Compound events in Bavaria:

Multivariate analysis of climatological and hydrological drivers of low flow events

Theresa Meier & Nikita Paschan

Project Partners: Andrea Böhnisch & Alexander Sasse (LMU, Department of Geography)
Supervisors: Prof. Helmut Küchenhoff & Henri Funk

03.03.2023

The Observer

Europe's rivers run dry as scientists warn drought could be worst in 500 years

Crops, power plants, barge traffic, industry and fish populations devastated by parched waterways

13 Aug 2022

The Guardian

The Observer

Europe's rivers run dry as scientists warn drought could be worst in 500 years

Crops, power plants, barge traffic, industry and fish populations devastated by parched waterways

13 Aug 2022

The Guardian

Rivers

Source of River Thames dries out 'for first time' during drought

Head of the Thames is now more than 5 miles downstream as forecasters warn of further high temperatures to come

4 Aug 2022

The Observer

Europe's rivers run dry as scientists warn drought could be worst in 500 years

Crops, power plants, barge traffic, industry and fish populations devastated by parched waterways

13 Aug 2022

The Guardian

Rivers

Source of River Thames dries out 'for first time' during drought

Head of the Thames is now more than 5 miles downstream as forecasters warn of further high temperatures to come

4 Aug 2022

Italy

Venice canals start to run dry as low tide and lack of rain hit

Gondolas unable to navigate some of its famous canals as Italy faces prospect of another drought

21 Feb 2023

Research Questions

1. How can the occurrence of low flow events (dt.: Niedrigwasser) be explained?
2. Are the drivers of an extreme event themselves extreme? Or is it a compound event (i.e. a combination of moderately pronounced drivers) that leads to extreme low flows?
3. Which drivers are relevant? Does their significance differ depending on the catchment?
4. What happens for more extreme weather conditions?
5. Is it possible to group catchments according to the drivers?

Research Questions

1. How can the occurrence of low flow events (dt.: Niedrigwasser) be explained?
2. Are the drivers of an extreme event themselves extreme? Or is it a compound event (i.e. a combination of moderately pronounced drivers) that leads to extreme low flows?
3. Which drivers are relevant? Does their significance differ depending on the catchment?
4. What happens for more extreme weather conditions?
5. Is it possible to group catchments according to the drivers?

Research Questions

1. How can the occurrence of low flow events (dt.: Niedrigwasser) be explained?
2. Are the drivers of an extreme event themselves extreme? Or is it a compound event (i.e. a combination of moderately pronounced drivers) that leads to extreme low flows?
3. Which drivers are relevant? Does their significance differ depending on the catchment?
4. What happens for more extreme weather conditions?
5. Is it possible to group catchments according to the drivers?

Research Questions

1. How can the occurrence of low flow events (dt.: Niedrigwasser) be explained?
2. Are the drivers of an extreme event themselves extreme? Or is it a compound event (i.e. a combination of moderately pronounced drivers) that leads to extreme low flows?
3. Which drivers are relevant? Does their significance differ depending on the catchment?
4. What happens for more extreme weather conditions?
5. Is it possible to group catchments according to the drivers?

Research Questions

1. How can the occurrence of low flow events (dt.: Niedrigwasser) be explained?
2. Are the drivers of an extreme event themselves extreme? Or is it a compound event (i.e. a combination of moderately pronounced drivers) that leads to extreme low flows?
3. Which drivers are relevant? Does their significance differ depending on the catchment?
4. What happens for more extreme weather conditions?
5. Is it possible to group catchments according to the drivers?

Agenda

1. Introduction to the Project
2. Descriptive Analysis
3. Model choice, Results and Evaluation
4. Weather Scenarios
5. Clustering
6. Outlook

Introduction

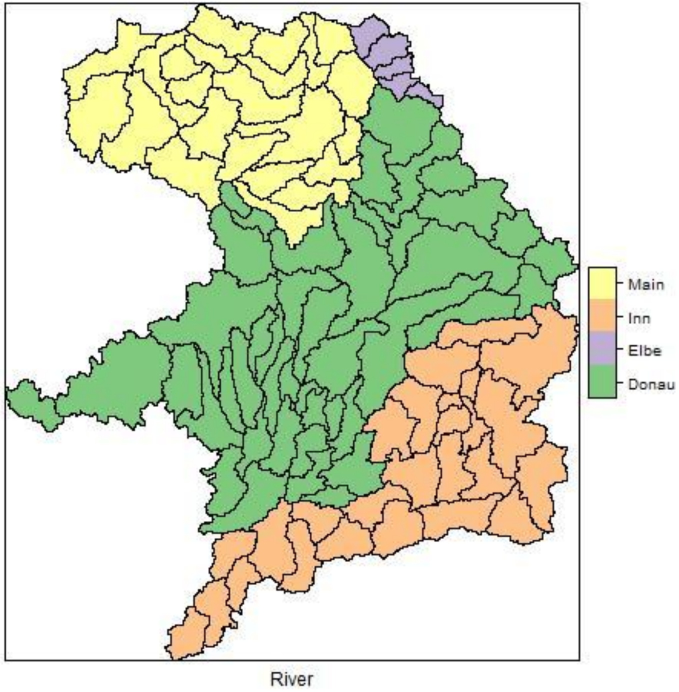
ClimEx Project

- Cooperation between Bavaria and Québec
- Hydrological simulation model
- 50 different sets of simulated data (members) with different starting conditions
- **Goal:** Investigation of effect of climate change on meteorological & hydrological extreme events in “hydrological Bavaria”

  → Implications for water management
- Account for natural variability

Data

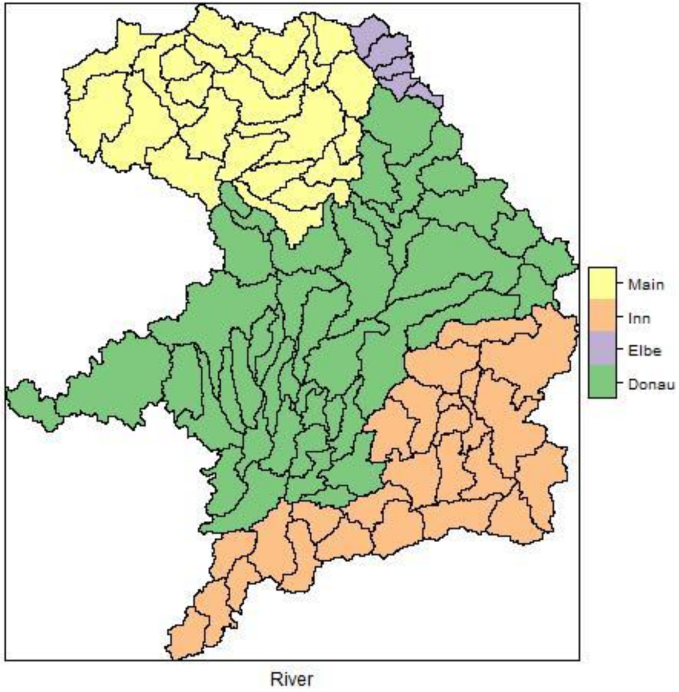
- Hydrological Bavaria: partition into 98 catchments (regional averages)
- “WaSim” data set:
    - Time series: 3 hourly data
    - Spatial resolution: 500m
- Aggregated daily data over 1990-2020
- Data of 10 different members
- Total number of data points: 11,088,700 where
    - 1,108,870 data points per member
    - 11,315 data points per catchment



Data

- **Provided variables**
  - Drainage (m³/s)
  - Temperature (°C)
  - Precipitation (mm)
  - Soil water (%)
  - Snow storage (mm)
  - Radiation (Wh/m²)
  - Relative humidity (%)
  - Time constant variables (dgm, slope, exposition, land use)

- **Hydrological half-year**
  - Summer: May-October
  - Winter: November - April

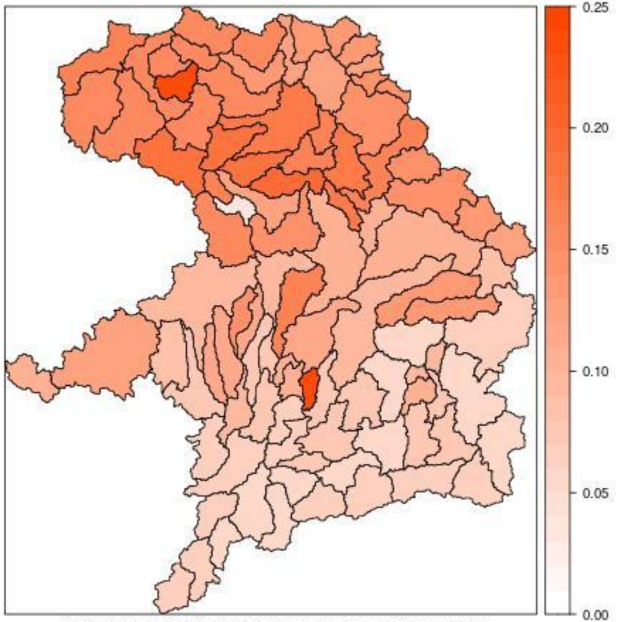


Classification of Low Flow

- Threshold: NM7Q

  lowest 7-day mean of drainage averaged over 31 years & all members for summer and winter

- Drainage falling below NM7Q for at least 3 days in a row
- In total: ~ 11.4 % of low flow events (similar for all members)

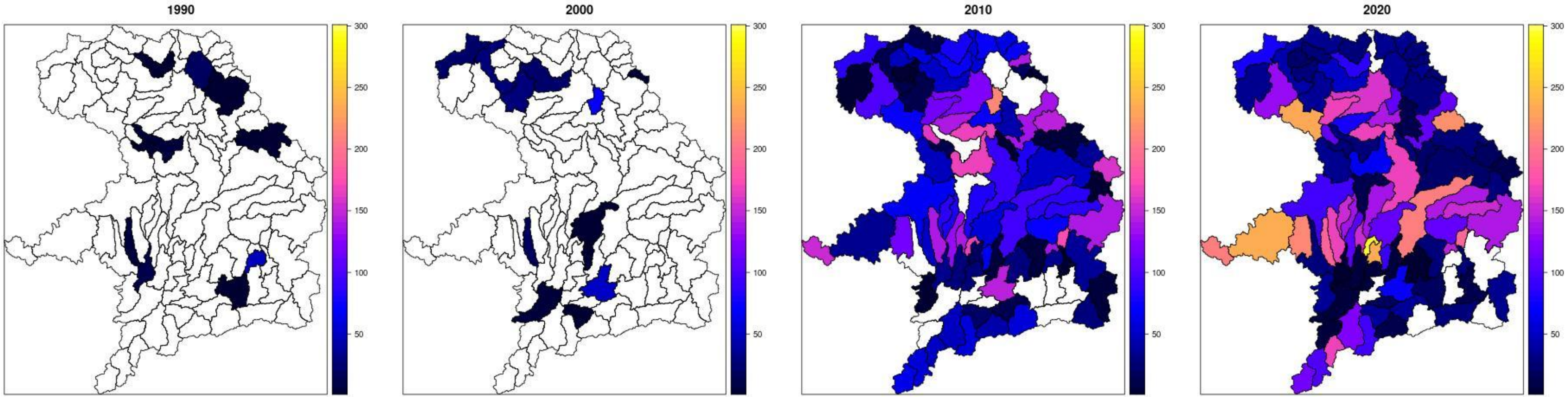


Percentage of low flow days averaged over all members

Descriptive Analysis

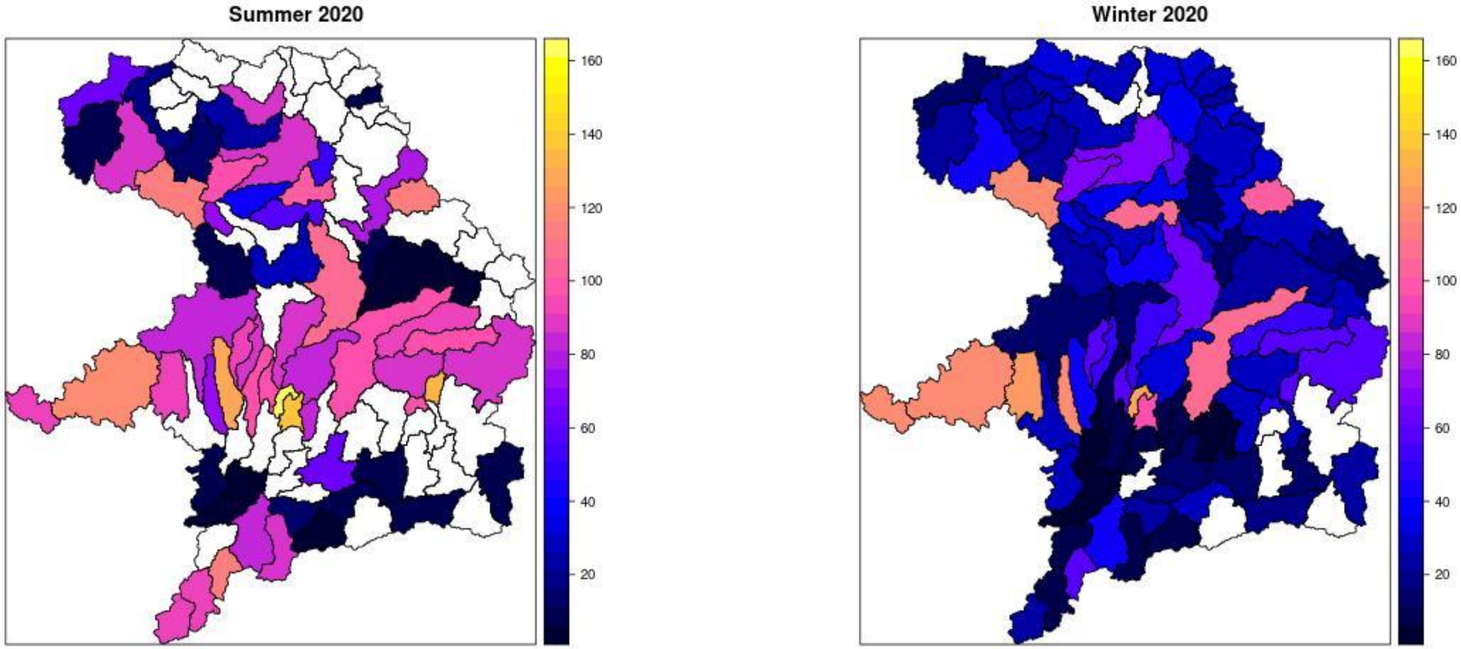
Day of Low Flow

Number of Days of Low Flow for One Member



For member “kbt”

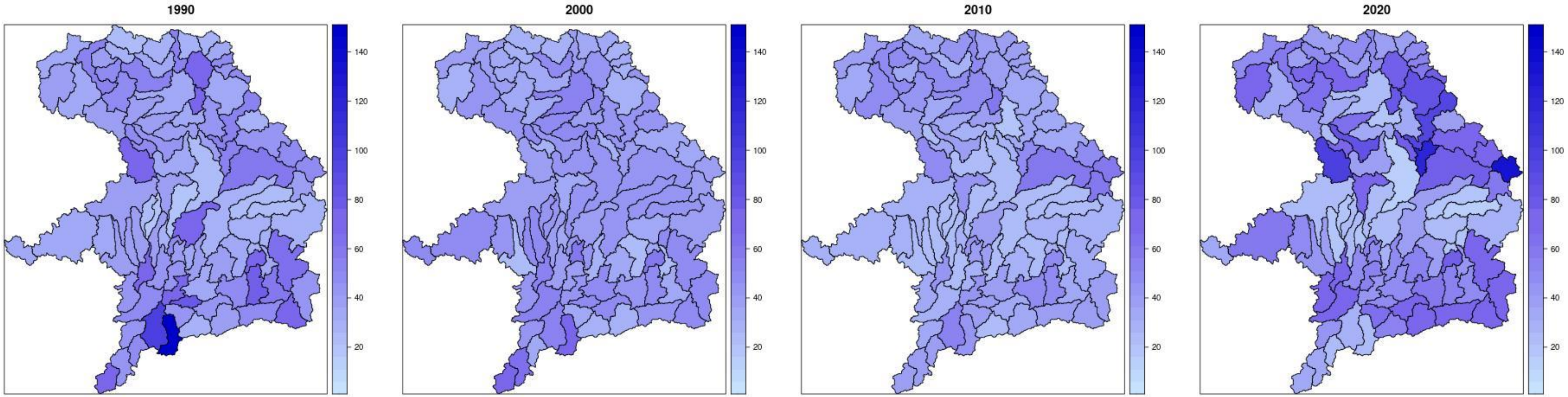
Number of Days of Low Flow for One Member



For member “kbt”

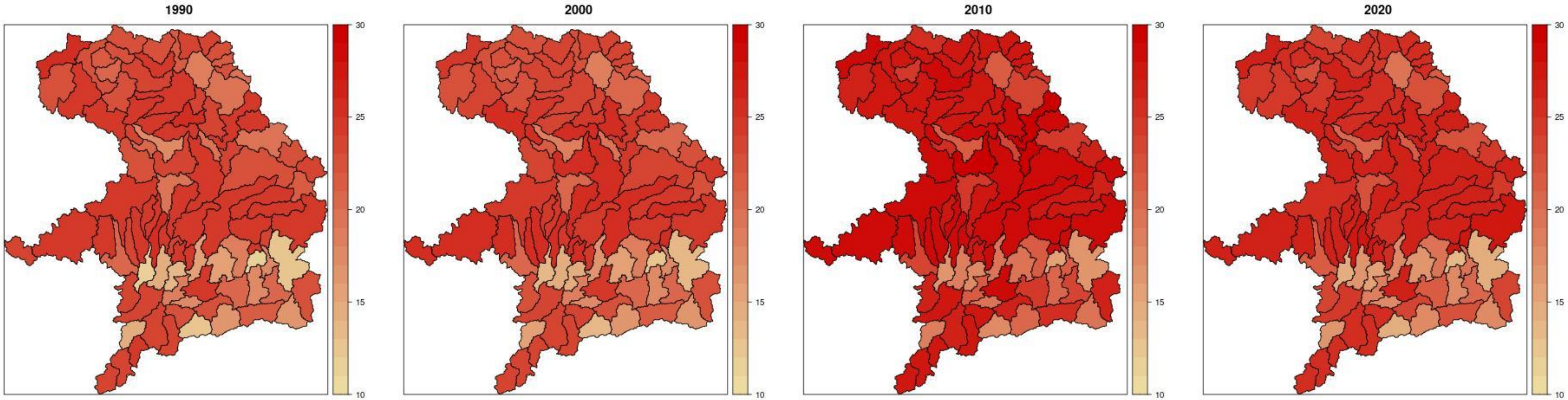
Drivers

Maximum Precipitation for One Member



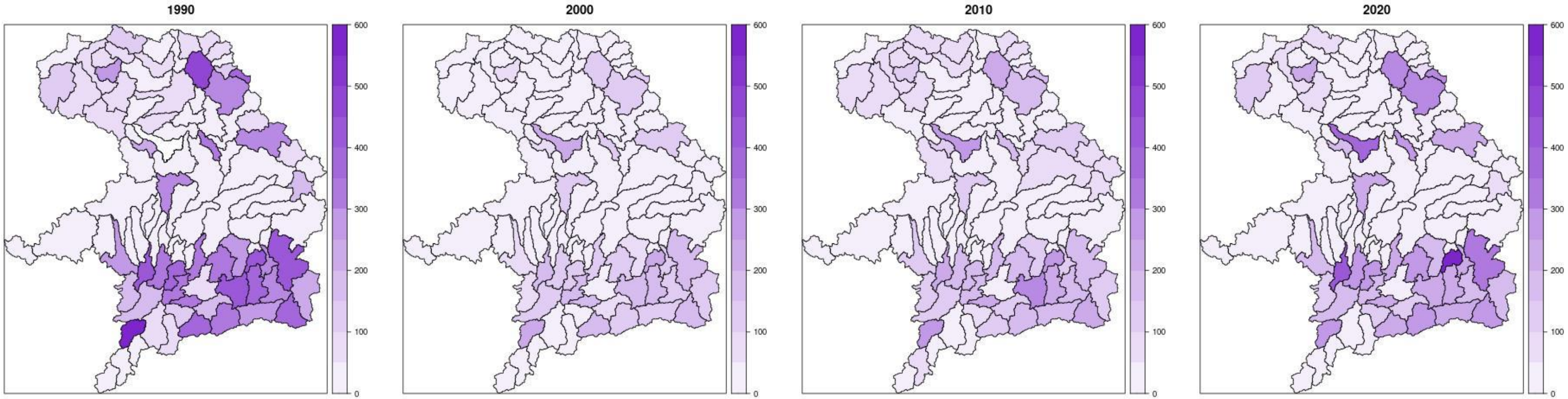
For member “kbt”

