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RESEARCH ARTICLE

Comparing the utility of LiDAR data vs. multi-spectral imagery for parcel scale water demand modeling

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ABSTRACT
In this paper we examine whether land-cover measures derived from multi-spectral (MS) imagery in combination with light detection and ranging (LiDAR) data sources better predict parcel scale urban water consumption than measures derived solely from MS imagery. Land-cover measures such as the percentage of impervious surface and vegetative cover are important predictors of household level water use. This study found that the additional effort required to obtain LiDAR data does not appear to add predictive power for water demand modeling. We suggest that MS imagery is just as useful estimating household level water demand.

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Introduction

Urban water sustainability is a critical issue in many arid regions of the world (Loáiciga, 2014). In regions where outdoor irrigation is the major use of water, land-cover such as lawns, trees, and impervious surface are principle determinants of household water use (Stoker & Rothfeder, 2014). In general, a larger lawn requires more water, while impervious cover needs no water. Therefore the amount of impervious and vegetative cover per household is valuable information to predict household level urban water use.

The challenge for water managers and researchers is *how* to collect this information. Water use data may be available through a public utility (Haque et al., 2013), and some building characteristics may be available from a tax assessor (Dziedzic et al., 2014), but presumably no organization collects land-cover data for every building. Therefore, it is up to the water manager, public utility employee, or researcher to measure the amount of vegetative and impervious cover. Barring months of field work, the best way to collect this information is through remote sensing.

Vegetative cover, canopy cover, and impervious surface can all be measured by remote sensing. Several sources of remotely sensed information are available. The most basic data source is visible-wavelength (RGB) aerial imagery, which is commonly available for municipal regions. The next available source is multi-spectral (MS) imagery, which includes a near-infrared (NIR) band, allowing differentiation between vegetative cover and impervious surface because of the high NIR reflectance of healthy vegetation. A third source is light detection and ranging (LiDAR), which provides additional information by generating a vertical profile of land surfaces (Antonarakis et al., 2008). In a water use context, LiDAR data enables researchers to differentiate between turf cover, tree canopy, and impervious surface (Stoker & Rothfeder, 2014). When combined with MS data, MS+LiDAR data provides very accurate and detailed measures of land-cover (Hodgson et al., 2003). However, LiDAR has drawbacks: existing data are less available and new acquisitions are more expensive than MS imagery, and the processing time and skill level required for processing is greater than multi-spectral images. We ask: do land-cover measures derived from MS+LiDAR better predict household-level urban water consumption than measures derived solely from MS imagery?

We answer this question by comparing measures of land-cover derived from MS imagery with measures derived from MS+LiDAR, as predictors of urban water demand. Using a detailed disaggregated water use database developed for Salt Lake City, Utah, we test whether measures of land-cover derived from MS+LiDAR better predict household-level urban water consumption than measures derived solely from MS imagery in Salt Lake City, UT (Figure 1). These results provide evidence of whether urban water use modelers should incur the cost and complexity of including LiDAR in their models.

Landscaping and urban water use

It is well established that landscaping choices influence urban water use. In many arid and semi-arid regions, the primary residential use of water is for vegetated landscapes (Arizona Department of Water Resources, 2013; Utah Division of Water Resources, 2010). The academic research indicates that landscaping practices affects water use, including the amount of

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Figure 1. Location of Salt Lake City, Utah.

outdoor space (Campbell et al., 2004; House-Peters et al., 2010), preference for landscaping type (Clary et al., 2009), and the presence and importance of a garden (Domene & Sauri, 2006; Fox et al., 2009; Jorgensen et al., 2009). Therefore it is critical for water demand modelers to understand the areal extent, and possibly the composition of the vegetated landscape on a property.

Urban water use and remote sensing

Remote sensing has been used to study several phenomena related to water and water use. An early application in this domain was stormwater runoff modeling. The impervious fraction of a watershed is an important variable for accurate rainfall runoff modeling and this fraction can be derived from remotely sensed data (Hodgson et al., 2003; Lohani et al., 2002; Warwick & Tadepalli, 1991). Remote sensing has also been used to classify urban land-cover and vegetation types in urban environments at a fine scale across large urban landscapes (Chen et al., 2009; Tooke et al., 2009). Studies have also used remotely-sensed MS imagery to estimate evapotranspiration (Nouri et al., 2014) and to discriminate between turf and tree cover (Farag et al., 2011). To model water demand, Endter-Wada et al. (2008) used MS imagery to classify landscape type and quantify the extent of irrigated landscaping for residential parcels.

