Academic Symposium on Sustainable Agricultural Development in Central Asia.
12 - 13 October 2023
Tashkent, Uzbekistan

Simulating Mountain Snowpack and Seasonal Water Availability in Central Asia

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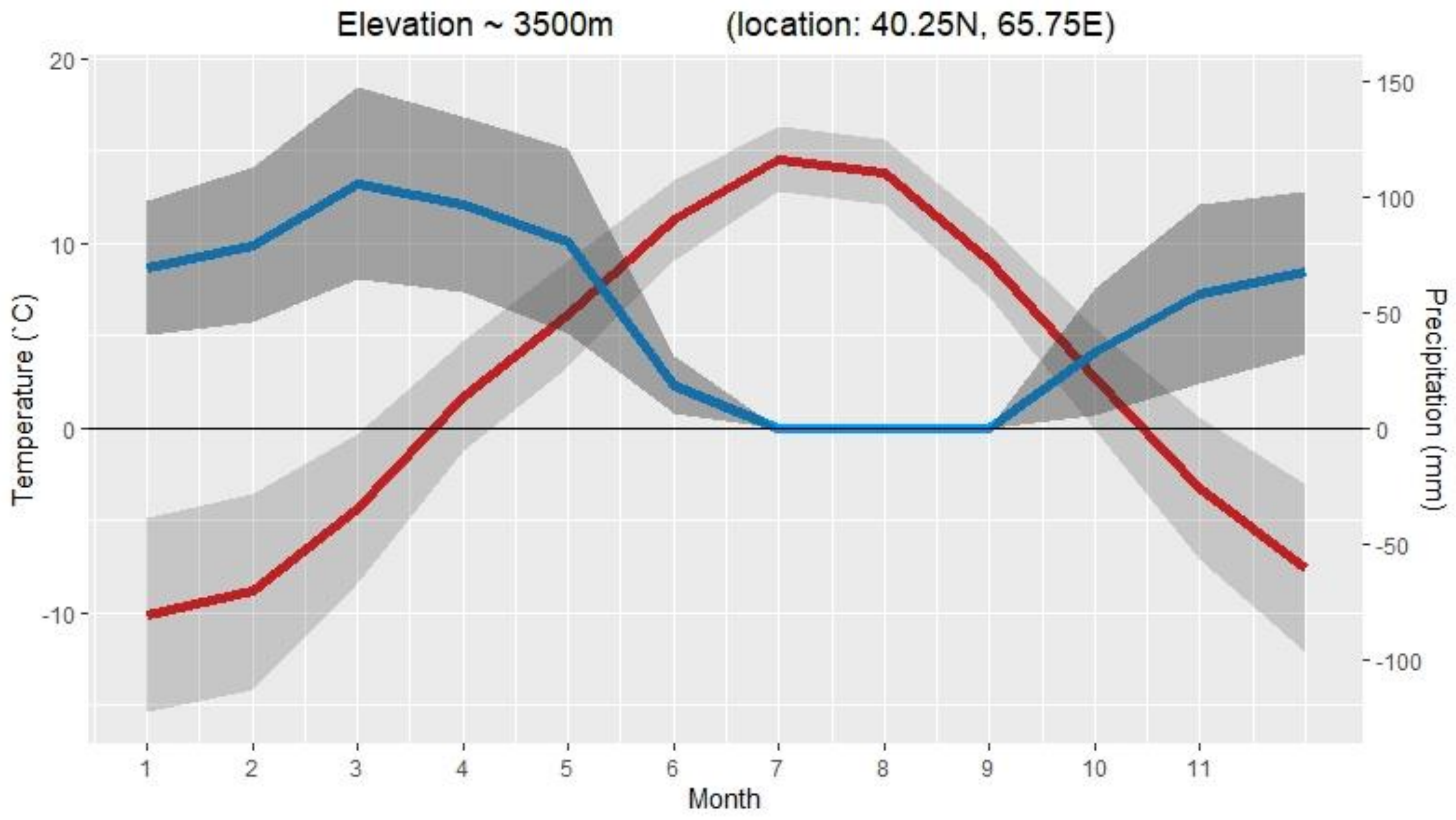
Prof. Dr. Daniel Müller

The mountains are "water towers" in the region

Source: http://www5.worldbank.org

Seasonal climate variability in the mountainous areas



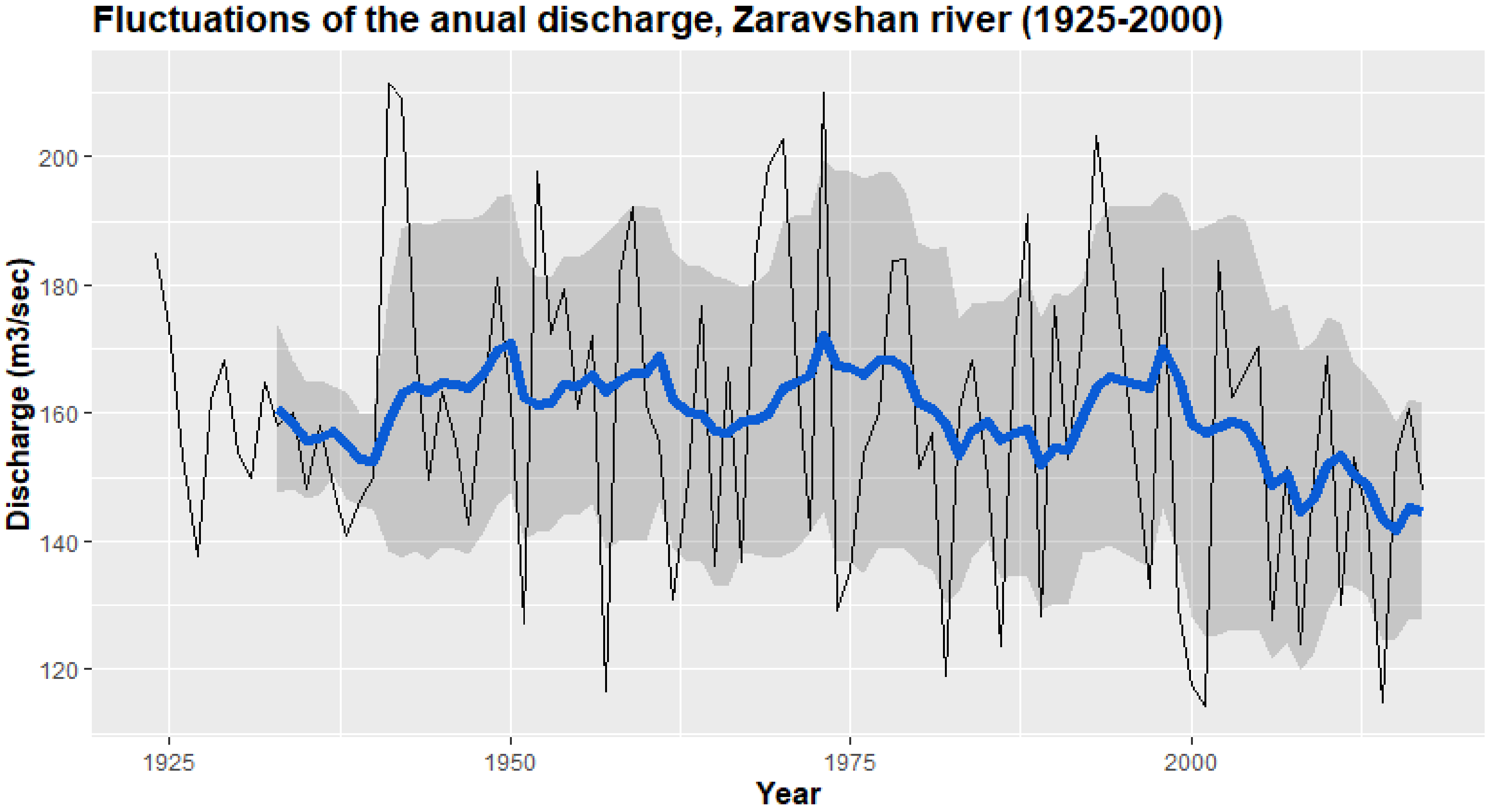
Data: CRU TS v. 4.01 - Harris et al 2014

- Inverse seasonal patterns between temperature and precipitation
- Higher seasonal volatility of precipitation and temperature during winter-spring time
- Winter-spring snowpack as a water storage for summer discharge

Hydrological variability

Seasonal climate and snowpack variability determines hydrological volatility in the region

seasonal water availability uncertainty



Chapter II

"Generalizable empirical model of snow accumulation and melting based on learning from daily snowmass changes in response to climate and topographic drivers"

Background

- Many snow models of varying complexities exist
- Data availability issues in the region:
  - few data type options as input for the model
  - no snow observations in the region (hard to calibrate and validate if a model is accurate)
- Few snow studies in the region

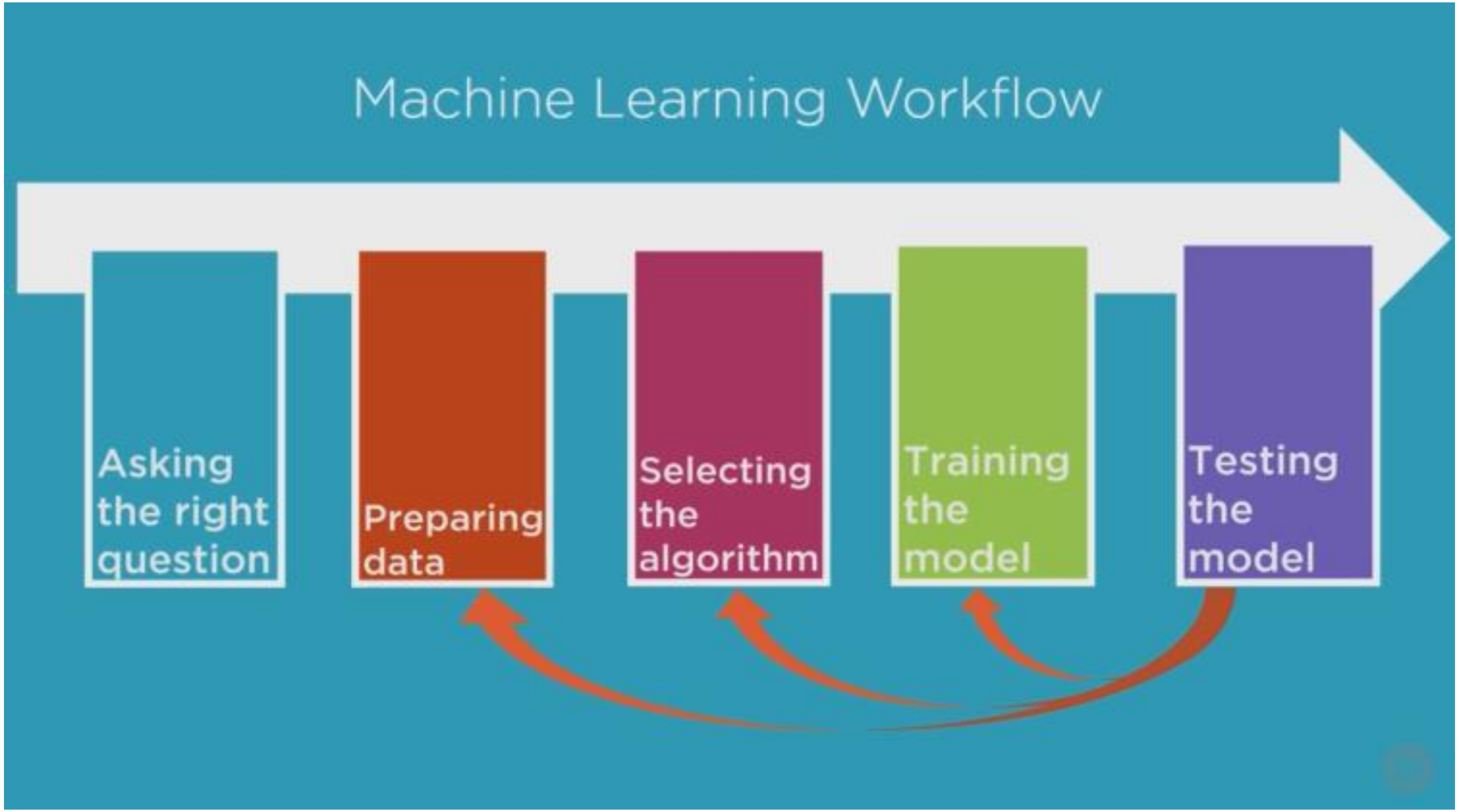
The approach

1. Develop an empirical snow model using extensive snow and climate observations

2. Evaluate the model using locations/data which were not used for its development

3. Evaluate the model performance in your study area using proxy data

Machine learning as a modelling platform

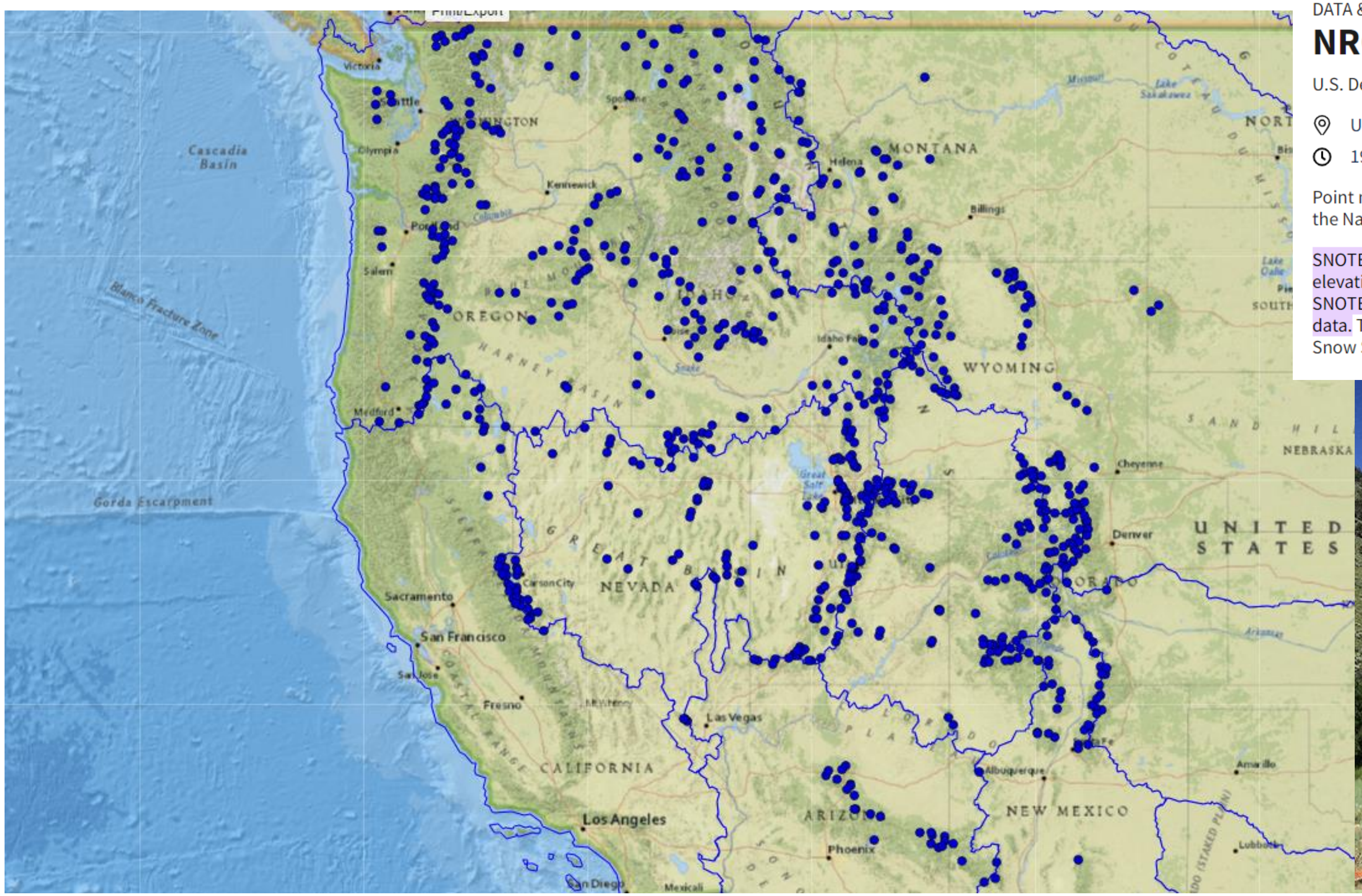


https://www.linkedin.com/pulse/machine-learning-workflow-rao-nisar/

Machine learning as a modelling platform

$$\text{snow water equivalent} = f\,(\text{climate} + \text{topographic variables})$$

Data: Where the snow data is abundant?



