This is not a peer-reviewed article.
5th National Decennial Irrigation CD-ROM Proceedings
Phoenix Convention Center, 5 - 8 December 2010, Phoenix, AZ USA
M. Dukes ed. St Joseph Mich: ASABE
ASABE Publication Number 711P0810cd

2950 Niles Road, St. Joseph, MI 49085-9659, USA
269.429.0300 fax 269.429.3852 hq@asabe.org www.asabe.org

An ASABE Conference Presentation

Paper Number: IRR10-8406

Downscaling Surface Temperature Image with TsHARP

Wonsook Ha, Research Agricultural Engineer
USDA-ARS-CPRL, P.O. Drawer 10, Bushland, TX 79012

Prasanna H. Gowda, Research Agricultural Engineer
USDA-ARS-CPRL, P.O. Drawer 10, Bushland, TX 79012

Terry A. Howell, Agricultural Engineer & Research Leader
USDA-ARS-CPRL, P.O. Drawer 10, Bushland, TX 79012

George Paul, Graduate Student
Department of Agronomy, Kansas State University, Manhattan, KS 66506

Jairo E. Hernandez, Research Agricultural Engineer
USDA-ARS-CPRL, P.O. Drawer 10, Bushland, TX 79012

Sukanta Basu, Associate Professor
Department of Marine, Earth, and Atmospheric Sciences, North Carolina State University, Raleigh, NC 27695

Written for presentation at the
5th National Decennial Irrigation Conference
Sponsored jointly by ASABE and the Irrigation Association
Phoenix Convention Center
Phoenix, Arizona
December 5 - 8, 2010

Abstract.
Daily evapotranspiration (ET) maps would significantly improve assessing crop water requirements especially in Texas High Plains (THP) where supply of irrigation water is limited. ET maps derived from satellite data with daily coverage such as MODIS and GOES sensors are inadequate, because their thermal pixel size is larger than individual agricultural fields. However, there exists an opportunity to use simultaneously acquired high resolution visible, near-infrared, and shortwave-infrared images from MODIS, and thermal-infrared images from other high resolutions sensors such as LANDSAT 5 Thematic Mapper (TM) or ASTER to improve spatial and temporal resolution of ET maps. Image downscaling methods are useful to improve spatial resolution by examining relationships between simultaneously acquired coarser thermal and finer non-thermal datasets. In this study, the TsHARP, an image downscaling technique, was evaluated for its capability to downscale land surface temperature (LST) images for ET mapping. LANDSAT 5 TM images taken from a southern part of the THP area were utilized to implement TsHARP. For this purpose, we developed a synthetic image with a spatial resolution of 960x960 m using TM based 120x120 m LST image. The 960x960 m resolution was used to mimic a LST image derived from MODIS thermal data. TsHARP was implemented to develop a LST image at 120x120 m resolution using a statistical relationship between LST and normalized difference vegetation index (NDVI). Comparison of downscaled 120x120 m LST image against original LST image from TM data yielded a correlation coefficient of 0.93.Results indicate that TsHARP has the potential to be used to downscale LST images with simultaneously acquired high resolution NDVI image derived from MODIS data.

The authors are solely responsible for the content of this technical presentation. The technical presentation does not necessarily reflect the official position of the American Society of Agricultural and Biological Engineers (ASABE), and its printing and distribution does not constitute an endorsement of views which may be expressed. Technical presentations are not subject to the formal peer review process by ASABE editorial committees; therefore, they are not to be presented as refereed publications. Citation of this work should state that it is from an ASABE conference presentation. Irrigation Association 2010. Ha, W. et al., 2010. Downscaling Surface Temperature Image with TsHARP. IA10-xxxx. St. Joseph, Mich.: ASABE. For information about securing permission to reprint or reproduce a technical presentation, please contact ASABE at rutter@asabe.org or 269-932-7004 (2950 Niles Road, St. Joseph, MI 49085-9659 USA).

Keywords. Downscaling, Remote Sensing, Irrigation, TsHARP, LANDSAT, MODIS, Texas High Plains.