LiDAR and MS imagery

LiDAR is a significant advancement in remote sensing. LiDAR produces dense point clouds using airborne laser scanners (Rottensteiner et al., 2007) and allows analysis of land-cover height. Early work on impervious surface classification using remote sensing data used entirely MS imagery as the only input data source (Hodgson et al., 2003). Now, advances are combining LiDAR and multispectral imaging (Chen et al., 2009; Coops et al., 2004; Hodgson et al., 2003). LIDAR data has been shown to increase land-cover classification accuracy (Chen et al., 2009) and to increase crown detection in forests (Coops et al., 2004). Thus far, it would seem that land-cover measures informing urban water use models would be best derived from a combination of LiDAR and MS imagery.

Similar research questions

To our knowledge, one other study asked a similar research questions, albeit in a different context. Hodgson et al. (2003) asked if there is additional information gained from using LiDAR in addition to aerial imaging for purposes of impervious surface mapping. In their study, LiDAR improved classification of impervious cover.

Research design

This research uses a longitudinal research design, and compares models that utilize land-cover measures derived from two different sources: MS only, and MS+LiDAR, to test whether MS+LiDAR-derived data produce more accurate water demand models.

We collected climate, demographic, and built environment variables at the parcel level for Salt Lake City, Utah, in 2011 to model outdoor water use. The full methodology for the derivation of our predictor variables and the generation of the data set can be found in Stoker and Rothfeder (2014). This data building parallels recent efforts by Dziedzic et al. (2014) to model urban water demand. Our database was built from the following:

(1) The Salt Lake City Public Utilities database provided monthly water use (gallons) for all customers of the Salt Lake City public utility (n = 88,245). Summer water use was our dependent variable, and was calculated as the water used in May through September 2011. These months are when the majority of water is used outdoors for irrigation in Salt Lake City (Stoker & Rothfeder, 2014; Utah Division of Water Resources 2010). We also use the meter size from this database, which is measure of the size of the connection between the water line and the property.
(2) The Salt Lake County Assessors database provided final valuation of the property and land, whether the building is owner or renter occupied, and the number of bedrooms. This data was joined to the public utilities database based on matching parcel numbers.
(3) The PRISM (Parameter-elevation Regressions on Independent Slopes Model) Climate Group data (PRISM Climate Group, 2004) provided annual precipitation and temperature measures for our study area. We transferred climate variable pixel values to parcels using geoprocessing tools in ArcGIS v10.0.
(4) The National Agricultural Imagery Program (NAIP) 2011 Utah collection provided MS imagery with one meter spatial resolution for our study area. The imagery was acquired during leaf-on conditions when vegetation is easiest to differentiate from impervious surfaces.
(5) The Utah State geodata portal (AGRC) provided LiDAR data acquired in 2006 for most of the greater Salt Lake City metropolitan area in 2006.

Table 1. Model results using measures of vegetated land-cover.

Variable	*B*	Std. Error	*t*	Sig.	Tolerance
Model 1: MS+LiDAR Data: $R^2 = 0.520$					
Constant	1.436	.066	21.727	.000	
Final valuation (dollars)	1.117 E-007	.000	.023	.001	.481
Average precipitation (mm)	.003	.000	26.376	.000	.591
Annual use in 2010 (gallons)	4.583 E-006	.000	98.807	.001	.652
Owner occupied (1 = yes)	.102	.013	7.852	.000	.964
Number of bedrooms	.069	.004	18.302	.000	.742
Turf fraction	.381	.032	12.004	.000	.913
Tree fraction	−.128	.026	-4.851	.000	.944
Model 2: MS Data: $R^2 = 0.519$					
Constant	1.431	.066	21.566	.000	
Final valuation (dollars)	1.071 E-007	.000	3.244	.001	.481
Average precipitation (mm)	.003	.000	26.866	.000	.592
Annual use in 2010 (gallons)	4.63 E-006	.000	99.693	.000	.656
Owner occupied (1 = yes)	.120	.013	9.248	.000	.973
Number of bedrooms	.066	.004	17.612	.000	.744
Vegetated fraction	*.068*	*.022*	*3.027*	*.002*	*.971*

