Remote sensing for species distribution models: An illustration using sentinel taxon of world's driest ecosystem



Khum B. Thapa-Magar, Eric R. Sokol, Michael N. Gooseff, Mark R. Salvatore, John E. Barrett, Joseph S. Levy, Paul Knightly, Sarah N. Power

Institute of Arctic and Alpine Research, University of Colorado, Boulder

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Species Distribution Models(SDMs)

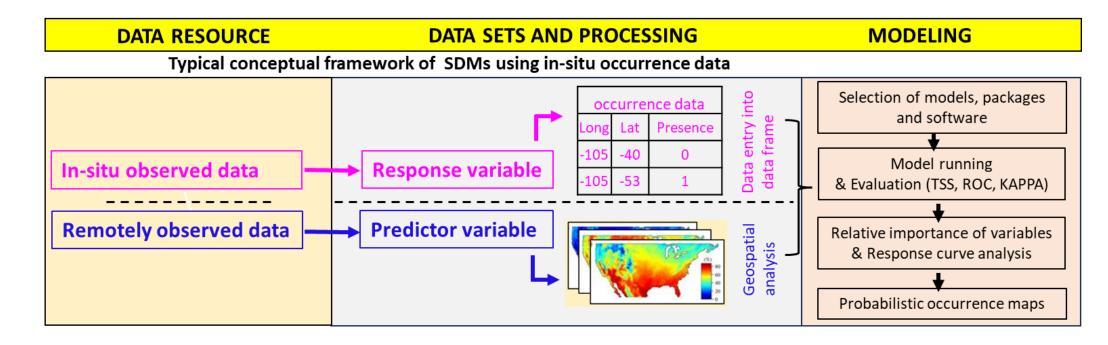
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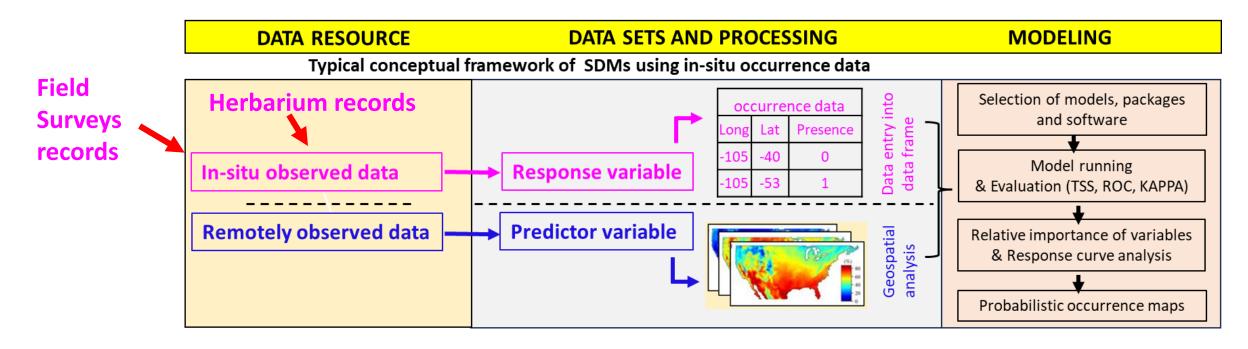
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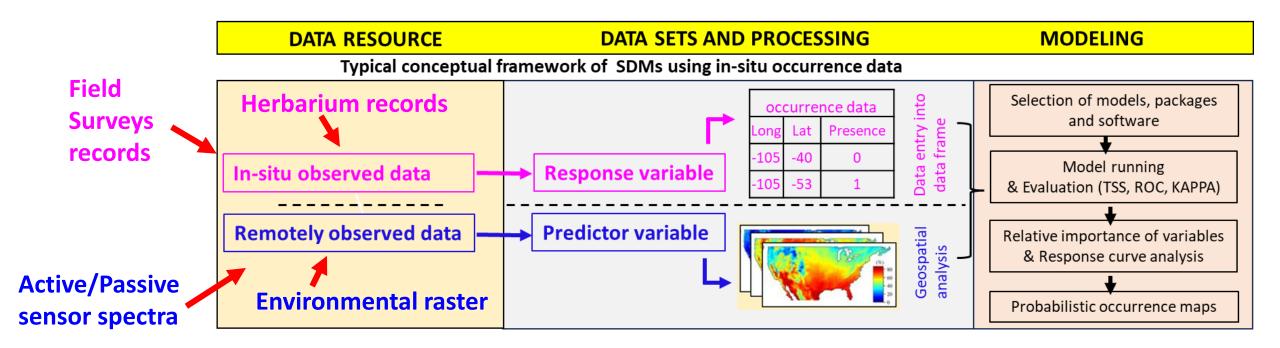
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- >Among them, Species Distribution Models (SDMs), particularly correlative SDMs are popular in ecological research