The authors are solely responsible for the content of this technical presentation. The technical presentation does not necessarily reflect the official position of the American Society of Agricultural and Biological Engineers (ASABE), and its printing and distribution does not constitute an endorsement of views which may be expressed. Technical presentations are not subject to the formal peer review process by ASABE editorial committees; therefore, they are not to be presented as refereed publications. Citation of this work should state that it is from an ASABE conference presentation. Irrigation Association 2010. Ha, W. et al., 2010. Downscaling Surface Temperature Image with TsHARP. IA10-xxxx. St. Joseph, Mich.: ASABE. For information about securing permission to reprint or reproduce a technical presentation, please contact ASABE at rutter@asabe.org or 269-932-7004 (2950 Niles Road, St. Joseph, MI 49085-9659 USA).

Introduction

Evapotranspiration (ET) is a critical element for energy, hydrologic, carbon, and nutrient cycles and a key component of water balance in soil-vegetation-atmosphere continuum (Yang et al., 2006). It includes water evaporation from land and water surfaces and transpiration by vegetation (Gowda et al., 2008). It is important to agriculture as it is the major consumptive use of irrigation water and precipitation on agricultural land. Attempts to improve water use efficiency for irrigated lands can be based on reliable ET maps provided with high spatial and temporal resolutions. Remote sensing based ET models are better suited, compared to other conventional techniques, for estimating crop water use from field to regional scale (Allen et al., 2007; Gowda et al., 2008).

Remote sensing based energy balance algorithms are commonly used for mapping ET at a regional scale. Energy balance method is based on the rationale that ET is a change of the state of water using available energy in the environment for vaporization (Su et al., 2005). This method uses remotely-sensed surface reflectance in the visible (VIS) and near-infrared (NIR) portions of the electromagnetic spectrum and surface temperature (radiometric) from a thermal-infrared (TIR) band. This approach is implemented in energy balance algorithms such as Mapping Evapotranspiration with Internalized Calibration (METRIC; Allen et al., 2007) and SEBAL (Bastiaanssen et al., 1998).

Remote sensing energy balance algorithms require thermal data for estimating ET. However, thermal data from satellite-based sensors often provide coarser spatial resolutions than other non-thermal bands such as VIS, NIR, and shortwave-infrared (SWIR) bands (Gowda et al., 2008). ET maps derived from remote sensing data acquired by satellite-based sensors with daily coverage such as Moderate Resolution Imaging Spectroradiometer (MODIS), Geostationary Operational Environmental Satellite (GOES), and Advanced Very High Resolution Radiometer (AVHRR) are too coarse to be useful in agricultural regions because pixel size of thermal data is larger than individual fields in most cases causing significant errors in ET estimation (Tasumi et al., 2006). The errors in the estimated ET are partly due to the presence of pixels having multiple land uses/vegetation types with significant differences in cover, roughness and/or moisture content (Kustas et al., 2004). This condition is more common in arid and semi-arid regions such as Texas High Plains where fully irrigated fields are usually surrounded by an extremely dry landscape. Therefore, there is a research need to utilize simultaneously acquired high resolution VIS, VNIR and SWIR images from the MODIS as well as data from other sensors such as Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Land Remote-Sensing Satellite (LANDSAT) 5 Thematic Mapper (TM) to scale up the ET maps (in terms of frequency and spatial resolution). Limited research has been done to develop and evaluate existing downscaling techniques to improve spatial resolution of surface temperature or resulting ET maps.