Maximum Temperature for One Member



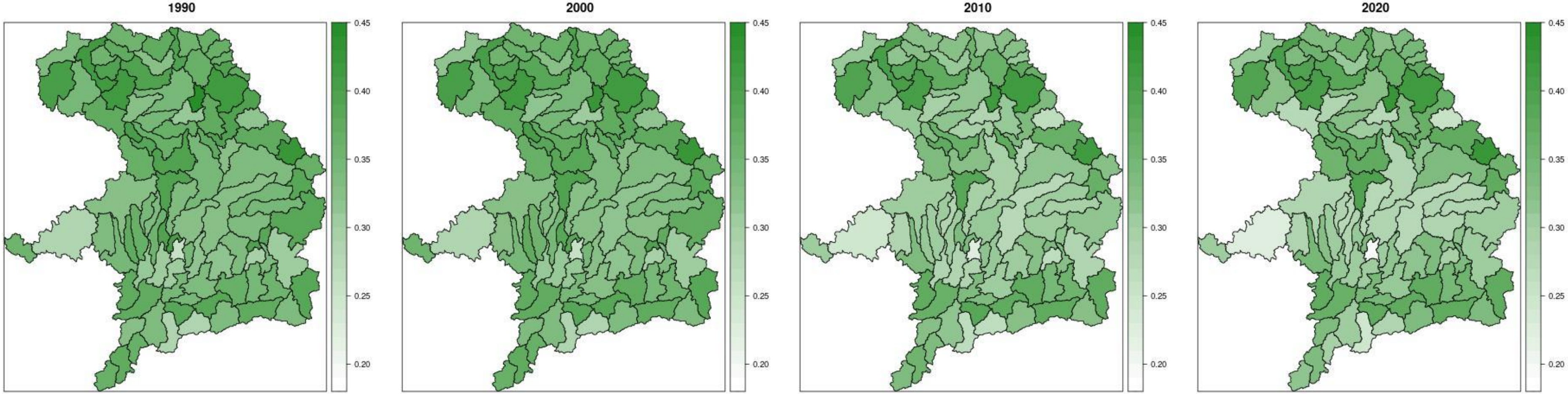
For member “kbt”

Maximum Snow Storage for One Member



For member “kbt”

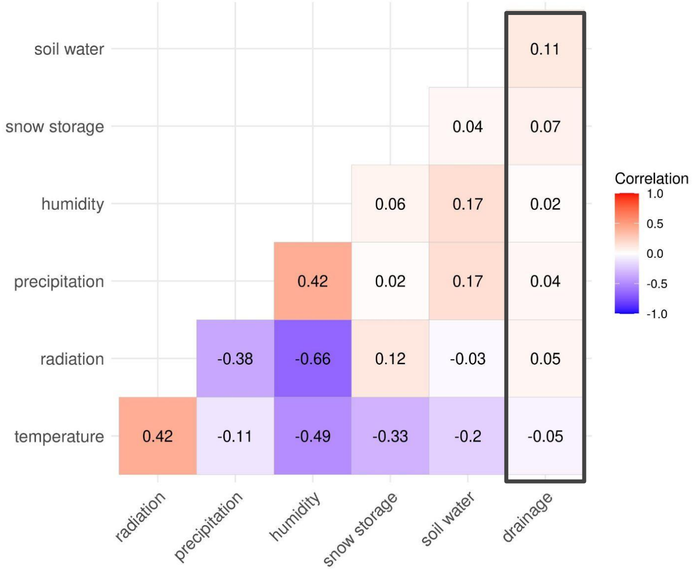
Average Soil Water for One Member



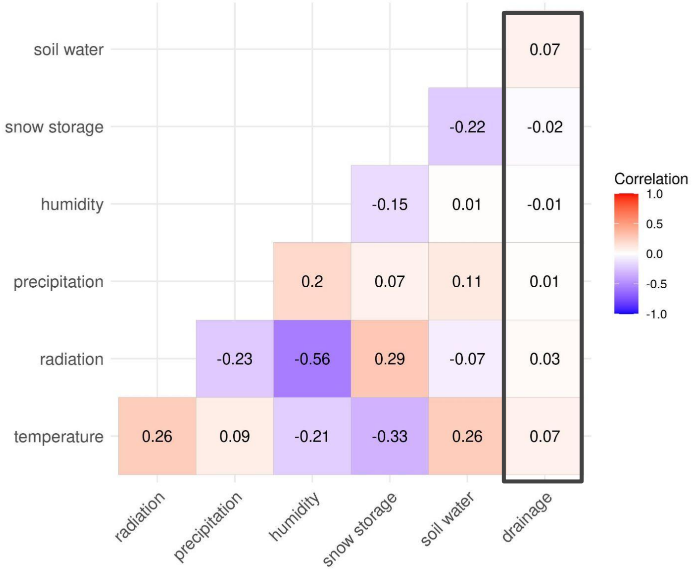
For member “kbt”

Relationship Between Drainage & Drivers

Correlation Matrix



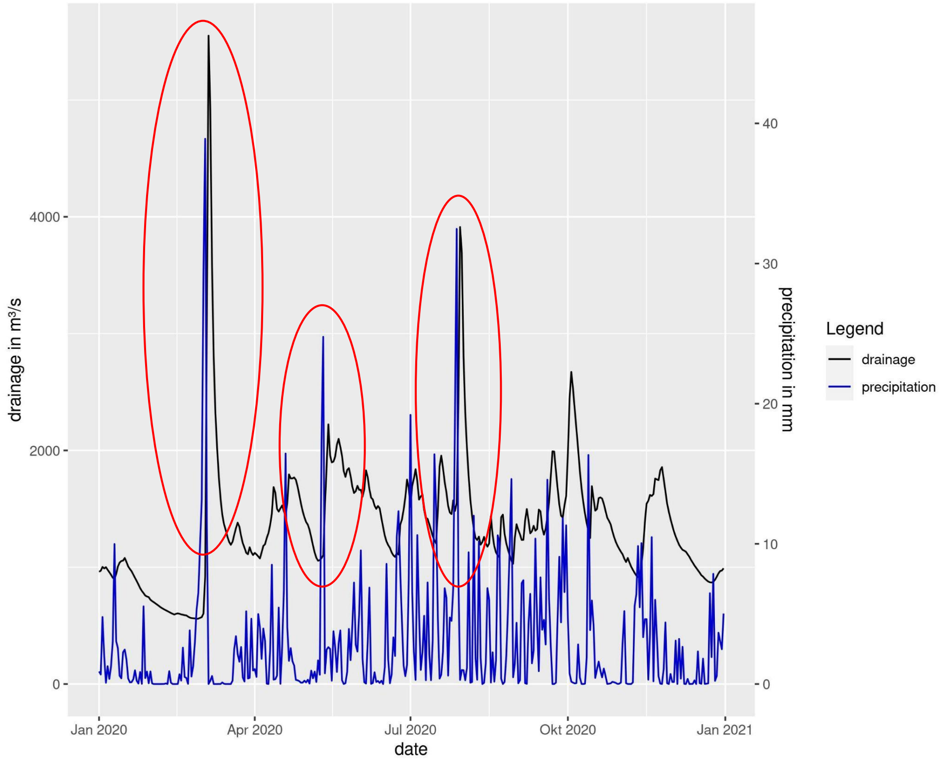
Summer

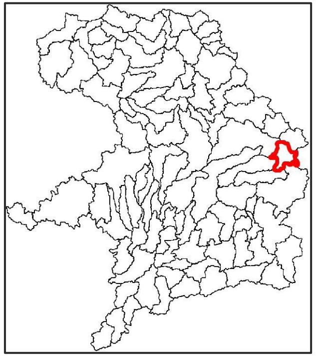


Winter

For member “kbt”

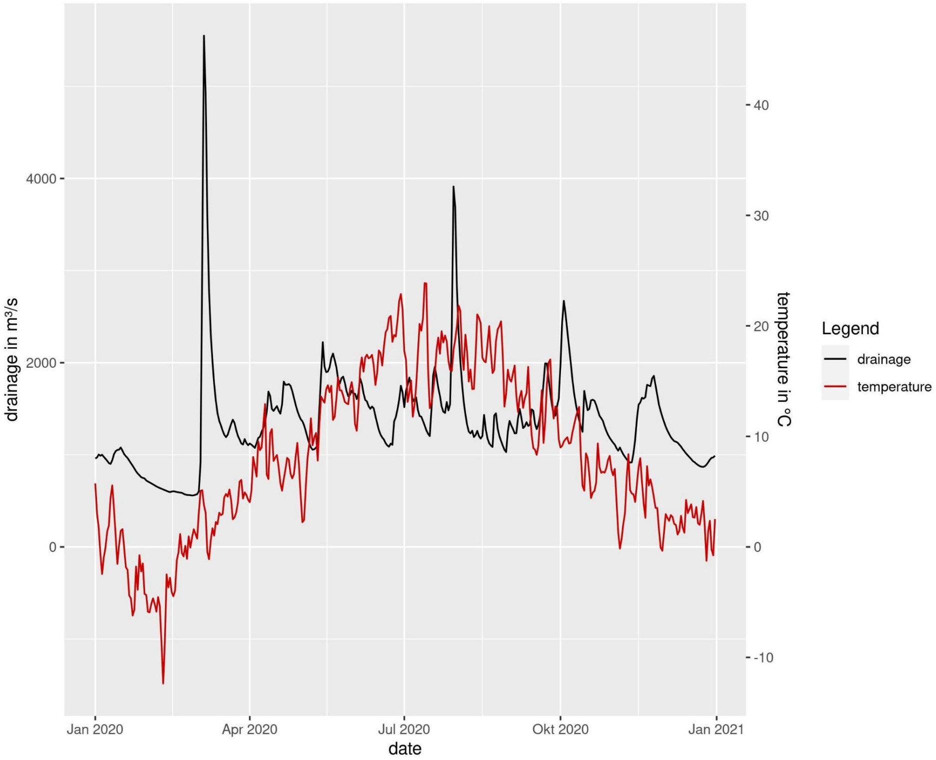
For Catchment Donau-Achleiten

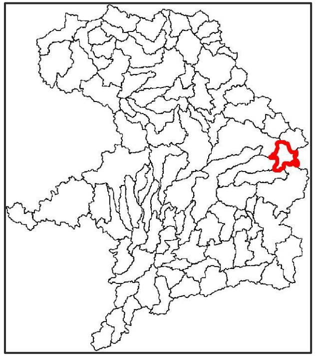




For member “kbt”

For Catchment Donau-Achleiten

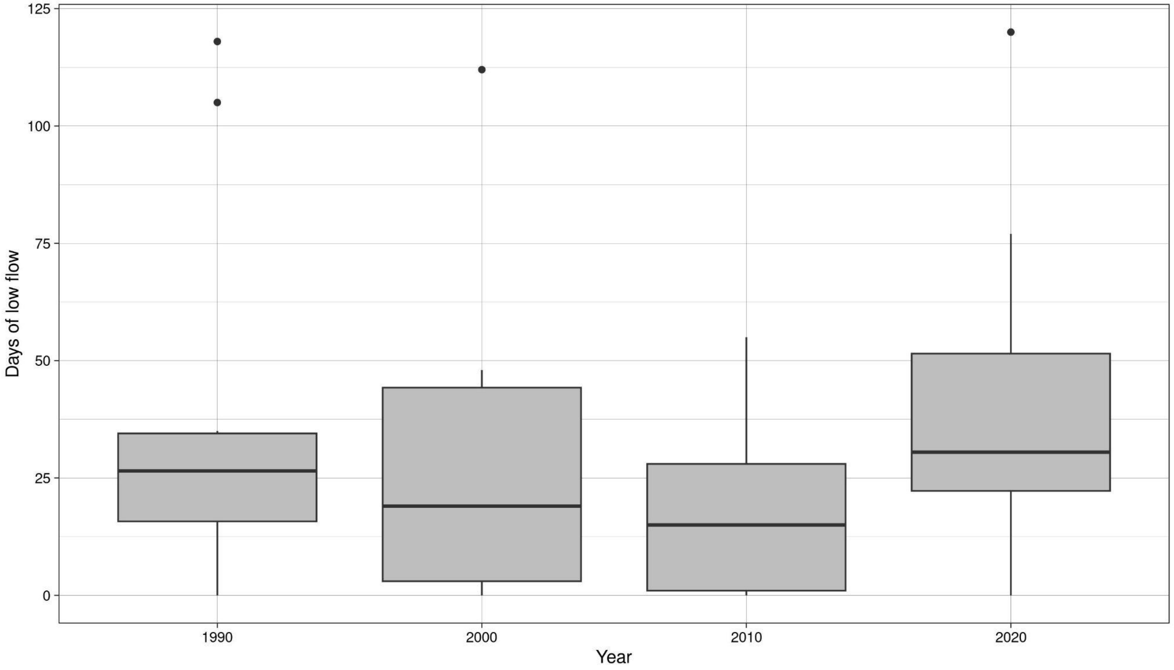


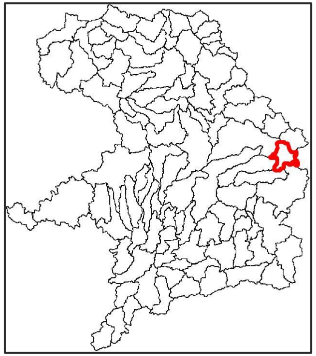


For member “kbt”

Differences Between Members

Annual Days of Low Flow for Catchment Donau-Achleiten





- Annual days of low flow calculated for each member
- Boxplot over 10 calculated sums

Modelling

Theory

Logistic Regression

- **Goal of regression:** model expected value of response
- **Response variable:** binary $Y \in \{0,1\}$, independently Bin(1, π_i)-distributed
- **Desired output:** probabilities between 0 and 1 for event yes/no
- Logistic response function for linear predictor:

$$E(Y_i|X) = P(Y_i = 1) = \pi_i = \frac{exp(\eta_i)}{1 + exp(\eta_i)}$$

with $\eta_i = \beta_{i0} + x_{i1}\beta_{i1} + ... + x_{ik}\beta_{ik}$

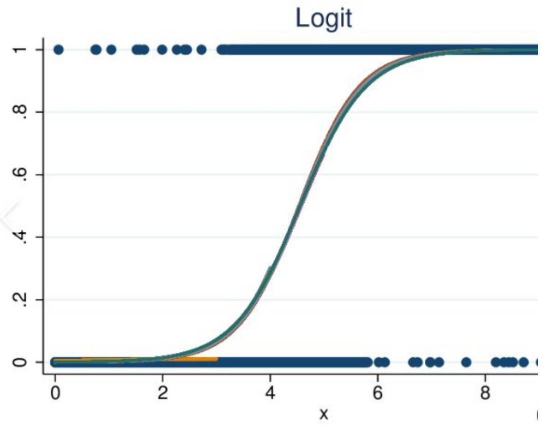


Figure: https://teaching.sociology.ul.ie/bhalpin/wordpress/?p=483

Interpretation in Logistic Regressions

- **Odds:** proportion of an event's chances of happening to its chances of not happening

$$\frac{P(Y_i = 1)}{1 - P(Y_i = 1)} = exp(\beta_{i0}) * exp(x_{i1}\beta_{i1}) * ... * exp(x_{ik}\beta_{ik})$$

- **Log-Odds:** logarithmic transformation of the odds → interpretation as linear model

$$\log\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right) = \beta_{i0} + x_{i1}\beta_{i1} + ... + x_{ik}\beta_{ik}$$

- **Interpretation:**
  - $\beta_i > 0 \Rightarrow \exp(\beta_i) > 1$: odds increase with growing x_i
  - $\beta_i < 0 \Rightarrow \exp(\beta_i) < 1$: odds decrease with growing x_i
  - $\beta_i = 0 \Rightarrow \exp(\beta_i) = 1$: odds stay the same

Challenges

Time lag	Rolling mean: ● 7 days: precipitation, temperature, humidity, radiation ● 30 days: snow storage ● 60 days: soil water
Seasonality	● Summer/winter split ● Including variable year as trend
Catchment specific effects	Individual models for each catchment
Compound events	Include interactions
Negligibly small values for snow storage in summer	Inclusion criteria for each catchment: maximum $\geq$ 1 cm for every member

Challenges

Time lag	Rolling mean: ● 7 days: precipitation, temperature, humidity, radiation ● 30 days: snow storage ● 60 days: soil water
Seasonality	● Summer/winter split ● Including variable year as trend
Catchment specific effects	Individual models for each catchment
Compound events	Include interactions
Negligibly small values for snow storage in summer	Inclusion criteria for each catchment: maximum $\geq$ 1 cm for every member

Challenges

Time lag	Rolling mean: • 7 days: precipitation, temperature, humidity, radiation • 30 days: snow storage • 60 days: soil water
Seasonality	• Summer/winter split • Including variable year as trend
Catchment specific effects	Individual models for each catchment
Compound events	Include interactions
Negligibly small values for snow storage in summer	Inclusion criteria for each catchment: maximum $\geq$ 1 cm for every member

