Hydrol. Earth Syst. Sci. Discuss., 10, C2722–C2733, 2013
www.hydrol-earth-syst-sci-discuss.net/10/C2722/2013/

Hydrology and Earth System Sciences
Open Access
Discussions

Interactive comment on "Modeling regional evaporation through ANFIS incorporated solely with remote sensing data" *by* F.-J. Chang and W. Sun

F.-J. Chang and W. Sun

changfj@ntu.edu.tw

Received and published: 21 June 2013

Dear Professor Zehe,

I write in reply to the referee comments for our paper hess-2013-167 'Modeling regional evaporation through ANFIS incorporated solely with remote sensing data'.

We sincerely appreciate the referee for providing valuable comments and/or suggestions that benefit our manuscript. We pay special attention to 1) the implementation procedure of the estimation model (ANFIS) to increase the readability of readers that are not familiar with ANNs, and 2) clarifying that the proposed model incorporated solely with remote sensing data can reasonably well generate evaporation estimation for operational estimation of evaporation over large areas where the network of ground-based meteorological gauging stations is not dense enough or readily available. We have responded to the comments and/or suggestions as follows (the original response note is uploaded as a supplement), and the relevant responses and corrections in consideration of the comments/suggestions will be made in the revised manuscript accordingly.

We hope that, with referee's comments and suggestions being addressed now, our responses are satisfactory to you and the referee and the paper can continue towards acceptance for publication. We look forward to your response to our revision.

Best Regards,

Professor Dr. Fi-John Chang

Referee #1 (RC C2303): Dr. Maik Renner

The manuscript addresses the practically important question how regional evaporation (ET) can be estimated from remote sensing data. The authors make use of a highly sophisticated machine learning technique to estimate evaporation from aggregated Landsat images. The authors argue that other remote sensing based ET approaches may fail in heterogeneous terrain such as in Taiwan. While I personally believe that remote sensing based data can actually improve regional ET estimation, the authors got hit by several issues with this approach. So here is a list of scientific concerns which should be addressed by the authors:

Response: We are grateful to Dr. Maik Renner for this comment and his agreement on the importance of the subject that this paper addresses. We fully agree that remote sensing based data can actually improve regional ET estimation. Indeed, we attempt to enhance its applicability through developing a robust and operational neuro-fuzzy network model for estimating regional evaporation by the sole use of satellite imagery

HESSD
10, C2722–C2733, 2013

products (EVI and LST) as model inputs, without locally measured meteorological data. We demonstrate the proposed method can effectively deliver an island-wide evaporation map with reasonable accuracy and substantially reduce the possible cost of manpower and measurements involved in ground-based models.

To focus on our objective and diminish the ambiguity of the argument arose by the referee, we therefore suggest the following revision to the text to ensure greater clarity.

Estimation methods of evaporation were implemented mainly with ground-based observations, which achieved different degrees of success (Blyth and Harding, 2011). However the accuracy of estimation highly relies on meteorological data measured locally, and the constructed estimation models are usually subject to rigorous local calibrations so that brings limited global availability. Moreover, it is impractical to estimate evaporation over large areas using surface meteorological parameters. Due to these limitations, conventional regression modeling techniques and ground-based observation networks need further refinement to effectively improve estimation accuracy. Adopting advanced techniques, such as artificial neural networks, with the global coverage of remotely sensed hydro-meteorological data can be a positive solution. The responses to the scientific concerns raised by the referee are addressed as follows:

References:

Blyth, E., and Harding, R.J.: Methods to separate observed global evapotranspiration into the interception, transpiration and soil surface evaporation components, Hydrol. Processes, 25, 4063-4068, 2011

1. Pan vs actual ET: it remains vague what exact evaporation measurements are used to train the model and hence what type of evaporation is being predicted. I guess pan evaporation is observed, but I believe that actual evaporation should be predicted. So the authors should make at least make clear that they are extrapolating potential (pan) evaporation and that this is different from actual ET.

Response: In this study, the observed evaporation was measured by Class A Pan, and the predicted evaporation is pan evaporation. We will clarify the pan vs. actual ET in the revised manuscript.

2. Skill: the results analysis does not allow to judge if ANFIS is actually better than simpler tools.

Response: Thanks for the valuable comment. We will add more references and results to better judge the results obtained in this study, which we believe they are suitable and valuable. Our previous studies did demonstrate several ANNs (ANFIS, BPNN and SOM) performed better than simpler tools such as the modified Penman or Penman–Monteith methods for the estimation of pan evaporation under several circumstances (Chang et al., 2010; Chung et al., 2012).