Note:
*Model 1, F = 3455.3983, $p < 0.01$. Model 2, F = 4006.315, $p < 0.01$

In order to generate vegetation cover variables for the water use models, we prepared two different land-cover classifications. For the first, we classified the four-band NAIP imagery using a maximum likelihood classifier to create a binary vegetation/non-vegetation classification. We then combined this with a canopy map derived from LiDAR first-minus last-return for a four-class land cover map of non-vegetation, ground vegetation, ground vegetation overlapped by tree canopy, and non-vegetation overlapped by tree canopy. For the second, using a support vector machines (SVM) classifier we classified the four-band NAIP imagery together with three LiDAR-derived layers: first-return minus bare-earth (indicates high surfaces), first- minus last-return (indicates tree canopy), and last-return minus bare-earth (indicates building rooftops). We digitized polygons of training and validation data (~3000 pixels total; ~50 pixels per polygon) throughout the study area from the NAIP imagery using ESRI ArcGIS 10.0 software. All classifications were performed using ENVI 4.3 image processing software. Classification accuracy was assessed to be in greater than 88.9% in all classes. With the MS and MS+LiDAR land-cover classifications, we used GIS tools to calculate the fraction of turf cover and canopy cover of every parcel in Salt Lake City.

Modeling

The central question of the present study is: does the additional information about vegetative cover at the parcel scale, inherent in LiDAR data, improve our ability to predict water consumption? Ordinary least squares (OLS) models are useful for evaluating the additional contributions of predictor variables as measured by R^2 values. Our dependent variable was not normally distributed, so we log-transformed our dependent variable to the natural log of summer use. Once normalized, the assumptions to employ ordinary least squares regression were met. We estimate models to relate average summer water use (gallons) for all buildings in the Salt Lake City which we have complete records ($n = 25{,}775$). A complete record includes monthly water use, tax assessor's data, climate data, and remotely sensed land cover measurements. We isolate the contribution of MS imaging and the combined MS+LiDAR by running two models. For example, model 1 = MS imagery only, model 2 = MS+LiDAR. We include predictor variables that are likely to have an influence on outdoor water use. We minimize collinearity in our models, and tolerance values reflected the degree of collinearity in the models, where high values (on a scale of 0 to 1) indicate that no collinearity exists. Our research question is answered by comparing the model fits of the two models.

Results

The model results from the OLS models are presented in Tables 1 and 2. Each variable displays intuitive direction of effect as well as effect size except for average annual precipitation. The model indicates that higher average annual precipitation is associated with higher water use, which is likely related to the fact that the largest residential properties in the Salt Lake Valley are characteristically found at higher elevations, which receive more rain. As the value of turf fraction increases, so does water use. As the value of tree fraction increases, water use decreases. Both measures are the percentage of the property that is covered by either vegetation or tree canopy. While the previous year's annual water use has a very small coefficient, the very high t-ratio indicates it is a substantial predictor of the dependent variable. The small coefficient suggests that water use varies very little from year to year. The two model fits differ negligibly, where the MS+LiDAR data explains 0.001% more of the variance in the data.

It was also possible that measures of impervious surface would be better predictors of urban water use at the parcel level, so we compared model results using measures of impervious surface. The results are similar to the first two models, except that higher fractions of impervious cover are associated with less water use. Using impervious surface measures, the MS+LiDAR explains an additional <0.001 of the variance in the data (Table 2). Interestingly, the models are almost identical even with different measures of impervious surface. The Pearson's correlation coefficient between the MS+LiDAR and MS measures is 0.968: indicating that the two data sources produce nearly identical measures of impervious fraction.

Table 2. Model results using measures of impervious cover.