Challenges

Time lag	Rolling mean: ● 7 days: precipitation, temperature, humidity, radiation ● 30 days: snow storage ● 60 days: soil water
Seasonality	● Summer/winter split ● Including variable year as trend
Catchment specific effects	Individual models for each catchment
Compound events	Include interactions
Negligibly small values for snow storage in summer	Inclusion criteria for each catchment: maximum $\geq$ 1 cm for every member

Challenges

Time lag	Rolling mean: ● 7 days: precipitation, temperature, humidity, radiation ● 30 days: snow storage ● 60 days: soil water
Seasonality	● Summer/winter split ● Including variable year as trend
Catchment specific effects	Individual models for each catchment
Compound events	Include interactions
Negligibly small values for snow storage in summer	Inclusion criteria for each catchment: maximum $\geq$ 1 cm for every member

Model Specification

- **Response variable:** day of low flow (yes/no)
- **Explanatory variables:** precipitation, temperature, soil water, snow storage, humidity, radiation
  - Rolling means
  - Centered → interpretable interaction
  - Linear trends
- **Interactions** between
  - Temperature & precipitation
  - Temperature & soil water
  - Temperature & snow storage
- Variable Year as trend
- **Goodness of fit criteria:** AIC, accuracy, AUC, effective degree of freedom (edf)

Model Procedure

1. Fit logistic model to every catchment and every member for summer and winter

   → in total 2 x 98 x 10 = 1960 models

2. Average coefficients for each catchment over all members

   → one coefficient for each catchment in summer and winter respectively

3. Analysis of significance via Bonferroni correction

Bonferroni Correction

- 10 estimated coefficients for the same catchment, i.e. 10 different p-values

  → multiple testing problem

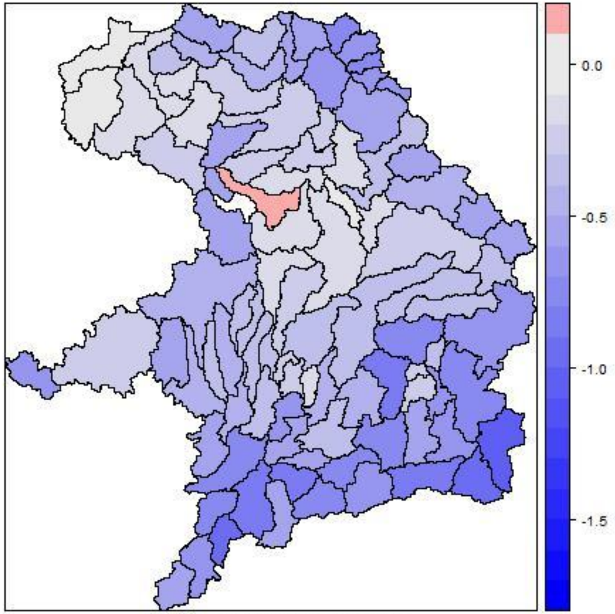
- Idea of Bonferroni correction: decrease the significance level for each test:

$$\alpha_B = \alpha / 10$$

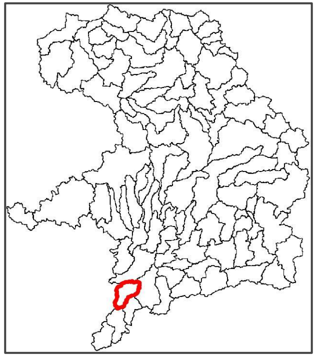
  → driver has a significant effect on development of low flow if all 10 p-values are smaller than 0.05/10 = 0.005

Results

Effect of Precipitation for Sanna-Landeck-Bruggen



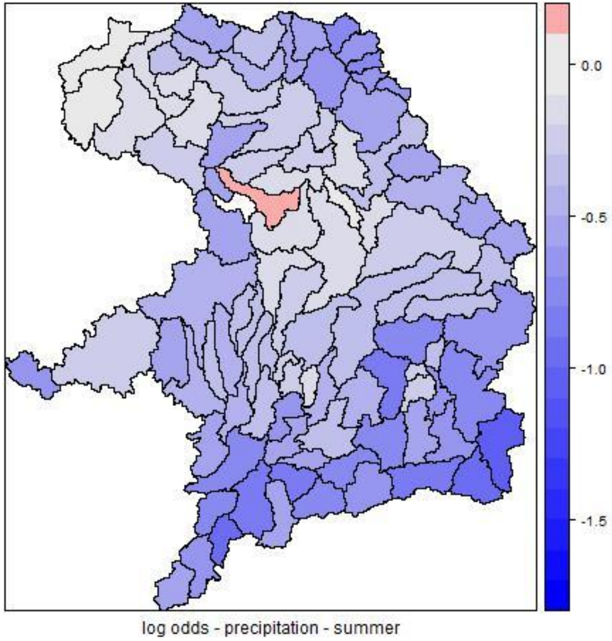
log odds - precipitation - summer

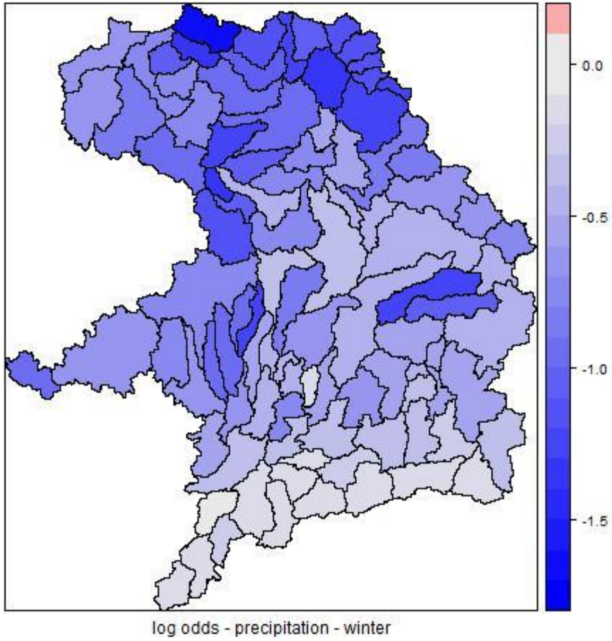


Keeping all other variables constant, for average temperature, increasing the 7-day mean of precipitation by one millimeter, the log-odds of occurring low flow that day decrease by 0.75 additively on average.

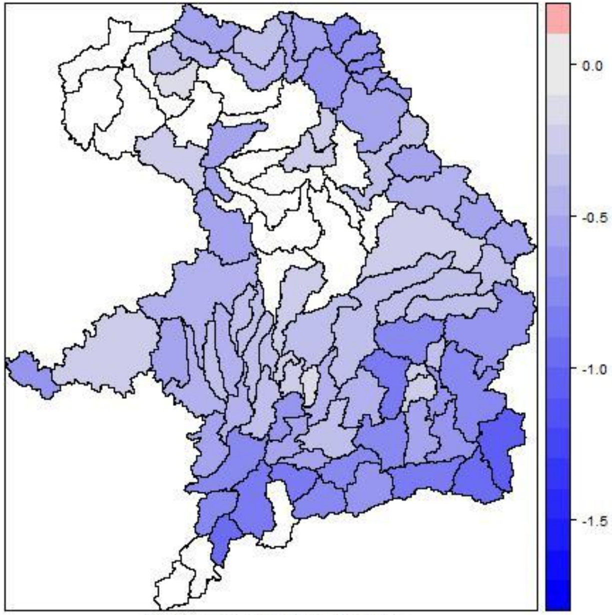
→ the odds of occurring low flow decrease by exp(-0.75) = 0.47 multiplicatively