References:

Chang, F.J., Chang, L.C., Kao, H.S., and Wu, G.R.: Assessing the effort of meteorological variables for evaporation estimation by self-organizing map neural network, J. Hydrol., 384(1-2), 118-129, 2010.

Chung, C.H., Chiang, Y.M., and Chang, F.J.: A spatial neural fuzzy network for estimating pan evaporation at ungauged sites, Hydrol. Earth Syst. Sci., 16, 255-266, 2012.

3. Improve discussion (see below)

Detailed comments

Skill The authors should assess the performance of the proposed model more rigorously, such as the ability to discern the temporal and spatial variability. Further, the authors introduced a skill score in the methods. Here I would wish that the authors look for an independent reference to predict ET. This could be a naive model (mean ET over Taiwan) or a more sophisticated model which produces some climatology of ET from available data (maybe a standard ET model from the meteorological data pre-

HESSD

10, C2722–C2733, 2013

sented). The results should also be compared with the prior paper of Chung et al. (2012), who use ANFIS and meteorological station data to predict pan evaporation. Further, a RMSE of 1mm/d at an average of 4mm/d (Table 2) refers to a uncertainty of about 25% which is quite large. Also the correlation of LST to ET is in the range of the model predictions (Fig. 9a). Hence, so far I am skeptical with the conclusions of the authors, that an acceptable product has been derived.

Response: Yes, indeed, the combined use of remote sensing observations and meteorological data is commonly implemented for estimating evaporation. The motivation of this study derived from the difficulty encountered in regional evaporation estimation due to the heterogeneous terrains (70 percent of the island is occupied by mountains with elevations up to 4000 m), where the network of ground-based meteorological gauging stations is not dense enough or readily available. Therefore we attempted to use only remote sensing data to provide regional estimation. Two types (Model-T: temporal; Model-S: spatial) of models are configured and tested. Model-T provides clear temporal characteristics of evaporation for the whole study area through incorporating data covering all 16 meteorological gauging stations into the ANFIS while Model-S can suitably estimate evaporation at ungauged sites.

In this revised manuscript, we will add the following results to more rigorously assess the performance of the proposed model.

In this study, the mean of evaporation is 3.44 mm/day. The RMSE in the testing phase of the best estimation model, Model-T (EVI, LST), is 0.997 mm/day while the mean RMSE values of the observed evaporation at each stations fall between 1.8 and 4.9 mm/day. The CE and CC value of Model-T (EVI, LST) are 0.558 and 0.756, respectively. To better depict the results of this study, the results of our current and previous studies (Chang et al., 2010; Chung et al., 2012; Chang et. al., 2013) are summarized in Table A. In sum, the results of this study can be considered acceptable and the proposed approach can be applied practically.

References:

Chang, F.J., Chang, L.C., Kao, H.S., and Wu, G.R.: Assessing the effort of meteorological variables for evaporation estimation by self-organizing map neural network, J. Hydrol., 384(1-2), 118-129, 2010.

Chang, F.J., Sun, Wei, and Chung, C.H.: Dynamic factor analysis and artificial neural network for estimating pan evaporations at multiple stations in northern Taiwan, Hydrol. Sci. J, DOI:10.1080/02626667.2013.775447, 2013

Chung, C.H., Chiang, Y.M., and Chang, F.J.: A spatial neural fuzzy network for estimating pan evaporation at ungauged sites, Hydrol. Earth Syst. Sci., 16, 255-266, 2012.

Improve discussion

The authors should discuss their methodology and results wrt. to :

. enable the reader to judge the potential of ANFIS + Landsat images; e.g. for now I can not compare the model results with respect to standard models

Response: Thanks. We will add a discussion and give a reference (standard) for comparison. Please also refer to the responses to Comments 1 and 2.

. what can be learnt from the ANFIS model selection results? Explain and show formulae in the methods section related to the input radius and the rules. I think that these explanations should enable the reader, who is not familar with machine learning (like me), to understand the model output. One question to solve is for example, why is an RMSE difference of 0.04 critical to decide for a model with 6 rules than an model with less rules? Or can ANFIS compute some uncertainty of the estimates?