Variable	B	Std. Error	t	Sig.	Tolerance
Model 1: MS+LiDAR Data: $R^2 = 0.519$					
Constant	1.497	.068	22.157	.000	
Final valuation (dollars)	1.069 E-007	.000	3.240	.001	.481
Average precipitation (mm)	.003	.000	26.880	.000	.592
Annual use in 2010 (gallons)	4.631 E-006	.000	99.672	.000	.656
Owner occupied (1=yes)	.120	.013	9.224	.000	.973
Number of bedrooms	.066	.004	17.601	.000	.744
Impervious fraction	-.064	.021	-2.980	.003	.971
Model 2: MS Data: $R^2 = 0.519$					
Constant	1.499	.068	22.150	.000	
Final valuation (dollars)	1.071 E-007	.000	3.244	.001	.481
Average precipitation (mm)	.003	.000	26.866	.000	.592
Annual use in 2010 (gallons)	4.63 E-006	.000	99.693	.000	.656
Owner occupied (1=yes)	.120	.013	9.215	.000	.973
Number of bedrooms	.066	.004	17.659	.000	.744
Impervious fraction	-.068	.022	-3.027	.002	.971

Notes:
*Model 1, $F = 4006.218$, $p < 0.01$; Model 2, $F = 4006.315$, $p < 0.01$.

Summary and conclusions

This paper was the first to test the additional value of MS+LiDAR-derived land-cover data over MS imagery alone for water demand modeling. Using a detailed disaggregated database of building water consumption for Salt Lake City, we compared measures of model fit using predictors derived from MS imagery with those derived from MS imagery and LiDAR in combination. The differences between the model fits are negligible. When using measures of vegetative cover, MS+LiDAR data only explains an additional 0.001% of the variance in the data. When using measures of impervious surface, the MS+LiDAR data explains no additional percentage of the variance. These findings are evidence that MS+LiDAR data does not better explain urban water use in Salt Lake City in 2011. We recognize that our study might not be valid for regions that differ substantially from Salt Lake City (e.g. more humid locations where landscape watering doesn't represent the bulk of household water usage), and further research is needed in other research locations to extend the external validity of these results.

However, the additional efforts required to obtain LiDAR data, which may include financing flight time, as well as specialized data analysis efforts, do not appear to add predictive power for water demand modeling. MS imagery on the other hand is regularly collected nationally by the United States Department of Agriculture's National Agriculture Imagery Program and is available for most of the globe via commercial satellite imagery providers. Moreover the technical processing demands are much less for MS imagery than for LiDAR data. So unless LiDAR is already readily available, the results of this study indicate that MS imagery is just as useful for water demand modeling.

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References

Antonarakis, A., Richards, K., and Brasington, J., 2008. Object-based land cover classification using airborne LiDAR. *Remote Sensing of Environment*, 112, 2988–2998. doi:10.1016/j.rse.2008.02.004

Arizona Department of Water Resources 2013. Residential Water Use. Available from: http://www.azwater.gov/azdwr/StatewidePlanning/Conservation2/Residential/Residential_Home2.htm [Accessed 21 November 2013].

Campbell, H. E., Johnson, R. M., and Larson, E. H., 2004. Prices, devices, people or rules: The relative effectiveness of policy instruments in water conservation. *Review of Policy Research*, 21 (5), 637–662. doi:10.1111/j.1541-1338.2004.00099.x

Chen, Y., *et al.*, 2009. Hierarchical object oriented classification using very high resolution imagery and LIDAR data over urban areas. *Advances in Space Research*, 43, 1101–1110. doi:10.1016/j.asr.2008.11.008

Clary, J., *et al.*, 2009. *Literature Review to Assist in Quantification of Expected Benefits of Landscape Water Conservation Best Management Practices*. Colorado Water Conservation Board, State Government BMP Manual.