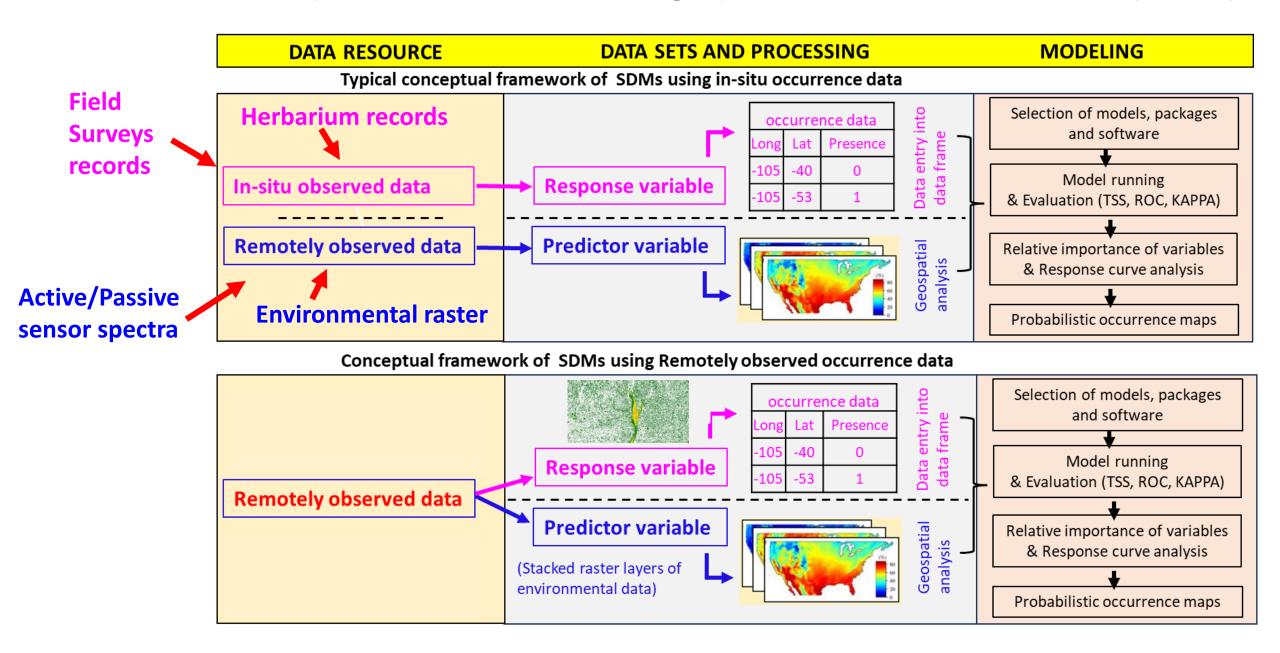
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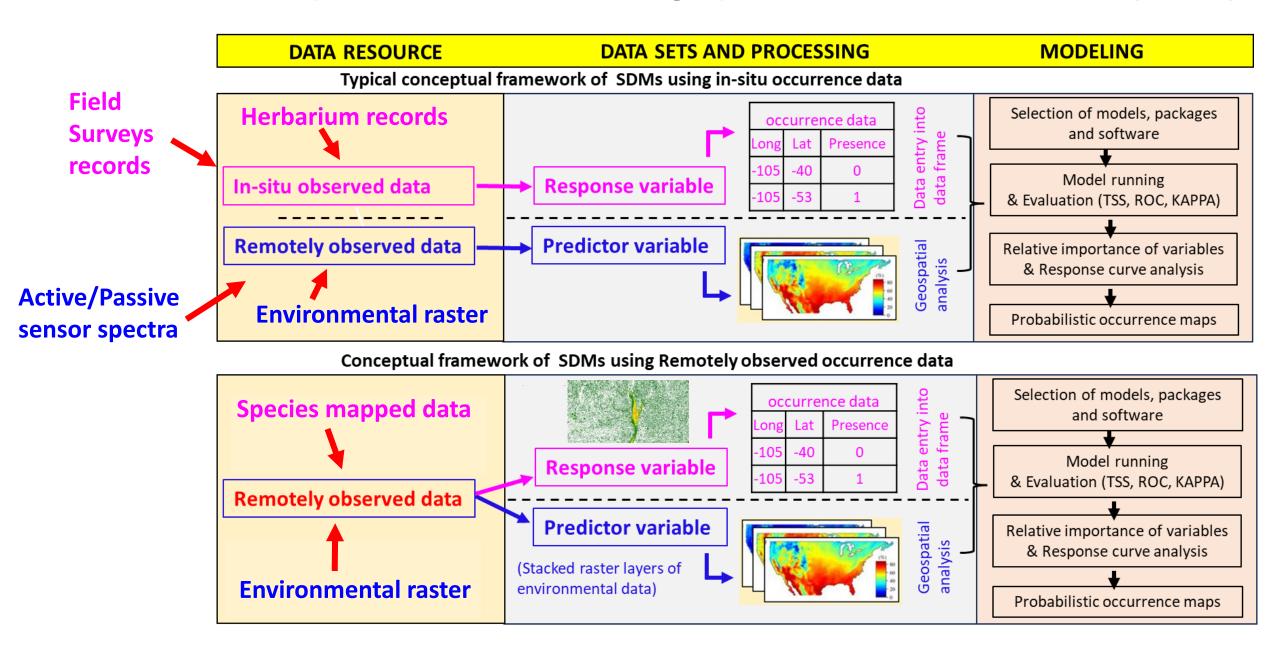
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- >Correlative **SDMs predict** the potential current and future distribution of biological organisms
- >SDMs are important for species management and conservation area planning

