Response to Editor

On top of the comments made by the referees, I also have a suggestion in combination with Fig. 7 which shows the synthetic and a field acquired hemispherical photograph. Since this figure shows qualitatively the sensitivity to small errors in the exact location, it would be beneficial to show the daily timeserie of the pyranometer (as in Fig. 4) with the simulated timeseries of a couple of points surrounding the pyranometer. This may show that points located 1 or 2 meters away from the pyranometer give simulated solar radiation similar to the observed one.

WE HAVE ADDED A FIGURE 8 WHICH SHOWS THE PYRANOMETER TIMESERIES FOR FIGURE 7. THE PREDICTED SOLAR RADIATION IS ACTUALLY VERY SIMILAR TO THE OBSERVED PYRANOMTER DATA (0.58 VS 0.55 VS 0.57 kW/m^2. IT WAS CHOSEN BECAUSE IT WAS PARTICULARY EASY TO OBSERVE HOW SMALL LOCATION ERRORS COULD POTENTIALLY AFFECT THE SIMULATED SUNPATH. WE DO NOT HAVE A METHODOLOGY TO SIMULATE A TIMESERIES, BUT WE ARE WILLING TO DO ADDITIONAL ANALYSES IF YOU THINK THEY WOULD BE HELPFUL.

In stream temperature models it often does not matter that much if the exact location of solar insolation is shifted a few meters.

Having said this, I was also wondering if you have taken into account that the pyranometer was located 1 m above the surface. Especially if solar angels are low, this may influence your result.

THE HEMISPHERICAL PHOTOGRAPH AND PYRANOMETER WERE TAKEN AT THE SAME HEIGHT, BUT IT IS A GOOD POINT THAT THE ADDITIONAL METER IS NOT PROPERLY ACCOUNTED FOR IN COMPARING LIDRA AND THE FIELD METHODS. WE WILL ADD LANGAUAGE POINTING OUT THIS COULD BE A SOURCE OF ERROR.

Response to Reviewer 1

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On three substantive issues I have concerns: Model vs predictor. The abstract clearly states this paper is testing two models with two validation datasets. However, under Model Comparisons, the discussion changes to four "predictors" without explanation how these relate to the two models or why effective leaf area index is included, as it is part of neither model. This confusion is compounded under Model Application, where the predictors are now referred to as Model G and Model E, in reference to graphs in figure 6. More consistent naming from methods through the discussion would make this easier to follow.

AGREED THAT THIS IS CONFUSING AND IMPRECISE. THE FINAL VERSION WILL BE EDITED TO CLARIFY THE EXACT PREDICTORS USED IN THE ABSTRACT, METHODS, RESULTS AND DISCUSSION.

Pyranometer validation. The spectral response of silicon-cell photodiodes is calibrated to clear sky direct sunlight conditions, because it is not sensitive to the full shortwave spectrum and responds to various wavelengths with different intensities. Leaf shading selectively blocks certain wavelengths, which causes silicon pyranometers to decalibrate. Apogee estimates that this produces roughly a 19% error under conifer canopy (https://www.apogeeinstruments.com/content/SP-100-200- specsheet.pdf, page 15). Black body thermopile pyranometers are recommended for subcanopy light measurements. They have an even spectral response across the shortwave spectrum even under leaves. I recommend the authors acknowledge this as a source of uncertainty in their discussion.

THANK YOU FOR POINTING THIS OUT. WE WILL ADD THIS SOURCE OF UNCERTAINTY TO THE DISCUSSION.

Conclusions. Line 256 "While both the raster-based LPI approach and the lidar point reprojection synthetic hemispherical photograph approach achieve satisfactory model performance, the limited range of solar insolation conditions at the point locations in our study limits some of the conclusions that an be drawn." While I appreciate this study and the intent behind it, perhaps more validation data is needed? Was there insufficient information to effectively evaluate the two models? How are both approaches satisfactory

AGREED THAT "SATISFACTORY" IS NOT WELL-DEFINED AND THUS THIS STATEMENT IS NOT VERY USEFUL. WILL REWORD TO INDICATE THAT THE RESULTS MAY BE SATISFACTORY DEPENDING ON THE APPLICATION BUT MORE VALIDATION DATA IS NEEDED.

SPECIFIC COMMENTS

Line 146: The dates are not given for when the pyranometers were recorded. This makes a significant difference for the models. On June 20, summer solstice, the shifted LPI and general LPI will look almost identical, but December 20, winter solstice, will look radically different. Is there a reason this is not mentioned, while the date for the Lidar is mentioned?

THIS WAS AN OVERSIGHT. PYRANOMETER AND HEMIPHOTO DATA WERE COLLECTED OVER TWO WEEKS AROUND THE SUMMER SOLSTICE IN 2015. THIS INFORMATION WILL BE ADDED TO THE METHODS.

Line 251: Table 3 linear regression slope and intercept. I think this can be removed without loss to the paper.

THIS IS INCLUDED FOR COMPLETENESS SAKE AND BECAUSE CERTAIN SCATTER PLOTS IN FIGURE 6 (eg. G AND H MIGHT BE DIFFICULT TO INTERPRET WITHOUT THE INCLUSION OF A 1:1 LINE)

Line 269: Models should agree better in areas without shading. I am not sure how this is a conclusion. While true, the whole point of these models is to tackle the uncertainty of heavily shaded landscapes.

THAT SENTENCE WILL BE REMOVED

Line 271: small registration errors. Recommend identifying which model this is an error for. Relevant for synthetic photo, but not for raster.

AGREED. WILL INCLUDE IN REVISED VERSION

Line 281: understory vegetation. This is actually an argument against the directions this paper recommends on Line 335 regarding ray tracing. Note the raster approach was developed with this issue as one of the problems it was solving in its design.

GOOD OBSERVATION AND AGREED. WILL REMOVE RAY TRACING FROM THE CONCLUSION EXCEPT TO NOTE THAT FURTHER RESEARCH IS NEEDED.

Line 294: "Model G and Model E (figure 6) performed the best..." This statement is unclear. How are plots models? What criteria states that they performed the best? Their performance and the performance of the hemispherical photos all seem within error of each other. Is this incorrect?

THIS CONCLUSION WAS BASED ON THE COEFFICIENT OF DETERMINATION. WE ARE CONSIDERING THE SIMPLE LINEAR REGRESSION AS THE MODEL.

Line 337: "The results of this study suggest that refined ray-tracing approaches should not require calibration." I do not see this statement supported by the paper. Both models used in this study did not perform point cloud ray tracing. That is their strength. Musselman and Lee (referenced in introduction) used voxel ray-tracing. Both required calibration.

AGREED. THIS SENTENCE WILL BE REMOVED AND RAY TRACING WILL BE REMOVED FROM CONCLUSION EXCEPT FOR SHORT STATEMENT ON FURTHER RESEARCH.

RESPONSE TO REVIEWER 2

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I appreciate very much that the authors provide their data and analysis (as is HESS standard now). While I could easily follow the general setup of the study, I found it difficult to grasp the information residing in the Lidar data set and how it has been used. Since the latter is not included in the repository: Did I understand correctly that the Lidar data was commercially acquired and preprocessed to 1m pixels? So each pixel has values about all point returns, the number of highest hits (canopy) and the number of lowest hits (ground)?

THE LIDAR WAS PRE-PROCESSED BY THE VENDOR INTO 1 M PIXELS CONTAINING HIGHEST ELEVATION AND GROUND MODEL. THE AUTHORS CREATED ADDITIONAL RASTERS USING THE RAW LIDAR POINTS IN ORDER TO DETERMINE NUMBER OF CANOPY HITS AND GROUND HITS PER 1 M PIXEL

Please be more specific about the calculation methods than naming the Software ArcGIS. I suppose this is an array operation which could be done in R (or any other math software) too. Which approaches did you employ? What can be understood about the "10m Buffer around the field points" (L187) and how does it differ to the "shifted square buffer" (L188f.)?

THESE CALCULATIONS COULD BE PERFORMED IN R OR ANY OTHER SOFTWARE BUT IT IS QUITE SIMPLE TO DO IN ARCGIS. THE SPECIFIC OPERATIONS INCLUDED USING THE BUFFER TOOL AND SUMMING THE NUMBER OF CANOPY AND GROUND POINTS QUANTIFIED IN THE VALUE FIELD OF THE RASTER USING THE ZONAL STATISTICS TOOL. THE SHIFT CALCULATION WAS PERFORMED IN THE SAME WAY AFTER USING THE EDITOR TOOL AND MOVE COMMAND TO SHIFT THE POINTS SOUTH BY 3.42 M. THE FINAL VERSION WILL BE EDITED TO INCLUDE THIS SPECIFIC INFORMATION.

Did you average within this area for comparison?

WE SUMMED THE VALUES AS DESCRIBED ABOVE.