DATA & MAPS

NRCS SNOTEL and Snow Course Data

U.S. Department of Agriculture's (USDA's) National Resources Conservation Service (NRCS)

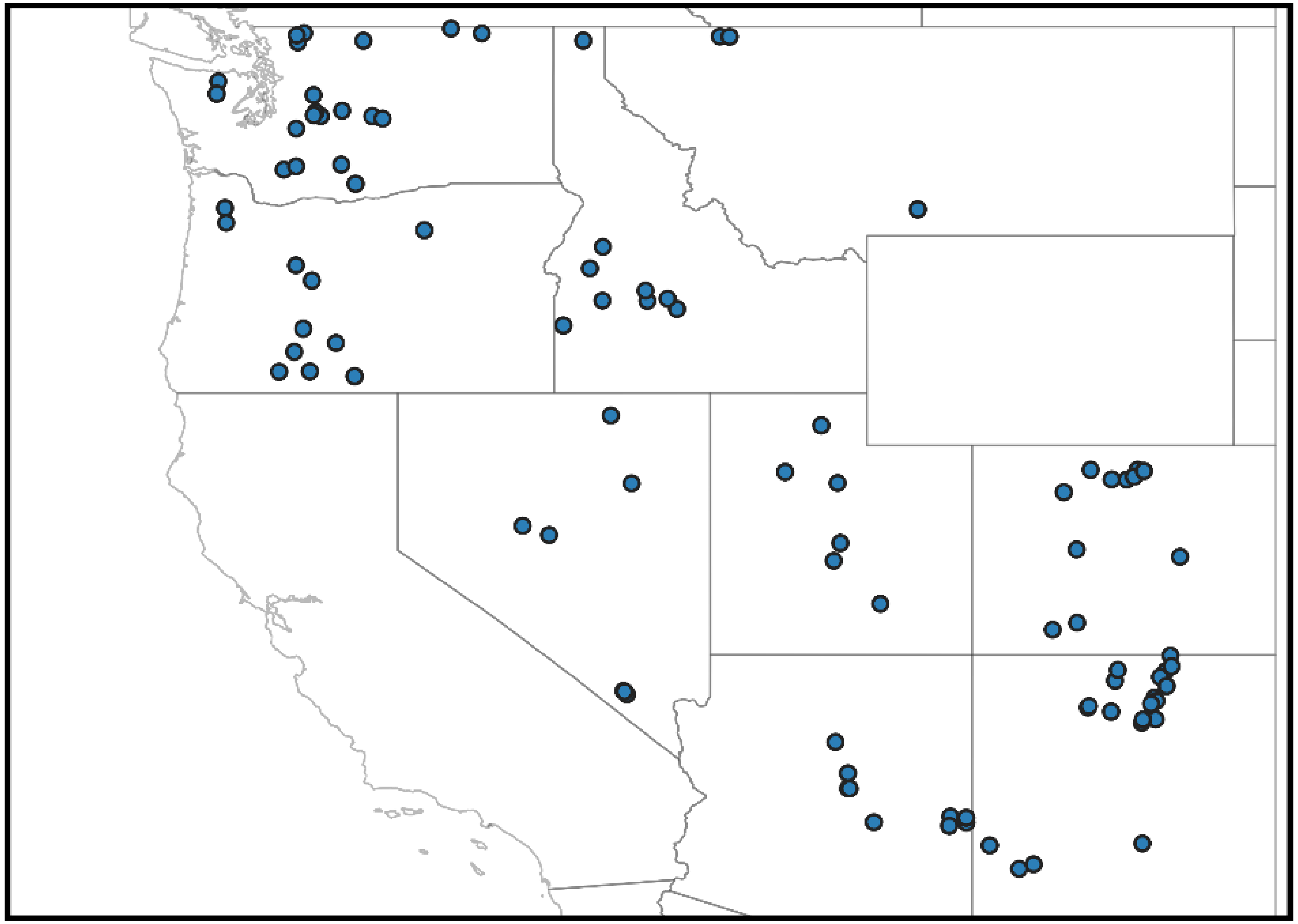
United States | Land-based Station
1980 - present | images

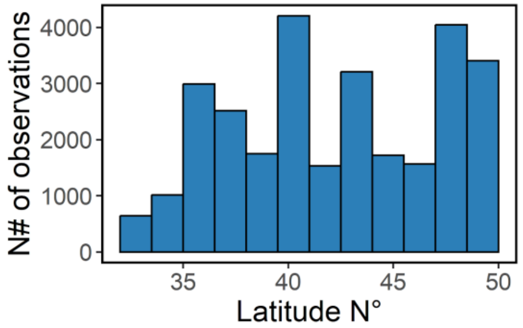
Point maps and interactive maps of snow water equivalent, snow depth, and snow density from the Natural Resources Conservation Service (NRCS) Snow Telemetry (SNOTEL).

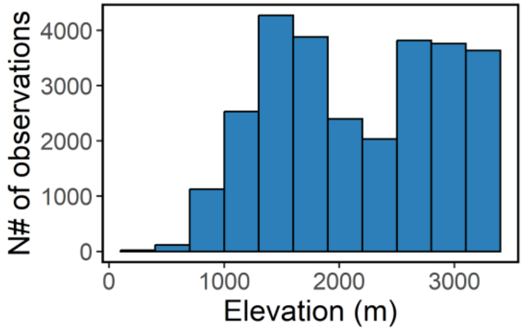
SNOTEL is an automated near real-time data collection network that provides mid- to high-elevation hydroclimatic data from mountainous regions of the western United States. A standard SNOTEL station provides snow water equivalent, snow depth, precipitation, and temperature data. The SNOTEL network is maintained by the USDA Natural Resources Conservation Service Snow Survey and Water Supply Forecasting Program.

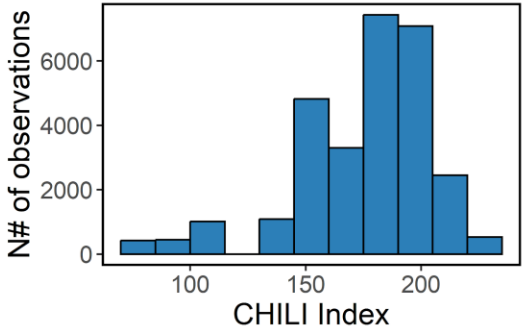
Source: National Water and Climate Center, USDA https://www.wcc.nrcs.usda.gov/snow/snow_map.html

Location of 96 SNOTEL stations used for training the SVR









Climate and topographic data used to train the model

Precipitation (mm)
Mean daily temperature (C°)
Maximum daily temperature (C°)
Minimum daily temperature (C°)
Rolling sum of temperature over preceding 3 days (C°)
Cumulative sum of precipitation over preceding 3 days (mm)

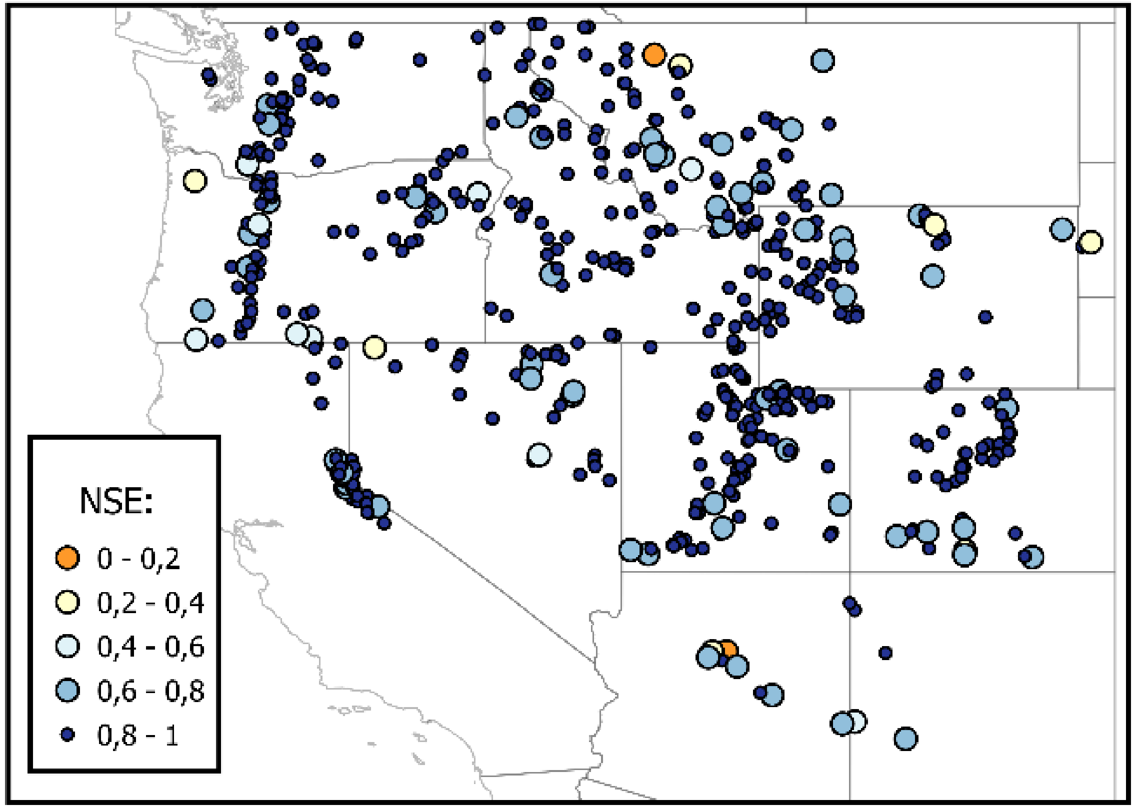
Daylength (hours)
Elevation (meter)
Heat-insolation index

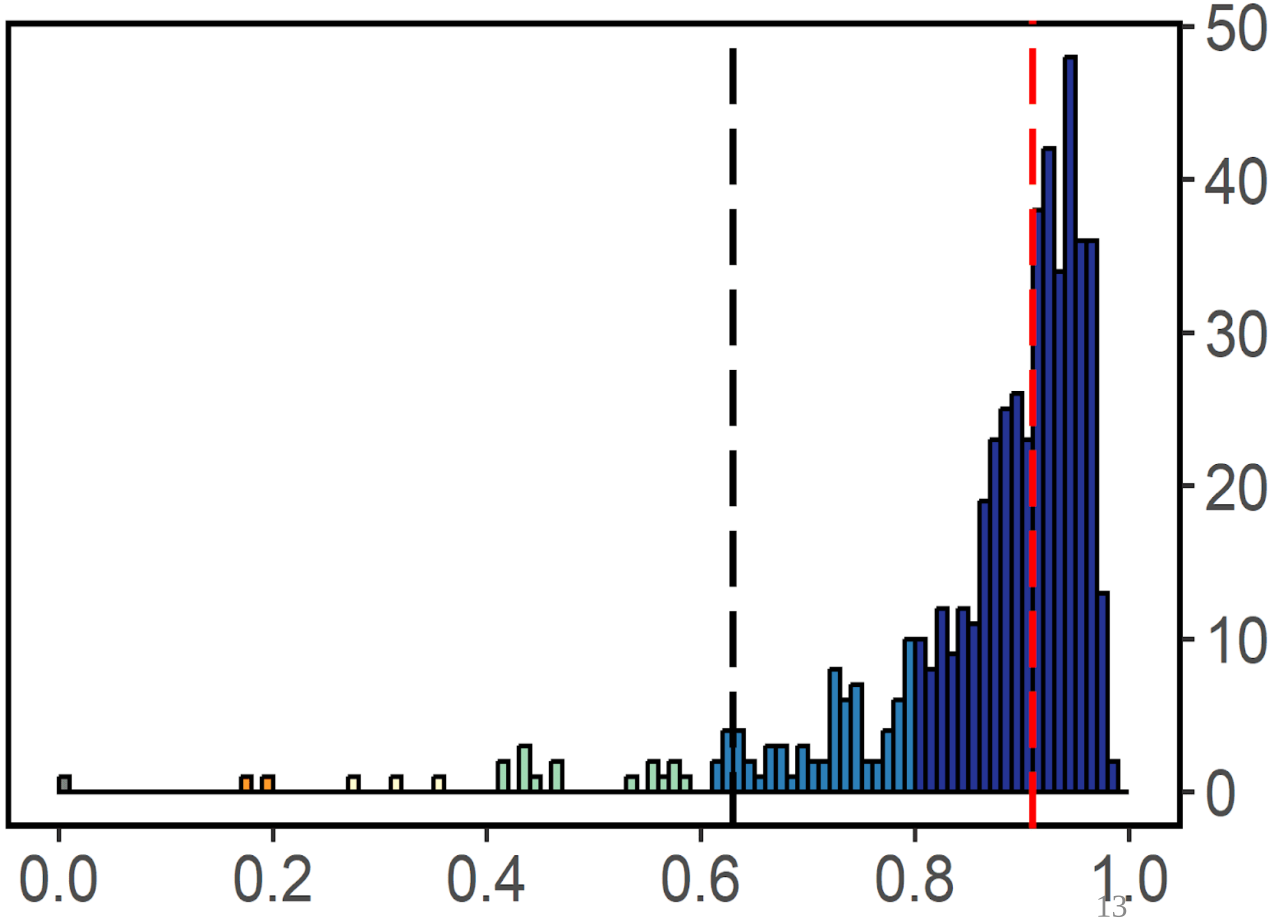
daily change of Snow water equivalent (mm)