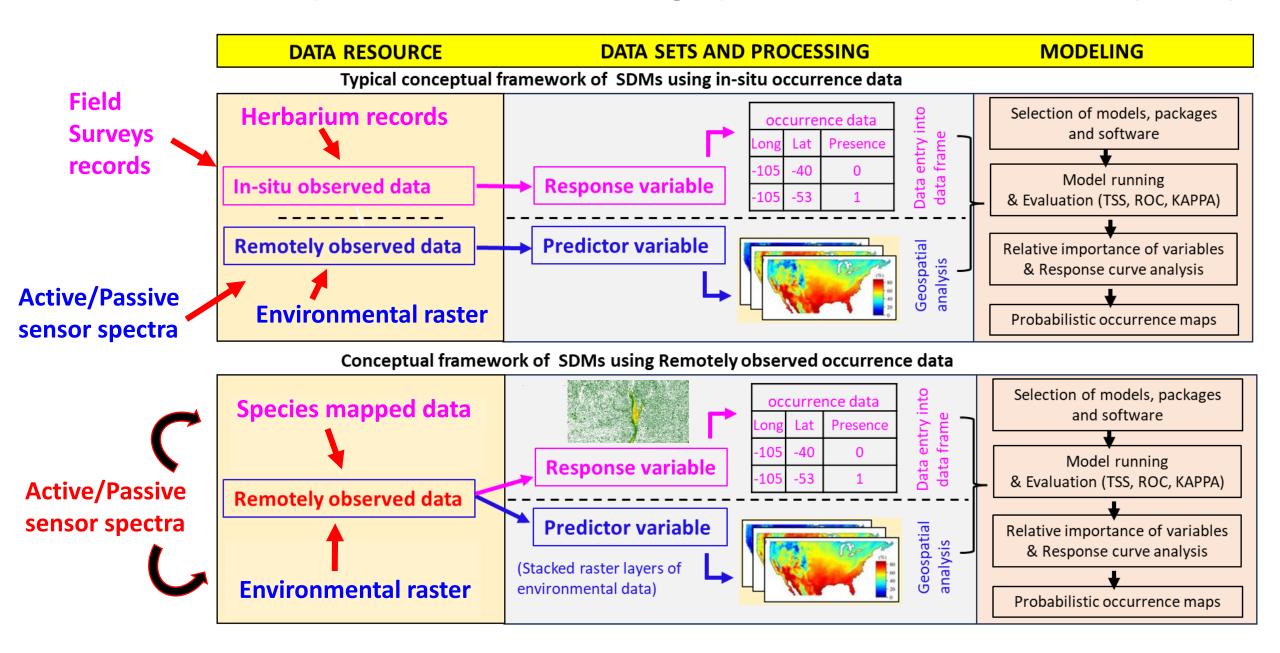












Benefits of Remotely observed data into SDMs



- > Reduce sampling biases
- > Can sample data in remote areas
- > Can minimize the human error

Trends in using Remotely observed data into SDMs

Example of SDMs using remotely estimate of species occurrence

Diversity and Distributions, (Diversity Distrib.) (2009) 15, 627–640 2009



Habitat suitability modelling of an invasive plant with advanced remote sensing data

Margaret E. Andrew* and Susan L. Ustin

Expanding ensembles of species present-day and future climatic suitability to consider the limitations of species occurrence data 2020



Ying Tang^{a,b}, Julie A. Winkler^{a,*}, Andrés Viña^{b,c}, Fang Wang^b, Jindong Zhang^b, Zhiqiang Zhao^b, Thomas Connor^b, Hongbo Yang^b, Yuanbin Zhang^d, Xiaofeng Zhang^e, Xiaohong Li^f, Jianguo Liu^b

Reviews on remotely estimates data in SDMs analysis

Remote Sensing in Ecology and Conservation





INTERDISCIPLINARY PERSPECTIVES 2015

Will remote sensing shape the next generation of species distribution models?

Kate S. He¹, Bethany A. Bradley², Anna F. Cord³, Duccio Rocchini⁴, Mao-Ning Tuanmu⁵, Sebastian Schmidtlein⁶, Woody Turner⁷, Martin Wegmann^{8,9} & Nathalie Pettorelli¹⁰

Monitoring biodiversity in the Anthropocene using remote sensing in species distribution models 2020