Numerous downscaling methods can be found in the literature (Gorenberg et al., 2001; Norman et al, 2003; Kustas et al., 2003; Liu and Pu, 2008; Trishchenko et al., 2006). However, most of these techniques are not developed and evaluated for downscaling surface temperature images or ET maps. The three methods specifically developed for downscaling surface temperature maps are Disaggregated Atmosphere-Land EXchange Inverse model (DisALEXI; Norman et al., 2003), Disaggregation of radiometric surface temperature (DisTrad; Kustas et al., 2003) and Thermal sHARPening (TsHARP; Agam et al., 2007). DisALEXI disaggregation procedure was proposed by Norman et al. (2003) to bridge the gap in spatial resolution between micrometeorological measurements and coarse scale remote sensing derived surface energy fluxes for model evaluation purposes. This downscaling algorithm was based on the blending

height concept that where wind speed and air temperature can be treated as uniform over the landscape (Wieringa, 1986). DisTrad (Kustas et al., 2003) is a simple technique for downscaling radiometric surface temperature images using a statistical relationship between normalized difference vegetation index (NDVI) and radiometric surface temperature. Agam and colleagues refined DisTrad with different linear and nonlinear statistical relationships between NDVI and radiometric surface temperature and renamed the method as TsHARP (Agam et al., 2007). Therefore, the objective of this paper was to evaluate the TsHARP method for its ability to downscale the spatial resolution of surface temperature images from 960 m to 120 m.

Description of DisTrad/TsHARP

DisTrad is based on the assumption that a unique statistical relationship between land surface temperature (LST) and vegetation indices exists at multiple spatial scales, largely related to percent vegetation cover. This is supported by well-documented evidence that an inverse relationship exists between percent ground cover and surface temperature (Badeck et al., 2004). However, the slope of this statistical relationship varies with land cover type and climatic conditions (Karnieli et al., 2006). Consequently, these statistical relationships are site- and image-specific (Agam et al., 2007). One of the limitations of this method is that it neglects the effects of spatial variability in soil moisture (Kustas et al., 2003). For example, water bodies in the image do not conform with the inverse LST-NDVI relationship.

Kustas and others (2003) employed the DisTrad approach for downscaling at 20-250 m resolutions using high resolution airborne imagery collected over the Southern Great Plains. They reported an accuracy of 1.5^{o}C for MODIS NDVI pixel resolution. However, at the ASTER/LANDSAT resolutions, DisTrad results were no more reliable than assuming uniformity within the coarser LST pixels. Anderson and colleagues (2004) applied DisTrad and DisALEXI algorithms on LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) (30-60m spatial resolutions) and GOES/AVHRR (5 km) data to disaggregate regional scale (1000 m) heat fluxes to micrometeorological scales (10-100 m). An effort was also made to introduce “convolved sharpening method” (CS) to further improve downscaling. The CS was used mainly to reduce boxlike chunk pixels in the resultant sharpened images derived with DisTrad by smoothing out residuals before being returned into the disaggregated image. However, implementing CS did not provide much different results by visual inspection, neither did CS improve percent error (9.2% from DisALEXI-CS vs. 9.0% from DisALEXI-DisTrad) or Root Mean Square Difference (RMSD) (34.6 W m^{-2} from DisALEXI-CS vs. 34.2 W m^{-2} from DisALEXI-DisTrad) in the estimation of instantaneous surface energy fluxes. Modeled surface energy fluxes from DisALEXI were in agreement with measured data within 10% relative error on an instantaneous basis and 15% for daytime model run. High daytime estimation error was probably caused partially by diurnal changes in the surface evaporative fraction and amplification on eddy covariance measurement during daily or annual time scales (Anderson et al., 2004).

In 2007, Agam and others explored alternative sharpening basis functions to refine DisTrad for downscaling surface temperature pixels at resolutions finer than 100 m and renamed the method as TsHARP (Agam et al., 2007). In their version, they explored linear and non-linear transformation of NDVI values associated with percent cover. However, their attempt showed negligible improvement over DisTrad. For example, disaggregation of 960 m resolution simulated MODIS thermal images to 240 m gave root mean square error (RMSE) of 0.67-1.35^{o}C whereas no sharpened images produced RMSE of 1.25-2.12^{o}C. Further, disaggregation of simulated LANDSAT 60 and 120 m resolution thermal images to 30 m yielded 1.80-2.39^{o}C, which is a little higher than that for MODIS images. No or minimum improvement in the disaggregation results were obtained due to the fact that percent cover is highly correlated to

NDVI and replacing NDVI with percent cover or combination of both may not improve the predictive capability of the regression model.