Model evaluation I

Using observations from independent 520 SNOTEL stations from 2012 to 2022

Nash-Sutcliffe efficiency (NSE)



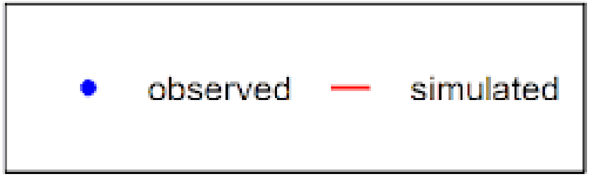


Model evaluation II

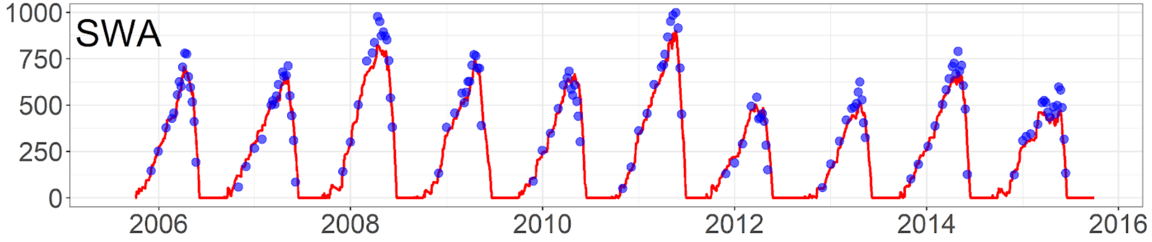
- *Using reference stations data from Snow models intercomparison project (SnowMIP)*

Site	Elevation (m)	Köppen climate classification
Col de Porte, France	1325	Warm-summer humid continental climate
Reynolds Mountain, East Idaho, USA	2060	Warm-summer humid continental climate
Sapporo, Japan	15	Hot summer continental climates
Senator Bec, Colorado, USA	3714	Polar and alpine (montane) climates
Swamp Angel, Colorado, USA	3371	Subarctic climate
Sodankylä, Finland	179	Subarctic climate
Weissfluhjoch,Switzerland	2536	Polar and alpine (montane) climates

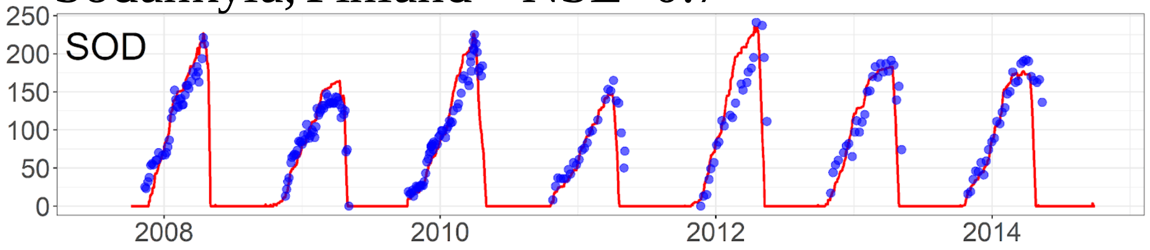
Model evaluation II



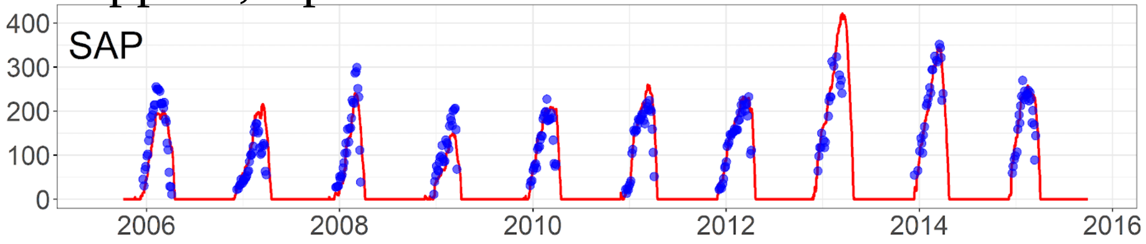
Swamp Angel, Colorado, USA NSE=0.86



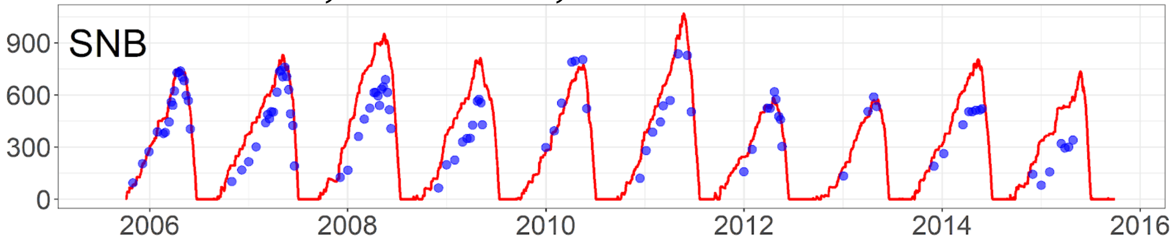
Sodankylä, Finland NSE=0.7



Sapporo, Japan NSE=0.72

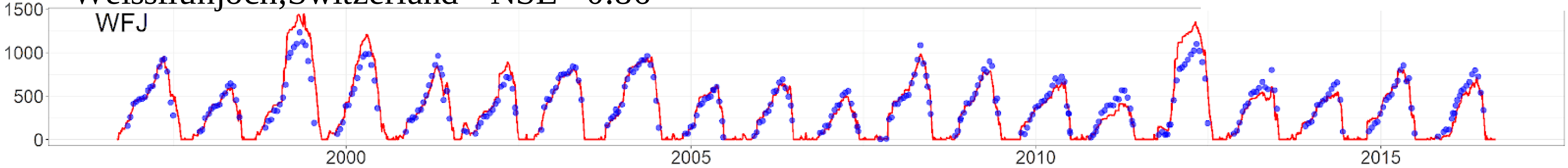


Senator Bec, Colorado, USA NSE= 0.35

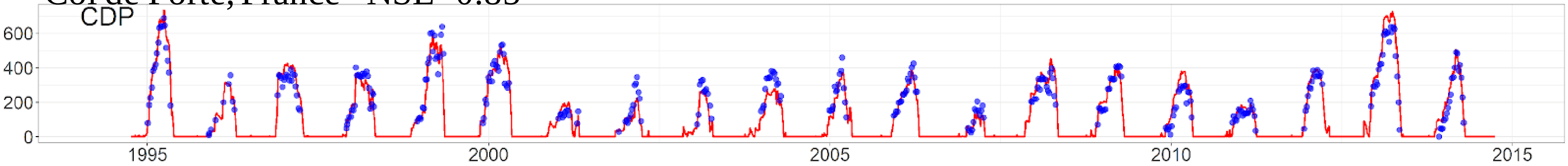


Model evaluation II

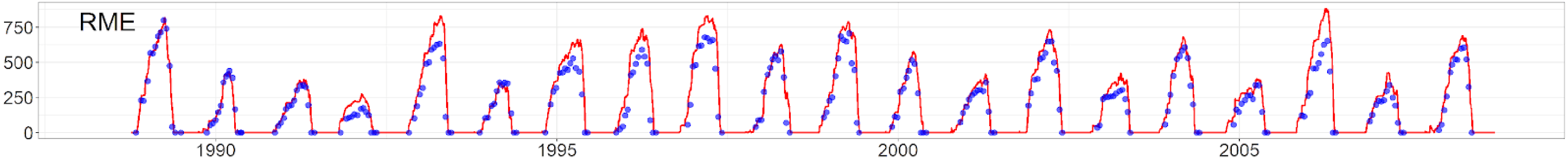
Weissfluhjoch,Switzerland NSE= 0.86



Col de Porte, France NSE=0.85

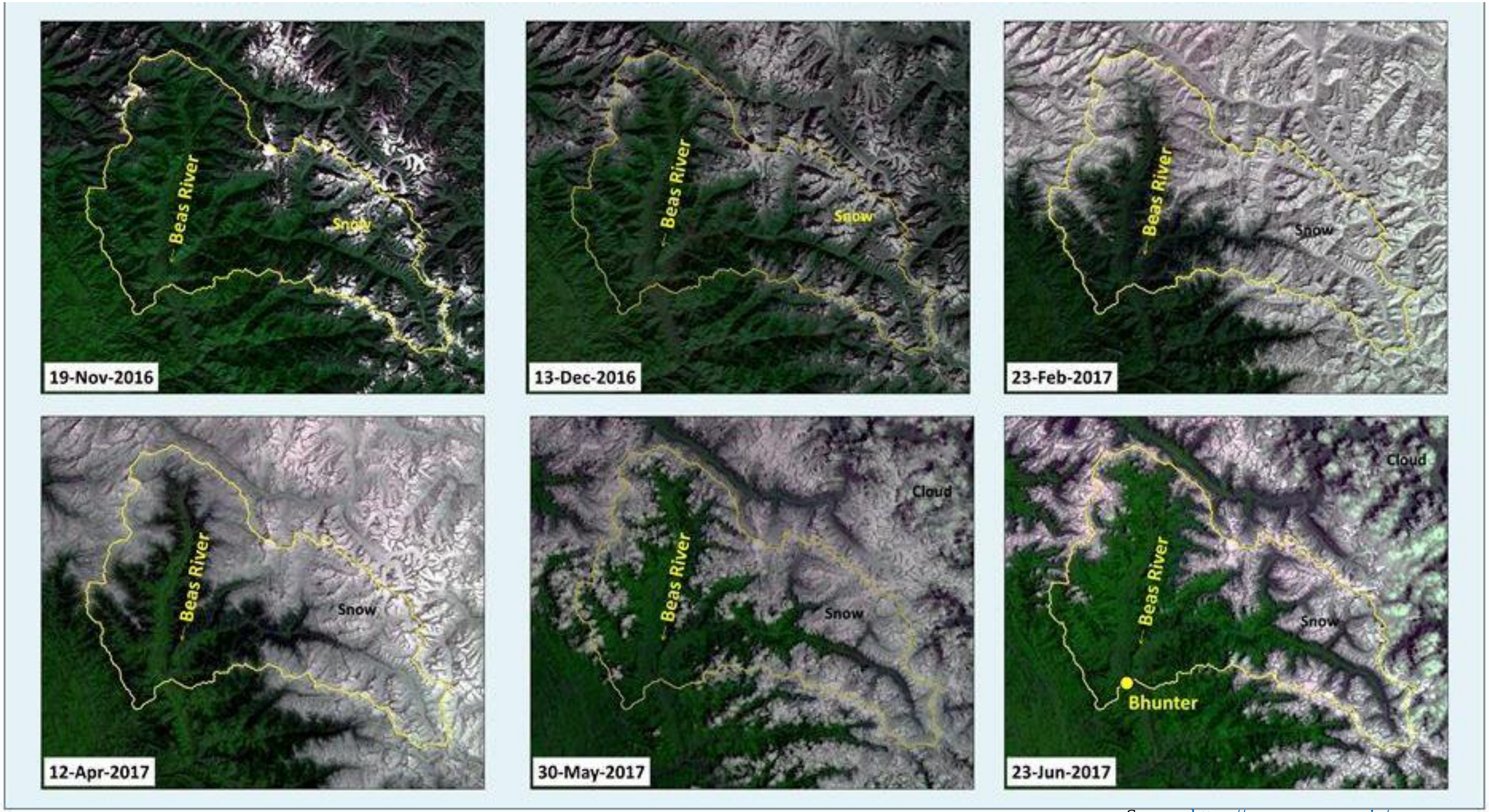


Reynolds Mountain, USA NSE= 0.83



Model evaluation III

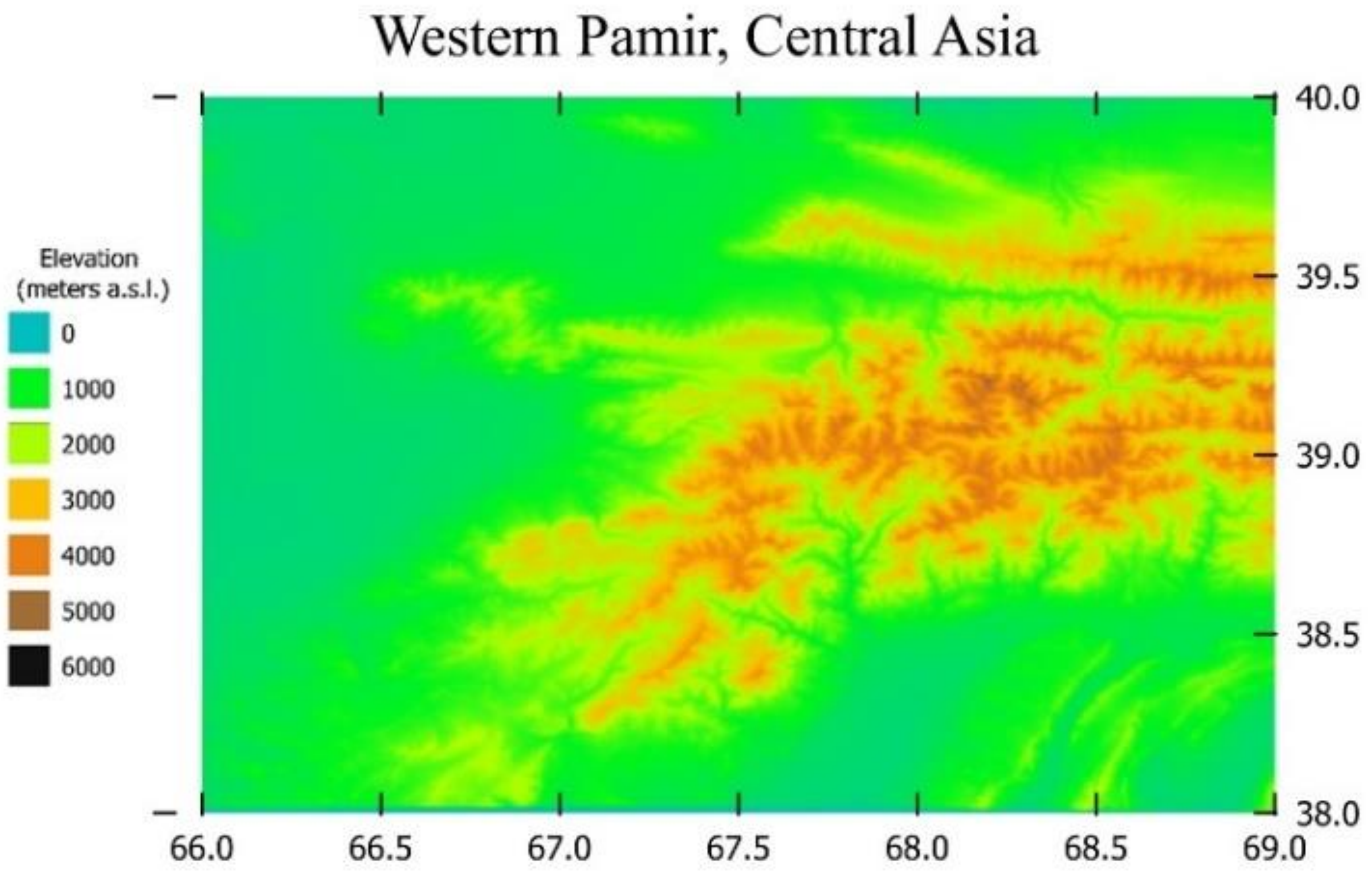
- *Using satellite images of snow cover extent and its temporal dynamics*