What are the effects on the performance of the estimates. Especially with regards to the issue of "registration errors" L277ff. would this mean that a higher resolution could be more accurate or in other words that the hemispherical photographs suffer from minor shading effects to become representative at stand scale?

YES, THIS IS VALID CONCLUSION FROM THESE RESULTS.

For a validation of the Lidar-derived solar insolation there is basically the correlation plot in Fig. 8 comparing it to pyranometer measurements. To me this does not appear very convincing to support the conclusion. By not allowing for an intercept in your linear regression model, you define the bias-term to be zero. While this is an understandable desire in comparing two measurements which should give the same results, I do not understand your statement in L298f.

AGREED THAT THIS IS NOT WELL STATED. THE INTENTION WAS TO BE ABLE TO PREDICT INSOLATION WITH A MODEL THAT WOULD ESTIMATE INSOLATION TO BE ZERO IN AREAS WHERE NO CANOPY POINTS WERE PRESENT. THIS WILL BE CLARIFIED IN REVISION

The 16 points appear to overestimate the pyranometer references in most cases. High insolation references are underestimated. With an R2 of 0.63, I find it rather problematic to speak of accurate: L329f. "a synthetic hemispherical photograph approach accurately predict solar insolation and light transmittance".

WE STRUGGLE WITH DESIGNATING A THRESHOLD FOR ACCURACY, BUT AGREE THAT THIS IS NOT VERY PRECISE TO DECLARE THIS ACCURATE WITHOUT A THRESHOLD. WILL REWORD TO SUGGEST THAT IT MAY BE ACCURATE DEPENDING ON APPLICATION.

In this respect, I moreover have difficulties to relate this back to the presented indices which leaves me with a couple of questions about the reason of their introduction in the first place. This confusion might partially stem from the mannifold usage of the term "model" in the manuscript. I would suggest to allow for a more precise terminology to differentiate regression analyses from conversion models, from indices and from spatial map models. From the title I was expecting several modelling approaches using the Lidar data, which I did not find in the manuscript.

REVIEWER 1 HAD A SIMILAR CRITICISM AND WE WILL REVISE TO INDICATE WHAT WE MEAN BY MODEL.

Coming back to the indices (Fig. 6, Tab. 3) I do not find the focus of the study specifically suitable to address these correlations.

YOUR CRITICISM IS NOT SUFFICIENTLY DETAILED FOR ME TO RESPOND IN DETAIL. I WILL SIMPLY SAY THAT THE CORRELATIONS IN MY OPINION ARE SUITABLE AS THE OBJECTIVE OF THE STUDY IS TO EVALUATE THE DIFFERENT METHODS COMPARED TO FIELD DATA.

Contrastingly, the comparison of synthetic and actual hemispherical photograph (Fig. 7) is very compelling but falls in my view a little short in its analysis and evaluation (e.g. applying this for all 16 locations). Since the validation of the "Lidar-based modelling" is rather difficult using the 16 measurements alone, maybe some further reference could be derived from remote sensing products? This could also provide the link to some of the addressed indices?

I'M NOT SURE WHAT SPECIFICALLY YOU ARE PROPOSING. WE ARE PRESENTING THIS WORK TO STAND ALONE AND CANNOT AT THIS TIME EXPAND THE SCOPE.

2 Minor comments: L28f.: why only ecological applications?

THE SCOPE OF THIS STUDY IS FOCUSED ON ECOLOGICAL APPLICATIONS.

L29: do trees really interact (so having feedbacks) with solar radiation?

I WOULD ARGUE THAT TREES INTERACT WITH PHOTONS THROUGH REFLECTION, TRANSMITTANCE, AND ABSORPTION. SHADING IS A COMBINATION OF THESE THREE EFFECTS.

L36: can (solar) energy intercept with something? maybe irradiate a stream?

WILL CHANGE TO IRRADIATE

L37: how does solar irradiation limit options for forest management? I do not understand.

THE REST OF THE PARAGRAPH EXPLAINS THIS, CULMINATING IN THE FINAL SENTENCE WHICH ANSWERS YOUR QUESTION

L48ff.: is it really necessary to describe the function of a pyranometer (at this broad level of detail)?

I DON'T THINK IT DETRACTS FROM THE PAPER. SINCE THIS IS A HYDROLOGY JOURNAL I WANT THE TECHNICAL INFORMATION TO BE WELL EXPLAINED.

L53: I do not see the difference between the time references of a direct state measurement and the photograph

IT IS IN THE DIRECT VS INDIRECT MEASUREMENT. THE DIRECT MEASUREMENT IS DEPENDENT ON THE ANGLE OF THE SUN WHILE THE INDIRECT MEASUREMENT IS NOT

L56: Depending on the type of pyranometer, diffuse radiation is directly measured too.

THIS IS REFERRING TO HEMISPHERICAL PHOTOGRAPHS

L67: Start new paragraph with "Airborne lidar..." ?

I SEE HOW IT COULD BE GOOD TO START A NEW PARAGRAPH THERE BUT THAT WOULD LEAD TO TWO VERY SHORT PARAGRAPHS AND PREFER IT AS IS.

L113f.: very confusing. please rephrase.

I'M NOT SURE WHAT IS CONFUSING. THE CITATION TO THE ORIGINAL PAPER IS ALSO THERE TO HELP READERS IF THEY ARE CONFUSED.

Fig 1: I would prefer all four Lidar models/maps instead of the grey box, which I assume to be the total Lidar dataset footprint. If you find my suggestion feasible, maybe a map of a satellite RS derived index could also be a reference here. A colourbar would be nice.

IT WOULD BE DIFFICULT TO FIT ALL FOUR MAPS IN THIS FIGURE WITHOUT MAKING THEM EXTREMELY SMALL. THE GREY FOOTPRINT AND EXPLANATION OF THE COLORING IS IN THE CAPTION.

L200f.: What happened to the longitudinal profiles? Were they processed?

YES, THOSE ARE IN FIGURE 10.

L215: See general comment. Which exactly are THE models? do you refer to the different indices? the calculus to derive them? a model to generate the synthetic hemispherical what are the assumptions behind the comparison approach? What is the observation reference deemed as closest to the true value?

SEE COMMENT ABOVE. WILL REVISE TO MAKE THIS MORE CLEAR.

L257: model performance? in reference to what? Is a R2 to each other really a good measure?

AGREED. IT IS A POINT THAT REVIEWER 1 ALSO BROUGHT UP AND WILL BE EDITED TO REMOVE SATISFACTORY AND CLARIFY THAT R2 IS THE METHOD OF EVALUATION AND DISCUSS THE LIMITS OF THE USE OF THAT STATISTIC.

L277ff.: I do not understand why this should not be desirable... actually, i find the results in fig 7 quite convincing and the sensitivity ght be quite an interesting feature. Pls. see my general comment on this, too.

IT IS UNDESIRABLE BECAUSE IT MAKES IT DIFFICULT TO EVALUATE THE ACCURACY OF THE MODELS. THIS WILL HOPEFULLY BE MORE CLEAR WHEN THE MODEL LANGUAGE IS REVISED.

RESPONSE TO REVIEWER 3

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The authors present an interesting study that compares two LiDAR based techniques (i.e., a raster-based method and a synthetic hemispherical photograph approach) for estimating under canopy solar insolation, which is an important variable for predicting stream temperature dynamics. They conduct their study for sites on the heavily forested Panther Creek and its tributary located in Oregon, USA While I am generally supportive of the merits of the study the authors present, I believe they could be more precise in their language and provide more connecting details about the methods used so that their work can be replicated and advanced. I also have some specific concerns about the methods in the models. Additionally, throughout the paper, there is an emphasis on the ecological implications of this work. However, stream temperature also has important implications for various biogeochemical processes. The work the authors present may be of interest to other research domains so I would recommend that the authors broaden their discussion to encompass them. I have provided some general comments and suggestions that I hope the authors will consider incorporating into their paper to address the problems I have enumerated.

General Comments 1. While the authors indicate that they used two LiDAR based approaches/models for estimating solar insolation, midway through the paper, they introduce the new term “predictors” and then switch back to models (Line 294). This is confusing. I would suggest that the authors select one term and consistently use it throughout the paper. I would actually recommend sticking to predictor since they are essentially correlating various shading surrogate indexes with measurements of solar insolation. I also think it will be good introduce the specific predictors used under each approach (i.e., raster & synthetic hemispheric photograph approaches) at the beginning of the paper so that their introduction later in the paper is not so abrupt. Under raster-based predictors they could introduce LPI, SLPI, and LAI and then introduce %Transmittance for hemispheric photograph approach. They could also discuss why they are good/suggested predictors for solar insolation citing references.

THIS IS SIMILAR TO COMMENTS MADE BY REVIEWER 1 AND 2. YOUR SPECIFIC RECOMMENDATIONS ARE WELL RECEIVED AND WILL BE INCORPORATED INTO THE REVISED MANUSCRIPT.