Effect of Precipitation

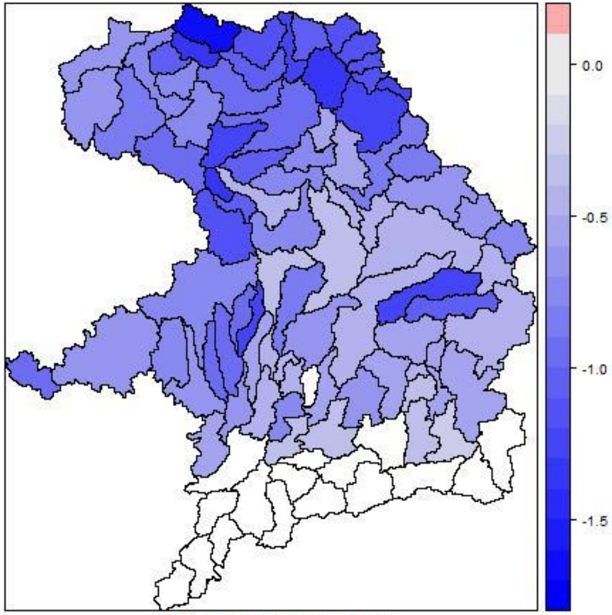




Significance of Precipitation

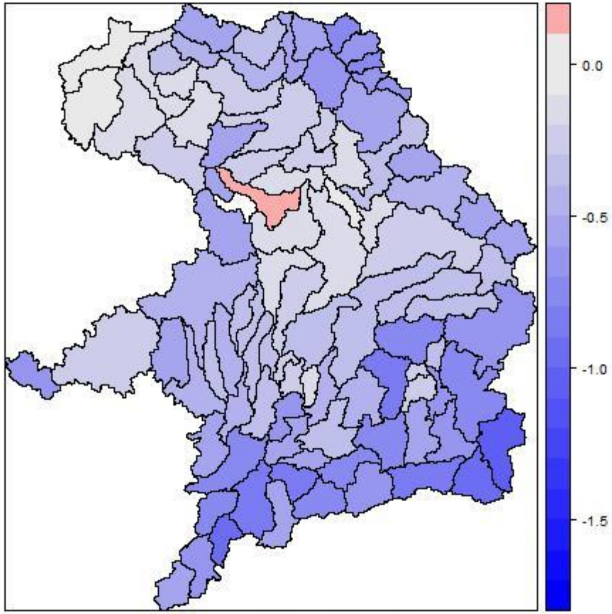


log odds - precipitation - summer

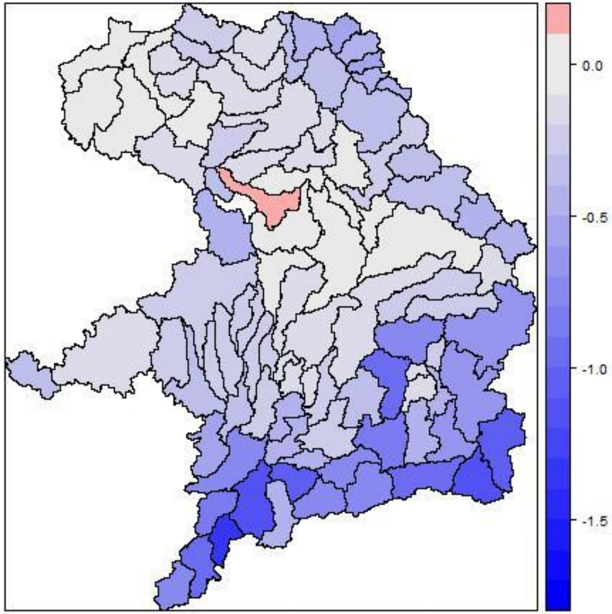


log odds - precipitation - winter

Effect of Interaction: Precipitation & Temperature

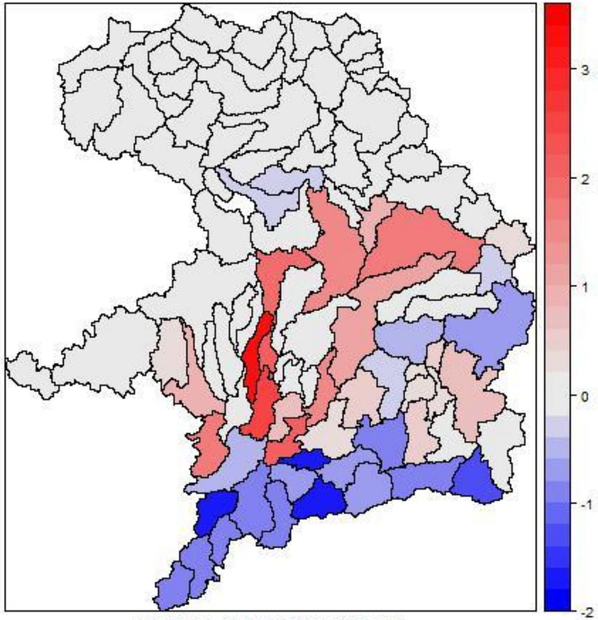


log odds - precipitation - summer

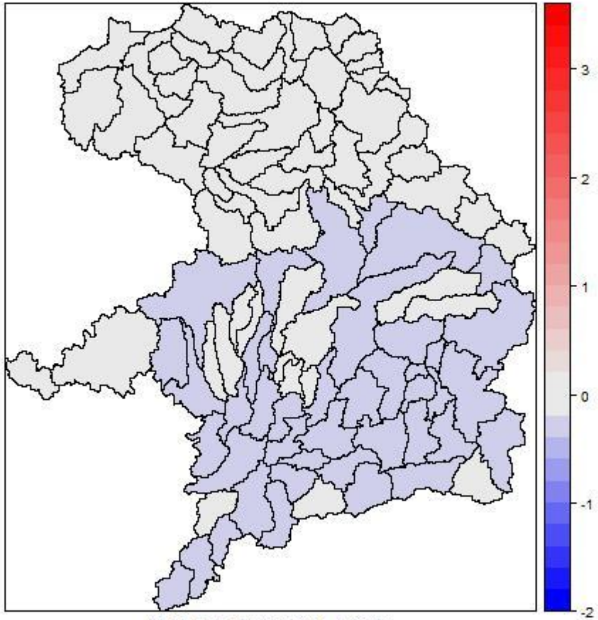


log odds - precipitation for +5°C - summer

Effect of Temperature

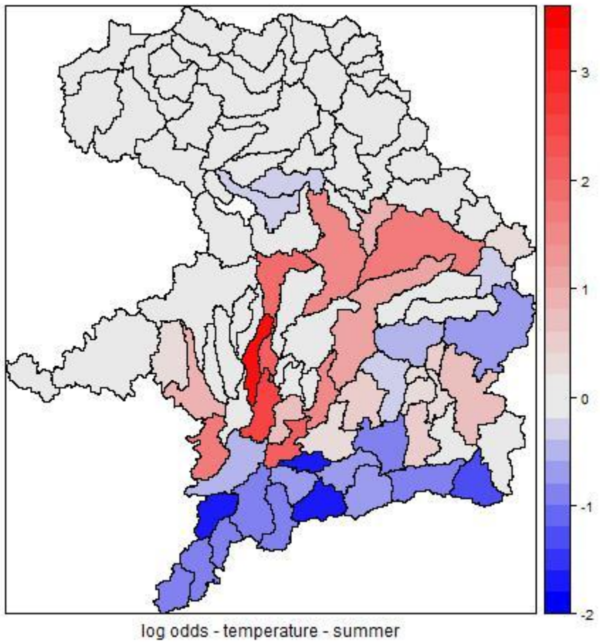


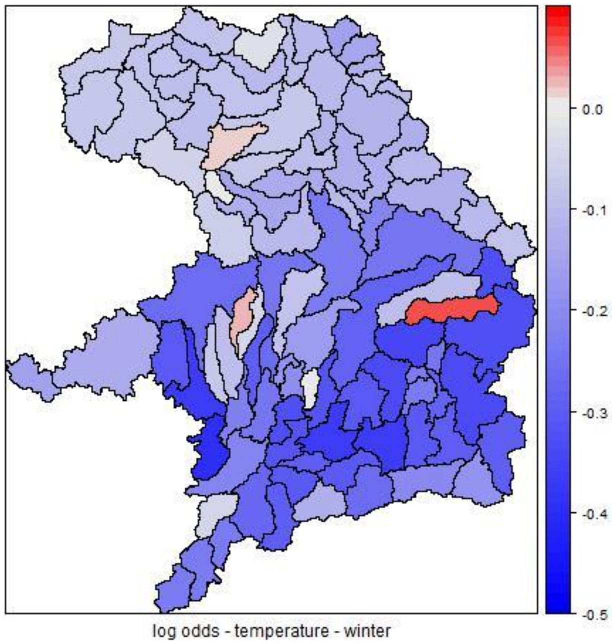
log odds - temperature - summer



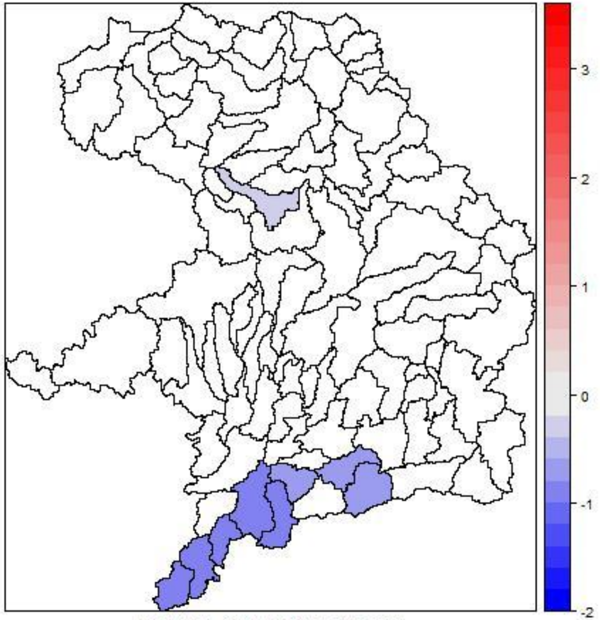
log odds - temperature - winter

Effect of Temperature - Winter Rescaled

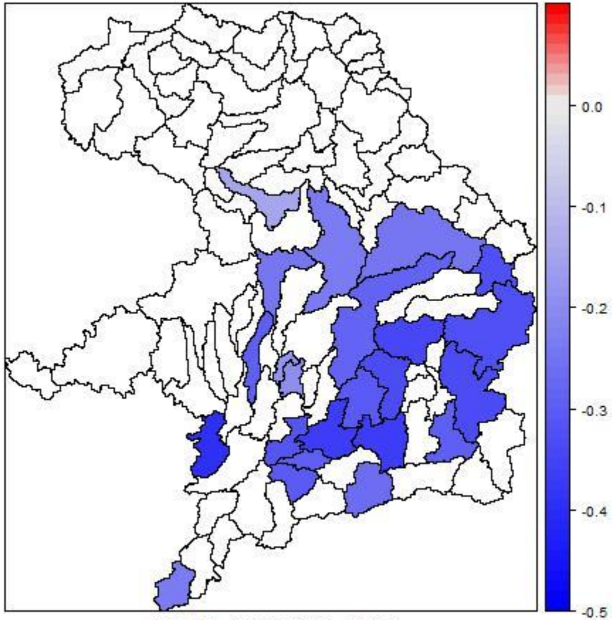




Significance of Temperature

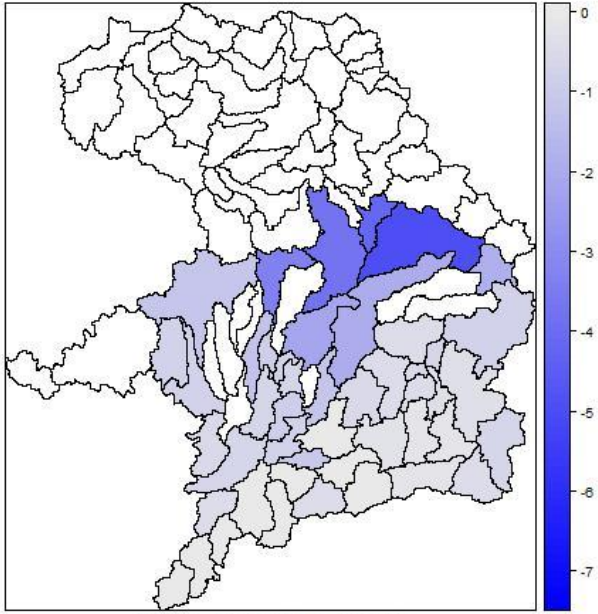


log odds - temperature - summer

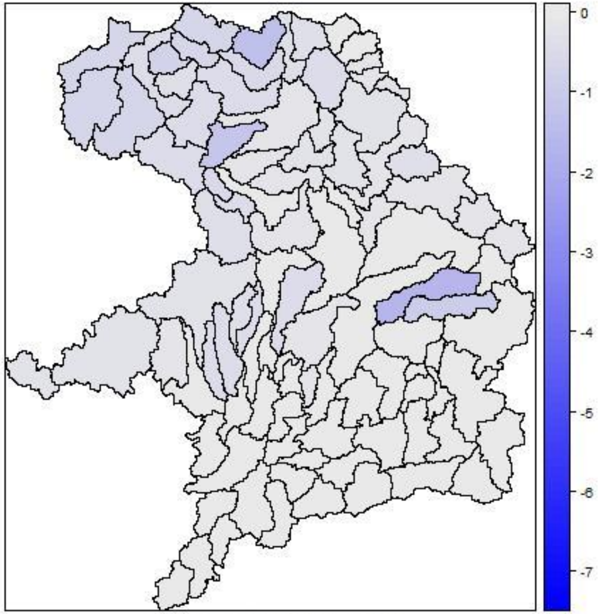


log odds - temperature - winter

Effect of Snow Storage

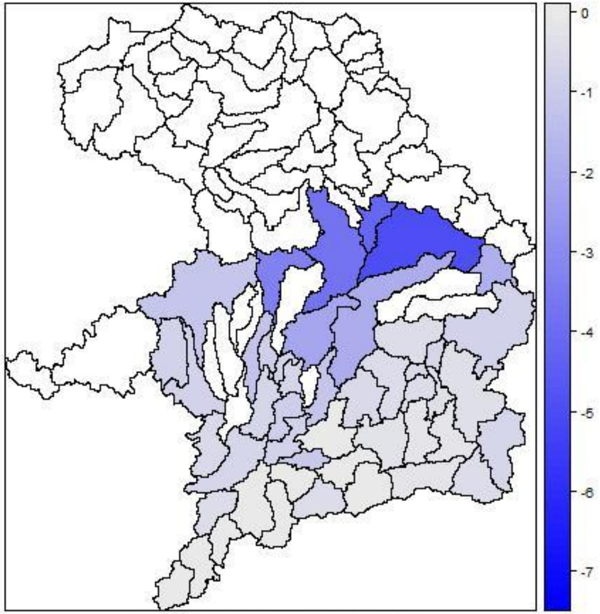


log odds - snow storage - summer

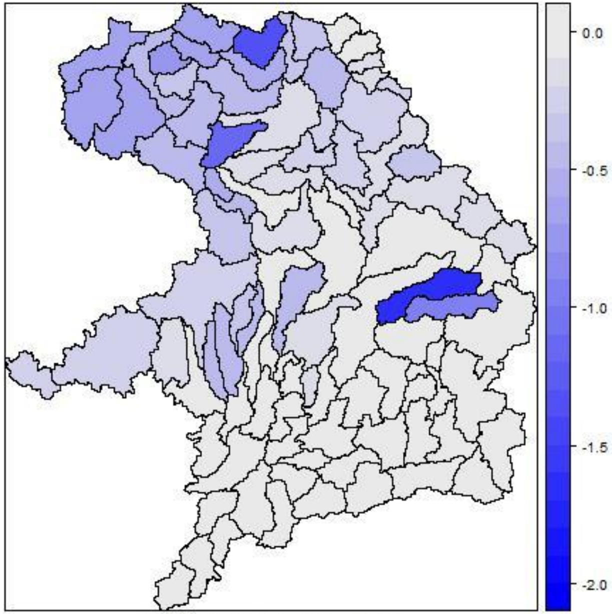


log odds - snow storage - winter

Effect of Snow Storage - Rescaled Winter

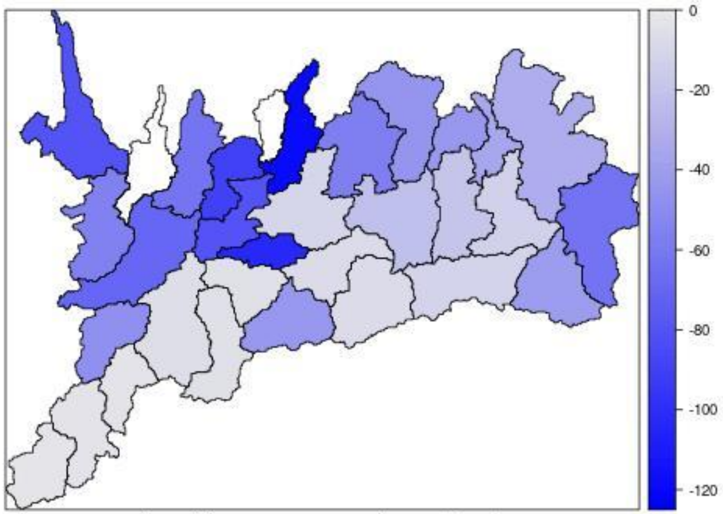


log odds - snow storage - summer

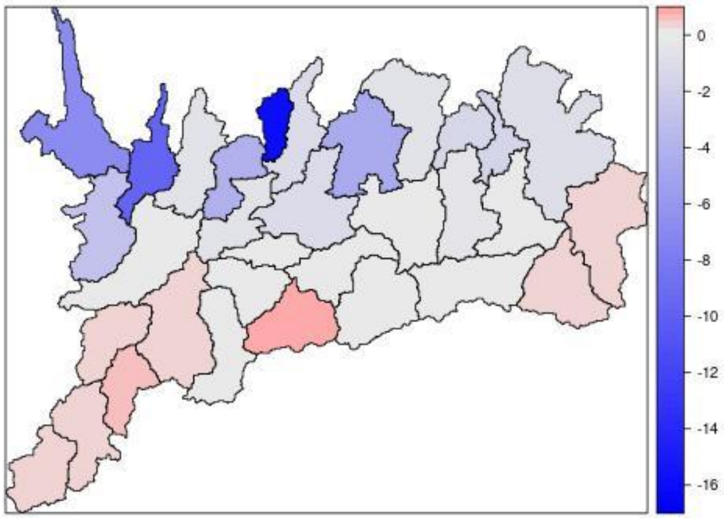


log odds - snow storage - winter

Effect of Snow Storage for 10 cm increase in alpine regions

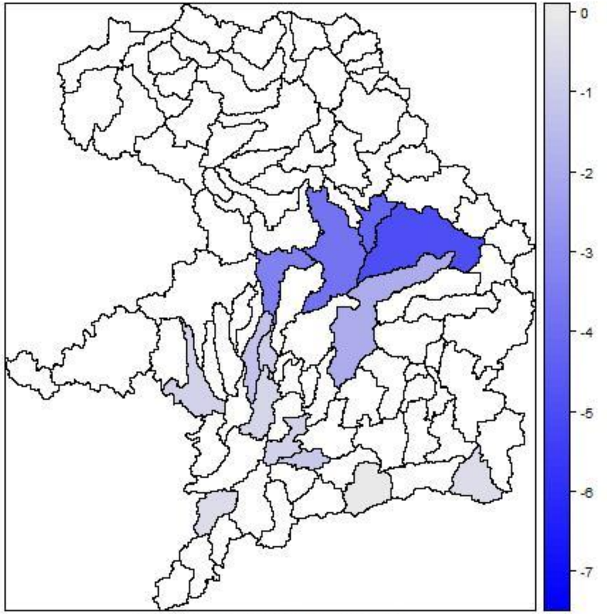


log odds - summer - snow storage (10 cm)

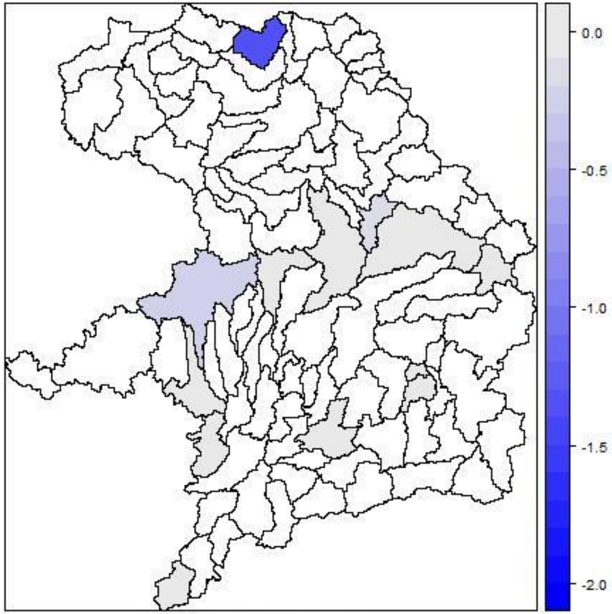


log odds - winter - snow storage (10 cm)