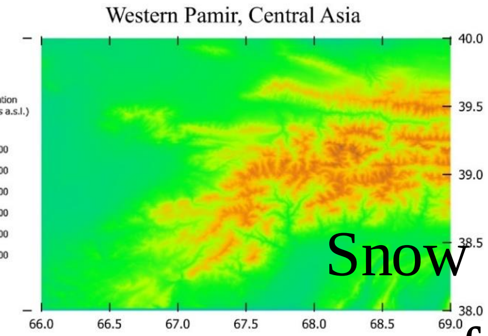


Source: https://www.nrsc.gov.in/snowcover

Model evaluation III

Snow cover over West Pamir region to validate the model performance

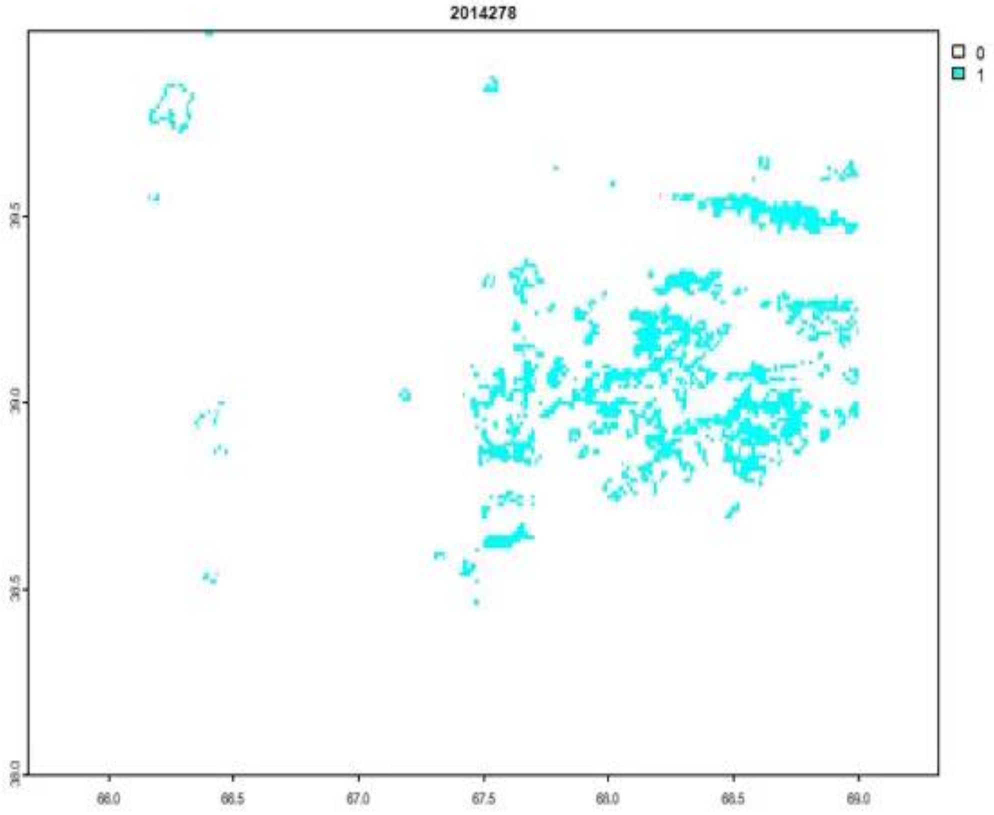




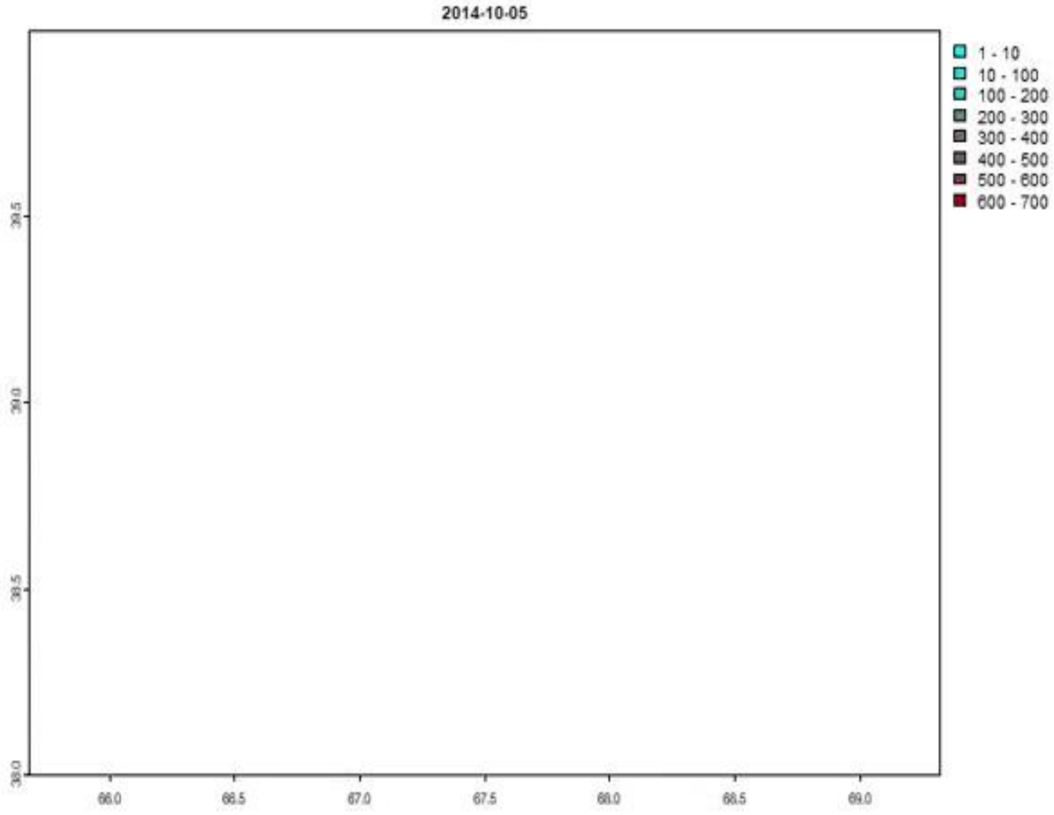
Model evaluation III

Snow cover dynamics over Western Pamir during 2015-2016 winter season

from satellite images

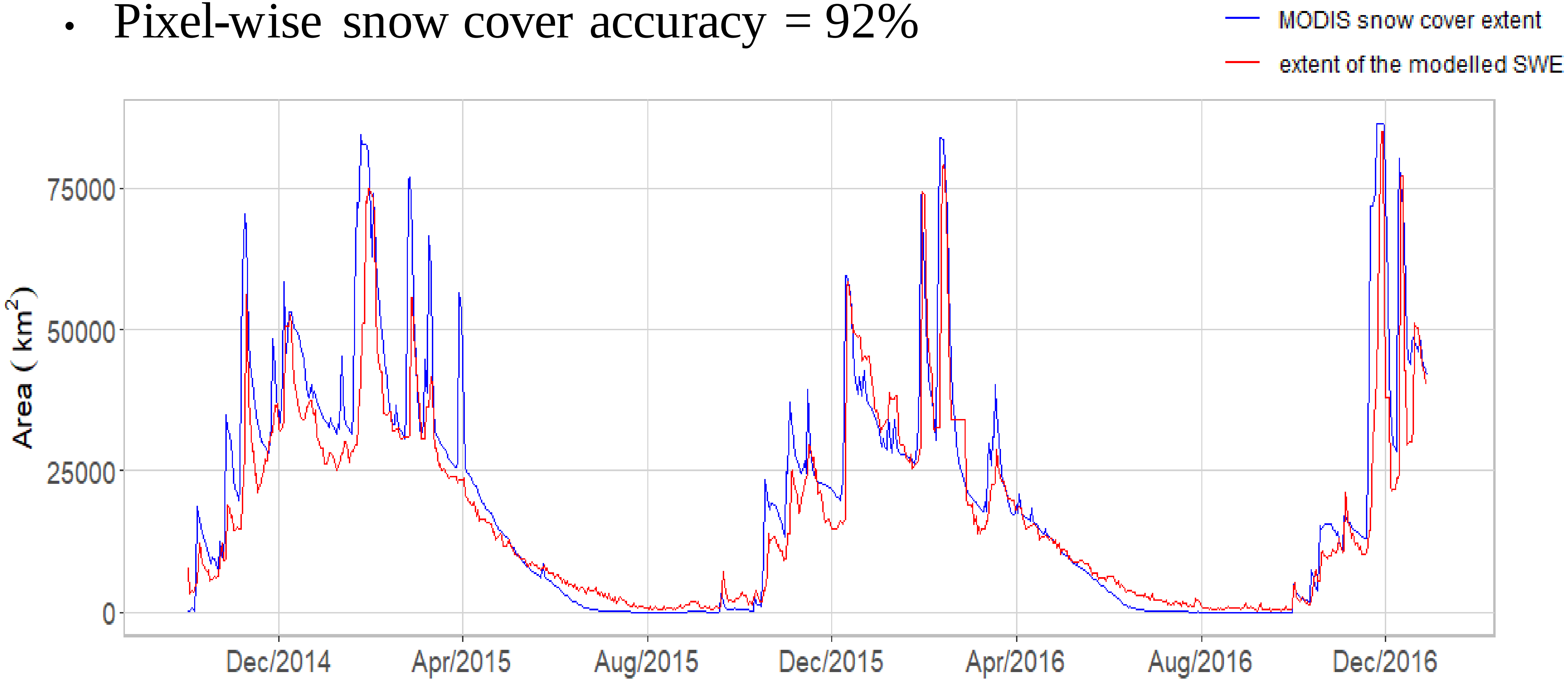


simulated by the model



Model evaluation III

- Pixel-wise snow cover accuracy = 92%

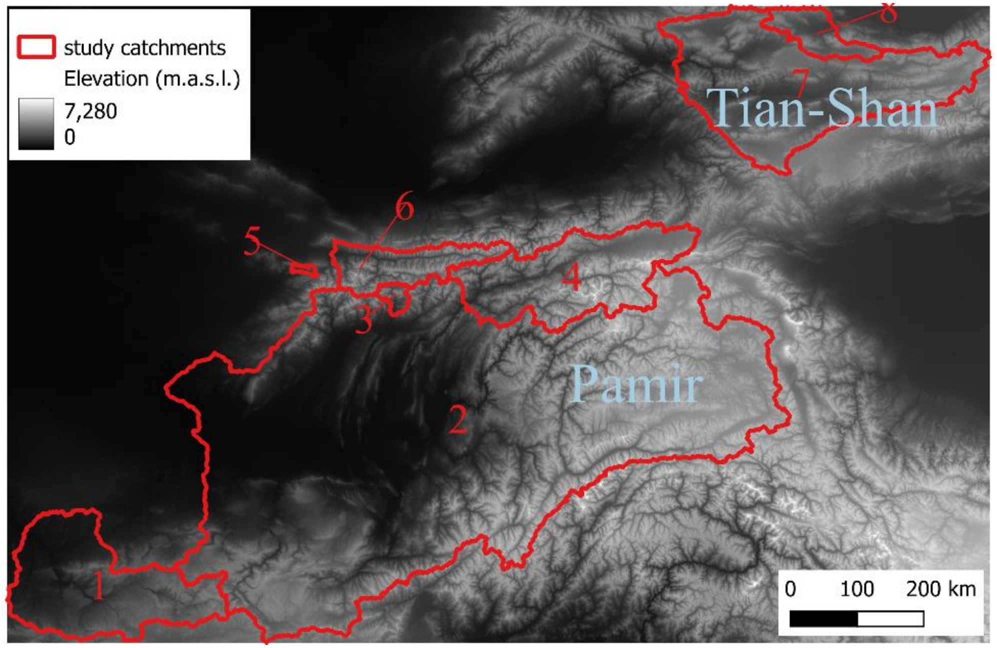


Chapter III

“Snowpack-based Seasonal Streamflow Forecasts”