Christophe F. Randin^{a,b,c}, Michael B. Ashcroft^d, Janine Bolliger^e, Jeannine Cavender-Bares^f, Nicholas C. Coops^g, Stefan Dullinger^h, Thomas Dirnböckⁱ, Sandra Eckert^j, Erle Ellis^k, Néstor Fernández^{l,m}, Gregory Giulianiⁿ, Antoine Guisan^{a,c,o}, Walter Jetz^p, Stéphane Joost^q, Dirk Karger^e, Jonas Lembrechts^r, Jonathan Lenoir^s, Miska Luoto^t, Xavier Morin^u, Bronwyn Price^e, Duccio Rocchini^{v,w,x,y}, Michael Schaepman^z, Bernhard Schmid^{aa}, Peter Verburg^{ab,e}, Adam Wilson^{ac}, Paul Woodcock^{ad}, Nigel Yoccoz^{ae}, Davnah Payne^{af,*}

Remote Sensing in Ecology and Conservation



REVIEW

2022

Mainstreaming remotely sensed ecosystem functioning in ecological niche models

Adrián Regos^{1,2,3,4} (D), João Gonçalves^{2,4} (D), Salvador Arenas-Castro^{2,4,5,6} (D), Domingo Alcaraz-Segura^{7,8} (D), Antoine Guisan^{9,10} (D) & João P. Honrado^{2,4,11} (D)

^a Department of Geography, Environment, and Spatial Sciences, Michigan State University, East Lansing, MI, United States

b Center for Systems Integration and Sustainability, Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI, United States

^c Department of Geography, University of North Carolina, Chapel Hill, NC, United States

d Institute of Mountain Hazards and Environment, Chinese Academy of Sciences, Chengdu, Sichuan, China

^e Shaanxi Forestry Department, Xi'an, Shaanxi, China

f Tianshui Normal University, Tianshui, Gansu, China

Objectives of our study

Specifically, we will:

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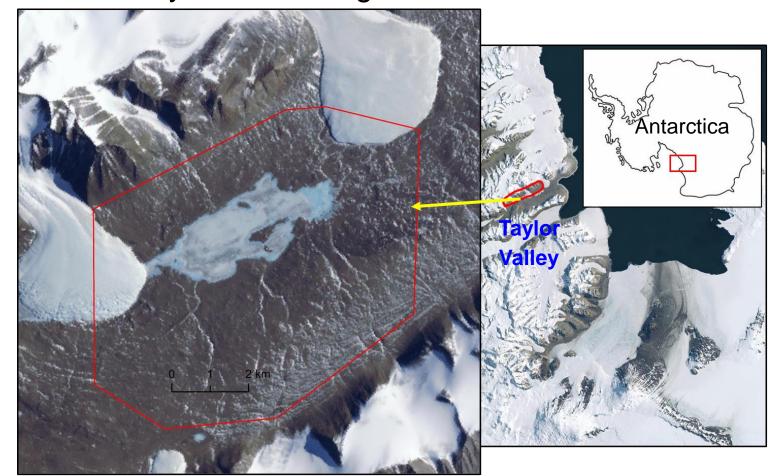
- >Use species occurrence data derived from high resolution multispectral images from worldview 2 in species distribution models (SDMs)
- >Identify the environmental factors that are important for *Nostoc* spp. distribution
- >Identify hotspot areas for *Nostoc* spp.

METHODOLOGY

Study area

- > AOI are good habitats of modeling species
- >We know where modeling species are inside AOI
- >Diverse predictor variables are already estimated in AOI

Lake Fryxell basin region



Modeling species

- >Nostoc spp. are primary producers
- > Endemic to AOI and whole Antarctic regions
- > Good example for SDMs in remote ecosystems

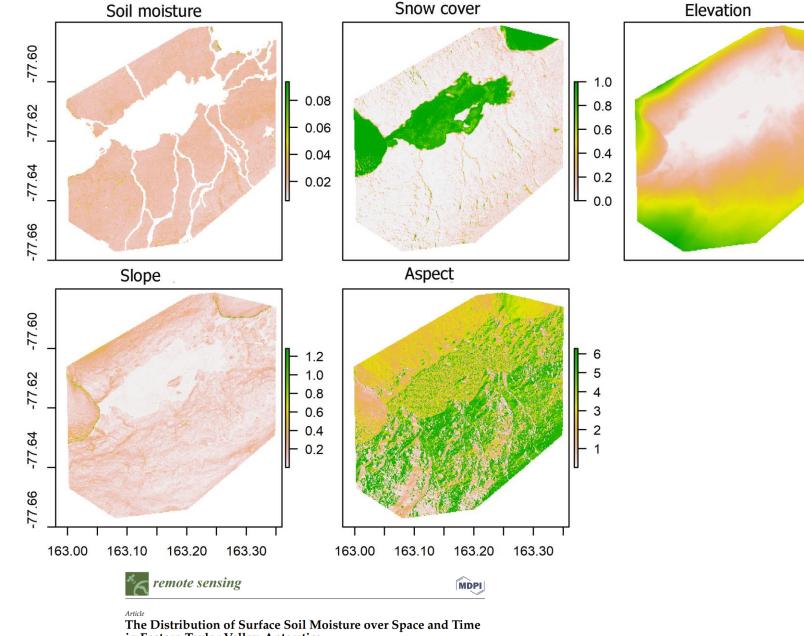


Predictor variables

>Soil moisture and snow cover were derived from Worldview-2 images from unmixing modeling

More detail in Salvatore et al 2023

>DEM layers derived from LiDAR data



150

100

in Eastern Taylor Valley, Antarctica

Mark R. Salvatore 1,*, John E. Barrett 2, Laura E. Fackrell 1,30, Eric R. Sokol 40, Joseph S. Levy 500 Lily C. Kuentz 5,6, Michael N. Gooseff 7, Byron J. Adams 80, Sarah N. Power 2, J. Paul Knightly 10, Haley M. Matul 1, Brian Szutu 1 and Peter T. Doran 5

Nostoc spp. mapped raster

Response variables

- >Raster output of *Nostoc* spp. abundance quantified using a linear unmixing on a calibrated WorldView-2 image
- >For more detail see Salvatore et al 2021