Methodology

This study was implemented using NDVI and surface temperature images derived from a LANDSAT 5 TM image acquired over the Texas High Plains (THP) during the 2007 summer growing season. For this study, we selected a southern part of the THP. This area was selected because of presence of circular irrigated fields surrounded by extremely dry landscape. Major crops grown in the study area are sorghum, winter wheat, cotton, and corn. The LANDSAT 5 TM data (Path 31 and Row 36) acquired on July 10, 2007 was obtained at the USGS website http://eros.usgs.gov/#Find_Data/Products_and_Data_Available/TM). Implementation of the TsHARP approach was done in six steps: (1) develop synthetic NDVI and surface temperature datasets from LANDSAT 5 TM image that is comparable to 120 m NDVI and MODIS based surface temperature (960 m) images; (2) select a subset of pixels from a finer image where NDVI is uniform, (3) aggregate the NDVI to develop a coarser resolution pixel that matches with LST pixels, (4) develop a statistical relationship between coarser resolution NDVI and LST, (5) use the resulting statistical relationship to estimate LST at both coarser and finer resolutions using respective NDVI values, and (6) finally, add the difference between the observed and predicted LST at the coarser resolution to the finer resolution LST image. The last step is expected to account for divergence of the retrieved temperatures from the observed temperature due to factors other than percent cover such as spatial variability in soil moisture.

An image including the area of interest was clipped using ERDAS[1] Imagine software for the easiness of representation of data. We developed a synthetic image with a spatial resolution of 960x960 m using LANDSAT 5 TM based 120x120 m LST image. For the LST calculation, the spectral radiance values were recalculated into effective at-satellite temperatures of the viewed earth-atmosphere system under an assumption of unity for surface emissivity and using pre-launch calibration constants by means of an inverted logarithmic formula. Furthermore, surface reflectance values were estimated after applying atmospheric interference corrections for shortwave absorption and scattering using narrowband transmittance values for each band as calibrated in Tasumi et al. (2005). The LST was acquired after correcting the at-satellite effective ‘brightness’ temperatures for surface emissivity (Allen et al., 2007). Implementation of the DisTrad/TsHARP was done within the MATLAB[2] environment. The correlation coefficient and RMSE were calculated to evaluate the performance of TsHARP approach.

Results and Discussion

TsHARP was successfully implemented within the MATLAB environment. A linear regression model was developed between NDVI and LST at a spatial resolution of 960 m (Fig. 1). It yielded an R^2 value of 0.63 with a slope and intercept of -23.55°C and 42.05°C, respectively. Comparison of the observed and predicted LST values (Fig. 2) gave a good R^2 of 0.87 with a RMSE of 1.90ºC. The RMSE value in this study was similar to that reported in Agam et al. (2007).

[1,2] DISCLAIMER

Mention of trade names or commercial products in this article is solely for the purpose of providing information and does not imply recommendation or endorsement by the U.S. Department of Agriculture.

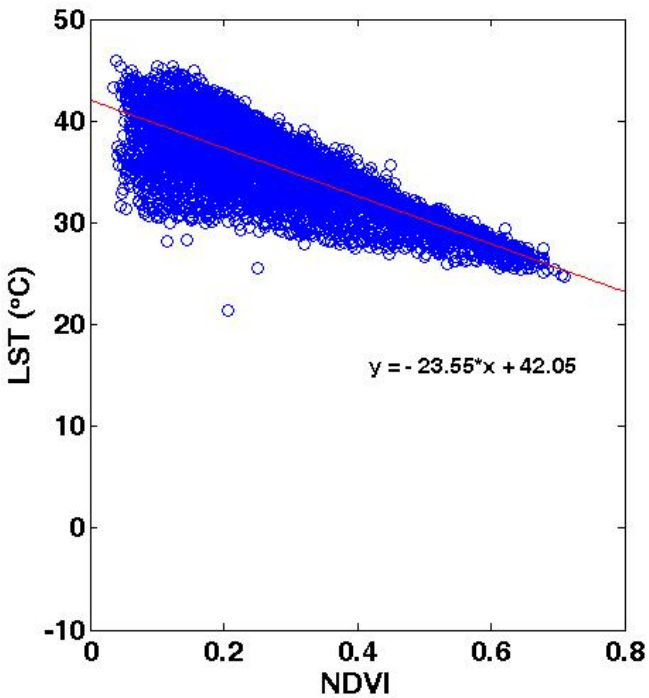

Figure 1. Regression relationship between NDVI and land surface temperature (LST) at 960x960 m spatial resolution (coarser resolution).