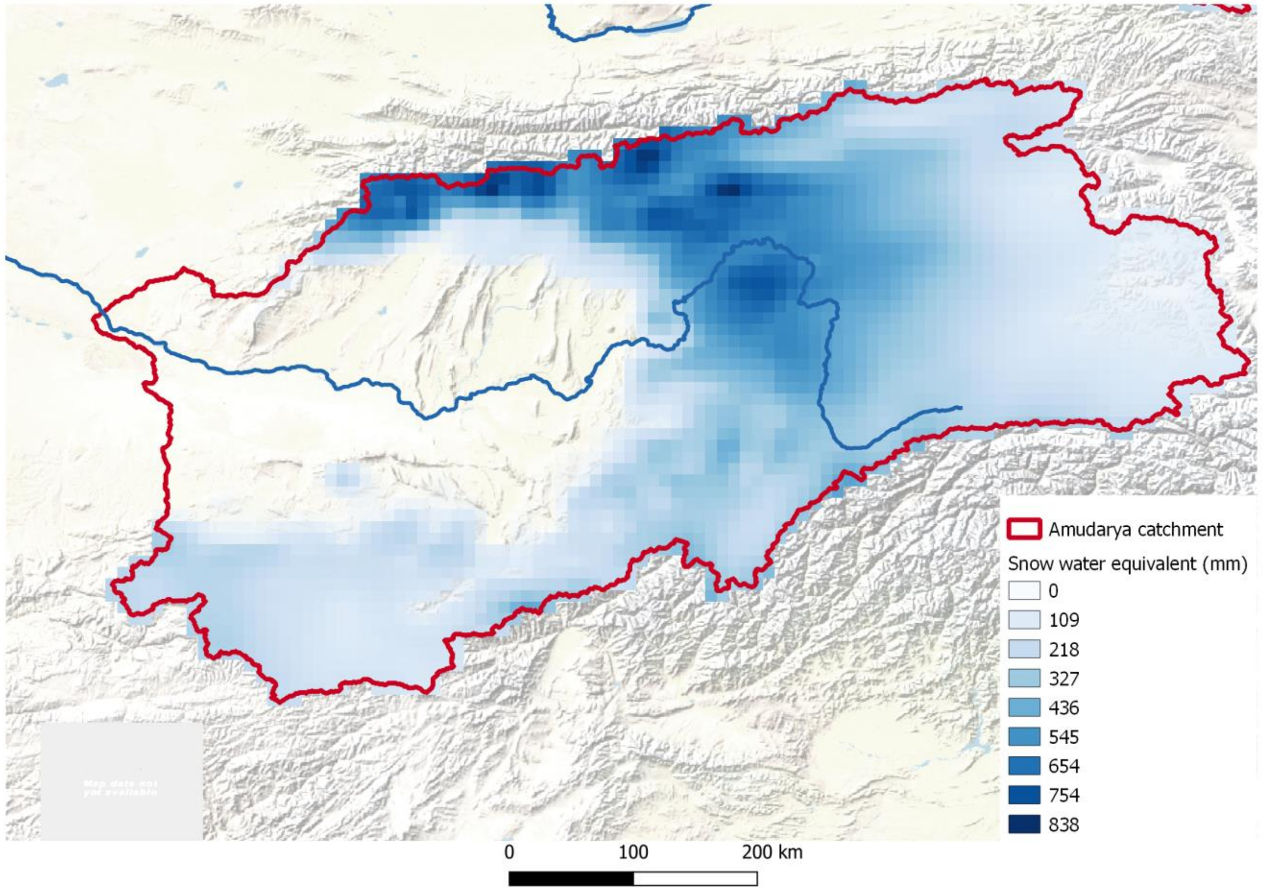
Study catchments

	Catchment	Catchment area (km^2)	Catchment mean altitude (m.a.s.l)	Mean seasonal discharge Apr-Sep (m^3/sec)	Mean annual precipitation (mm)
1	Murgab	35,582	1710	41	320
2	Amudarya	296,300	2550	1,876	380
3	Varzob	1,279	2700	79	654
4	Vaksh	28,908	3530	996	530
5	Kashkadarya	343	2663	18	530
6	Zaravshan	10,310	3125	243	516
7	Naryn	46,667	2940	561	392
8	Chu	5,305	2934	35	391



Simulated snow water equivalent

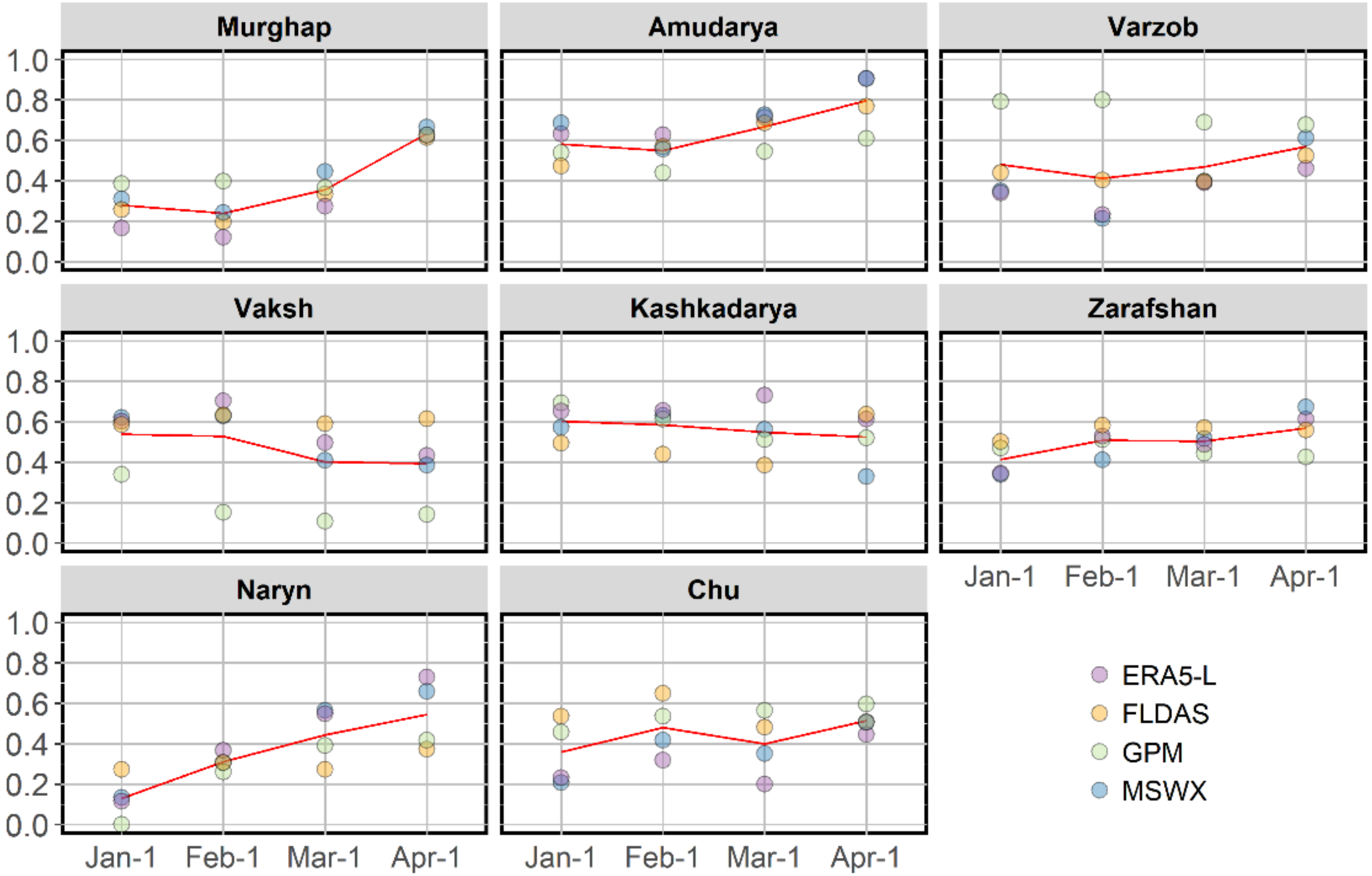
accumulated SWE as of 26.02.2020 simulated using MSWX dataset



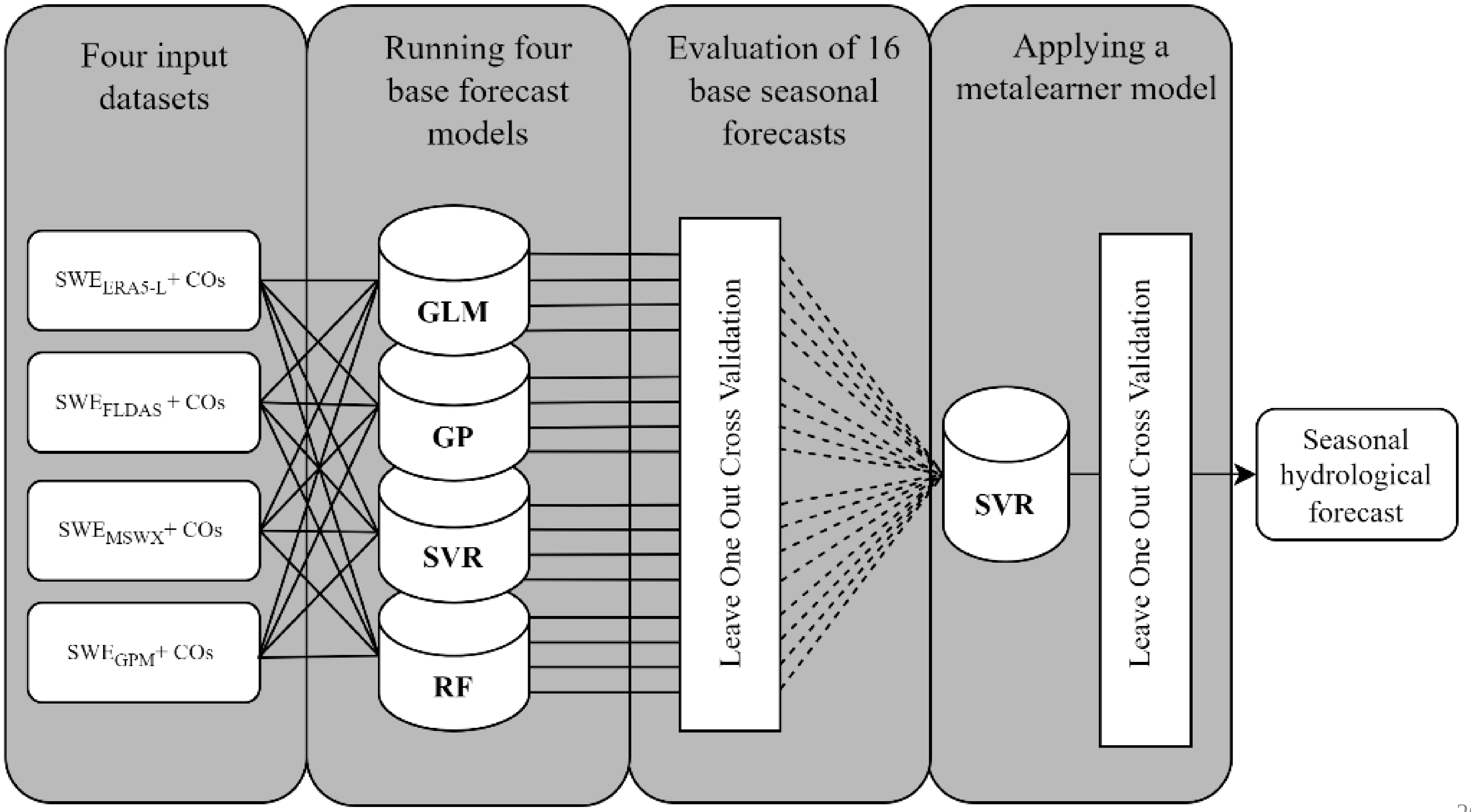
SWE estimates used as predictors

Predictor (abbreviation)	Description	Source
ERA5-L	SWE retrieved from the ERA5-Land reanalysis dataset	Muñoz-Sabater et al., 2021
FLDAS	SWE retrieved from the Land Data Assimilation System Central Asia	McNally et al., 2022
MSWX	SWE simulated using GEMS model forced by precipitation and temperature estimates from Multi-Source Weather dataset	Beck et al., 2021 (for precipitation and temperature)
GPM	SWE simulated using GEMS model forced by precipitation from GPM IMERG and temperature from MSWX datasets	Huffman et al., 2019 (precipitation)

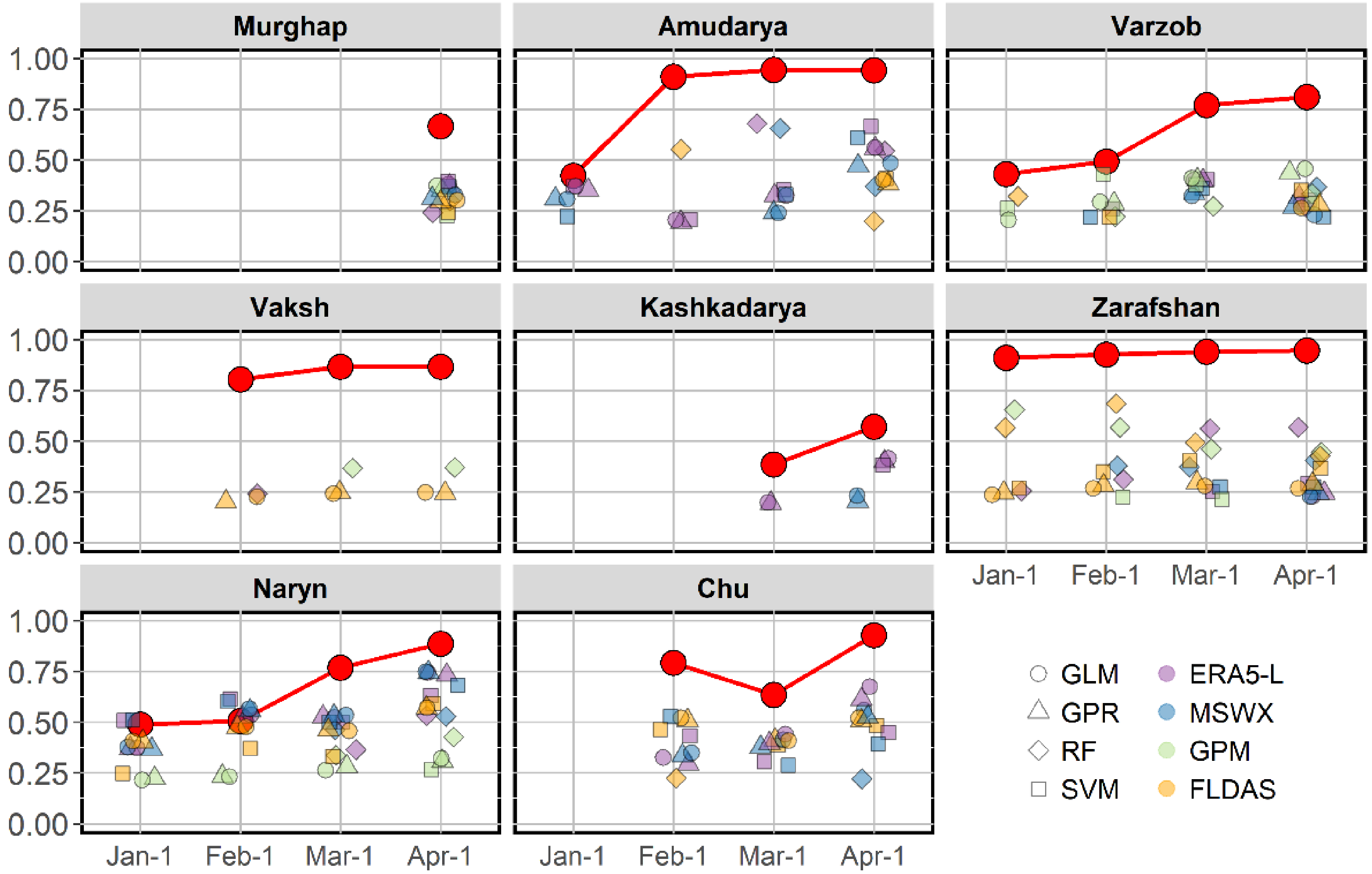
Pearson`s correlation coefficients between the SWE estimates and April-September mean seasonal discharge at different forecast lead months. Red line is the median across all snow products.