Significance of Snow Storage

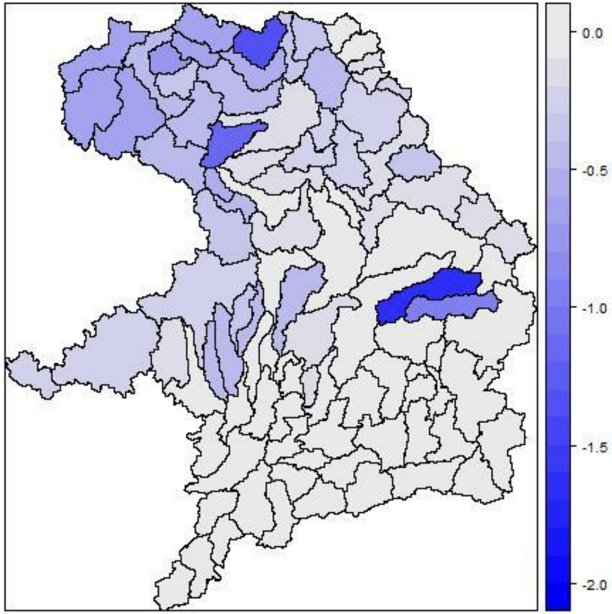


log odds - snow storage - summer

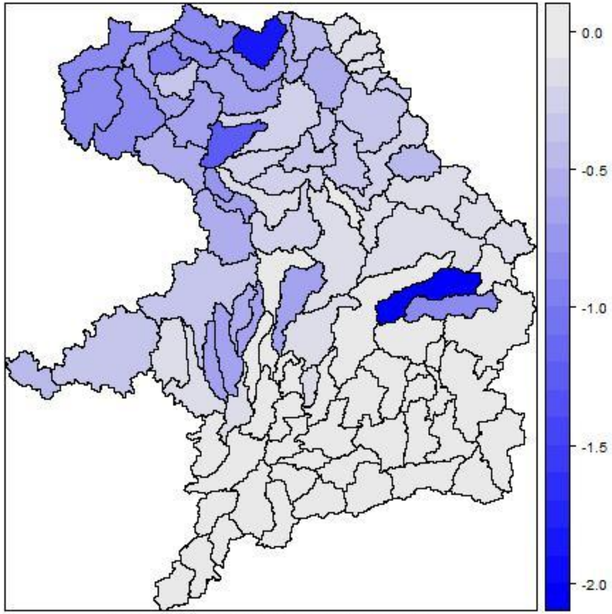


log odds - snow storage - winter

Effect of Interaction:
Snow Storage & Temperature

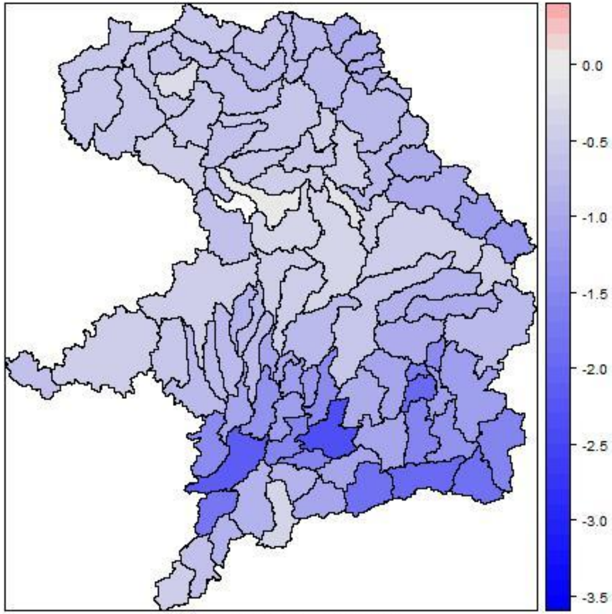


log odds - snow storage - winter

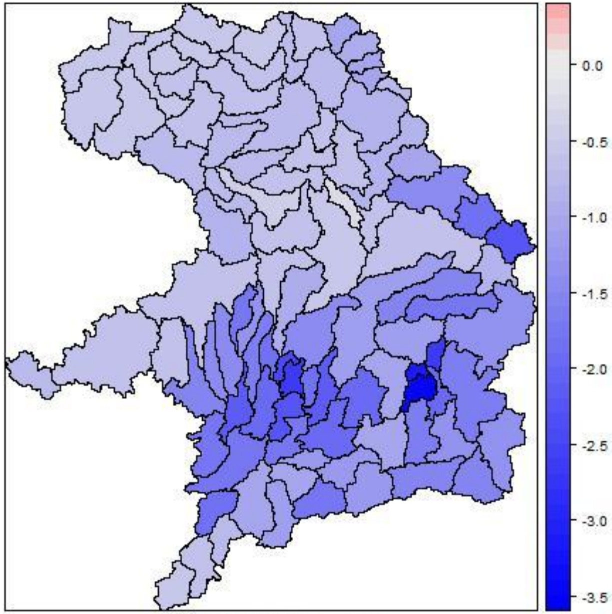


log odds - snow storage for +5°C - winter

Effect of Soil Water

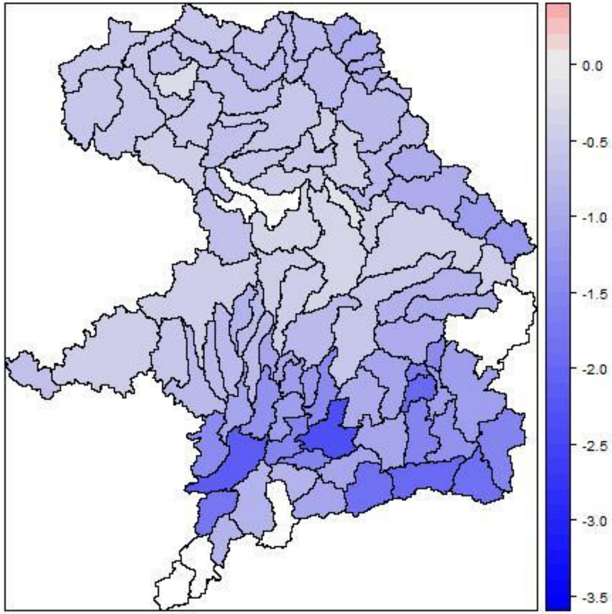


log odds - soil water - summer

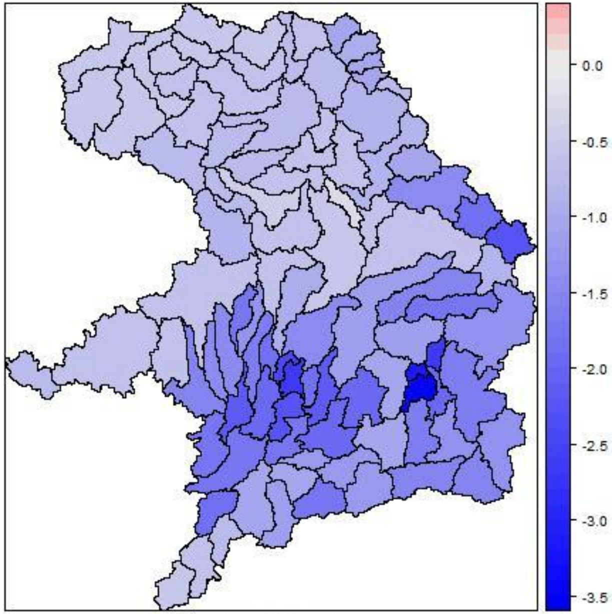


log odds - soil water - winter

Significance of Soil Water

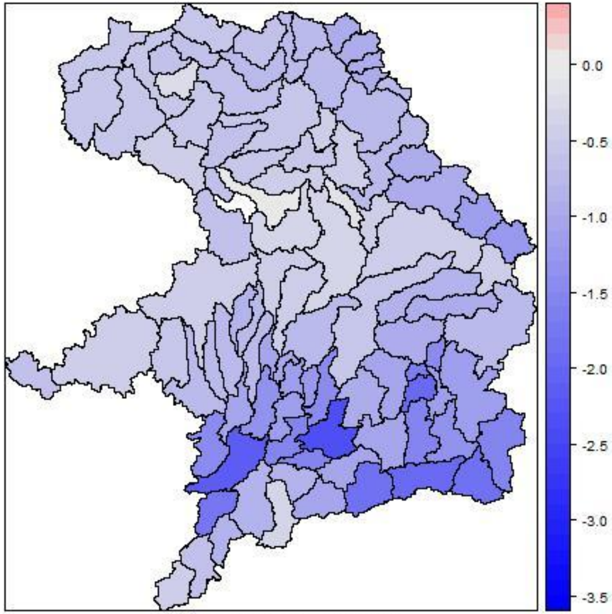


log odds - soil water - summer

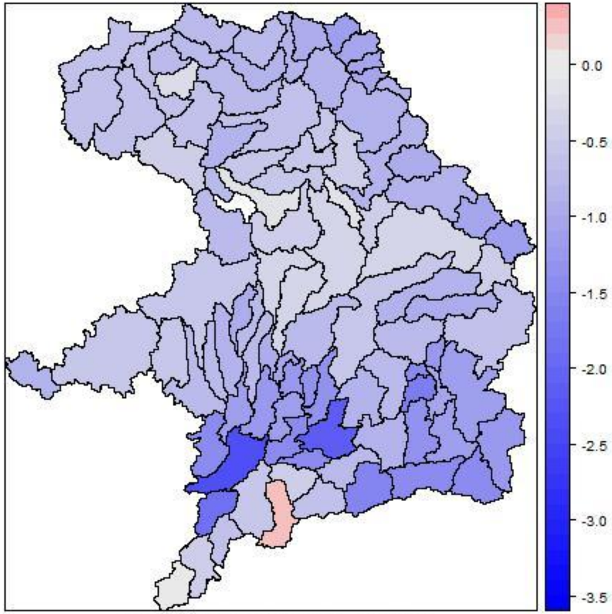


log odds - soil water - winter

Effect of Interaction: Soil Water & Temperature

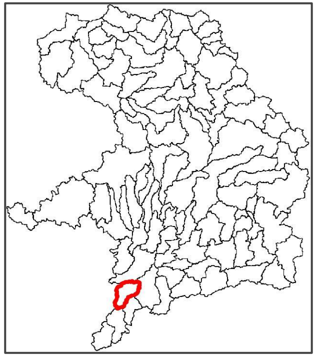


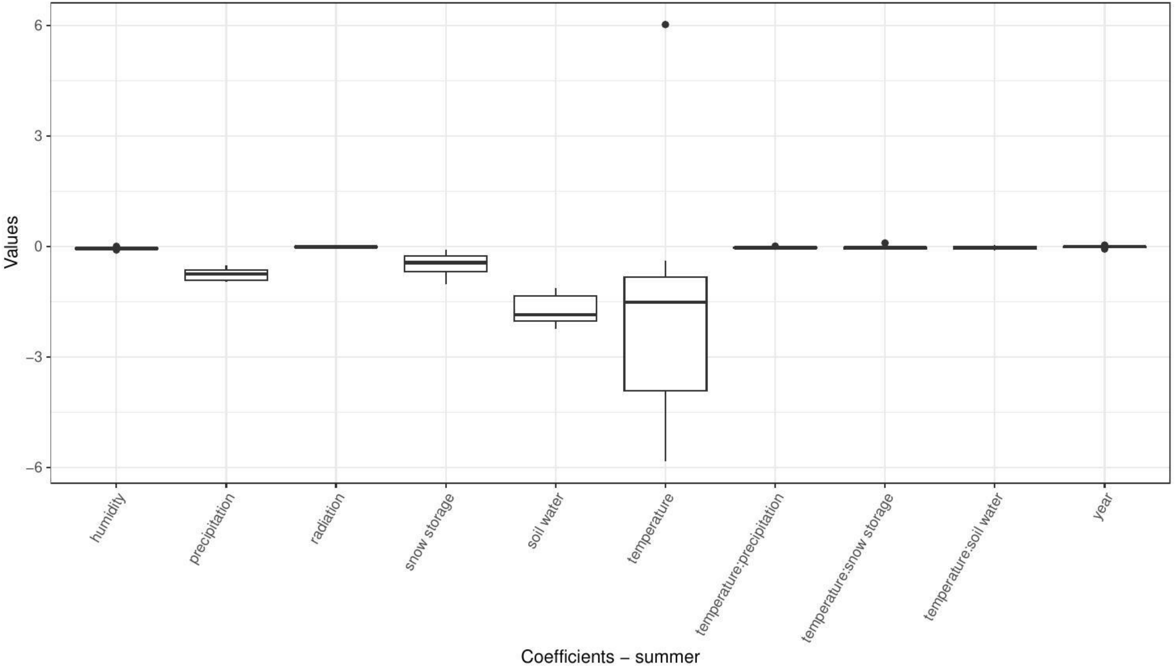
log odds - soil water - summer



log odds - soil water for +5°C - summer

Differences Between Members for Sanna-Landeck-Bruggen





ROC-Analysis

Idea

Model predictions: probabilities of day of low flow between 0 and 1 for each day, catchment and member

→ The closer to 1, the more likely a day of low flow occurs

→ **Question:** How to choose a threshold between 0 and 1 that determines if a day of low flow is classified as one or not?

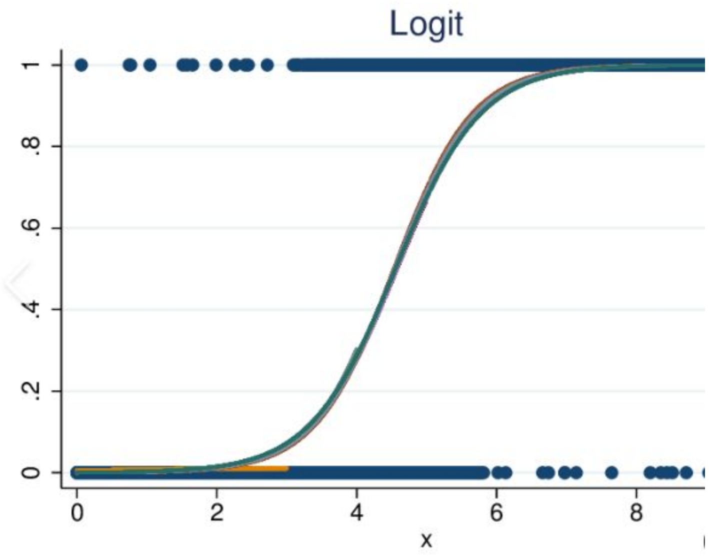


Figure: https://teaching.sociology.ul.ie/bhalpin/wordpress/?p=483

Evaluation Measures

Sensitivity	True Positive Rate (TPR)	Proportion of correctly predicted outcomes as positive when the actual outcome is positive
Specificity	1 - False Positive Rate (FPR)	Proportion of correctly predicted outcomes as negatives when the actual outcome is negative
	True Discovery Rate (TDR)	Proportion of correctly predicted outcomes as positive out of all predicted outcomes as positive

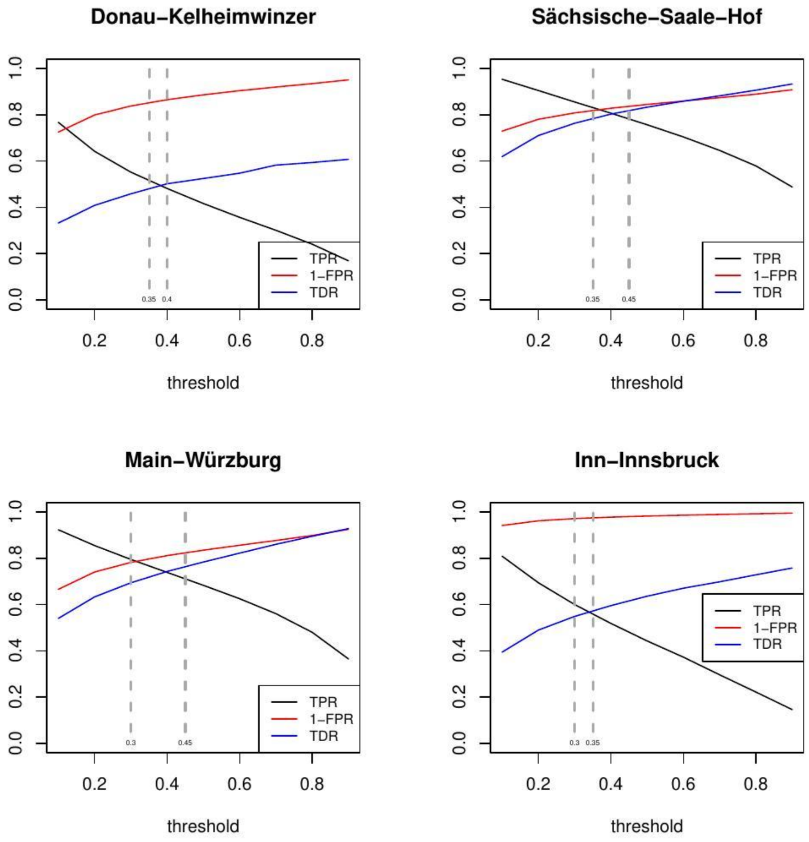
ROC Analysis for Summer Models

1) Train model on specific member and evaluate TPR, FPR and TDR on all other members for different thresholds

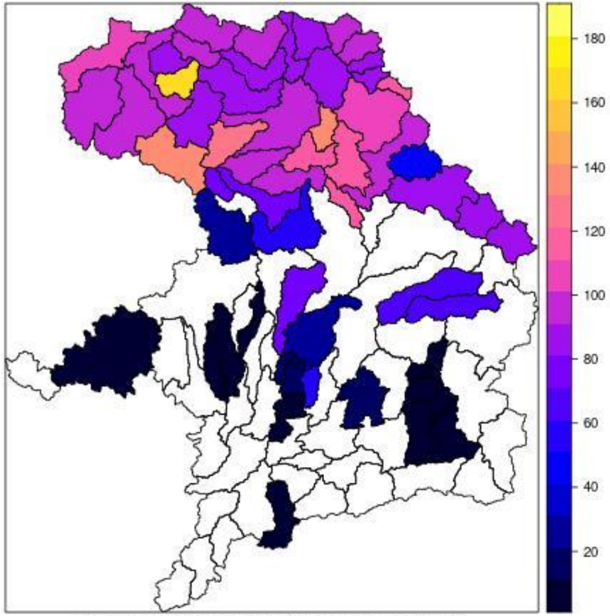
2) Average over all members for each catchment

3) Look for intersections points

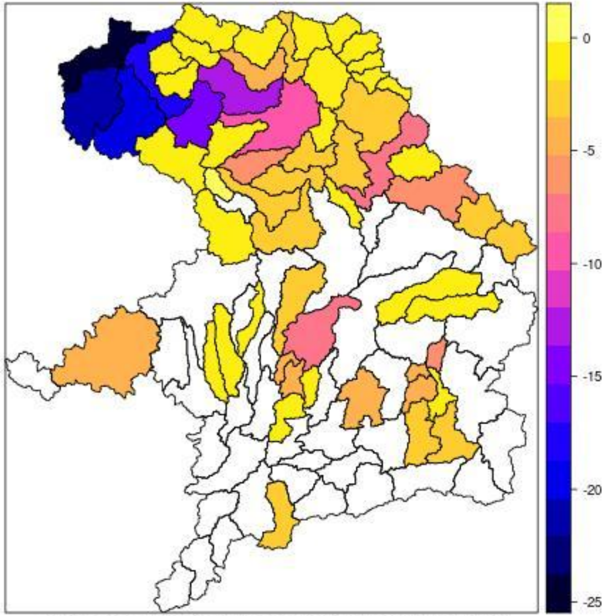
Analogous procedure for winter models



Analysis of Thresholds for Summer 2020 and One Member



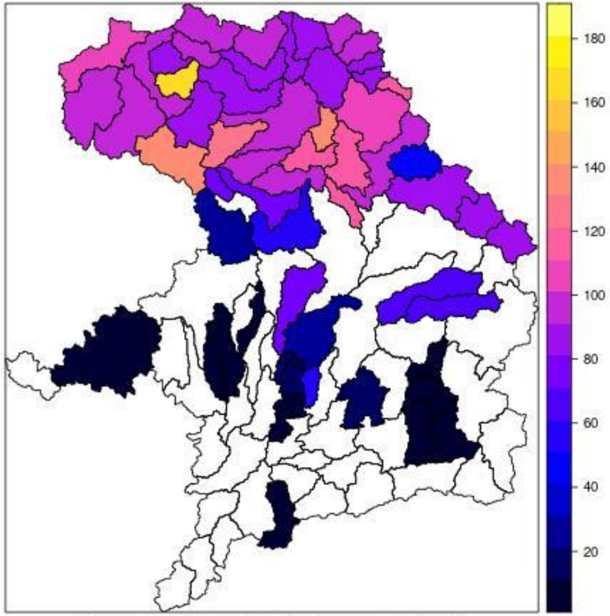
True number of days of low flow in summer of 2020



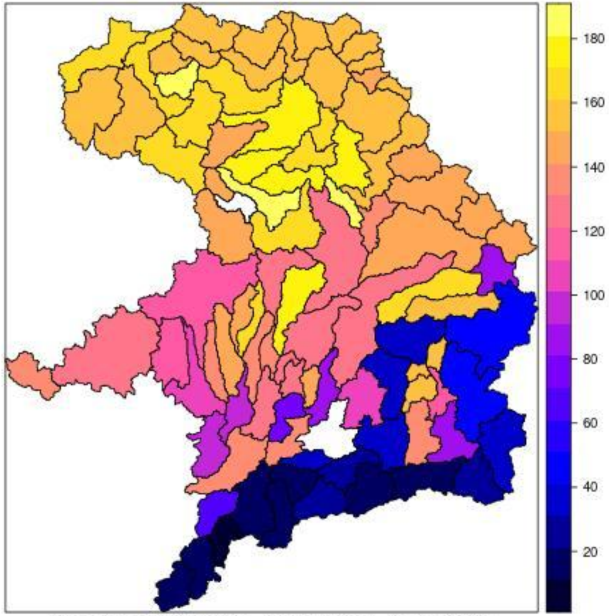
Maximal intensity of true days of low flow in summer of 2020

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



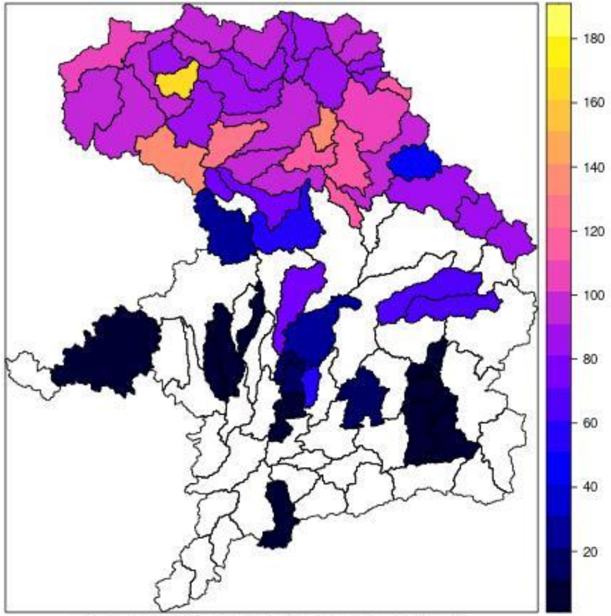
True number of days of low flow in summer of 2020



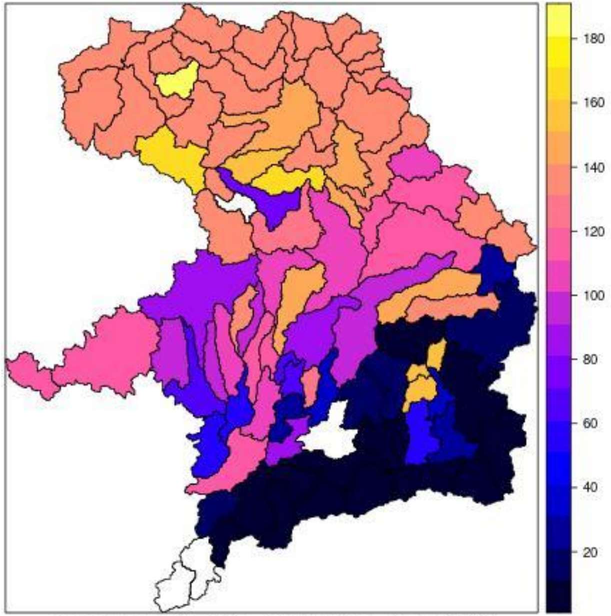
Days of predicted low flow - Summer 2020 - Threshold 0.1

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



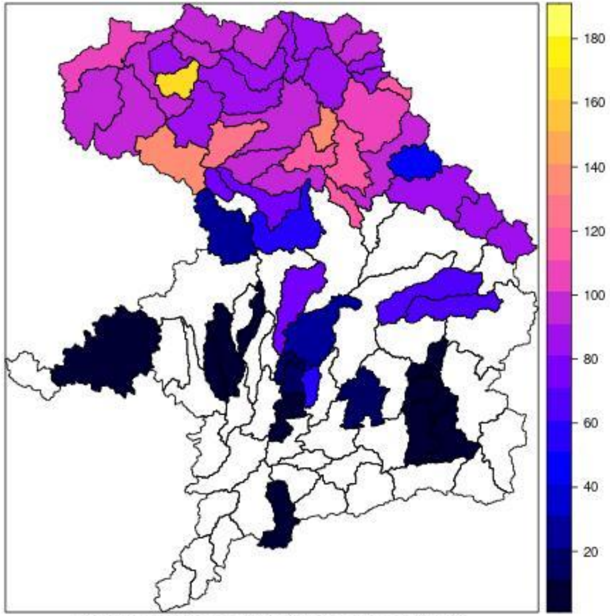
True number of days of low flow in summer of 2020



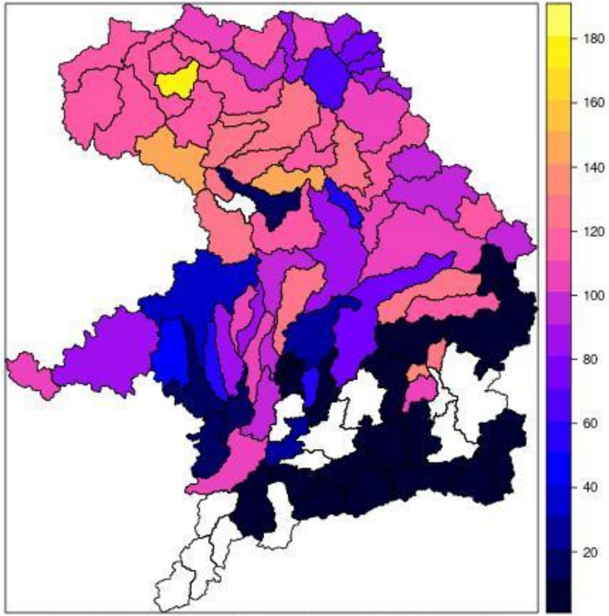
Days of predicted low flow - Summer 2020 - Threshold 0.2

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



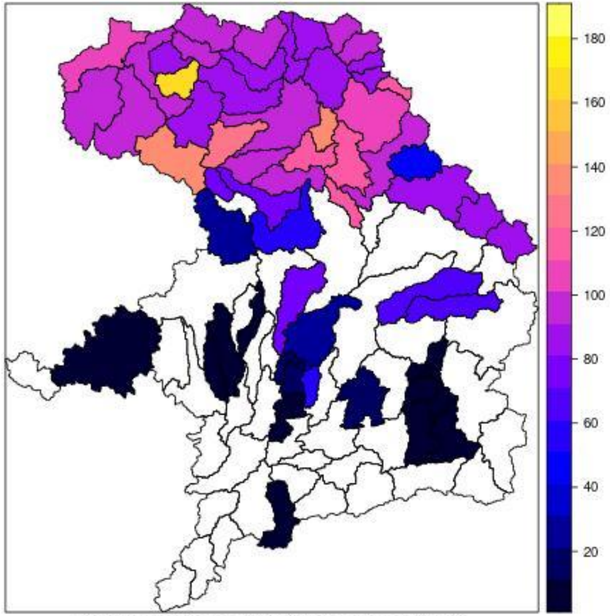
True number of days of low flow in summer of 2020