Coops, N., *et al.*, 2004. Comparison of forest attributes extracted from fine spatial resolution multispectral and LiDAR data. *Canadian Journal of Remote Sensing*, 30 (6), 855–866. doi:10.5589/m04-045

Domene, E. and Saurí, D. 2006, Urbanization and water consumption: Influencing factors in the metropolitan region of Barcelona. *Urban Studies*, 43 (9), 1605–1623. doi:10.1080/00420980600749969

Dziedzic, R., *et al.*, 2014. Building an integrated water–land use database for defining benchmarks, conservation targets, and user clusters. *Journal of Water Resource Planning Management*, 141 (4), 04014065. doi:10.1061/(asce)wr.1943-5452.0000462

Endter-Wada, J., *et al.*, 2008. Situational waste in landscape watering: residential and business water use in an urban Utah community. *Journal of the American Water Resources Association*, 44 (4), 902–920. doi:10.1111/j.1752-1688.2008.00190.x

Farag, F.A., Neale, C.M., Kjelgren, R.K. and Endter-Wada, J., 2011. Quantifying urban landscape water conservation potential using high resolution remote sensing and GIS. *Photogrammetric Engineering & Remote Sensing*, 77 (11), 1113–1122. doi:10.14358/pers.77.11.1113

Fox, C., McIntosh, B.S., and Jeffrey, P., 2009. Classifying households for water demand forecasting using physical property characteristics. *Land Use Policy*, 26, 558–568. doi:10.1016/j.landusepol.2008.08.004

Haque, M.M., Hagare, D., Rahman, A. and Kibria, G., 2013. Quantification of water savings due to drought restrictions in water demand forecasting models. *Journal of Water Resources Planning and Management.*, 140 (11), 04014035. doi:10.1061/(ASCE)WR.1943-5452.0000423

Hodgson, M., *et al.*, 2003. Synergistic use of LiDAR and color aerial photography for mapping urban parcel imperviousness. *Photogrammetric Engineering and Remote Sensing*, 69 (9), 973–980. doi:10.14358/pers.69.9.973

House-Peters, L., Pratt, B., and Chang, H., (2010). Effects of urban spatial structure, sociodemographics, and climate on residential water consumption in Hillsboro, Oregon. *Journal of the American Water Resources Association*, 46 (3), 461–472. doi:10.1111/j.1752-1688.2009.00415.x

Jorgensen, B., Graymore, M., and O'Toole, K., 2009. Household water use behavior: an integrated model. *Journal of Environmental Management*, 91 (1), 227–236. doi:10.1016/j.jenvman.2009.08.009

Lohani, V., Kibler, D. F., and Chanat, J., 2002. Constructing a problem solving environment tool for hydrologic assessment of land use change. *Journal of the American Water Resources Association*, 38 (2), 439–452. doi:10.1111/j.1752-1688.2002.tb04328.x

Loáiciga, H., 2014. Managing municipal water supply and use in water-starved regions: looking ahead. *Journal of Water Resources Planning and Management*, 141 (1), 01814003. doi:10.1061/(asce)wr.1943-5452.0000487

Nouri, H., *et al.*, 2014. High spatial resolution WorldView-2 imagery for mapping NDVI and its relationship to temporal urban landscape evapotranspiration factors. *Remote Sensing*, 6 (1), 580–602. doi:10.3390/rs6010580

PRISM Climate Group, 2004. Oregon State University. Retrieved from http://prism.oregonstate.edu

Rottensteiner, F., *et al.*, 2007. Building detection by fusion of airborne laser scanner data and multi-spectral images: performance evaluation and sensitivity analysis. *Journal of Photogrammetry and Remote Sensing*, 62, 135–149. doi:10.1016/j.isprsjprs.2007.03.001

Stoker, P. and Rothfeder, R., 2014. Drivers of urban water use. *Sustainable Cities and Society*, 12, 1–8. doi:10.1016/j.scs.2014.03.002

Tooke, T., *et al.*, 2009. Extracting urban vegetation characteristics using spectral mixture analysis an decision tree classifications. *Remote Sensing of Environment*, 113, 398–407. doi:10.1016/j.rse.2008.10.005

Utah Division of Water Resources. 2010. *Municipal and Industrial Water Use in Utah*. Report prepared by Utah Division of Water Resources, Salt Lake City, UT. Available from: http://www.water.utah.gov/Reports/MUNICIPAL%20AND%20INDUSTRIAL%20WATER%20USE%20in%20UTAH.pdf [Accessed 21 November 2013].

Warwick, J.J. and Tadepalli, P., 1991. Efficacy of SWMM application. *Journal of Water Resources Planning and Management*, 117 (3), 352–366. doi:10.1061/(asce)0733-9496(1991)117:3(352)