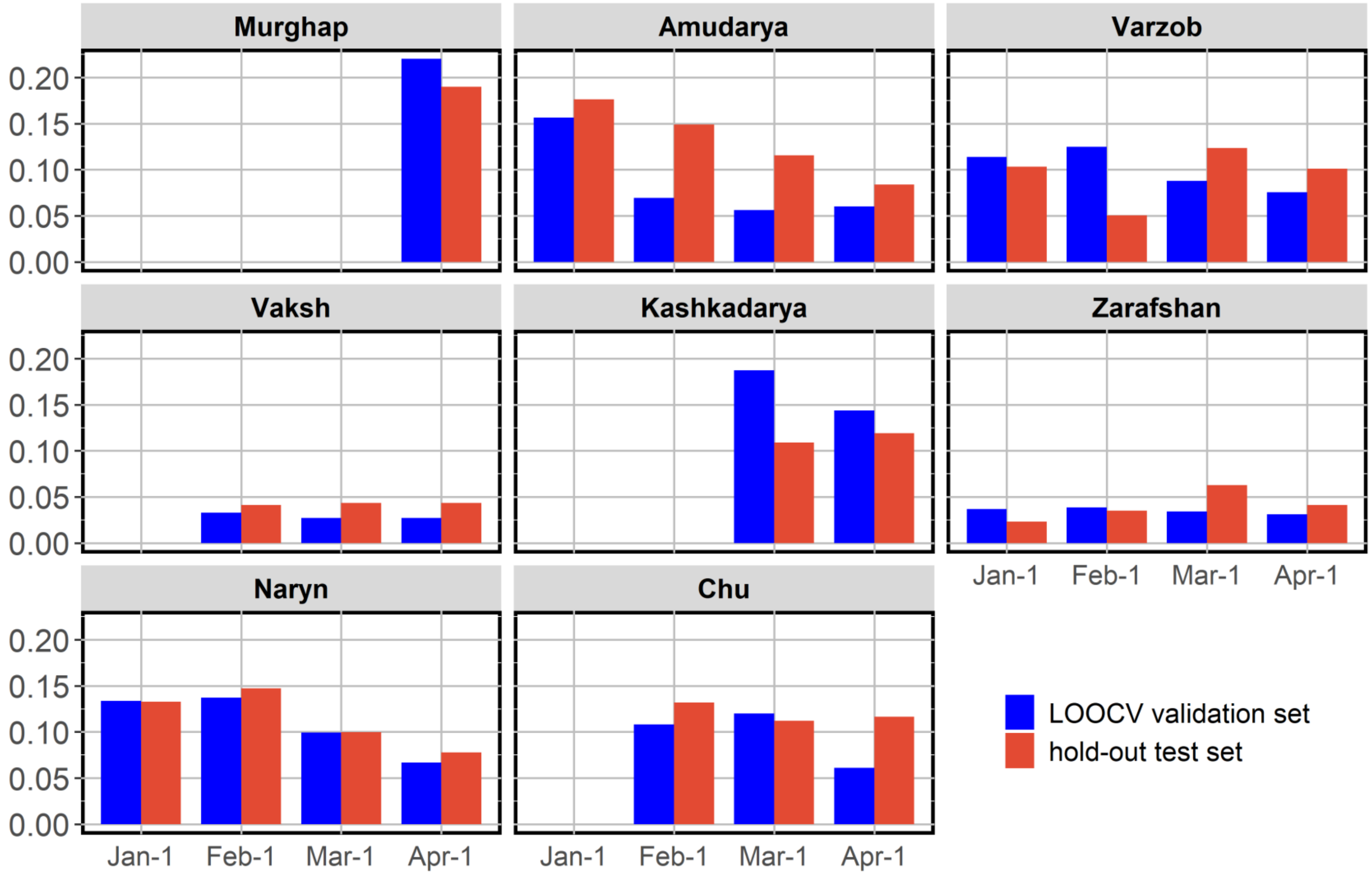
Method: Ensemble-based streamflow forecasting



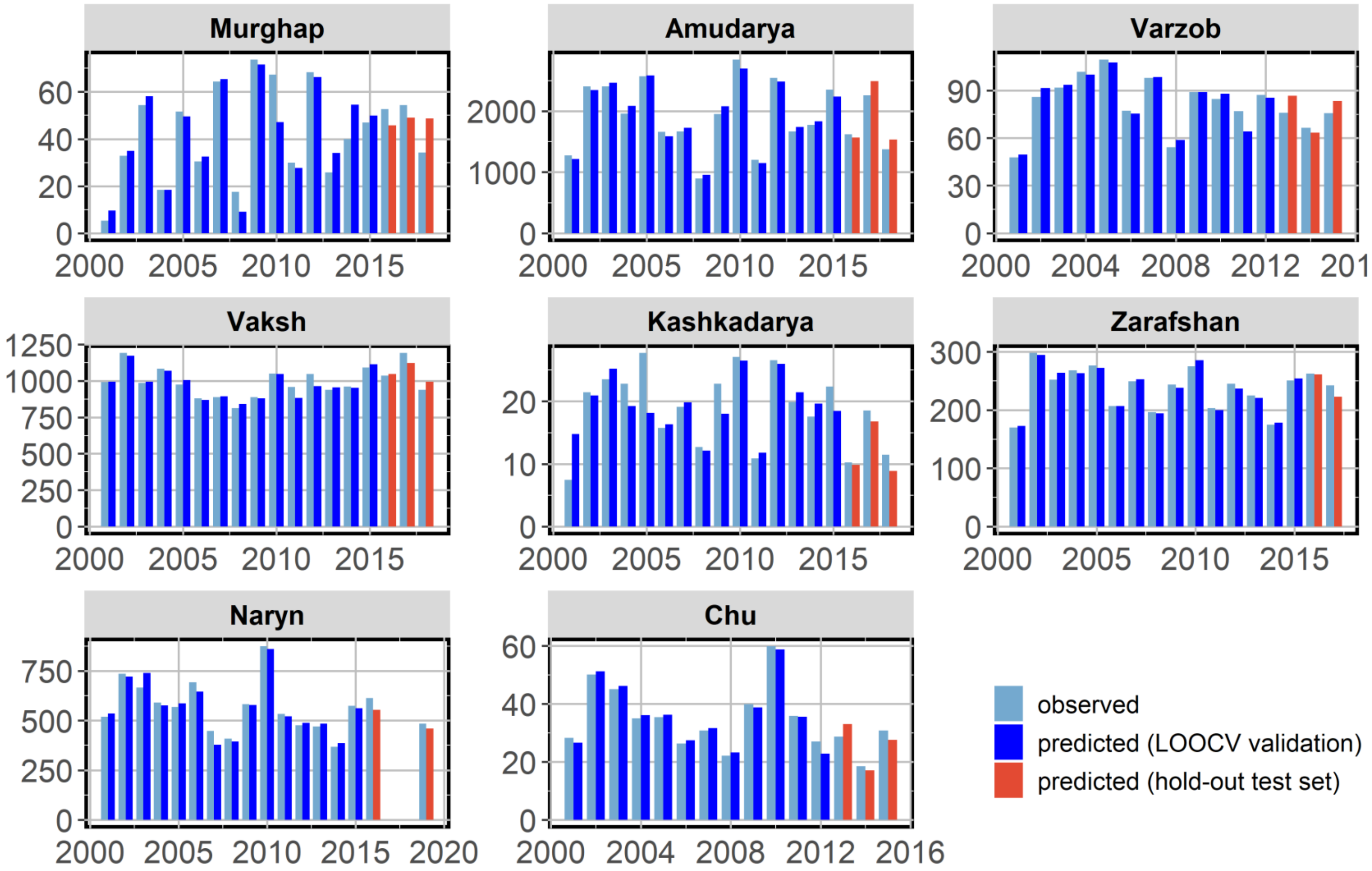
Results: Resulted LOOCV R-squared coefficients of individual base models at different lead months, and the LOOCV R-squared of the meta-learner model (red line).



Results: Normalized Mean Absolute Error of the simulated seasonal discharge by ensemble models for training and hold-out sets at different forecast lead months



Results: Observed vs simulated seasonal discharge using Apr 1st forecast ensemble model



Thank you

References

Aralova, D., Toderich, K., Jarihani, B., Gafurov, D., & Gismatulina, L. (2016). Monitoring of vegetation condition using the NDVI/ENSO anomalies in Central Asia and their relationships with ONI (very strong) phases. *Earth Resources and Environmental Remote Sensing/GIS Applications VII*, *10005*, 1000512. https://doi.org/10.1117/12.2242164

Beck, H. E., Wood, E. F., Pan, M., Fisher, C. K., Miralles, D. G., Van Dijk, A. I. J. M., … Adler, R. F. (2019). MSWep v2 Global 3-hourly 0.1° precipitation: Methodology and quantitative assessment. *Bulletin of the American Meteorological Society*, *100*(3), 473–500. https://doi.org/10.1175/BAMS-D-17-0138.1

Bobojonov, I., & Aw-Hassan, A. (2014). Impacts of climate change on farm income security in Central Asia: An integrated modeling approach. *Agriculture, Ecosystems and Environment*, *188*, 245–255. https://doi.org/10.1016/j.agee.2014.02.033

DeBeurs, K., Henebry, G. M., Owsley, B. C., & Sokolik, I. N. (2018). Large scale climate oscillation impacts on temperature, precipitation and land surface phenology in Central Asia. *Environmental Research Letters*, *13*(6). https://doi.org/10.1088/1748-9326/aac4d0

Dixon, S. G., & Wilby, R. L. (2016). Forecasting reservoir inflows using remotely sensed precipitation estimates: a pilot study for the River Naryn, Kyrgyzstan. *Hydrological Sciences Journal*, *61*(1), 107–122. https://doi.org/10.1080/02626667.2015.1006227

FAO. (2019). AQUASTAT database. Retrieved September 20, 2012, from http://www.fao.org/aquastat/en/

Gerlitz, L., Steirou, E., Schneider, C., Moron, V., Vorogushyn, S., & Merz, B. (2019). Variability of the Cold Season Climate in Central Asia. Part II: Hydroclimatic Predictability. *Journal of Climate*, *32*(18), 6015–6033. https://doi.org/10.1175/jcli-d-18-0892.1

Hu, Z., Zhou, Q., Chen, X., Li, J., Li, Q., Chen, D., … Yin, G. (2018). Evaluation of three global gridded precipitation data sets in central Asia based on rain gauge observations. *International Journal of Climatology*, *38*(9), 3475–3493. https://doi.org/10.1002/joc.5510

Liu, J., Luo, M., Liu, T., Bao, A., de Maeyer, P., Feng, X., & Chen, X. (2017). Local climate change and the impacts on hydrological processes in an arid alpine catchment in Karakoram. *Water (Switzerland)*, *9*(5). https://doi.org/10.3390/w9050344

Mariotti, A. (2007). How ENSO impacts precipitation in southwest central Asia. *Geophysical Research Letters*, *34*(16), 2–6. https://doi.org/10.1029/2007GL030078

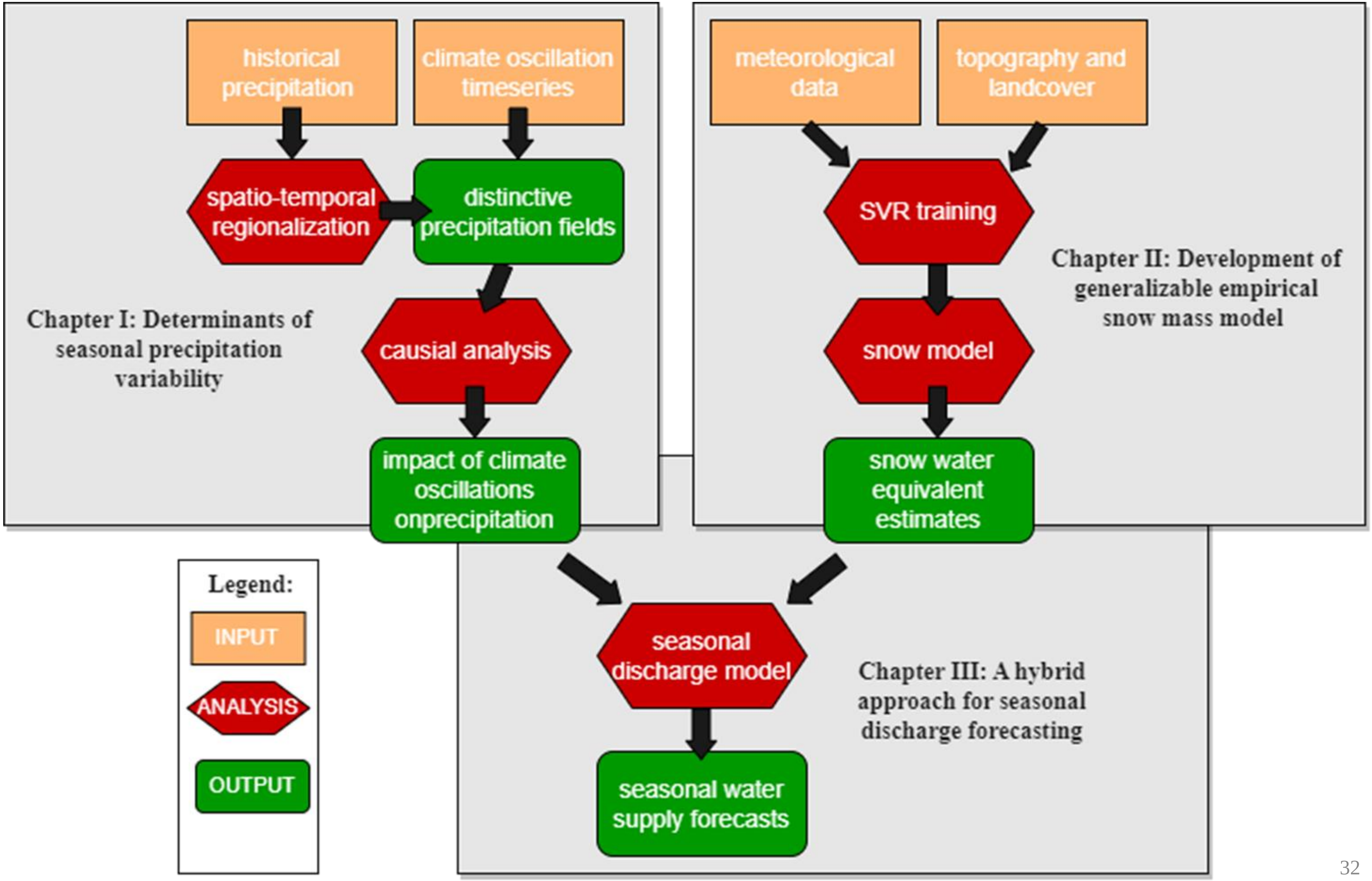
Pohl, B., Kramer, A., Hull, W., Blumstein, S., Abdullaev, I., Kazbekov, J., … Görlitz, S. (2017). *Rethinking Water in Central Asia – The costs of inaction and benefits of water cooperation*. Bern.