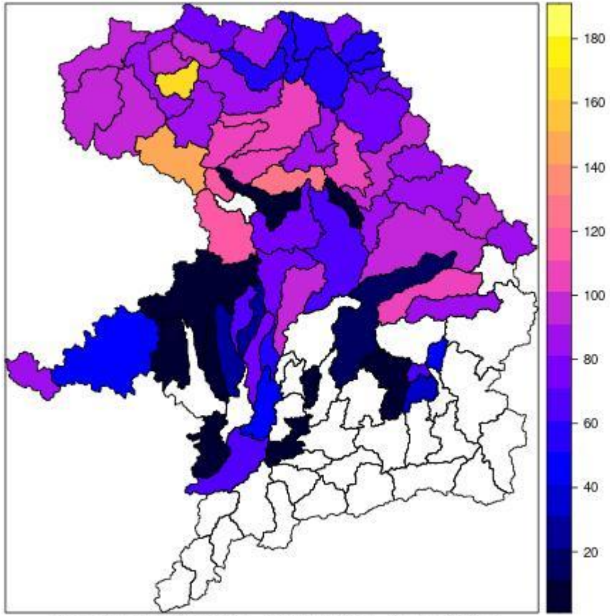
Days of predicted low flow - Summer 2020 - Threshold 0.3

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



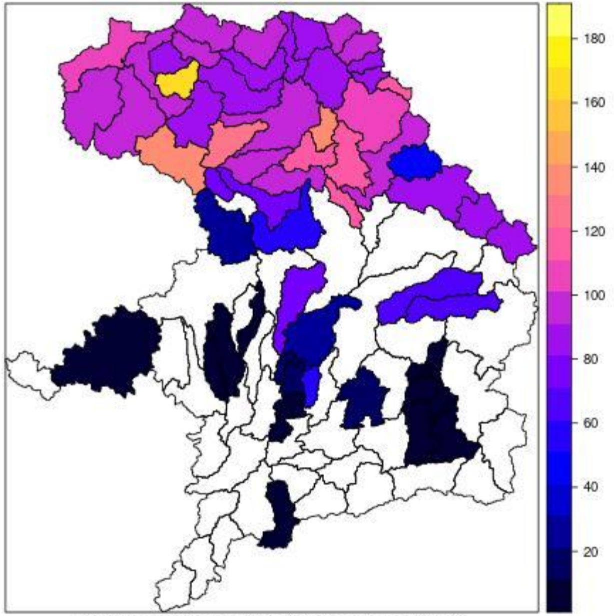
True number of days of low flow in summer of 2020



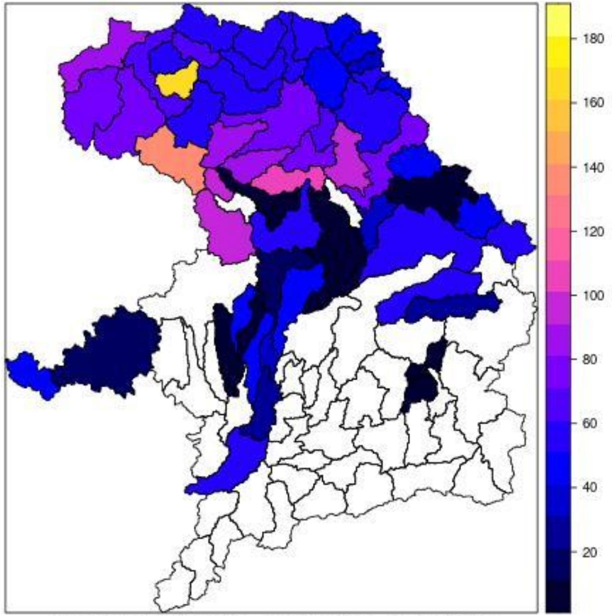
Days of predicted low flow - Summer 2020 - Threshold 0.4

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



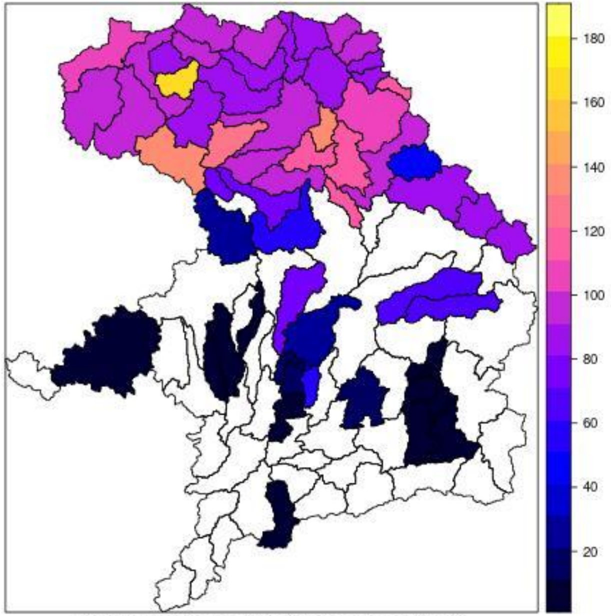
True number of days of low flow in summer of 2020



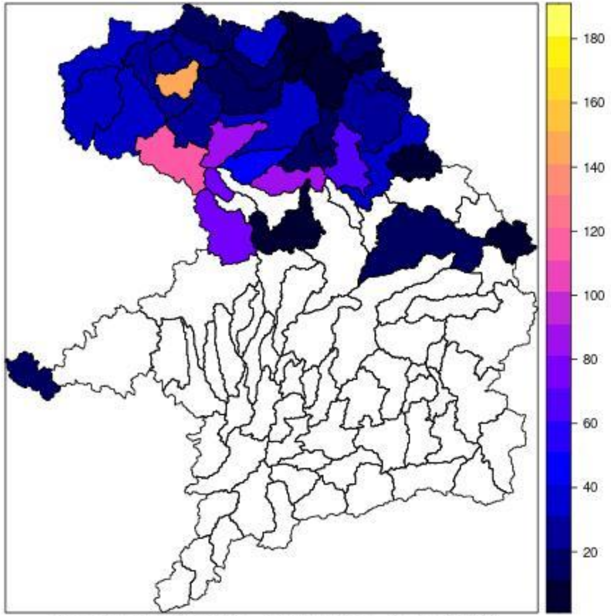
Days of predicted low flow - Summer 2020 - Threshold 0.5

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



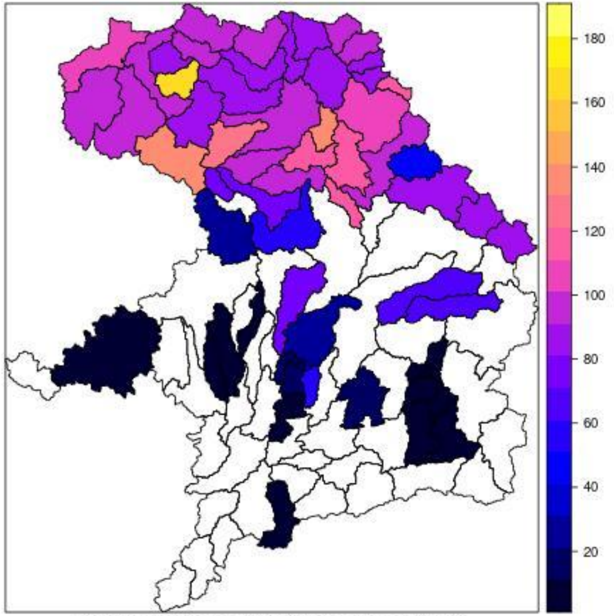
True number of days of low flow in summer of 2020



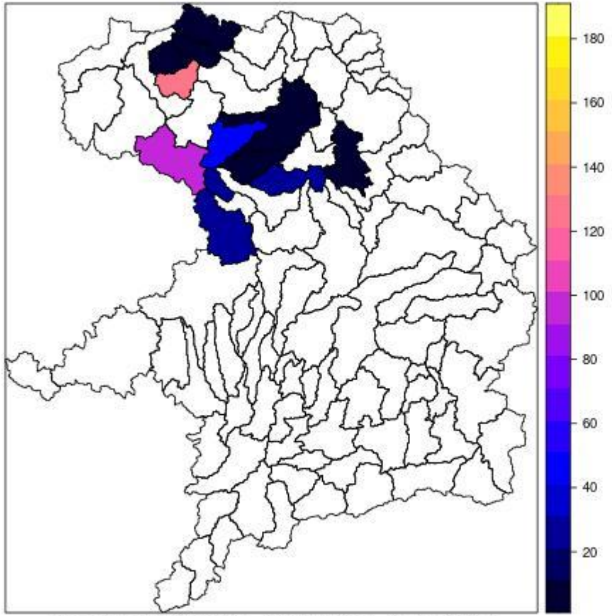
Days of predicted low flow - Summer 2020 - Threshold 0.6

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



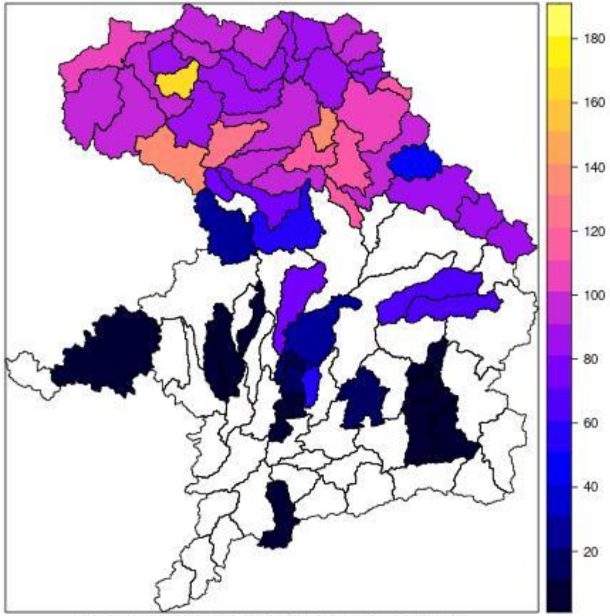
True number of days of low flow in summer of 2020



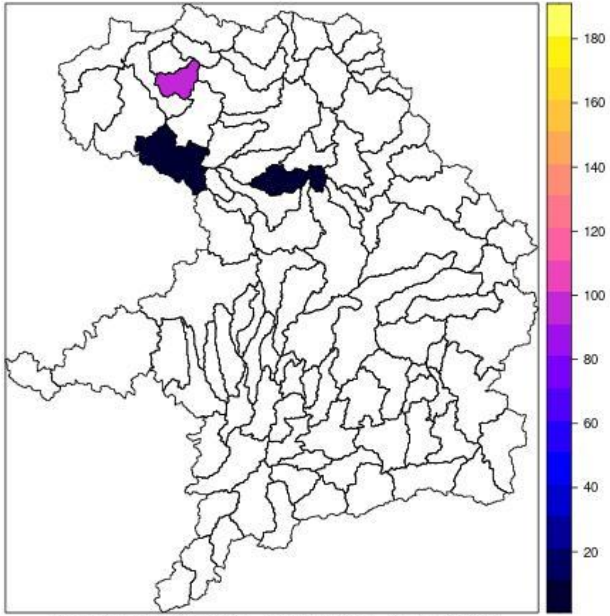
Days of predicted low flow - Summer 2020 - Threshold 0.7

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



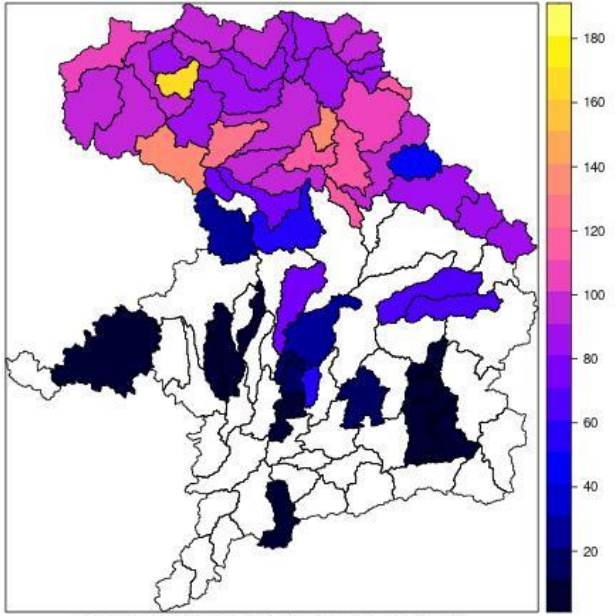
True number of days of low flow in summer of 2020



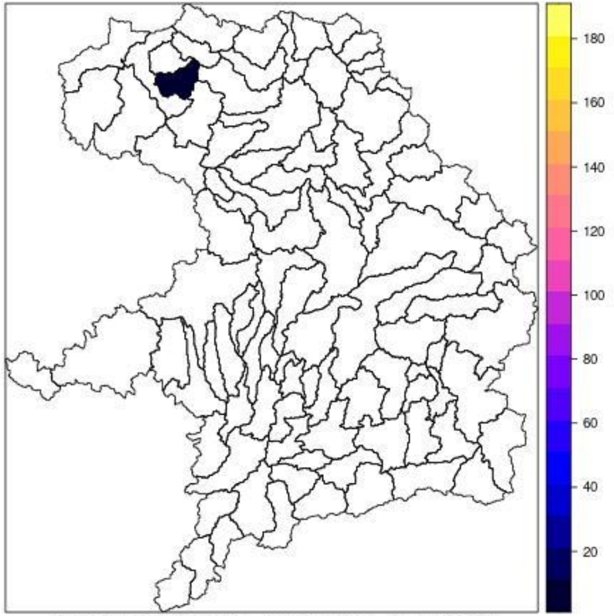
Days of predicted low flow - Summer 2020 - Threshold 0.8

For member “kbt”

Analysis of Thresholds for Summer 2020 and One Member



True number of days of low flow in summer of 2020



Days of predicted low flow - Summer 2020 - Threshold 0.9

For member “kbt”

Scenarios

What Happens if Temperature, Precipitation and Snow Storage Change?

Goal: comparison of model predictions for different weather scenarios

Procedure:

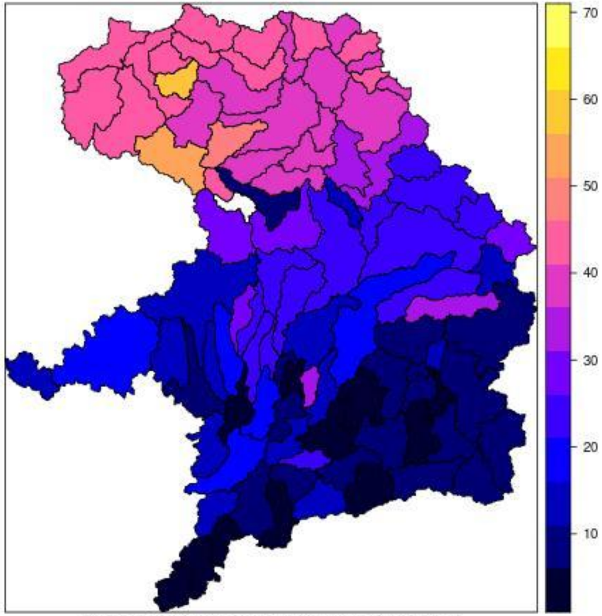
- Calculate predictions for every model with test data consisting of data of all other members not used for training for summer and winter of 2010
- Average number of days over ten members
- Threshold for prediction yes/no: 0.4

Weather Scenarios

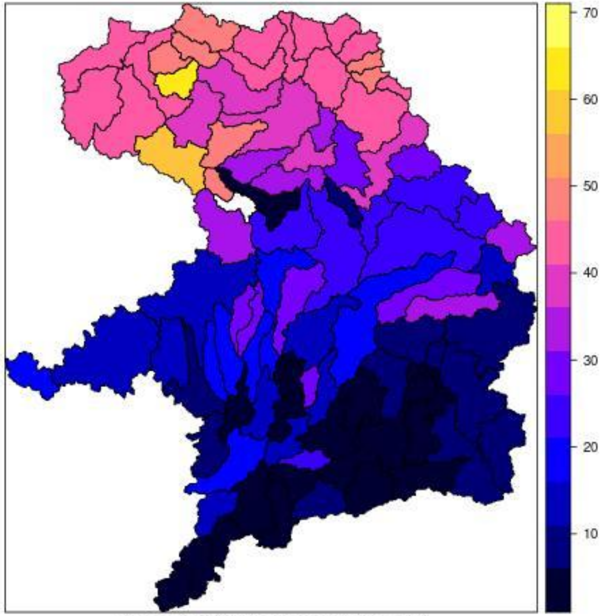
Scenario 1	• 3°C warmer
Scenario 2	• 3°C warmer • 50% less/more precipitation for summer/winter
Scenario 3	• 3°C warmer • 50% less/more precipitation for summer/winter • No snow storage