2. The authors conclude that the limitation of their study was the lack of more monitoring points with large insolation values and that inclusion of more of these points would have increased the model accuracy (Line 266), but the point of their study was to derive approaches for estimating solar insolation for streams with heavily forested riparian zones. This is in practice the areas where insolation estimation uncertainty is greatest. My recommendation is to make this their focus and perhaps remove the points with higher insolation values from their regression.

AGREE WITH THE GENERAL SENTIMENT OF THIS COMMENT. THE WORDING WAS INTENDED TO INDICATE THAT IT WOULD HAVE BEEN EASY FOR US TO CHOOSE LOCATIONS WITH LOW CANOPY COVER

TO INCREASE THE ACCURACY OF THE MODEL, BUT THAT WOULD HAVE NOT BEEN PARTICULARLY USEFUL. WE WILL REWORD THIS SECTION TO MAKE IT SEEM LESS LIKE A LIMITATION AND MORE A RESULT THAT SHOULD STAND ON ITS OWN. NOTE THAT THE POINTS WITH HIGHEST %TRANSMITTANCE ONLY HAD 35% SO WE DON'T THINK IT'S NECESSARY TO REMOVE THOSE AS THEY AREN'T PARTICULARLY HIGH. WETHINK THE ISSUE IS MORE THAT WE WERE NOT ABLE TO CAPTURE ENOUGH POINTS IN THE 15% TO 35% RANGE.

3. Throughout the paper, the authors use the word "significant" to describe differences between values conjuring up an image of statistical significance. I would recommend that the authors state the actual numerical differences or use other words.

AGREE AND THIS IS SIMILAR TO FEEDBACK GIVEN BY REVIEWER 1 AND 2.

4.

While the connection between solar insolation is self-apparent. I would recommend making that connection more explicit in the paper. You could say something along the lines of "Solar radiation is a major source heat flux into streams providing up to y% of heat fluxes" and the then cite a reference.

AGREE AND WILL ADD IN SIMILAR WORDING.

5. For the synthetic hemispherical photographs, what resolution was used for the hemisphere? Did it match the field photographs? If different, what are the implications of the differences for the authors analysis. I think the comparison of these too and the reasons why they might differ is an important contribution.

IT'S A BIT DIFFICULT TO COMPARE AS THE SYNTHETIC PHOTOGRAPHS ARE CREATED USING POINTS THAT ARE RENDERED WITH A RELATIVELY LARGE "DOT" SIZE COMPARED TO THE INDIVIDUAL PIXELS OF THE CAMERA. THE "DOT" SIZE WAS DETERMINED BY THE MOESER ET AL (2014) ALGORITHM. THE INTENTION IS FOR THE READER TO USE FIGURE 7 TO JUDGE THESE DIFFERENCES. WE ARE NOT SURE HOW DIFFERENCES IN RESOLUTION WOULD AFFECT THE ANALYSIS.

Specific Comments 1. Line 16 – "due to the importance of temperature to aquatic biota". This makes it sound like aquatic biota is the only reason why quantifying solar insolation is important. Consider revising to broaden its implications.

IT WAS OUR MAIN MOTIVATION FOR EMBARKING ON THIS STUDY, BUT IT DOES LIMIT ITS IMPLICATIONS. WILL CHANGE TO "USEFUL FOR A VARIETY OF APPLICATIONS, AND A SPECIFIC FOCUS OF THIS STUDY IS THE IMPORTANCE OF STREAM TEMPERATURE TO AQUATIC BIOTA.

2. Line 17-19: I suggest changing "two approaches. . ." to something like "four predictor indexes computed using two approaches for estimate shading effects from LiDAR" or something along these lines. The larger point is that it is important to be precise in describing what was actually done.

AGREED. WE WILL MAKE THIS CHANGE.

3. Line 28 “is essential to a diversity of ecological. . .” Again, I think you can broaden this.

WILL ADD ANOTHER SENTENCE TO BROADEN THE SCOPE BEFORE FOCUSING ON ECOLOGICAL APPLICATIONS.

4. Line 36 “solar energy intercepting a stream. . .” Consider revising to “solar energy irradiating a stream”

SAME COMMENT WAS MADE BY REVIEWER 2 AND IT WILL BE CHANGED. 5.

Line 36-37 “can in turn limit options for forest management”. Could the authors explain how increasing temperatures limit options for forest management? I am not sure this is true.

A SIMILAR COMMENT WAS MADE BY REVIEWER 2. UPON FURTHER REFLECTION WE SEE HOW THIS SENTENCE IS CONFUSING AND WILL EDIT IT TO MAKE THE CONNECTION BETWEEN STREAM TEMPERATURES AND THE REQUIREMENT TO KEEP UNHARVESTABLE BUFFERS NEAR STREAMS

6. Line 45-46 “models may be needed...” I would argue that this is actually often the approach that is used and is not a new insight so please consider revising to "models are therefore often employed to estimate temperature"

GOOD POINT. WILL CHANGE TO ADOPT THAT LANGUAGE

7. Line 57: “solar output” consider revising to extra-terrestrial solar radiation.

WILL CHANGE. THANKS!

8. Line 60: “All ground-based. . .” Sounds a little too strong. Consider removing "All".

AGREED. WILL CHANGE

9. Line 78-79. “GIS software solar radiation calculators. . .” Consider revising to “Solar radiation calculators in GIS software”

GOOD EDIT. WILL CHANGE.

10. Line 80-82. I think you are missing some words somewhere. Please rephrase for clarity. E.g., “r.sun solar insolation model for the GRASS GIS software. . .”

AGREED THAT THIS IS PHRASED POORLY. WILL REWORD.

11. Line 89: What are Ellenburg indicator values? While ecologist might be familiar with them, I think it will be good to explain.

WILL ADD A SHORT DESCRIPTION.

12. Line 169 Figure 4: Does the y axis name need to be solar irradiance for consistency? GOOD CATCH. WILL CHANGE.

13. Line 195-197: I am not sure why this sentence is part of the paper. I feel it is unnecessary. Please consider removing.

THE METHOD THAT WE USED BASED ON BODE ET AL (2014) USED THIS TOPOGRAPHIC CORRECTION AND WE WANTED TO EXPLAIN WHY WE DID NOT FOLLOW THEIR METHOD COMPLETELY.

14. Line 198-199: Are the authors able to delve more into the details of the creation of these synthetic photos?

THE CODE USED TO CREATE THESE WAS SHARED WITH PERMISSION BY DAVE MOESER AND WOULD REFER YOU TO HIM FOR FURTHER DETAIL.

15. Line 222. “significantly improved” remove significantly for the reasons I raised earlier.

AGREED

16. Line 278: Please remove the word "significant". for the same reasons as before.

AGREED

17. Line 298-299: I am not sure I am comfortable removing the intercept and saying the resulting model has little bias. By removing the intercept, the authors are making the RË ,E2 value no longer useful.

THE INTERCEPT WAS REMOVED SO THAT PIXELS WITH NO CANOPY POINTS WOULD YIELD A PREDICTED VALUE OF 0. WILL MAKE THIS REASONING EXPLICIT IN THE REVISED VERSION.

18. Line 311 & Figure 9: Please consider adding an inset that zooms to one of the monitoring points.

WE ARE NOT SURE WHAT YOU MEAN BY MONITORING POINTS. ARE YOU SUGGESTING AN INSET SIMILAR TO FIGURE 1? IF SO, WE DON’T THINK A SIMILAR INSET WOULD BE PARTICULARLY USEFUL FOR INTERPRETATION OF FIGURE

9. 19. Line 337-340: The authors pivots to ray tracing. However, the methods they use does not include any ray tracing.

THIS POINT WAS BROUGHT UP BY REVIEWER 1 AND WE AGREE THAT IT DOES NOT BELONG. IT WILL BE EDITED TO INCLUDE ONLY A SHORT REFERENCE TO RAY TRACING AS A POTENTIAL AVENUE OF FUTURE RESEARCH

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Lidar-based ~~modelling~~ approaches for estimating solar insolation in heavily forested streams

Richardson, Jeffrey J.*[1]; Torgersen, Christian E.[2]; and Moskal, L. Monika[3]

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~~*This draft manuscript is distributed solely for the purposes of scientific peer review. Its content is deliberative and predecisional, so it must not be disclosed or released by reviewers. Because the manuscript has not yet been approved for publication by the U.S. Geological Survey (USGS), it does not represent any official USGS finding or policy.*~~

Abstract

Methods to quantify solar insolation in riparian landscapes are needed due to the importance of stream temperature to aquatic biota. We have tested ~~two~~ three lidar predictors using ~~approaches~~two approaches developed for other applications of estimating solar insolation from airborne lidar using field data collected in a heavily forested narrow stream in western Oregon, USA. We show that a raster methodology based on the light penetration index (LPI) and a synthetic hemispherical photograph

approach both accurately predict solar insolation, explaining more than 73% or the variability observed in pyranometers placed in the stream channel. We apply the LPI based model to predict solar insolation for an entire riparian system, and demonstrate that no field-based calibration is necessary to produce unbiased prediction of solar insolation using airborne lidar alone.