Sommer, R., Glazirina, M., Yuldashev, T., Otarov, A., Ibraeva, M., Martynova, L., … de Pauw, E. (2013). Impact of climate change on wheat productivity in Central Asia. *Agriculture, Ecosystems and Environment*, *178*, 78–99. https://doi.org/10.1016/j.agee.2013.06.011

Ward, J. (1963). Hierarchical Grouping to Optimize an Objective Function. *Journal of the American Statistical Association*, *58*(301), 236–244. https://doi.org/10.1198/016214503000000468

Zandler, H., Haag, I., & Samimi, C. (2019). Evaluation needs and temporal performance differences of gridded precipitation products in peripheral mountain regions. *Scientific Reports*, *9*(1), 1–15. https://doi.org/10.1038/s41598-019-51666-z

Zhong, F., Cheng, Q., & Ge, Y. (2019). Relationships between spatial and temporal variations in precipitation, climatic indices, and the normalized differential vegetation index in the upper and middle reaches of the Heihe River Basin, Northwest China. *Water (Switzerland)*, *11*(7). https://doi.org/10.3390/w11071394


historical precipitation
climate oscillation timeseries
spatio-temporal regionalization
distinctive precipitation fields
causial analysis
impact of climate oscillations onprecipitation
Chapter I: Determinants of seasonal precipitation variability
meteorological data
topography and landcover
SVR training
snow model
snow water equivalent estimates
Chapter II: Development of generalizable empirical snow mass model
seasonal discharge model
seasonal water supply forecasts
Chapter III: A hybrid approach for seasonal discharge forecasting
Legend:
INPUT
ANALYSIS
OUTPUT

Research Directions

Chapter I: Determinants of seasonal precipitation variability

- Objective: How large-scale climate oscillations affect seasonal precipitation in Central Asia
- Status: published (Umirbekov A., Peña-Guerrero M.D., Müller D. (2022) "Regionalization of Climate Teleconnections across Central Asian Mountains Improves the Predictability of Seasonal Precipitation.", Environmental Research Letters)

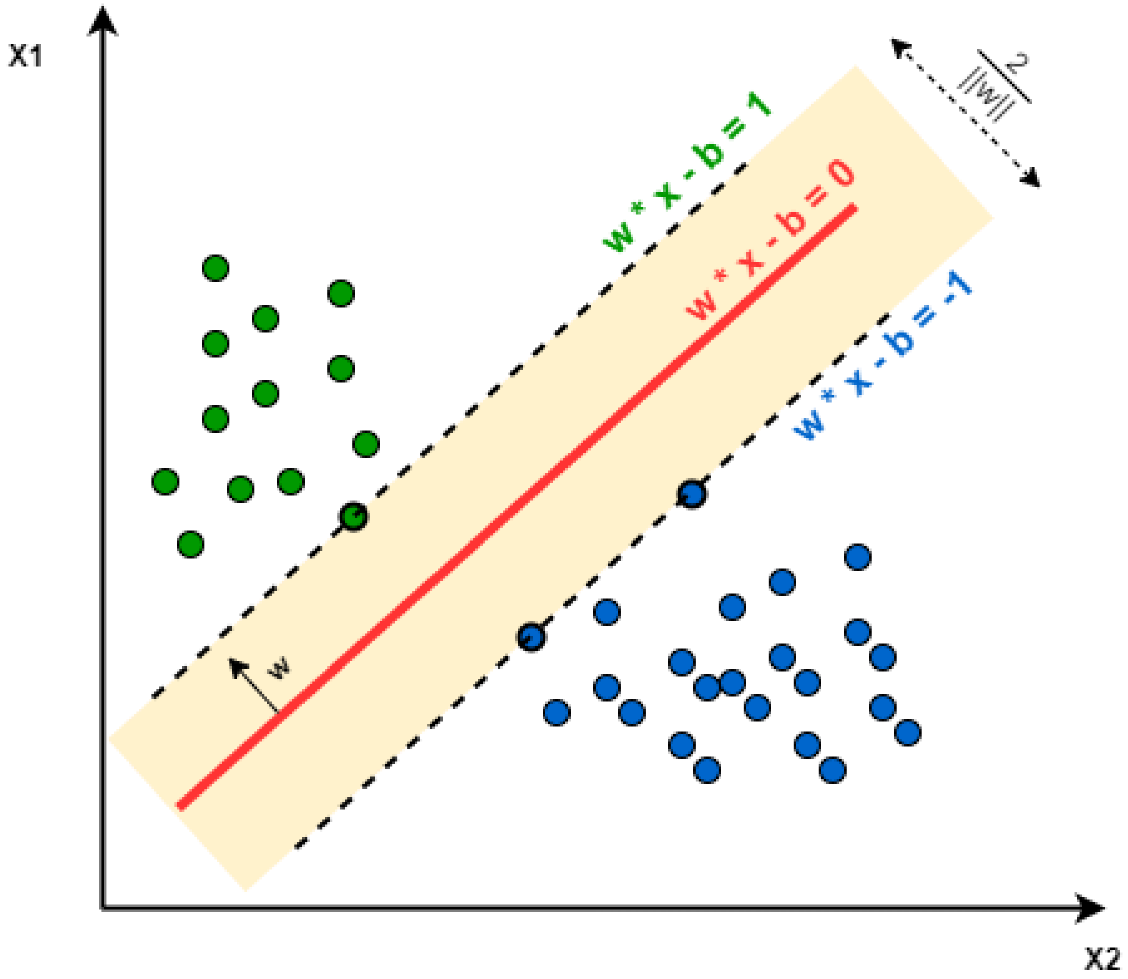
Chapter II: Development of generalizable empirical snow mass model

- Objective: Elaboration of machine learning-based snow model and assessment of its transferability across diverse climatic and geographic domains
- Status: submitted

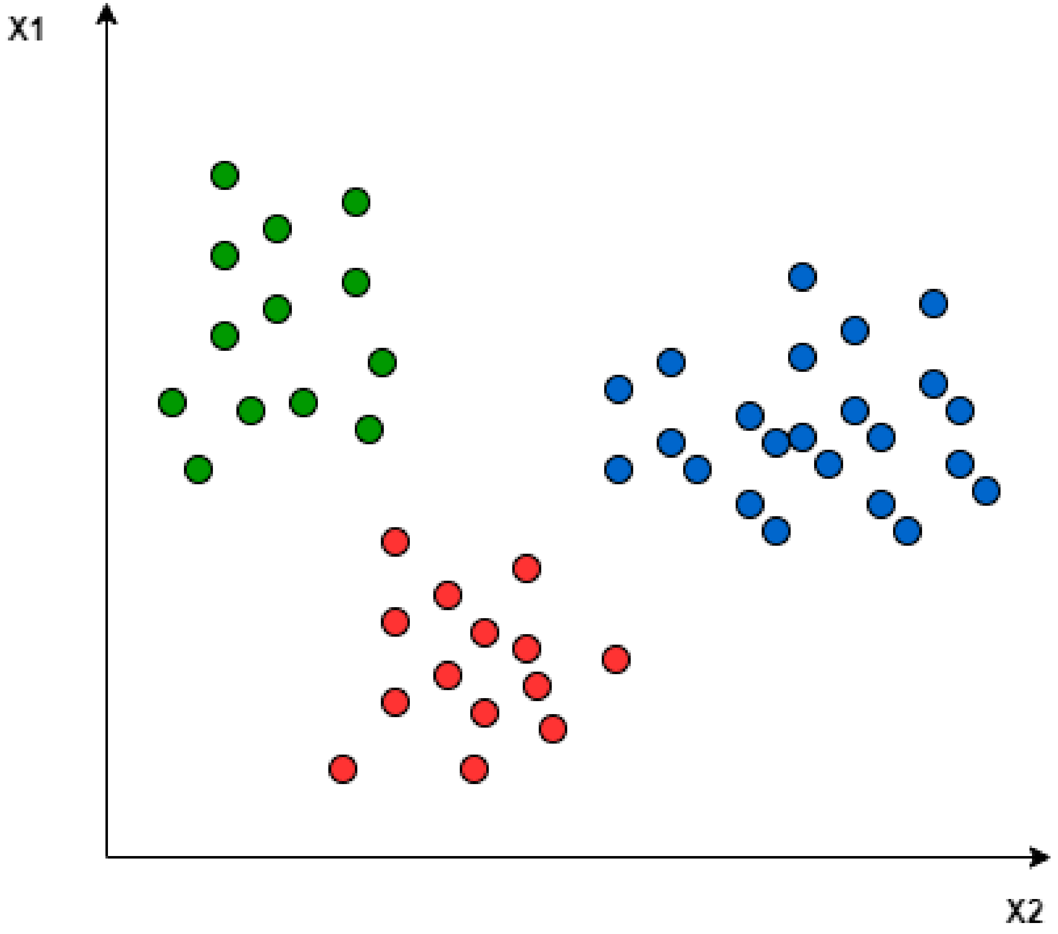
Chapter III: A hybrid approach for seasonal discharge forecasting

- Objective: How fusion of snow water equivalent estimates and the climate teleconnections can reduce uncertainty of water availability in major basins of Central Asia
- Status: internal review

Linearly Separable Data



Source: “Multiclass classification using SVM”, by @baeldung (2021) https://www.baeldung.com/cs/svm-multiclass-classification



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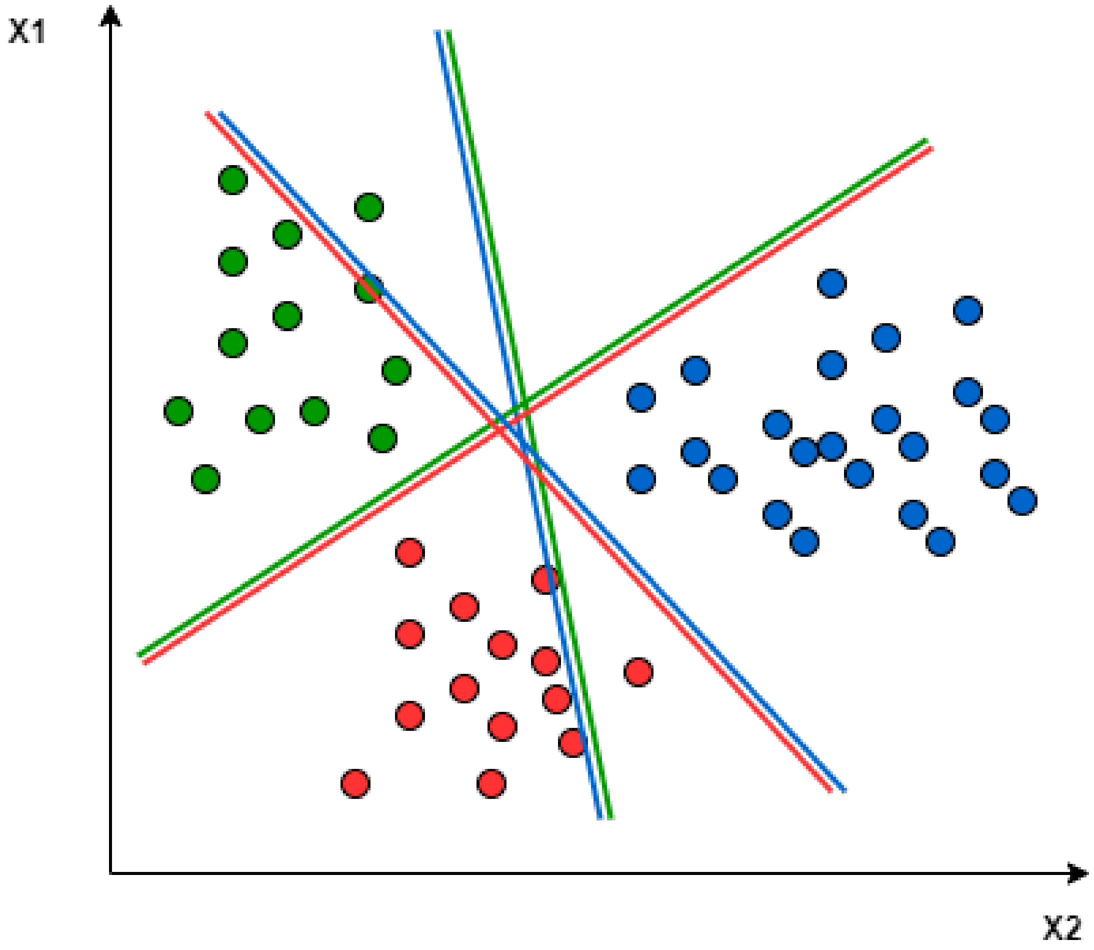