Scenarios Summer

Difference Between Predictions for Original Data & Scenario 1

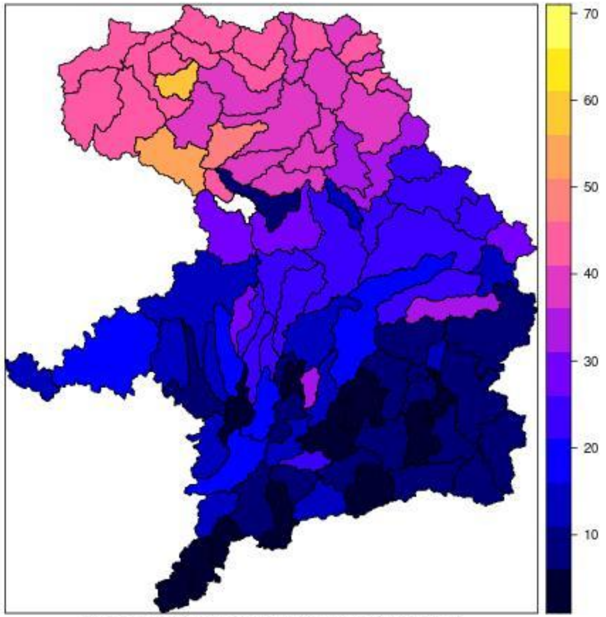


Days of low flow in summer 2010 for original data

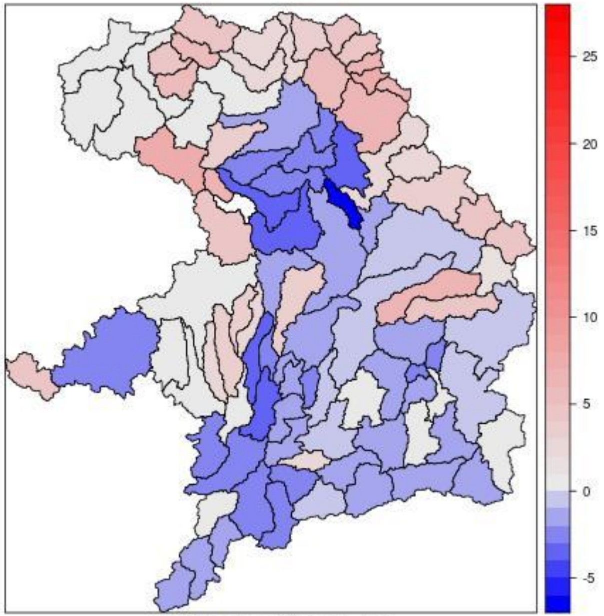


Days of low flow in summer 2010: +3°C

Difference Between Predictions for Original Data & Scenario 1

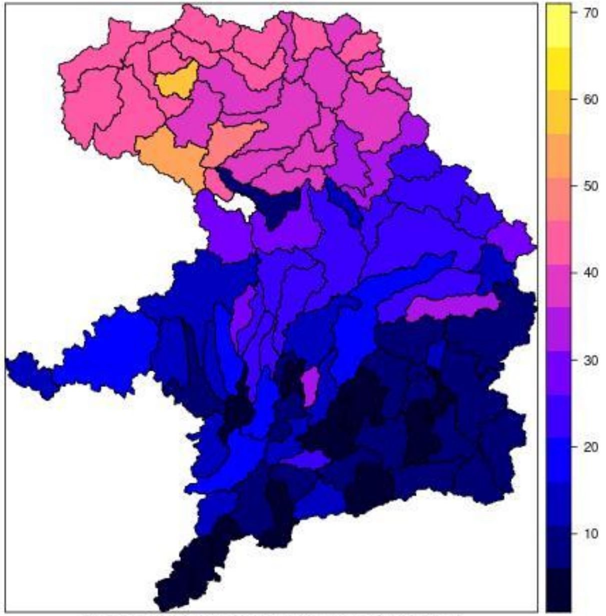


Days of low flow in summer 2010 for original data

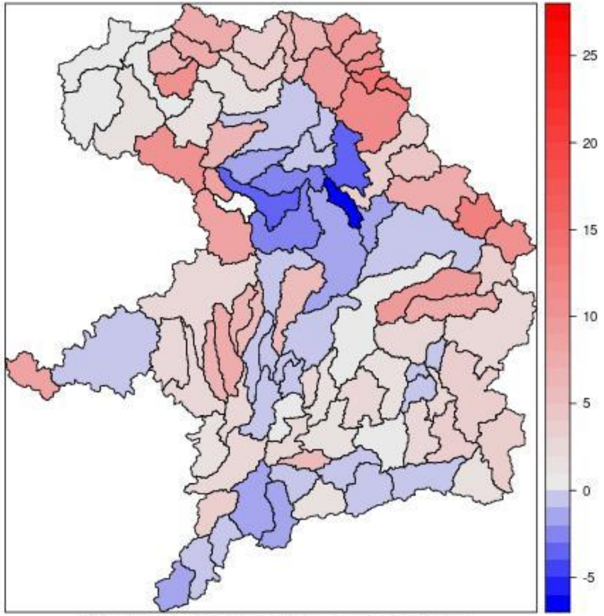


Difference to predictions: +3°C

Difference Between Predictions for Original Data & Scenario 2

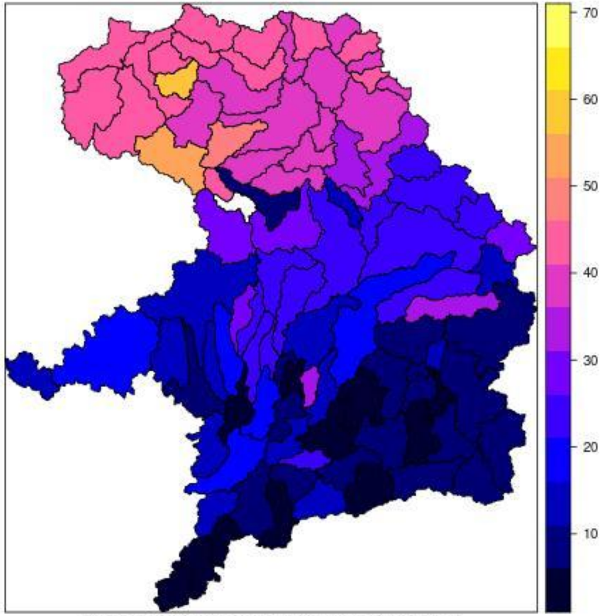


Days of low flow in summer 2010 for original data

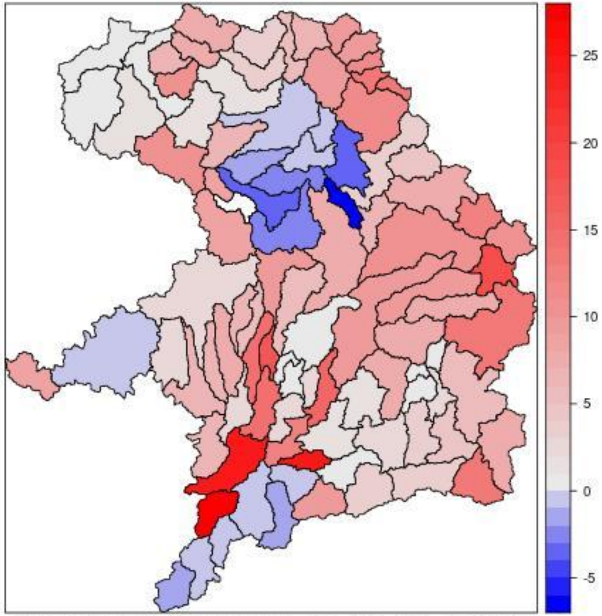


Difference to predicitions: +3°C, -50% precipitation

Difference Between Predictions for Original Data & Scenario 3



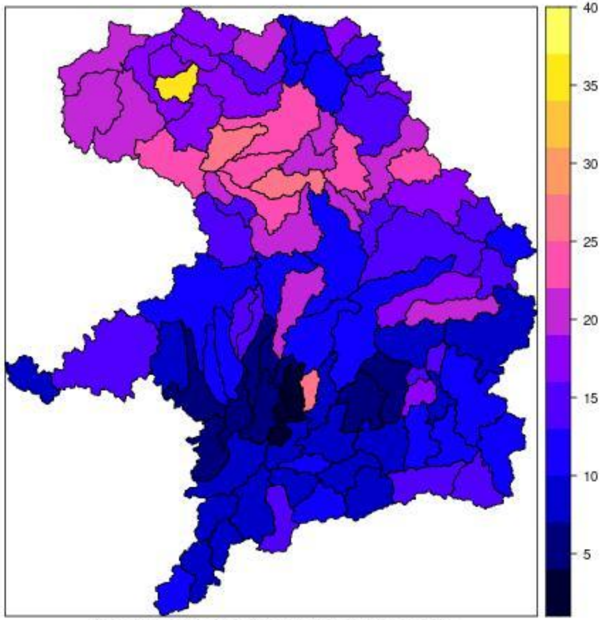
Days of low flow in summer 2010 for original data



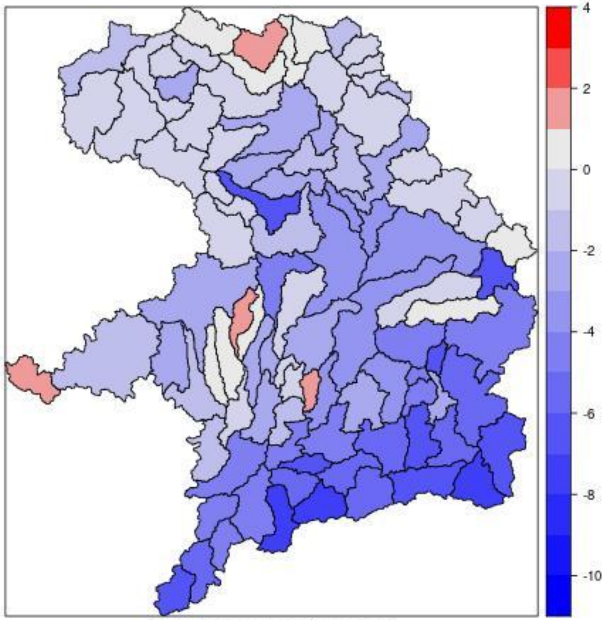
Difference to predicitions: no snow storage, +3°C, -50% precipitation

Scenarios Winter

Difference Between Predictions for Original Data & Scenario 1

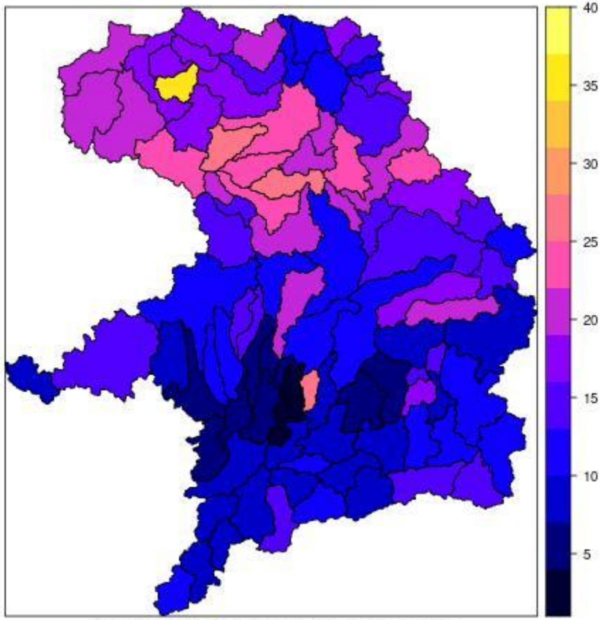


Days of low flow in winter 2010 for original data

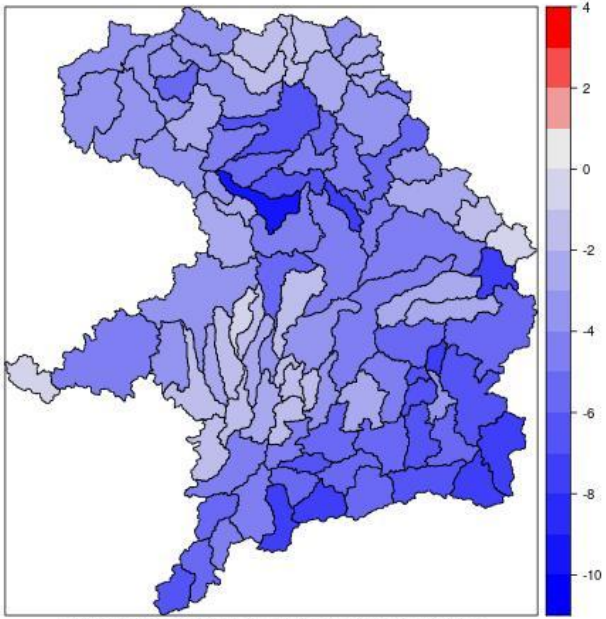


Difference to predictions: +3°C

Difference Between Predictions for Original Data & Scenario 2

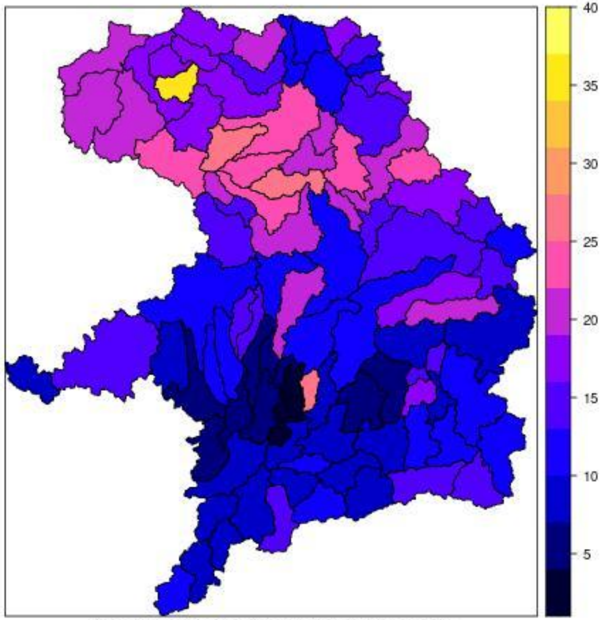


Days of low flow in winter 2010 for original data

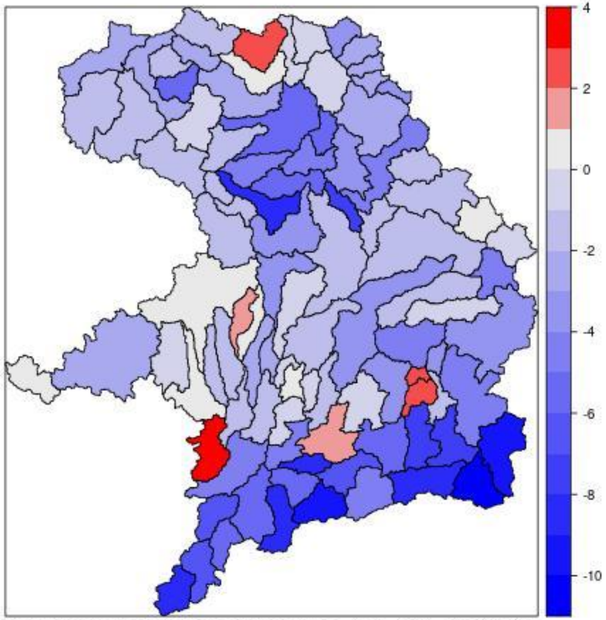


Difference to predicitions: +3°C and +50% precipitation

Difference Between Predictions for Original Data & Scenario 3



Days of low flow in winter 2010 for original data



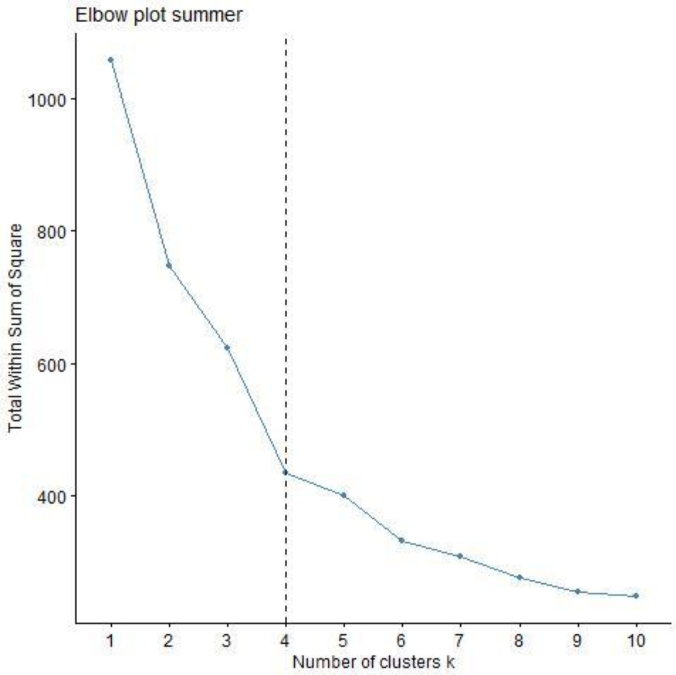
Difference to predicitions: no snow storage, +3°C, +50% precipitation

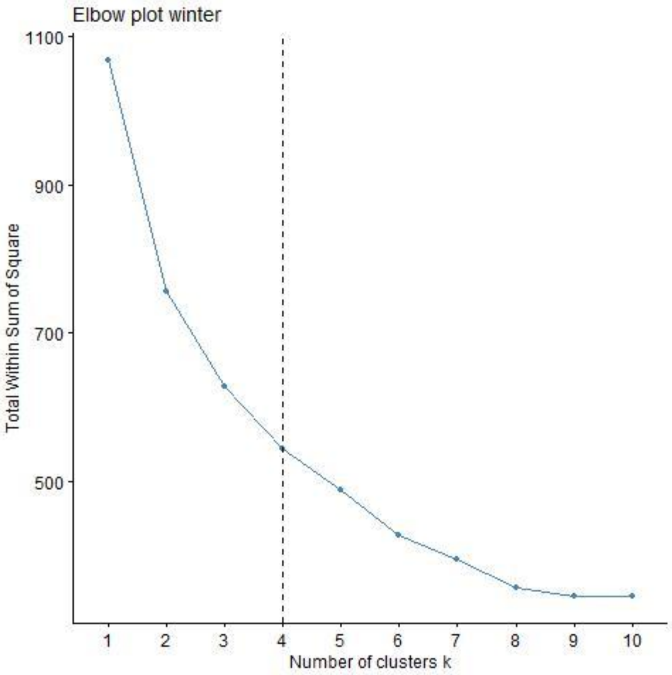
Clustering

K-Means Clustering

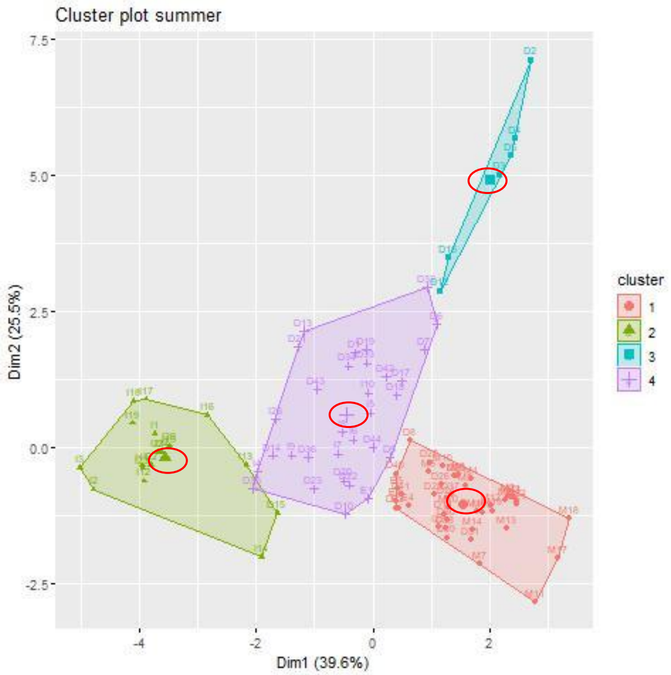
- Unsupervised machine learning technique
- **Iterative algorithm:** partitions the data set into k pre-defined subgroups
- **Goal:** find homogeneous subgroups → high similarity within cluster
- Similarity measured based on distance measure: euclidean distance
- Minimize total intra-cluster variation:
    - Sum of squared distances between cluster centroids (mean of data points belonging to cluster) & data points
- **Our analysis:** cluster over average coefficients