A. Introduction

Accurately quantifying solar insolation, defined as the amount of solar radiation incident on a specific point on the Earth's surface for a given period of time, is important to many fields of study such as solar energy, glacier dynamics, and climate modeling. In this study, we focus on the importance of solar insolation for ~~is essential to a diversity of~~ ecological applications. In forested ecosystems, trees interact with solar radiation through shading, and thus solar insolation at fine spatial scales in these systems can vary widely. Understanding the heterogeneous patterns of insolation below tree canopies has been important for numerous applications, such as understanding the importance of sunflecks for understory photosynthesis, gaining insight into the patterns of seedling regeneration in dense forests (Nicotra et al., 1999), and explaining patterns of snowmelt (Hock, 2003) and soil moisture (Breshears et al., 1997).

The relationship between stream temperature and solar insolation is of particular interest in this study, as high amounts of solar energy ~~intercepting~~ irradiating a stream can cause adverse ecological effects due to directly increasing the temperature of the streams. ~~, which can in turn limit options for forest management near streams~~. In northwestern North America, a large amount of research has focused on the relationship between forest practices, stream temperature, and the corresponding effect on river salmonid fishes (Holtby, 1988;Leinenbach et al., 2013;Moore et al., 2005a;Moore et al., 2005b). Direct measurement of stream temperature with in-stream thermographs can be used to quantify thermal diversity (Torgersen et al., 2012;Torgersen et al., 2007), but ground-based measurements are time consuming, expensive, and impractical for large areas. In addition, stream temperature measurements can only show the effect of forest management practices if taken before and after trees are removed. In order to predict the potential effect of forest management practices on stream temperature, models ~~may~~ are often employed to ~~be needed to~~ estimate the amount of solar insolation ~~intercepting~~irradiating streams using remotely sensed data (Forney et al. 2013).

Several different methods have been utilized for measuring or predicting solar insolation on the ground. Pyranometers are the most direct method for measuring insolation, capturing the solar radiation flux density above a hemisphere as an electrical signal and cataloguing those signals in a datalogger (Kerr et al., 1967). Once calibrated, these signals give a measure of the total direct and diffuse solar radiation ~~intercepting~~ irradiating a point for a given period of time (Bode et al., 2014;Forney et al., 2013;Musselman et al., 2015). While pyranometers give direct measurement of solar insolation for a defined period of time, hemipshperical photographs allow indirect estimation of solar insolation for any point in time (Bode et al., 2014;Breshears et al., 1997;Rich et al., 1994). Plotting the path of the sun in the area of sky captured by the hemispherical photograph allows for calculation of direct solar radiation through identified canopy gaps, while gap fraction across the entire hemisphere allows for calculation of diffuse radiation. Analysis of hemispherical photographs requires assumptions of ~~solar output~~extra-terrestrial solar radiation and sky conditions in order to produce solar insolation estimates. Understory light conditions can also be modeled by creating a three-dimensional reconstruction of a forest from field-based biophysical measurements (Ameztegui et al., 2012) or terrestrial laser scanning (Ni-Meister et al., 2008). ~~All g~~Ground-based measurements are limited by the time and cost required to collect data, and thus solar insolation can only be calculated for relatively small spatial extents.

Airborne and satellite remote sensing methods provide a means for estimating solar insolation over large spatial extents. Satellite-based methods utilizing passive remote sensing data can provide coarsescale estimates of solar radiation absorbed by tree canopies through radiative transfer models based on spectral indices (Field et al., 1995;Asrar et al., 1992), but these methods are not suitable for fine-scale application such as modeling stream temperature. Airborne lidar is the preferred method for characterizing three-dimensional structure of forest canopies, and thus is also used to assess the shading effect of those canopies. Below we discuss three different approaches that have been used in previous studies to quantify solar insolation at ground level using aerial lidar.

Raster Approaches

Lidar data can be used to create raster datasets by selecting various attributes of lidar points within a defined spatial neighborhood around a raster cell. One of the most common raster products for assessing canopy structure is the light penetration index (LPI), the ratio of ground first return points (typically less than 2 m in elevation above ground) to the total number of lidar first return points within a given raster cell. This ratio has been shown to be useful for characterizing light extinction in canopies according to the Beer-Lambert law (Richardson et al., 2009) and thus has been explored as a predictor of understory light conditions (Musselman et al., 2013;Alexander et al., 2013;Bode et al., 2014). Solar radiation calculators in GIS software ~~GIS software solar radiation calculators~~ can also be used to compute solar insolation on a lidar-derived digital elevation model (DEM). Bode et al. (2014) combined a ~~GRASS r.sun solar insolation estimation~~ r.sun solar insolation model for the GRASS GIS software based on a DEM with LPI to produce estimates of ground level solar insolation that showed high accuracy compared to pyranometer-collected field data in a mixed forest in Northern California, USA.

Lidar Point Reprojection

Lidar point returns can be reprojected from the X,Y,Z Cartesian coordinate system in which they are most often delivered by a vendor into a spherical coordinate system which centers the point cloud around a specific location on the ground. This reprojection allows for a circular graph of the lidar point returns to be created around a point at ground level. Alexander et al. (2013) created a canopy closure metric from these projected point graphs based on gap fraction, and found that this metric was correlated to Ellenburg indicator values (which relate plants to their ecological niche along an environmental gradient) of understory light availability. Moeser et al. (2014) created synthetic hemispherical photographs from reprojected lidar returns, and solar irradiance at ground level was calculated using traditional hemispherical photograph analysis software. The processed synthetic hemispherical photographs showed good correlation to pyranometer measured solar irradiance at three field sites in eastern Switzerland.

Point Cloud Approaches

Because lidar point clouds are typically represented in a three-dimensional Cartesian coordinate system, it is possible to model the sun's position in relation to that three-dimensional space. The number of lidar returns that are reflected from a defined volume between the direction of the sun and the ground can then be calculated. These methods are computationally intensive, but have shown promise for providing the most direct measure of understory light availability. Lee et al. (2008) calculated the number of points within a conical field of view directed at the sun's location and created a model to relate this to ceptometer measurements of photosynthetically active understory solar radiation at specific times and locations in a pine forest in northern Florida, USA. This method is limited by its reliance on raw lidar point counts specific to the actual and relative point densities within their lidar acquisition. Raw point counts are affected by both changes in flight characteristics between missions, and the patterns of flight line overlap within a mission. A different point cloud approach involves a linear tracing of the sun's rays along their path to the ground, and Martens et al. (2000) demonstrated how a ray-tracing algorithm could be used to characterize understory light conditions in a computer simulated forest. Peng et al. (2014) combined a lidar-based ray tracing algorithm with field-collected canopy base heights to produce an estimate of understory solar insolation based on the Beer-Lambert law that compared well to field-collected pyranometer data but is limited in practical application because of its reliance on field- measured data in its model. Musselman et al. (2013) used a ray-tracing algorithm to produce highly detailed estimates of direct beam solar transmittance in 5-minute increments by voxelizing the lidar data and summing the number of voxels that a ray intercepted between the point of origin and the sun. The algorithm relied on site specific pyranometer measurements to calibrate and adjust the beam transmittance, and therefore we were restricted from testing this method in this study.

Our objectives were to test the accuracy and precision of established methods of quantifying solar insolation from aerial lidar within areas of narrow, heavily forested streams. We utilized ~~the~~ two raster approaches and ~~the~~ one lidar point reprojection approach, ~~two~~ three methodologies that had not been previously applied and tested using high quality field data collected in heavily forested streams. We evaluated the ~~two~~ three ~~methods~~ methodologies using simple linear regressions that compared lidar derived metrics to~~using simple linear regressions that compared lidar derived metrics to~~ field-based pyranometer measurements of solar insolation and hemispherical photograph-based measures of shade in Western Oregon, USA. Further, we sought to apply this method to quantify solar insolation throughout a small headwater stream network.

B. Methods

Study Site

All field locations were located within the wetted channel of Panther Creek and a tributary (Figure 1) in narrow streams (1-6 m in width) located in the east side of the Coast Range of Oregon, USA within a larger research area in which lidar has been used to quantify forest canopy structure (Flewelling and McFadden, 2011). All field sites were within a mature Douglas-fir (*Pseudotsuga menziesii*) forest, with other dominant trees including red alder (*Alnus rubra*), Western red-cedar (*Thuja plicata*), and Western hemlock (*Tsuga heterophylla*). The elevation profile and description of the stream can be found in (Richardson and Moskal, 2014). The center of the channel was manually digitized as a polyline in ArcGIS using a combination of aerial imagery and the vendor-provided lidar DEM.