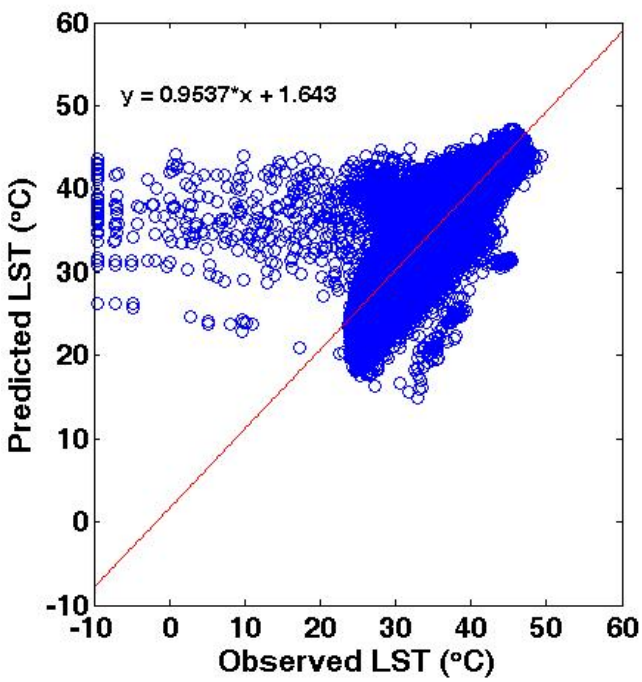

Figure 2. Regression relationship between observed and predicted land surface temperature (LST) at 120x120 m spatial resolution (finer resolution) derived from a 960x960 m spatial resolution.

Fitting methods among linear, quadratic, cubic, and polynomial fits were tested against data of NDVI and LST. The correlation was obtained based on computed NDVI and LST images at

960x960 m resolution (Fig. 1). The result showed that there was a strong linear relationship between NDVI and LST compared to other fitting methods (data not shown).

Summary

ET maps derived from satellite data such as MODIS, AVHRR, and GOES sensors are known to be inadequate for irrigation management if the spatial resolution is too coarse. This is caused by the fact that spatial resolutions of the thermal band pixels from these sensors are coarser than most individual agricultural fields and represent more than one land use or water management unit. This limitation is further extended by the fact that irrigated fields in semi-arid regions like Texas High Plains are usually surrounded by extremely dry landscapes. Fortunately, the pixel sizes of non-thermal band data are finer than that of the thermal-infrared data. Therefore, an opportunity exists to use simultaneously acquired high spatial resolution VIS, NIR and SWIR images from satellite-based sensors to improve spatial and temporal resolution of ET maps. In this study, the TsHARP method was implemented on a LANDSAT 5 TM image. A linear fit was chosen to obtain the best regression relationship between NDVI and LST at 960x960 m spatial resolution among different fitting methods. In general, TsHARP has the potential to be used for downscaling coarser surface temperature images using simultaneously acquired high resolution NDVI images.

References

Agam, N., W. P. Kustas, M. C. Anderson, F. Li, and C. M. U. Neale, 2007. A vegetation index based technique for spatial sharpening of thermal imagery. Remote Sens. Environ. 107: 545-558.

Allen, R. G., M. Tasumi, and R. Trezza, 2007. Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC)-Model. J. Irrig. Drain. E.-ASCE. 133: 380-394.