Response: Thanks for the valuable comment. Regarding the construction of the ANFIS models, we will add more description including the formulae to the re-submitted manuscript. More details of the ANFIS can be found in Chang and Chang (2006).

HESSD

10, C2722–C2733, 2013

As for model selection, the parameter ra of the ANFIS (using subtractive fuzzy clustering) is the radius that defines the neighborhood of a cluster center and thus ra should be determined at first. When ra is determined, the fuzzy rules can be determined automatically. The model with the minimum RMSE is then determined as the best model. The results are listed in Table 5. The detailed algorithm and process of implementing the subtractive fuzzy clustering into ANFIS model can be found in Chang and Chang (2006).

Besides, the determination of the rule numbers can be a balance between accuracy and parsimony (less rule number). In this case of Model-T (LST), yes, it seems 3 or 6 rules did not make much different (slightly better accuracy for 6 rules!). We consequently decided to choose the model with the minimum RMSE as the best model.

References:

Chang, F. J., and Chang, Y. T.: Adaptive neuro-fuzzy inference system for prediction of water level in reservoir, Adv. Water Res., 29, 1-10, 2006.

. Daily vs. temporal data: LST and ET have a dominant diurnal cycle, which is altered by the seasons. But in this case the remote sensing data only provides a snapshot which could be influenced by current cloudiness etc. The authors thus link this temporal snapshot with the cumulative sum of ET over a full day. I think this should be discussed, Delogu et al. (2012) might be a good reference for that.

Response: Thank you for the constructive comments. Cloudiness is always an issue when adopting remote sensing data, which is one of the major limitations in the applicability of the proposed method. To solve the problem under this circumstance, before implementing the estimation model, the Landsat data were pre-processed to select the cloud-free images with necessary atmospheric corrections performed. The observed data were the daily evaporation corresponding to the selected Landsat imagery, and these observations were the learning targets of the ANFIS. Under the same overpass frequency of Lansat imagery, the ANFIS could produce the outputs (daily evaporation) based on the inputs (EVI and LST), which was a matter of the mapping ability of the ANFIS. Therefore, we had already considered the cumulative sum of ET over a full day.

Alternatively, we appreciate the referee provides Delogu et al. (2012) relevant to evapotranspiration estimation. Delogu et al. (2012) reconstructed daily and seasonal evapotranspiration using instantaneous estimates at the time of satellite overpass, in which the evaporative fraction (EF) method and the stress factor (SF) method were investigated. Both EF and SF methods are classically used to reconstruct daily and seasonal evapotranspiration from an instantaneous estimate. The approach is very different from ANNs. However it is an interesting and valuable reference (will add into our revised manuscript and considered in our future study.

Reference:

Delogu, E., Boulet, G., Olioso, A., Coudert, B., Chirouze, J., Ceschia, E., Le Dantec, V., Marloie, O., Chehbouni, G., and Lagouarde, J.-P.: Reconstruction of temporal variations of evapotranspiration using instantaneous estimates at the time of satellite overpass, Hydrol. Earth Syst. Sci., 16, 2995–3010, 2012.

. Usability; there are about 5 irregular remote sensing images a year (?) at 10 AM local time in Taiwan; who could actually use this information?

Response: Thank you for the constructive comment. We will add a discussion to enhance (extend) the usability of the proposed method. We understand cloudiness always becomes an issue when adopting remote sensing data, especially for areas with variable climatic conditions, such as Taiwan. In our case, only 45 out of 342 images over the 10-year investigation period were selected to use due to cloudiness. Even under such condition, we feel encouraged that the evaporation can be suitably estimated based solely on remote sensing data. Besides, with the advances in remote sensing techniques coupled with the countermeasures to cloudiness, we believe our proposed approach can be adopted more easily and the results can be enhanced effectively.

HESSD
10, C2722–C2733, 2013

. Spatial resolution: its argued that the heterogeneous terrain of Taiwan challenges other ET estimation tools, so I think the aggregating the Landsat data from 30m to 1000m for evaluating the model skill might counteract this argument.

Response: Thanks for the suggestion. Yes, indeed, we implemented the nearest neighborhood method to aggregating the original pixel resolution of Landsat data from 30m x 30m into 1000m x 1000m.

Minor comments:

. "Is the description of experiments and calculations sufficiently complete and precise to allow their reproduction by fellow scientists (traceability of results)?" The ANFIS method requires complex supervised learning tools and the specification of fuzzy rules, which is not sufficiently described.