Four transects were installed in late June 2015 using a Leica Builder Total Station and georeferenced using a Javad Maxor GPS unit. The locations of the transects can be seen in Figure 1, with the 19 point locations used for capturing field data denoted by black dots surrounded by white circles (A contains 3 points, B and C contain 4 points, and D contains 8 points). Transect locations were chosen manually in order to maximize variability in forest shade while allowing for safe access by the field crew. Each point location was located within the stream channel and marked by driving rebar into the substrate until only 1 m was exposed above the water surface. Point locations were approximately 15 m apart within a transect in order to allow data from multiple point locations to be collected by a single datalogger.

Two datasets were collected at each point location during the last two weeks of June in 2015. A hemispherical photograph was collected using a Nikon CoolPix 4500 digital camera leveled on a tripod 1 m above the ground under uniform sky condition (Figure 2) utilizing a method to find the optimum light exposure (Zhang et al., 2005). Each hemispherical photograph was analyzed using the Gap Light Analyzer (GLA) program (Frazer et al., 1999) in order to produce estimates of percent transmittance for diffuse and direct sunlight. An Apogee Instruments SP-110 self-powered silicon-cell pyranometer, leveled and mounted to the rebar pole at 1 m height (Figure 3) was used to collect a full day's solar output at each point location using the datalogger. The raw voltage values collected by the datalogger were calibrated to solar irradiance using the closest publicly available meteorological data. All pyranometer datasets were collected on cloudless days, except for transect A, and pyranometer data from transect A was not used in this study. The calibrated pyranometer data from a point location from transect D is shown in

Figure 4. Note that the silicon-cell photodiodes, such as the SP-110 can, produce erroneous readings under conifer canopies. A black body thermopile pyranometer would have been more appropriate for this study but was not available to the authors.

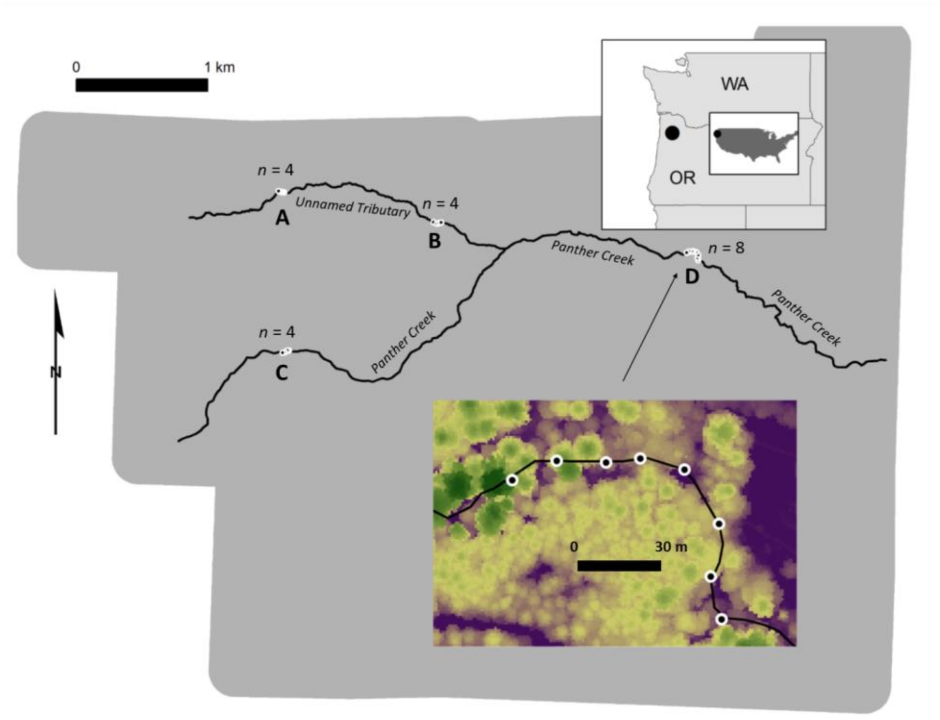


Figure 1: Study area in northwestern Oregon (USA). The grey polygon is the extent of the 2015 lidar acquisition. The black circles surrounded by white circles represent the 19 point locations. The letters A, B, C, and D denote the four transects. The inset shows transect D and the background raster in the inset is the lidar derived canopy height model with green representing tall trees and purple representing the lowest heights. The direction of flow is from west to east.

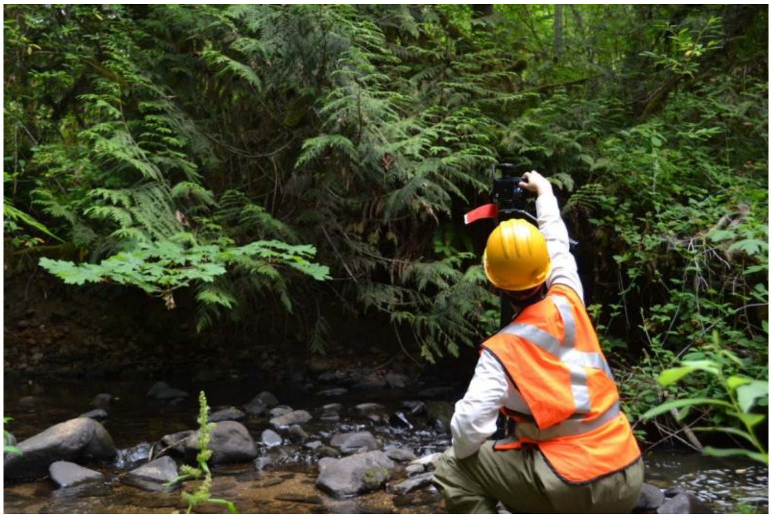
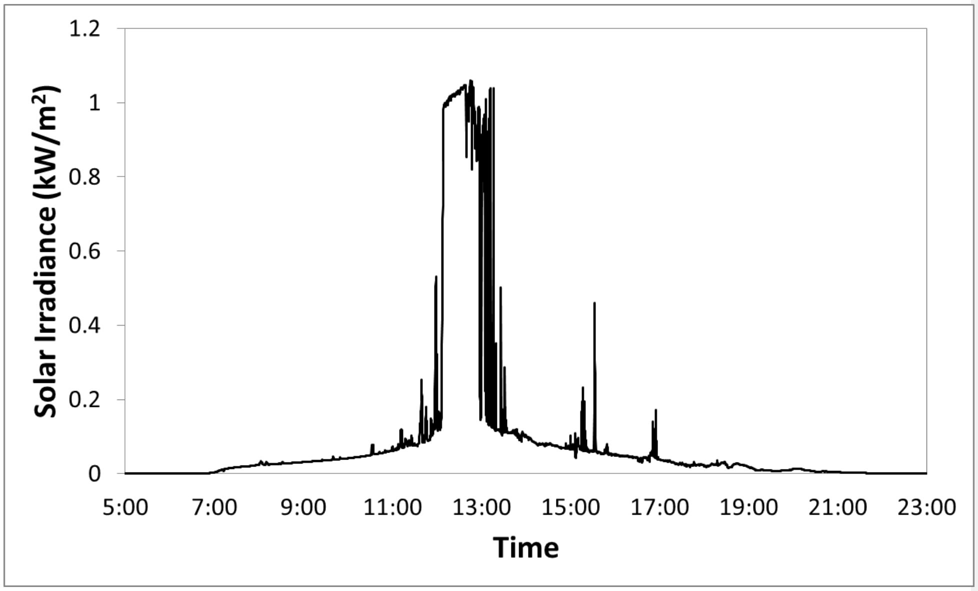


Figure 2: Example of hemispherical photograph acquisition at a plot location in transect D.

Figure 3: Example of pyranometer installation at transect D (note that pyranometer is mounted on south side of pole at a height of 1 m).