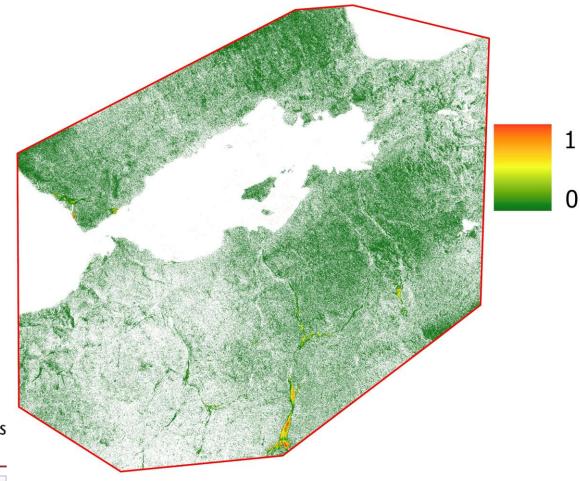
INTERNATIONAL JOURNAL OF REMOTE SENSING 2021, VOL. 42, NO. 22, 8597–8623 https://doi.org/10.1080/01431161.2021.1981559





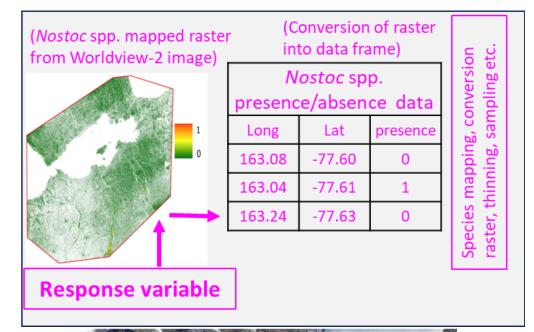
Counting Carbon: Quantifying Biomass in the McMurdo Dry Valleys through Orbital & Field Observations

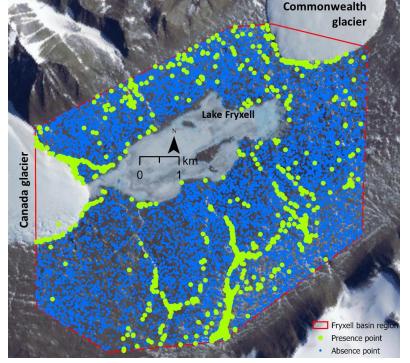
Mark R. Salvatore (Da, John E. Barrett (Db, Schuyler R. Borges (Da, Sarah N. Power (Db, Lee F. Stanish (Dc, Eric R. Sokol (Dc, and Michael N. Gooseff (Dc, e)



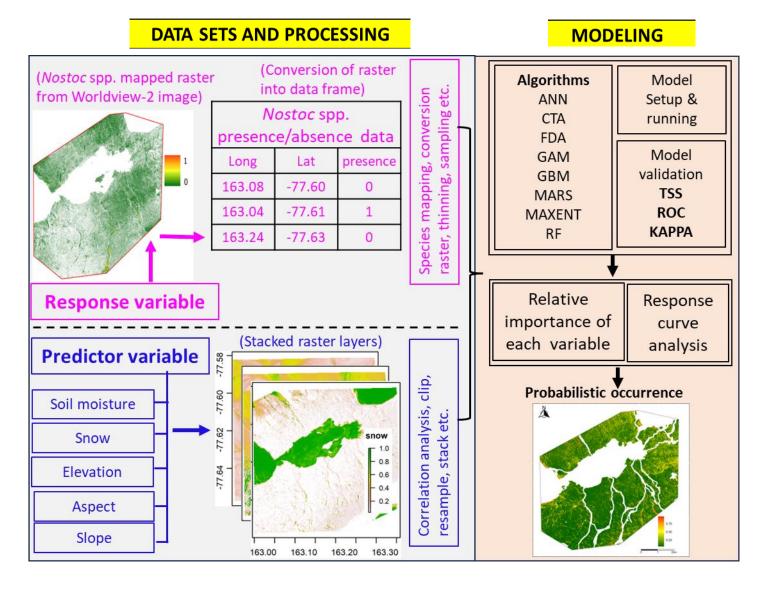
Species occurrence from species mapped raster

- Masked raster into AOI
- >Converted masked raster into points of a data frame of coordinates and pixel values
- >Classified the pixel values: greater >5% (0.05) = presence, less than 0.1% (0.001) = absent point (0) and between 0.% and 5% = NA.
- >Thinned by 20m distance using spThin R packages
- >Randomly selected 1000 presence and 10,000 absence points