Anderson, M. C., J. M. Norman, J. R. Mecikalski, R. D. Torn, W. P. Kustas, and J. B. Basara, 2004. A multiscale remote sensing model for disaggregating regional fluxes to micrometeorological scales. J. Hydrometeorol. 5: 343-363.

Bastiaanssen, W. G. M., M. Menenti, R. A. Feddes, and A. A. M. Holtslag, 1998. A remote sensing surface energy balance algorithm for land (SEBAL): 1. Formulation. J. Hydrol. 212-213: 198-212.

Badeck, F.-W., A. Bondeau, K. Böttcher, D. Doktor, W. Lucht, J. Schaber, and S. Sitch, 2004. Responses of spring phenology to climate change. New Phytol. 162: 295-309.

Gorenburg, P. I., D. McLaughlin, and D. Entekhabi, 2001. Scale-recursive assimilation of precipitation data. Adv. Water Resour. 24: 941-953.

Gowda, P. H., J. L. Chavez, P. D. Colaizzi, S. R. Evett, T. A. Howell, and J. A. Tolk, 2008. ET mapping for agricultural water management: present status and challenges. Irrigation Sci. 26: 223-237.

Karnieli, A., M. Bayasgalan, Y. Bayarjargal, N. Agam, S. Khudulmur, and C. J. Tucker, 2006. Comments on the use of the vegetation health index over Mongolia. Int. J. Remote Sens. 27: 2017-2024.

Kustas, W. P., J. M. Norman, M. C. Anderson, and A. N. French, 2003. Estimating subpixel surface temperatures and energy fluxes from the vegetation index-radiometric temperature relationship. Remote Sens. Environ. 85: 429-440.

Kustas, W. P., F. Li, T. J. Jackson, J. H. Prueger, J. I. MacPherson, and M. Wolde, 2004. Effects of remote sensing pixel resolution on modeled energy flux variability of croplands in Iowa. Remote Sens. Environ. 92: 535-547.

Liu, D. and R. Pu, 2008. Downscaling thermal infrared radiance for subpixel land surface temperature retrieval. Sensors 8: 2695-2706.

Norman, J. M., M. C. Anderson, W. P. Kustas, A. N. French, J. Mecikalski, R. Torn, G. R. Diak, T. J. Schmugge, and B. C. W. Tanner, 2003. Remote sensing of surface energy fluxes at 10^1-m pixel resolution. Water Resour. Res. 39, 1221, doi:10.1029/2002WR001775.

Su, H., M. F. McCabe, E. F. Wood, Z. Su, and J. H. Prueger, 2005. Modeling evapotranspiration during SMACEX: Comparing two approaches for local- and regional-scale prediction. J. Hydrometeorol. 6: 910-922.

Tasumi, M., R. Trezza, R. G. Allen, and J. L. Wright, 2005. Operational aspects of satellite-based energy balance models for irrigated crops in the semi-arid US. J. Irrig. Drain. Syst. 19: 355-376.

Tasumi, M., R. G. Allen, and R. Trezza, 2006. Calibrating satellite-based vegetation indices to estimate evapotranspiration and crop coefficients. In: Wichelns, D. and Anderson, S. S. (eds.), In Proceedings of the 2006 USCID Water Management Conference, Ground water and surface water under stress: competition, interaction, solutions. 103-112. USCID, Denver, CO.

Trishchenko, A. P., Y. Luo, and K. V. Khlopenkov, 2006. A method for downscaling MODIS land channels to 250 m spatial resolution using adaptive regression and normalization. Proceedings of SPIE – The International Society for Optical Engineering, 6366, Art. No. 636607.

Yang, F., M. A. White, A. R. Michaelis, K. Ichii, H. Hashimoto, P. Votava, A-X. Zhu, and R. R. Nemani, 2006. Prediction of continental-scale evapotranspiration by combining MODIS and AmeriFlux data through support vector machine. IEEE T. Geosci. Remote 44: 3452-3461.

Wieringa, J., 1986. Roughness-dependent geographic interpolation surface wind speed averages. Q. J. Roy. Meteor. Soc. 112: 867-889.