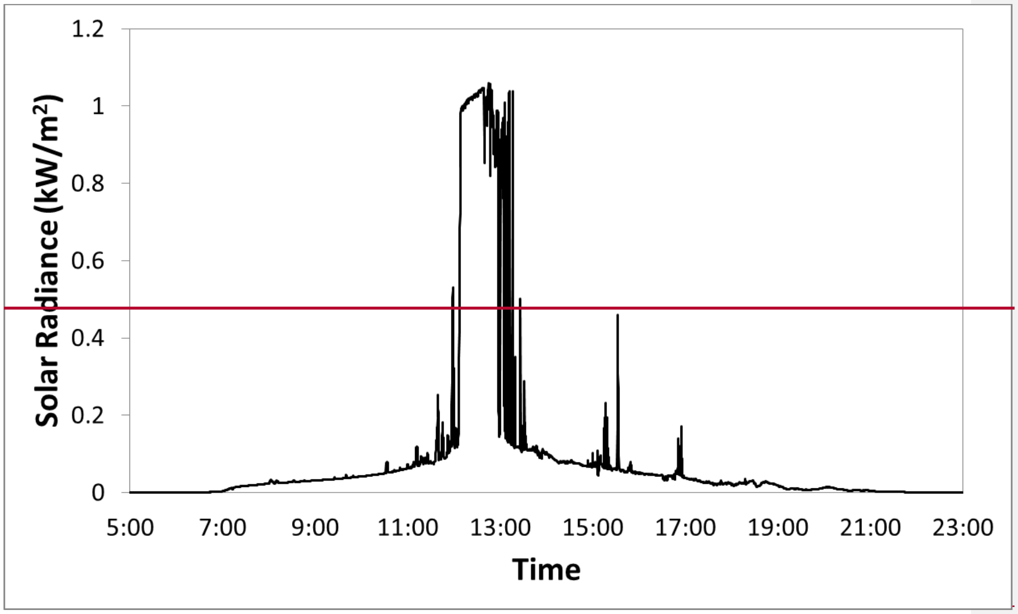


Figure 4: Daily pyranometer output from sunset to sundown for a plot in Transect D

Lidar Data and Analysis

Airborne discrete-return lidar was acquired in June of 2015 according to the specifications described in Table 1. The vendor provided processed discrete lidar point returns as well as a lidar DEM and highest hit model at a pixel resolution of 1 m. The highest hit model was subtracted from the DEM to create a canopy height model (CHM) describing the vegetation height normalized to the ground surface. In addition, Fusion (McGaughey, 2009) was used to subtract the elevations of the raw lidar points from the ground elevation in the DEM to produce a normalized point cloud dataset (NPCD). Note that the perspective of the lidar analyses is in reference to ground height while the field data were collected at 1 m above the ground. While this is a small difference, it could be a source of error in comparisons, especially at low solar angles.

Table 1: Lidar Data Specifications

Acquisition Date	June 18, 2015
Sensor	Leica ALS80
Survey Altitude	1,400 m
Pulse Rate	394.8 kHz
Field of View	30 degrees
Mean Pulse Density	25.35 pulses/m^2
Overlap	100% with 65% sidelap
Relative Accuracy	4 cm
Vertical Accuracy	5 cm

Effective Leaf Area Index (L_e) was computed using the NPCD according to the method in Richardson et al. (2009) :

$$L_e = -\frac{1}{k}\ln(R_g/R_t)$$

Where k is the extinction coefficient equal to 2, R_g is the number of first ground returns and R_t is the number of total first returns. LPI was computed as:

$$LPI = (R_g/R_t)$$

LPI was computed in ArcGIS using a circular buffer with radius 10 m around each field point location mirroring the radius used in Richardson et al. (2009) . *LPI* was also computed using a shifted square buffer modified from the method of Bode et al. (2014) where the buffer side length (s) was calculated based on:

$$s = \frac{h}{\tan\theta}$$

Where *h* is equal to the modal tree height across all our plots (34 m), and ϑ is equal to the maximum lidar scan angle subtracted from 90° (75°), resulting in a buffer side length of 9.12 m. The square buffer was shifted south to account for the seasonal solar angle in the northern hemisphere according to:

$$shift = \left(\frac{s}{1 + \cos\sigma}\right) - s$$

Where σ is equivalent to the solar angle at noon on the date of interest. A solar angle of 68° was used in this study, resulting in a southern shift of 3.42 m. The buffer tool, zonal statistics tool, and move command were used to achieve the shift in ArcGIS. We also computed topographically influenced solar radiation using the lidar DEM and the solar radiation function in ArcGIS, but found that there was no significant difference across the plot locations and thus did not use these results in subsequent analysis.

LPI and shifted *LPI*

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Synthetic hemiphotos were created in Matlab using the method of Moeser et al. (2014) and analyzed for diffuse and direct light transmittance in GLA. All statistical analyses were performed in R (version 3.4).

Longitudinal profiles of stream shading were created in ArcGIS in 1-m increments based on the intersections of the stream polyline centerline with the raster output of modeled solar insolation.

C. Results and Discussion

Comparison between Pyranometers and Hemispherical Photographs

Figure 5 shows the correlation between field-collected pyranometer data and processed hemispherical photographs, with data from transect A removed. These data are highly correlated (r^2 = 0.87), but these data are also not equally distributed across a range of solar insolation. Many more plot locations were at low levels of solar insolation than in areas of relatively low shade. This is very typical of the heavily forested streams in northwestern North America. Note that none of our plot locations contained transmittance greater than 40%.

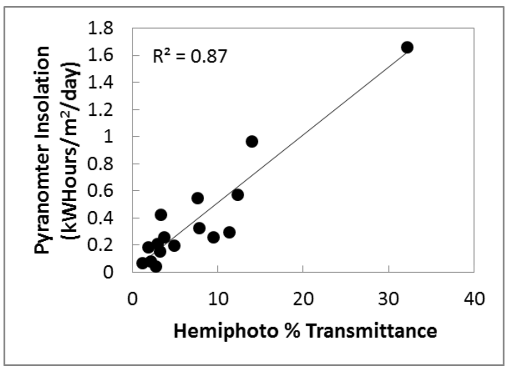
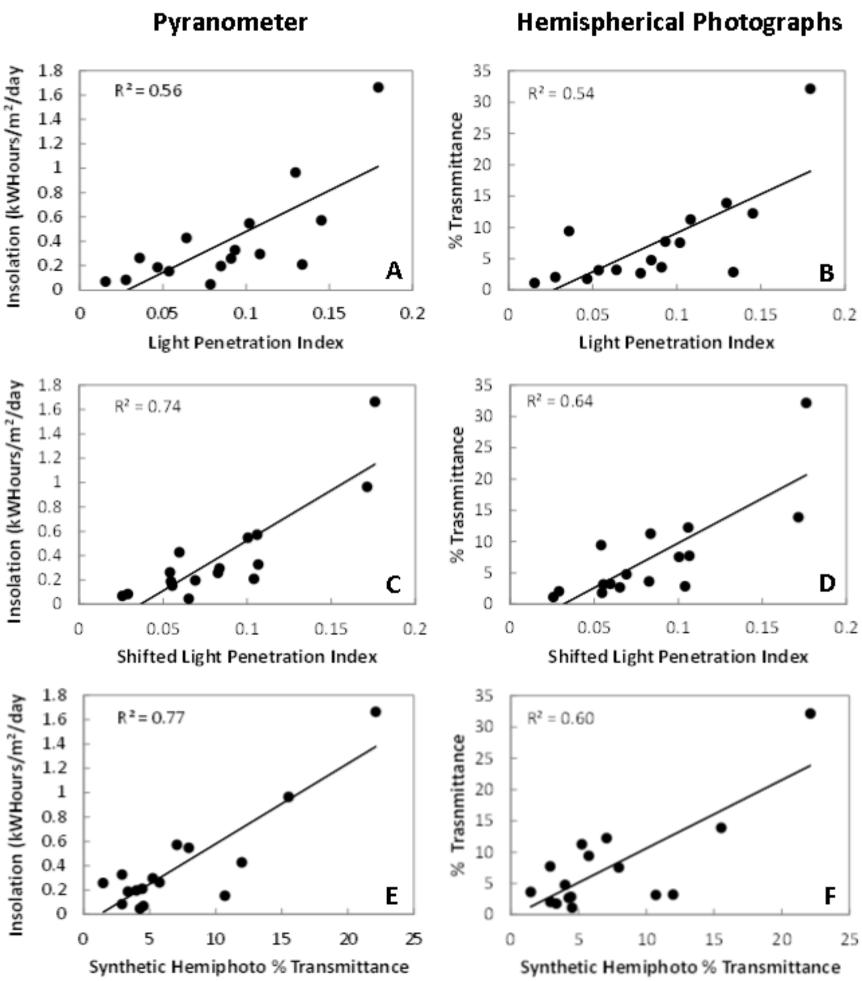


Figure 5: Comparison between pyranometer-measured solar insolation and daily diffuse and direct radiation canopy transmittance calculated from hemispherical photographs.

~~*Model Comparisons*~~ *Linear Regressions*

Pyranometer-based solar insolation and hemispherical photograph percent diffuse and direct radiation transmittance calculated at all point locations except transect A were compared to a ~~variety~~ three ~~of~~ lidar predictors using simple linear regression. These results are shown in Figure 6. The LPI calculated using a 10 m circle centered on the point location explained about 55% of the variability in both response variables, but the prediction accuracy ~~significantly~~ improved when LPI was calculated using the shifted square buffer. Shifted LPI explained 74% of the variability in solar insolation and 64% of the variability in percent transmittance. Synthetic hemispherical photographs explained 77% of the variability in solar insolation and 60% of the variability in percent transmittance. Figure 6 shows comparisons between transects B, C, and D to make interpretation easier, but Table 2 shows the results of linear regressions between predicted variables and hemispherical photograph transmittance for all plot locations resulting in small reductions in the amount of variability explained. Table 3 gives model parameters of slope and intercept resulting from the simple linear regression.


