the entire region and construct the spatial model by aggregating them as a factor Q.

Fig1: The Dark green image Towner-ship cannot be 10 x 40km?
Response: It was a typo and it should be 10 x10 km. Thank you!

Fig2: The land uses are 5 and not 3.
Response: The categories of land use are three including the farmland, forest and residential area. There are five plots, two of which are farmland, two are forest and one is residential area.

Fig 5: It is difficult to see the distinction between 40-80 and 80 categories in the first bar.
Response: The percentage of over 80 t $ha^{-1}y^{-1}$ is small. A different color will be used in the revision.

Fig. 7: Scale bar and overview map is missing. As a non-Chinese, I don’t know where this province is located.
Response: A figure with an overview map and land use map of Shaanxi province (Fig.1 as follows) will be added in the revision. Thank you!

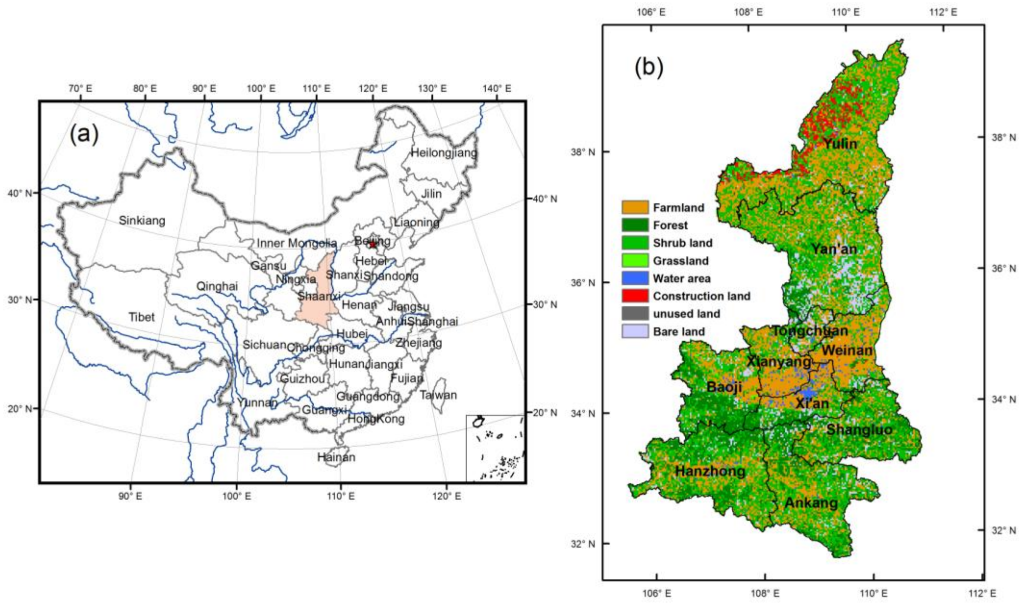

Fig. 1 Location of Shaanxi province (a) and land use map of Shaanxi province (b).

Minor comments:

- P5L7: please replace with “erodibility”

Response: There is a typo on P5L7 (erobility should be erodibility). Thanks!

- “soil species” is not a mature term

Response: We will change “soil species” on P7L3 into “soil series” according to Chinese Soil Taxonomy, in which the classification system is Order-Suborder-Group-Subgroup-Families-Series (Gong and Zhang, 2007).

- 3.1: Four or Five models?

Response: It was a typo and it was five models. It will be corrected in the revision.

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