Modeling



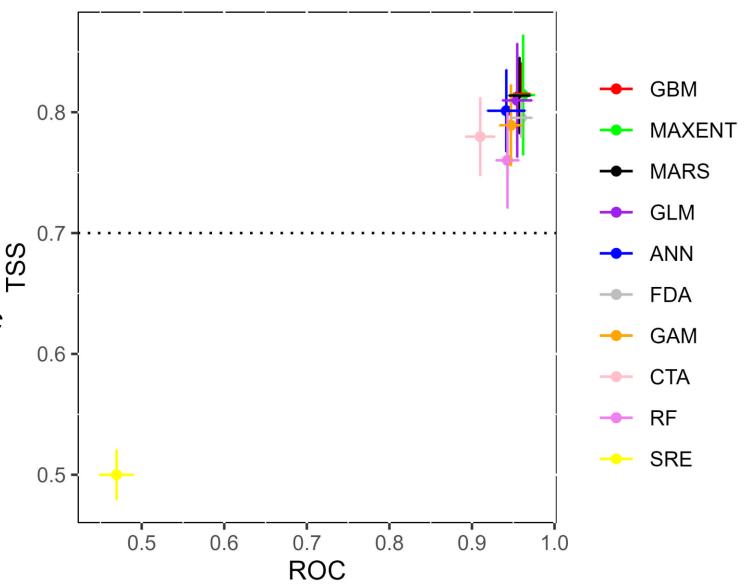
- > R package "biomod2"
- > 10 algorithms used in the SDMs
- > 70% data train & 30% to validate the model's performance
- Model ran for five times with total of 50 modeled results
- > TSS & ROC scores evaluated the models
- > TSS values range from -1 to +1. TSS< 0.50 low, 0.50 to 0.70 moderate and >0.70 good.
- > TSS >= 0.70 were included in ensemble models

RESULTS & DISCUSSION

Model evaluation

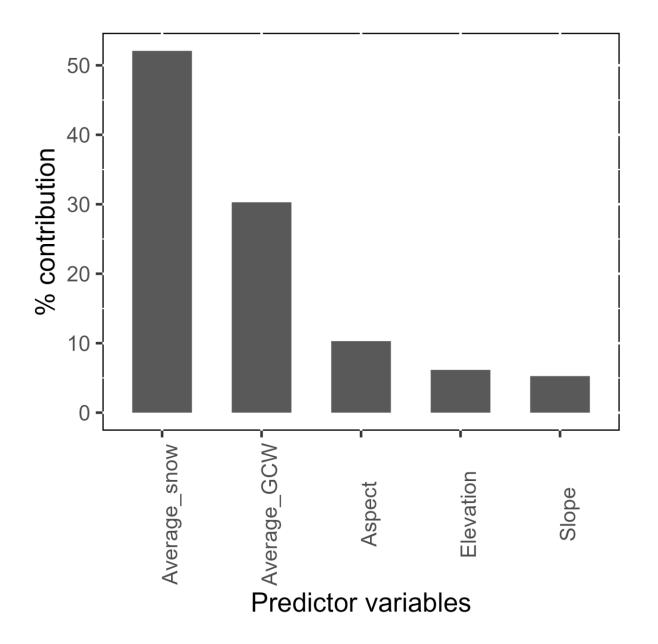
>Average TSS and AUC value of 0.79 and 0.90 respectively