Pyranometer
Hemispherical Photographs
R² = 0.56
A
Insolation (kWHours/m²/day
Light Penetration Index
R² = 0.54
B
% Trasnmittance
Light Penetration Index
R² = 0.74
C
Insolation (kWHours/m²/day
Shifted Light Penetration Index
R² = 0.64
D
% Trasnmittance
Shifted Light Penetration Index
R² = 0.77
E
Insolation (kWHours/m²/day
Synthetic Hemiphoto % Transmittance
R² = 0.60
F
% Trasnmittance
Synthetic Hemiphoto % Transmittance

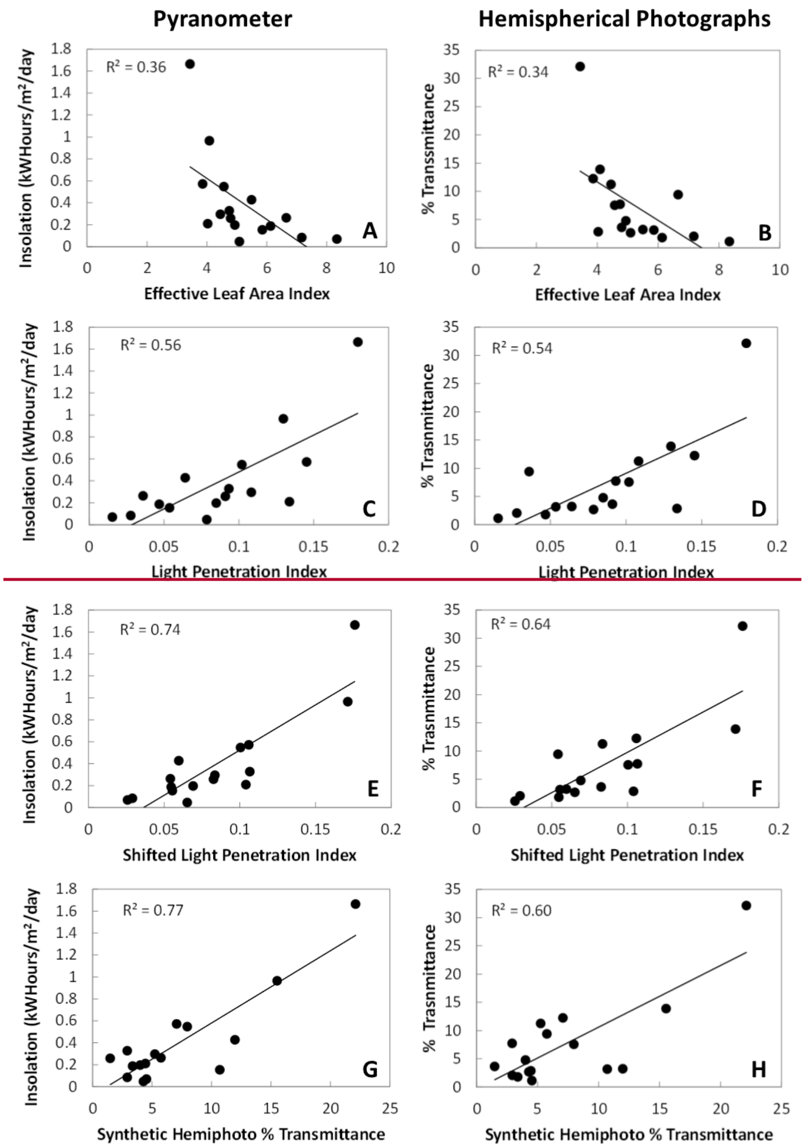


Figure 6: Simple linear regressions ~~between~~ between lidar predictor variables and field measured pyranometer solar insolation

(A, C, E) and hemispherical photograph % transmittance (B, D, F) omitting data from transect A

Table 2: Coefficients of determination for the simple linear regression between predictor variables and hemispherical photograph transmittance using three additional point locations from transect A

Predictor Variable	Coefficient of Determination (r^2)
Light Penetration Index	0.54
Shifted Light Penetration Index	0.54
Synthetic Hemispherical Photograph % Transmittance	0.45

Table 3: ~~Model p~~Parameters from simple linear regressions. Note that all regressions are significant ($p < 0.05$). Data from transect A are excluded.

Response Variable	Predictor Variable	Slope	Intercept
Hemispherical Photograph % Transmittance	~~Effective Leaf Area Index~~	~~-3.40~~	~~25.26~~
	Light Penetration Index	124.09	-3.29
	Shifted Light Penetration Index	142.2	-4.49
	Synthetic Hemispherical photograph % Transmittance	1.01	-0.32
Pyranometer Insolation	~~Effective Leaf Area Index~~	~~-0.19~~	~~1.37~~
	Light Penetration Index	6.73	-0.19
	Shifted Light Penetration Index	8.23	-0.30
	Synthetic Hemispherical Photograph % Transmittance	0.07	-0.08

While both the raster-based shifted LPI approach and the lidar point reprojection synthetic hemispherical photograph approach explained more than 60 % of the variability in the field data~~achieved satisfactory model performance~~, the limited range of solar insolation conditions at the point locations in our study may limit~~s~~ some of the conclusions that can be drawn. Excluding transect A, 14 of the 16 point locations received less than 0.8 kWHours/m^2/day, leading to the other two point locations to exert a large degree of leverage on the ~~model~~ results. Note that these two point locations received less than 35% of the maximum solar insolation. The three points in transect A all received less than 0.8 kWHours/m^2/day and their inclusion in Table 2 ~~the model results (Table 2)~~ did not improve ~~model results~~coefficients of determination, suggesting that all ~~models~~ methods are not as effective at predicting field measured values in areas of high canopy cover. The constraints of the study design requiring point locations to be located in the stream made it impossible to achieve a greater range in solar insolation. It is reasonable to expect that including more point locations receiving larger amounts of insolation would have led to improved ~~model~~ accuracy and greater coefficients of determination, as previous studies have shown that accuracy increases as canopy cover decreases (Moeser et al., 2014;Musselman et al., 2013;Richardson and Moskal, 2014). ~~In areas with no canopy and thus no lidar point returns above the ground, the models should show better agreement with field measurements.~~

One explanation of the decrease in variability ~~explained by the models at~~ at high canopy cover in regressions E and F shown in Figure is ~~is~~ demonstrated in Figure 7. Here, a synthetic hemispherical photograph from transect D is compared to a field-captured hemispherical photograph with the GLA modeled sunpath superimposed. This sunpath is critical for determining the quantity of direct light, but very small differences in the center location of the two images can produce large differences in the modeled direct light. The sunpath passes through a modeled canopy gap near solar noon on the synthetic hemispherical photograph, while it intersects only canopy and misses the gap on the field-collected hemispherical photograph. Very small registration errors can cause ~~significant~~ differences in transmittance at low light levels, and we suggest that these errors are likely to cause the errors observed in the ~~models~~regressions. The daily pyranometer output for the same point location is shown in Figure 8 to further aid comparison. The pyranometer is only briefly exposed to full sunlight, highlighting the contribution of small gaps in the canopy.

Understory vegetation is another likely cause of observed errors, as airborne lidar is inherently limited in its ability to fully sample multi-layered canopies (Richardson and Moskal, 2011). We noticed several points with ~~significant~~ differences ~~to the model results~~ between lidar predictors and field data that contained understory vegetation in close proximity to the field instruments. The ideal scenario would be for the lidar scan angles to precisely match the range of potential solar angles at each plot location, but this is currently impractical, leading to an incomplete sample of the canopy light environment which contributes to the observed errors.~~errors observed in the models.~~

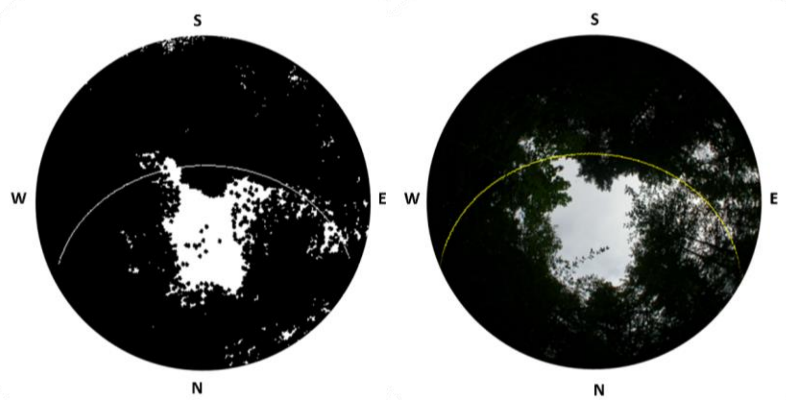


Figure 7: Sunpath superimposed on a synthetic hemispherical photograph (left) and a field acquired hemispherical photograph (right) at a point location in Transect D. The letters represent the four cardinal directions.