Response: Ok. The summary of relevant parameters of ANFIS models are shown in Table B. The ANFIS is implemented by using the software package "MATLAB 2008b", in which the function "genfis3" is applied to generating a FIS using fuzzy c-means (FCM) clustering through extracting a set of rules that simulate data behavior. The fuzzy inference system adopts the first-order Sugeno fuzzy model (Takagi & Sugeno 1985), and the fuzzy subtractive clustering is also implemented to determine the number of fuzzy rules (Chang and Chang, 2006). The determination of the number of rules in the ANFIS is by use of trial-and-error with RMSE as the selection criterion, and therefore the best model structures are determined by the minimum RMSE values in the testing phases. Table 6 of the revised manuscript shows the best ANFIS structure (in bold) for each model identified by the minimum RMSE in the testing phases.

References:

Chang, F. J., and Chang, Y. T.: Adaptive neuro-fuzzy inference system for prediction of water level in reservoir, Adv. Water Res., 29, 1-10, 2006. Takagi T., and Sugeno M.: Fuzzy identification of systems and its applications to modeling and control. IEEE

Trans Syst, Man, Cybernet,15, 116–32, 1985.

. “Is the language fluent and precise?” Mostly yes, but there is some room for improvement in the introduction.

Response: Thanks. We will refine the introduction section of the revised manuscript in order to gain a better enhancement.

. “Should any parts of the paper (text, formulae, figures, tables) be clarified, reduced, combined, or eliminated?” Generally, improve the readability (text size) of labels and text in figures! Table 1, Fig 2, Fig 6 into Appendix or supplement. Fig. 10 what location is shown, add borderlines.

Response: Thanks for the suggestions. The labels and text in figures will be enlarged to improve the readability, especially for Figs 7 and 10. Table 1 and Fig. 2 will be moved to the Appendix section. Fig 6 is relevant to our study area, and therefore it remains in the figure section. One of the conditions shown in Fig. 10 is the impact of clouds, and the borderlines are obvious in Figs. 10(a.1) and 10(b.1). Therefore, the borderlines will not be particularly highlighted in Figs. 10(a.2) and 10(b.2) that suffer from the impact of clouds.

References

Chung, C.-H., Chiang, Y.-M., and Chang, F.-J.: A spatial neural fuzzy network for estimating pan evaporation at ungauged sites, Hydrol. Earth Syst. Sci., 16, 255–266, doi:10.5194/hess-16-255-2012, http://www.hydrol-earth-syst-sci.net/16/255/2012/, 2012.

Delogu, E., Boulet, G., Olioso, A., Coudert, B., Chirouze, J., Ceschia, E., Le Dantec, V., Marloie, O., Chehbouni, G., and Lagouarde, J.-P.: Reconstruction of temporal variations of evapotranspiration using instantaneous estimates at the time of satellite overpass, Hydrol. Earth Syst. Sci., 16, 2995–3010, doi:10.5194/hess-16-2995-2012, http://www.hydrol-earth-syst-sci.net/16/2995/2012/, 2012.

Please also note the supplement to this comment:
http://www.hydrol-earth-syst-sci-discuss.net/10/C2722/2013/hessd-10-C2722-2013-supplement.pdf

---

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 10, 6153, 2013.

Table A. Results of evaporation studies in Taiwan

Study case (study data)	Study area/ # of gauging stations	Study period	Mean of evaporation (mm/day)	Performance in the testing phase	
				RMSE (mm/day)	CE
This study (Landsat data)	whole Taiwan/ 16	2001-2010	3.44	0.997	0.558
Chang et al. 2010 (ground data)	south Taiwan/ 1	2001-2006	4.50	1.160	0.570
Chung et al. 2012 (ground data)	whole Taiwan/ 19	2007-2009	3.19	0.980	0.700
Chang et al. 2013 (ground data)	northwest Taiwan/ 16	2007-2010	2.62	0.970	0.720

Table B. Parameters of the ANFIS models.

Parameter	Setting
Input membership function	Gaussian curve built-in membership function
Output membership function	Linear membership function
FIS generation method	fuzzy c-means
FIS structure type	Sugeno-type
the number of clusters	1-20 (subject to models)
And method	Prod
Or method	Probor
Defuzzification method	weighted average

Fig. 1.

HESSD

10, C2722–C2733, 2013

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Discussion Paper