>GBM, GLM, MAXENT etc. are good algorithms for *Nostoc* distribution



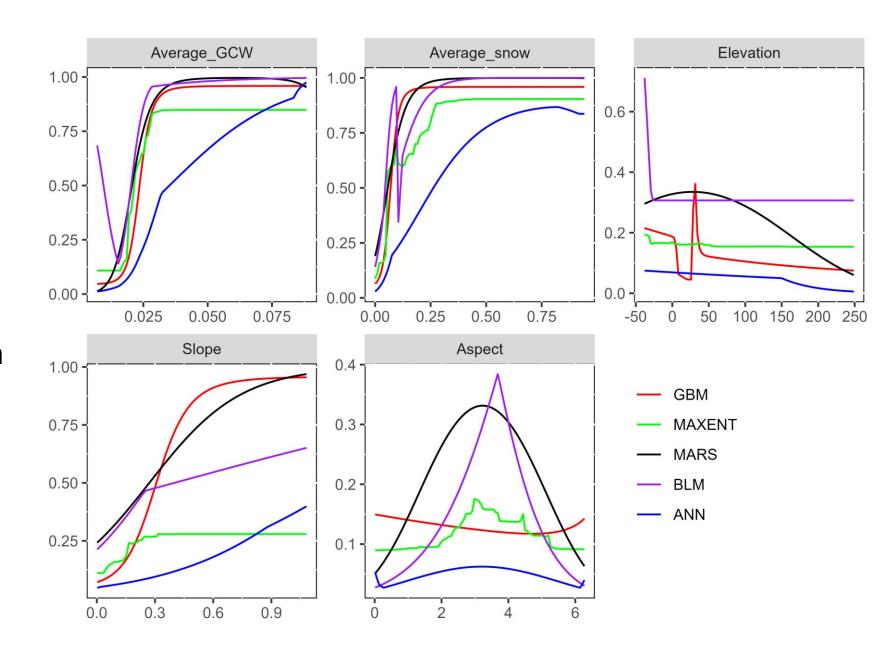
Predictor variables contribution in distribution of Nostoc spp.

- Snow cover & soil moisture contributed 80% of *Nostoc* distribution
- >DEM variables contributed 20% of *Nostoc* distribution



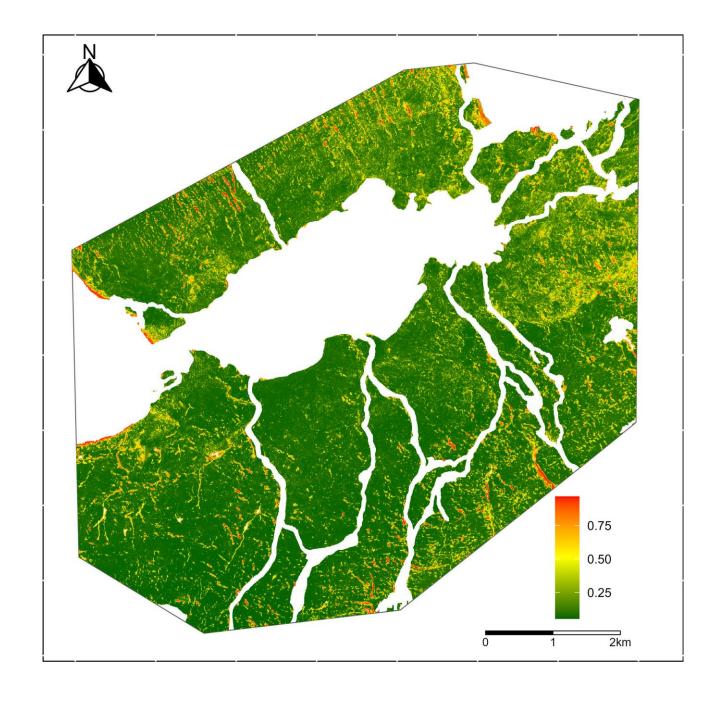
Response curve

- >Asymptote relation with snow cover & soil moisture
- Increasing trends with slope, unimodal with slope



Nostoc spp potential distribution

- >Scattered throughout the Fryxell basin region
- >Hotspots: edges of glaciers, lakes, streams, patches of moisture soils



CONCLUSIONS

>Able to run the ensemble SDMs with remotely estimate species occurrence in Biomod2 R package

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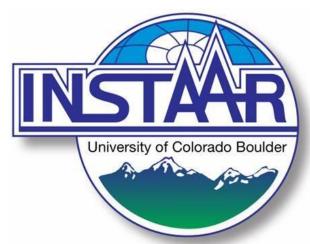
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- >Water related variables such as **snow cover** and **soil water** contributed **80%** of *Nostoc* distribution

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- >Able to run the ensemble SDMs with remotely estimate species occurrence in Biomod2 R package
- >Water related variables such as **snow cover** and **soil water** contributed **80%** of *Nostoc* distribution
- >Edges of glaciers, lakes and streams are hotspots for *Nostoc* spp. distribution

AKNOWLEGEMENTS







THANK YOU