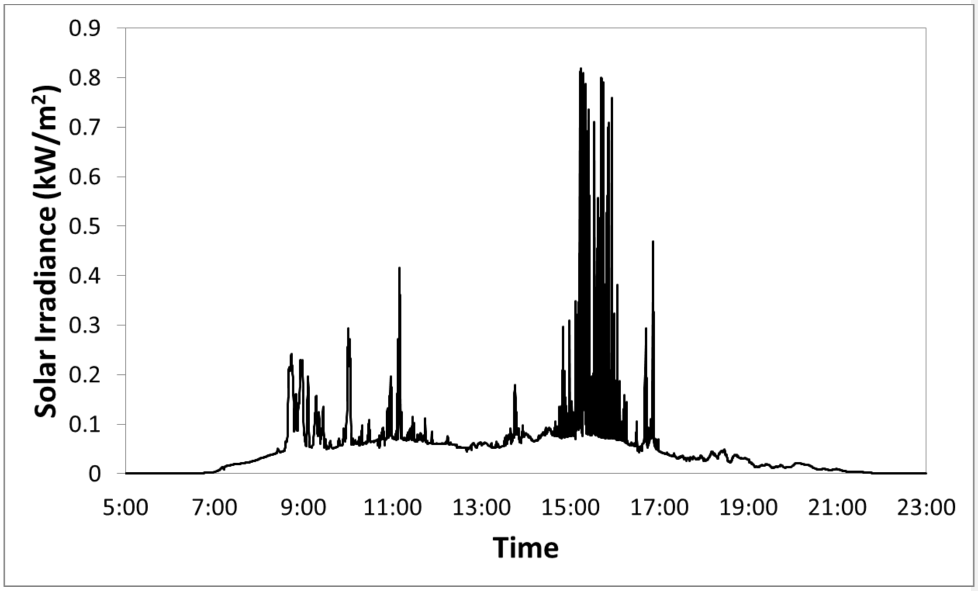


Figure 8: Daily pyranometer output from sunset to sundown for the same plot as Figure 7.

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Modeled ApplicationSolar Insolation

Model G and Model EThe correlations between lidar predictors and field data were strongest in ((Figure 6 C and Figure 6 E) performed the best and, and these lidar predictors are are both appropriate to use as the basis for estimating solar insolation across the study area. Implementation of Model G shifted *LPI* was the simplest and least time-intensive method, and we chose to model solar radiation modify Model G by multiplying shifted *LPI* by the maximum above canopy solar insolation for June 20, 2015 and then computing a non-intercept linear regression ((Figure (98). Removing the intercept from the model lowered the coefficient of determination but provided a model with very little bias, only slightly underestimating model insolationthat did not estimate negative values of solar insolation. Figure 109 shows the model applied across the study area. The graphs show the pattern of solar insolation across

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the two reaches in the study, highlighting the utility of these methods for predicting solar insolation in heavily forested streams across wide spatial extents. Figure 11~~0~~ shows the relative frequency of binned solar insolation values, highlighting the dominance of heavily shaded areas (note that a dammed reservoir, point D on the map, contributes the majority of the points in full sun).

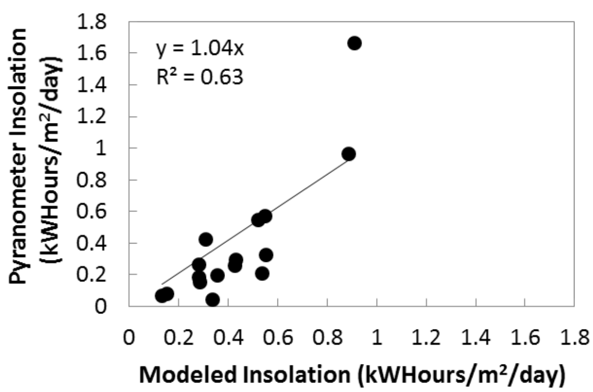

Figure ~~8~~9: Model used for generation of landscape scale solar insolation estimates

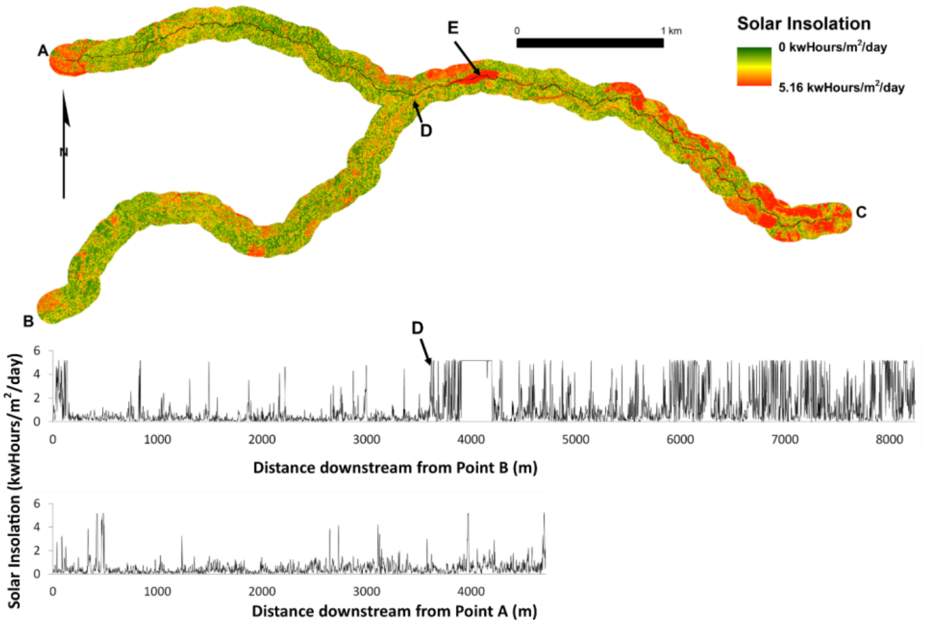

Figure 109: Map of model derived solar insolation for Panther Creek (top) and graph of model derived solar insolation for reach A-C (middle) and reach B-D (bottom). Point E is a dammed reservoir. Note the direction of flow is toward point C

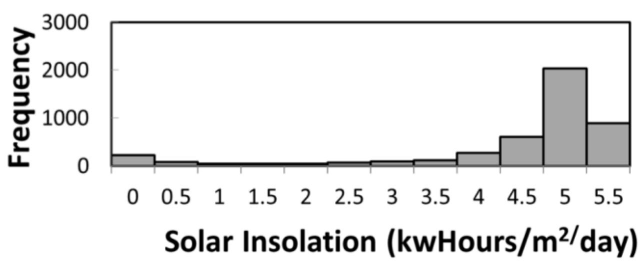

Figure 1110: Histogram of solar insolation pixel values along reach A-C from Figure 9

The relatively unbiased results shown in Figure 9~~8~~ show that field calibration is not required to produce accurate estimates of solar insolation. However, information is still needed on local above-canopy meteorological conditions, which can either be modeled from known solar outputs or collected from a nearby meteorological station. Little bias was observed in comparisons between synthetic hemispherical photograph transmittance and field-based hemispherical photograph transmittance (Table 3). Therefore, both approaches tested in this study should not require field calibration.

D.   Conclusions

We tested two approaches for estimating solar insolation from airborne lidar using field data collected in a heavily forested narrow stream, showing that an LPI-based raster approach and a synthetic hemispherical photograph approach can~~accurately~~ predict solar insolation and light transmittance. These results should be interpreted with the caveat that our point locations contained few areas with high insolation. We showed that the LPI-based model can be applied across the landscape, and we demonstrated that no field-based calibration was necessary to produce unbiased prediction of solar insolation.

This study lays the groundwork for additional research on remote sensing methods for quantifying light conditions in riparian areas over heavily forested streams. ~~First, point-cloud based approaches utilizing ray-tracing need to be further developed. The results of this study suggest that refined ray-tracing approaches should not require calibration. Ray-tracing is perhaps the most elegant method for accurately modeling the relationship between lidar points and the sun, but this method requires a large amount of computational power to model multiple sun angles for each lidar point~~One method that we were unable to test is ray-tracing and future research should continue to develop this approach. Second, research should focus on exploring the limit of matching ground-based measurements to lidar-predicted solar insolation. Lastly, the limitation of aerial lidar to quantify understory light conditions in multi-layered canopies should be explored in more detail to better understand when and if airborne sensors are inappropriate for these particular applications. In these circumstances, other sensors such as terrestrial lidar or ground-based digital photographs utilizing structure from motion may provide additional useful information.

E. Data availability

The GPS data, pyranometer data, processed hemispherical photograph data, spreadsheets used for data analysis, and access to the LiDAR data can be found at https://doi.org/10.17632/vwmxw4hcj7.1

F. Acknowledgements

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