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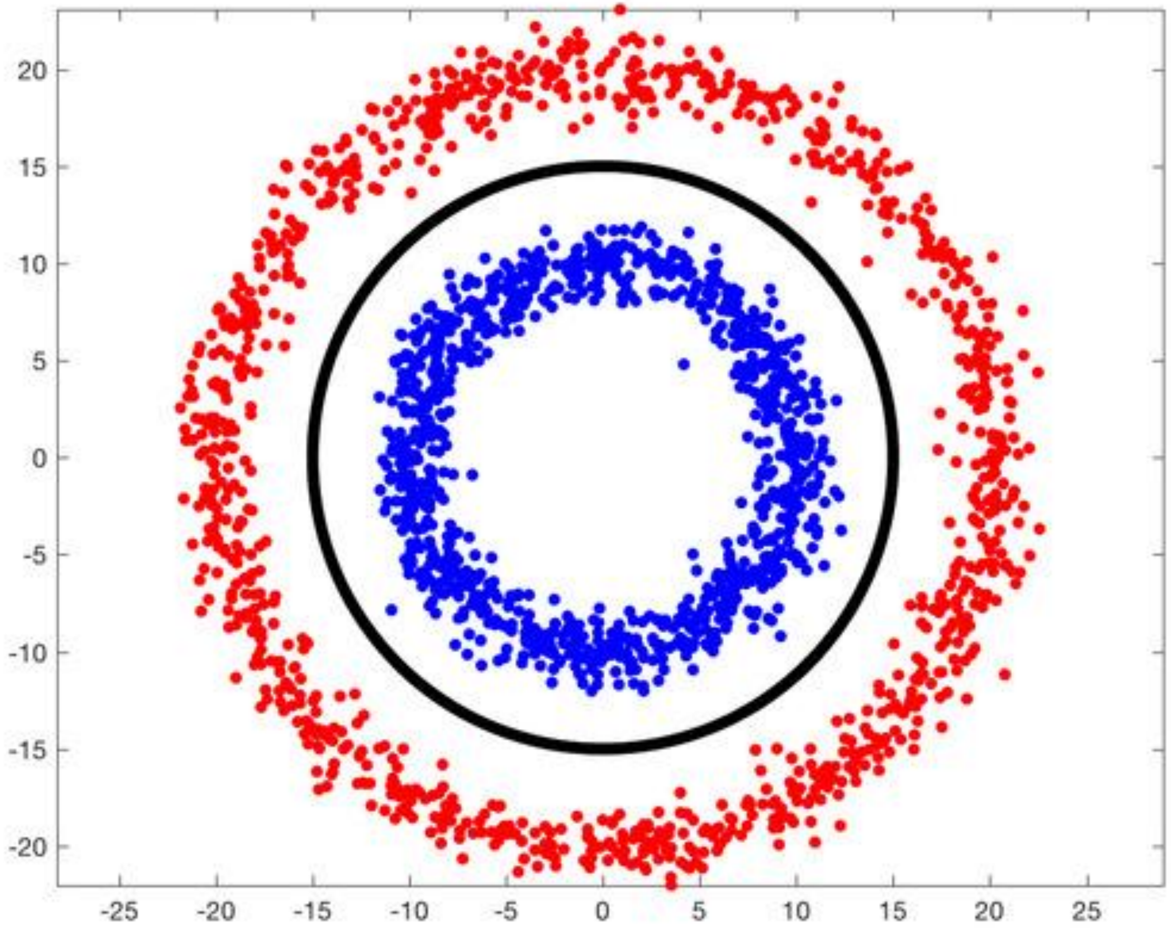
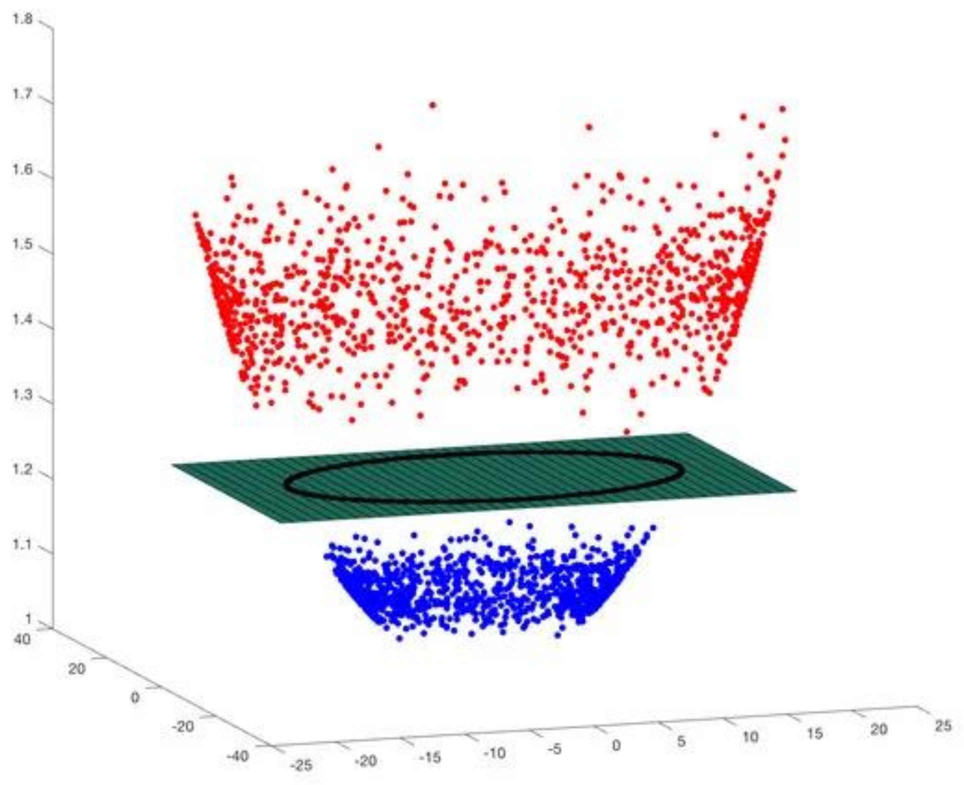
Non-Linearly Separable Data



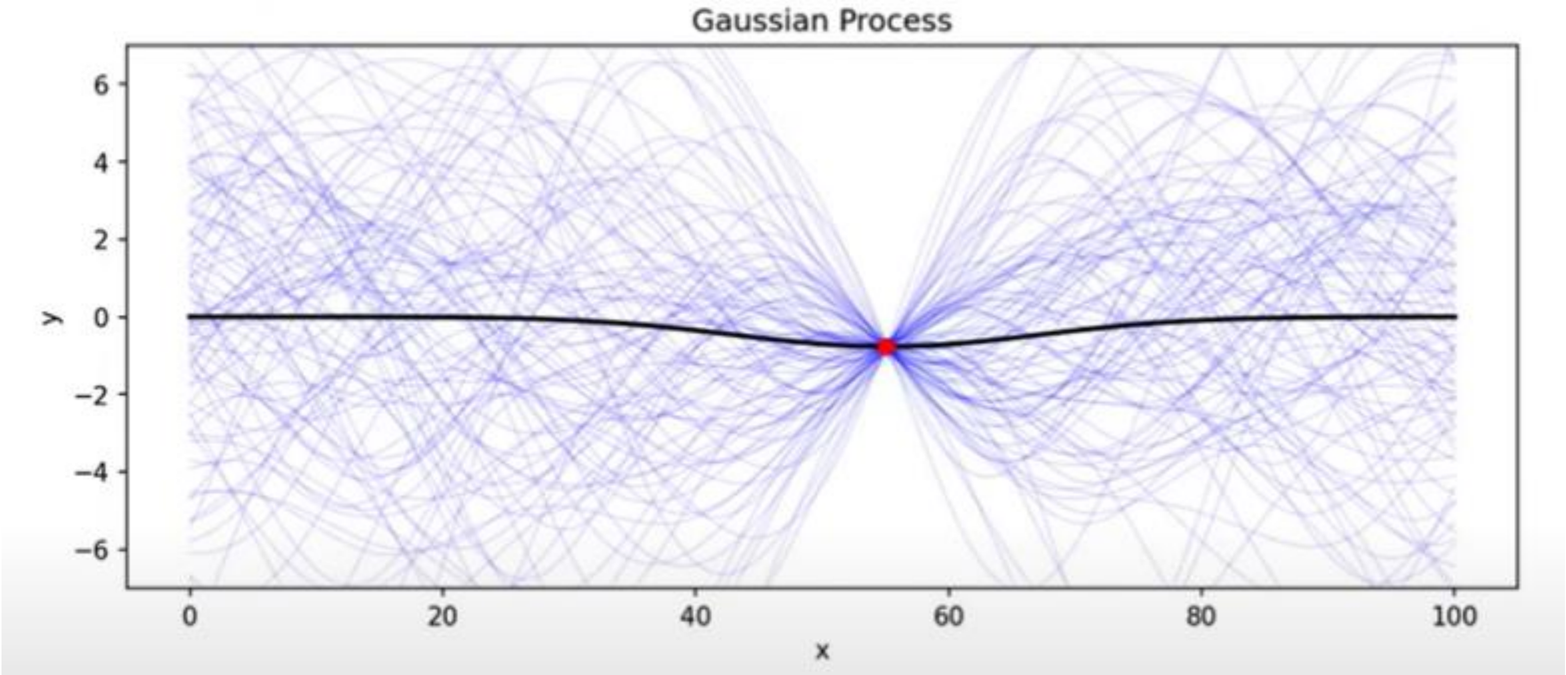
Source: “Support Vector Machines”, by @Satya Mallick https://learnopencv.com/support-vector-machines-svm/

Non-Linearly Separable Data



$$z = e^{-\gamma(x^2+y^2)}$$

Source: “Support Vector Machines”, by @Satya Mallick https://learnopencv.com/support-vector-machines-svm/


Gaussian Process
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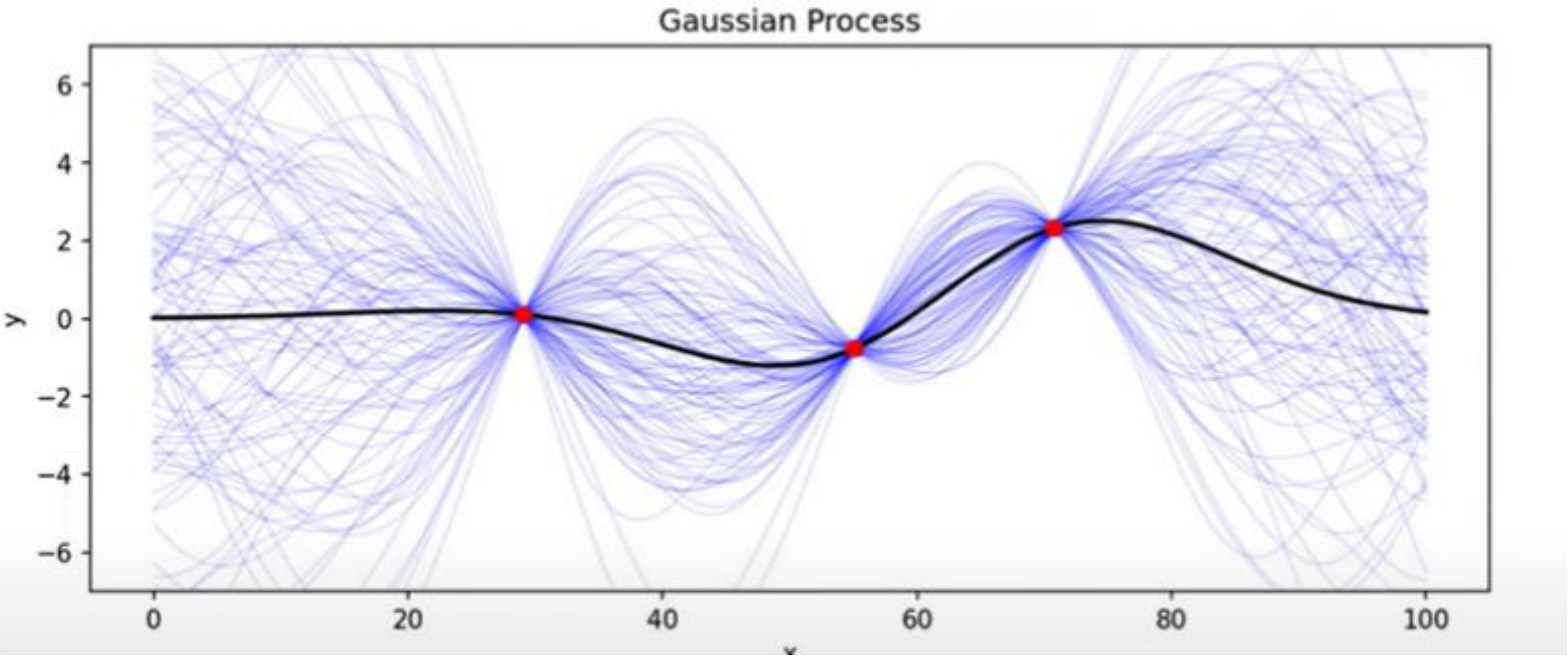

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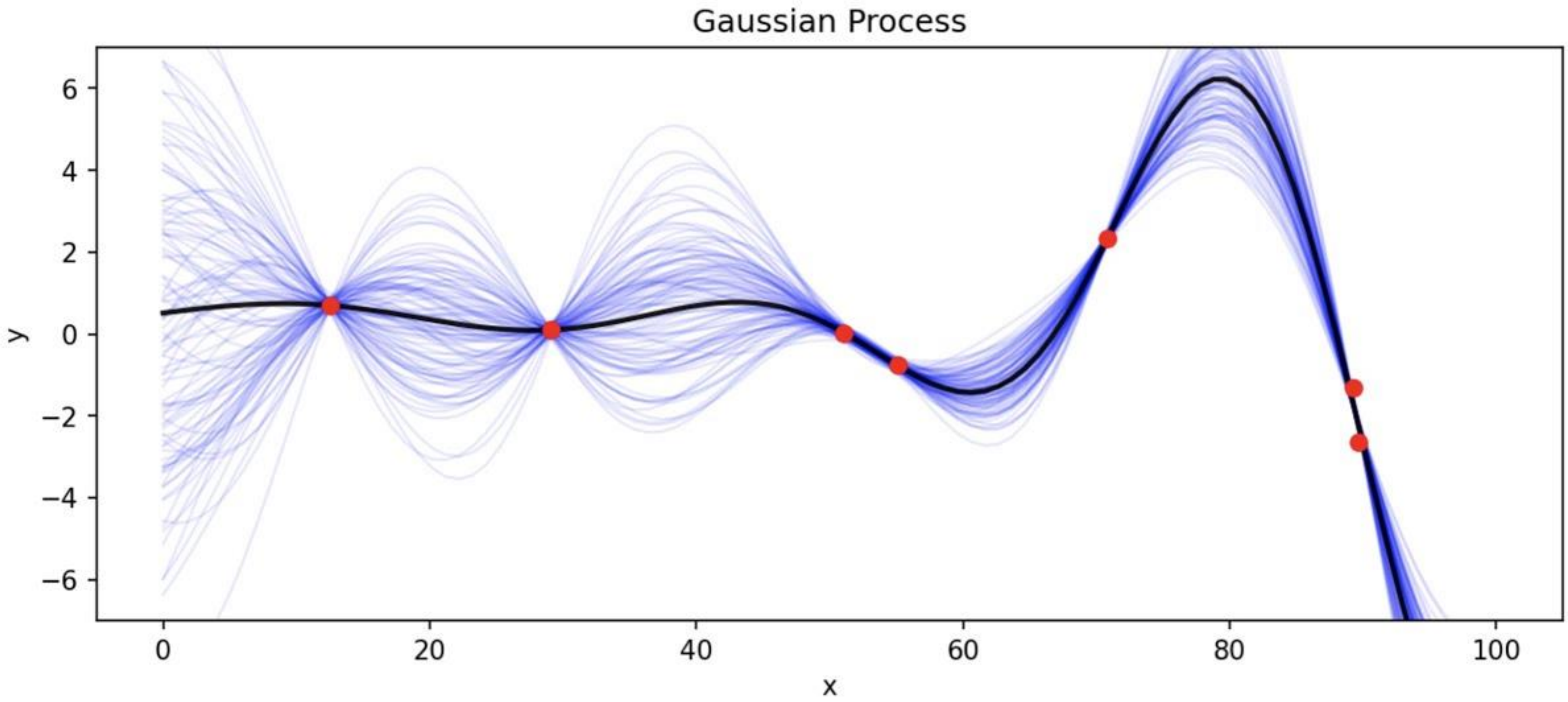

Gaussian Process
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