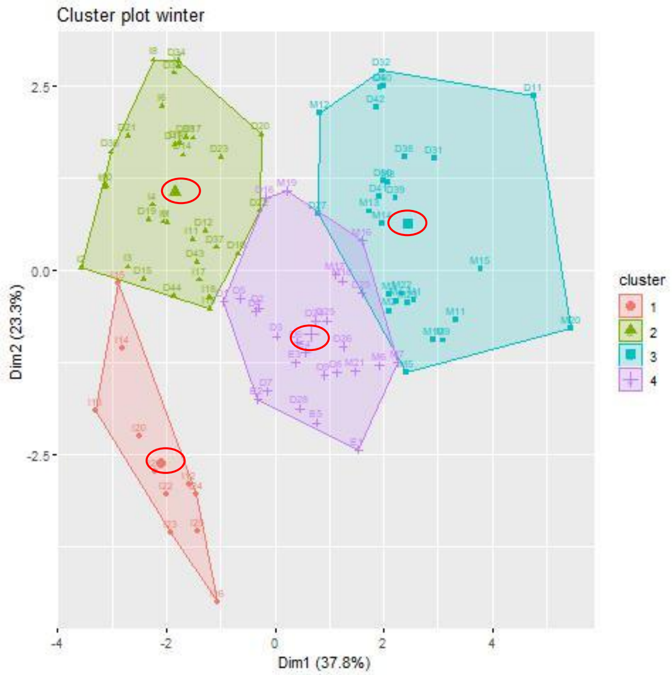
Elbow Plots


Elbow plot summer
1000
800
600
400
Total Within Sum of Square
1
2
3
4
5
6
7
8
9
10
Number of clusters k

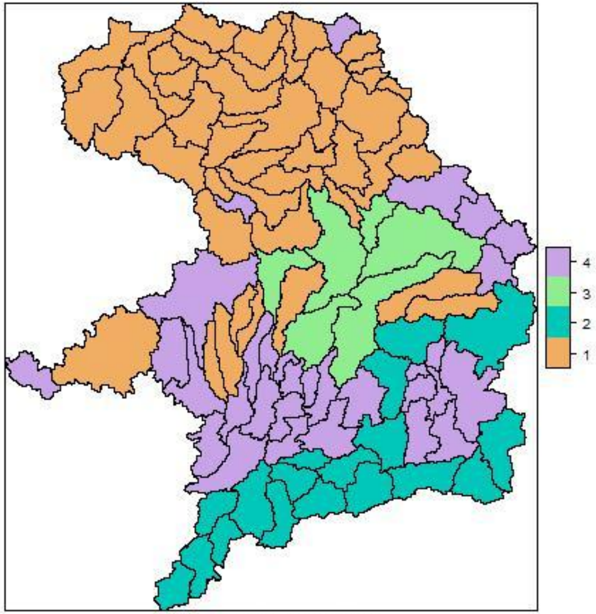

Elbow plot winter
1100
900
700
500
Total Within Sum of Square
1
2
3
4
5
6
7
8
9
10
Number of clusters k

Cluster Plots





Clusters for Averaged Coefficients in Summer

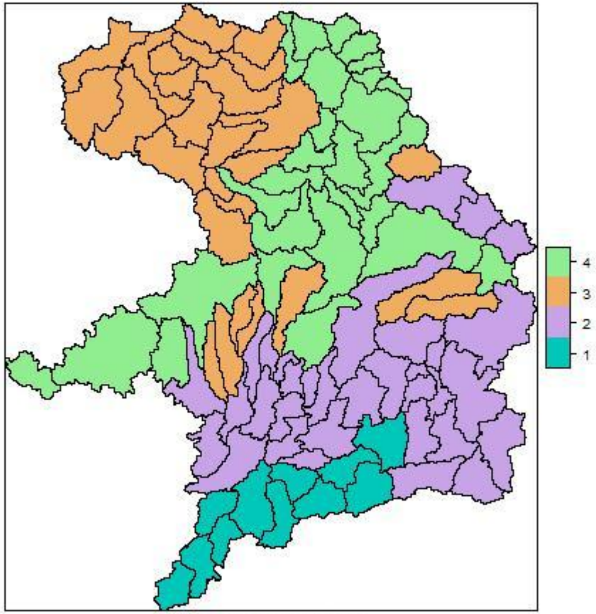


K-means cluster summer

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
N	43	18	6	31
Precipitation	-0.356	-0.759	-0.22	-0.474
Temperature	0.019	-0.878	1.209	0.627
Soil water	-0.63	-1.125	-0.492	-1.204
Snow storage	0	-0.296	-3.402	-0.535

Table 1. Clusteroids for averaged summer coefficients

Clusters for Averaged Coefficients in Winter



K-means cluster winter

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
N	11	33	27	27
Precipitation	-0.183	-0.459	-1.018	-0.799
Temperature	-0.242	-0.258	-0.066	-0.158
Soil water	-1.109	-1.859	-0.868	-0.746
Snow storage	0.003	-0.032	-0.594	-0.171

Table 2. Clusteroids for averaged winter coefficients

Conclusion

Summary

Research question	Answer
How can the occurrence of a day of low flow be explained?	Linear trend of precipitation, temperature, soil water, snow storage, humidity, radiation, year
Are the drivers of an extreme event themselves extreme? Or is it a compound event that leads to extreme low flows?	Main effect more relevant than interaction effect ⇒ less of compound events
Which drivers are relevant? Does their significance differ depending on the catchment?	Relevant drivers: precipitation, soil water, snow storage, temperature Significance depends on catchment (soil water most effects also significant)

Summary

Research question	Answer
How can the occurrence of a day of low flow be explained?	Linear trend of precipitation, temperature, soil water, snow storage, humidity, radiation, year
Are the drivers of an extreme event themselves extreme? Or is it a compound event that leads to extreme low flows?	Main effect more relevant than interaction effect ⇒ less of compound events
Which drivers are relevant? Does their significance differ depending on the catchment?	Relevant drivers: precipitation, soil water, snow storage, temperature Significance depends on catchment (soil water most effects also significant)

Summary

Research question	Answer
How can the occurrence of a day of low flow be explained?	Linear trend of precipitation, temperature, soil water, snow storage, humidity, radiation, year
Are the drivers of an extreme event themselves extreme? Or is it a compound event that leads to extreme low flows?	Main effect more relevant than interaction effect ⇒ less of compound events
Which drivers are relevant? Does their significance differ depending on the catchment?	Relevant drivers: precipitation, soil water, snow storage, temperature Significance depends on catchment (soil water most effects also significant)

Summary

Research question	Answer
What happens for more extreme weather conditions?	Summer: Scenario 3 leads to more low flow in most catchments (but regional differences) Winter: Scenario 3 leads to less low flow in most catchments (but regional differences)
Is it possible to group catchements according to the drivers?	4 clusters each for winter and summer models Cluster differ in size Regionality: mean effect of precipitation in summer smaller in north than south Bavaria

Summary

Research question	Answer
What happens for more extreme weather conditions?	Summer: Scenario 3 leads to more low flow in most catchments (but regional differences) Winter: Scenario 3 leads to less low flow in most catchments (but regional differences)
Is it possible to catchments levels according to the drivers?	4 clusters each for winter and summer models Cluster differ in size Regionality: mean effect of precipitation in summer smaller in north than south Bavaria

Limitations

- Number of low flow events quite low in some catchments
- No time constant variables
- Clustering: number of clusters for winter not optimal
- Lag structure

Possible Analyses

Alternative Approaches

Distributed Lag Models

- Model current and delayed effects of X_t , X_{t-1}, …, X_{t-s} on Y_i and define lag structure flexibly for each covariate X
- Future analysis: More accurate modelling of the main effects and day of low flow

Generalized Linear Mixed Models

- Mixed effects to integrate data structure of members & catchment to account for dependence structures between catchments
- **Limitation:** Random intercepts for each catchment and member does not take into account different effects of drivers for different regions → random slopes necessary

References

References

Literature:

- Ludwig Fahrmeir and Thomas Kneib and Stefan Lang and Brian Marx (2013). Regression: Models, Methods and Applications, Springer-Verlag Berlin.
- Jakob Zscheischler et al. (2020). *A typology of compound weather and climate events*, NREE. Volume 1, 333-347.
- Tom Fawcett (2006). An introduction to ROC analysis, Pattern Recognition Letters, Volume 27, Issue 8.
- Martin Leduc et al. (2019). *The ClimEx Project: A 50-Member Ensemble of Climate Change Projections at 12-km Resolution over Europe and Northeastern North America with the Canadian Regional Climate Model (CRCM5)*, Journal of Applied Meteorology and Climatology, Volume 2019.
- Matthias Aßenmacher and Jan Christian Kaiser and Ignacio Zaballa and Antonio Gasparrini and Helmut Küchenhoff (2019). Exposure–lag–response associations between lung cancer mortality
- and radon exposure in German uranium miners. Springer-Verlag Berlin.
- Mitra, Manu. (2019). K-Means Clustering in Machine Learning – a Review. 1. 1-19. 10.5281/zenodo.3401604.

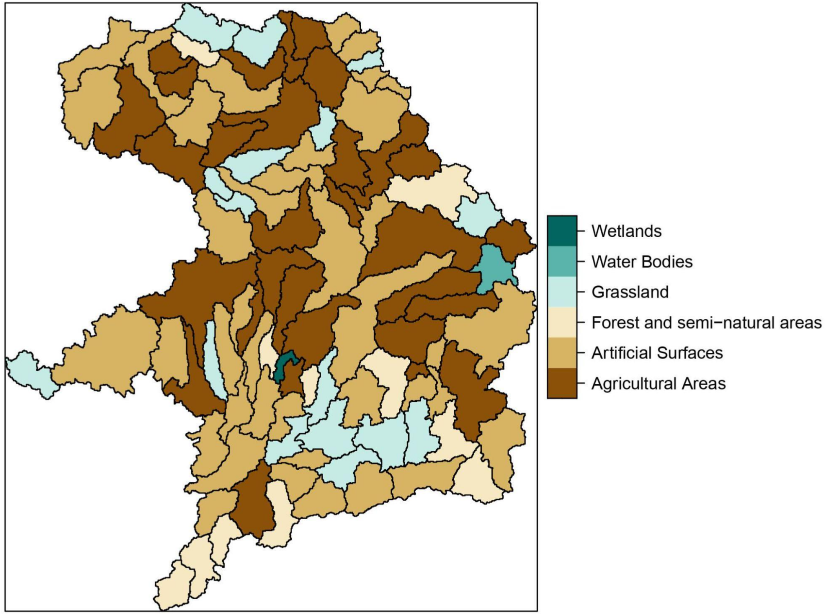
Links of The Guardian:

- https://www.theguardian.com/environment/2022/aug/04/source-of-river-thames-dries-out-for-first-time-during-drought (accessed on 27.02.2023)
- https://www.theguardian.com/world/2023/feb/21/italy-faces-new-drought-alert-as-venice-canals-run-dry (accessed on 27.02.2023)
- https://www.theguardian.com/environment/2022/aug/13/europes-rivers-run-dry-as-scientists-warn-drought-could-be-worst-in-500-years (accessed on 27.02.2023)

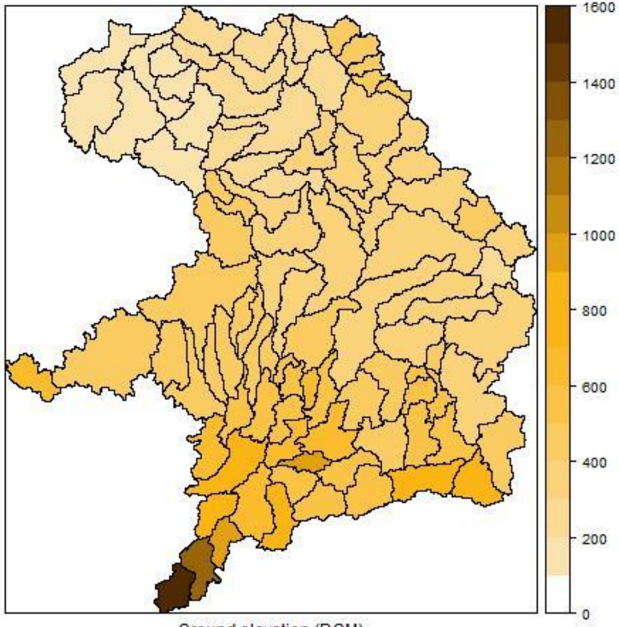
Appendix

Time Constant Variables

Time Constant Variables: Land Use & Ground Elevation



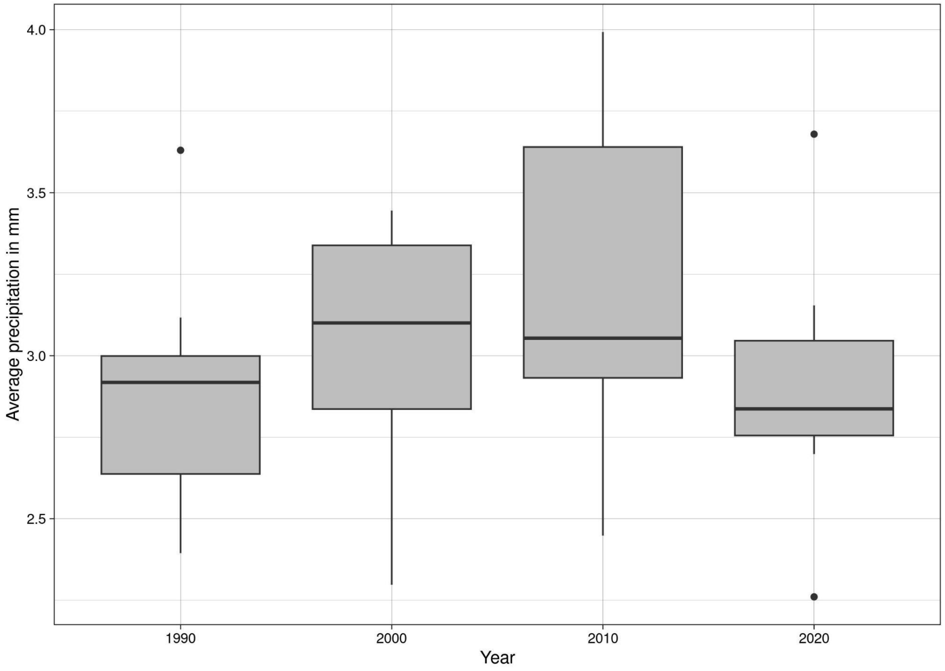
Landuse

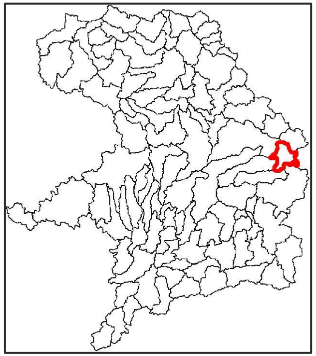


Ground elevation (DGM)

Relationship between Drainage & Drivers

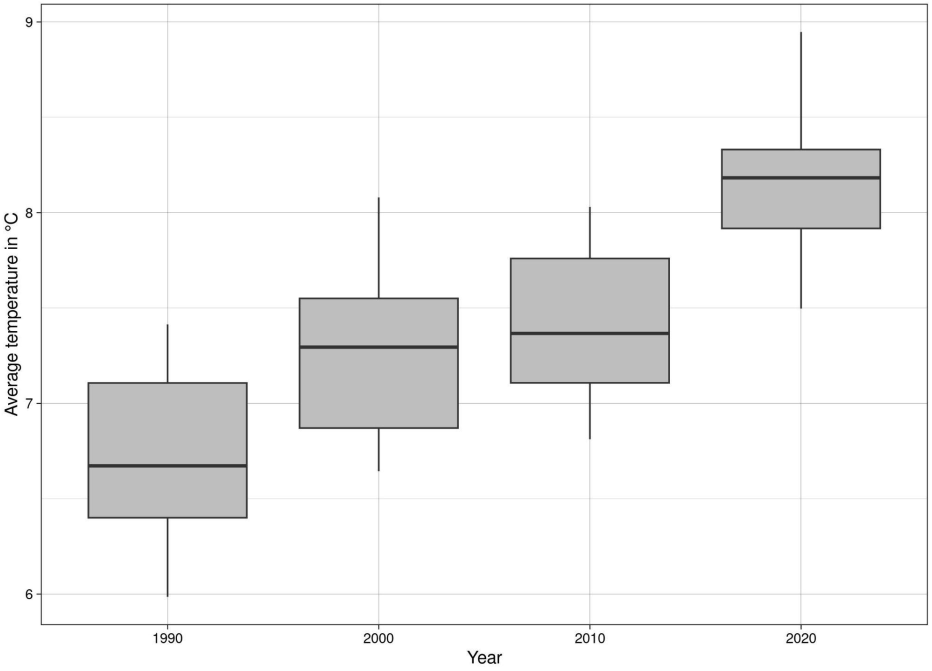
Average Annual Precipitation For Catchment Donau-Achleiten

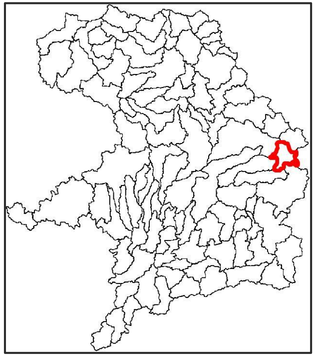




- Average annual precipitation calculated for each member
- Boxplot over 10 calculated averages

Average Annual Temperature For Catchment Donau-Achleiten

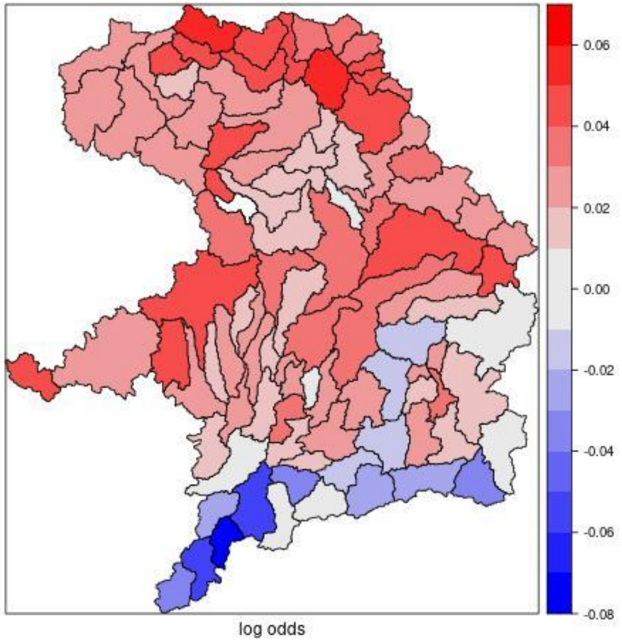




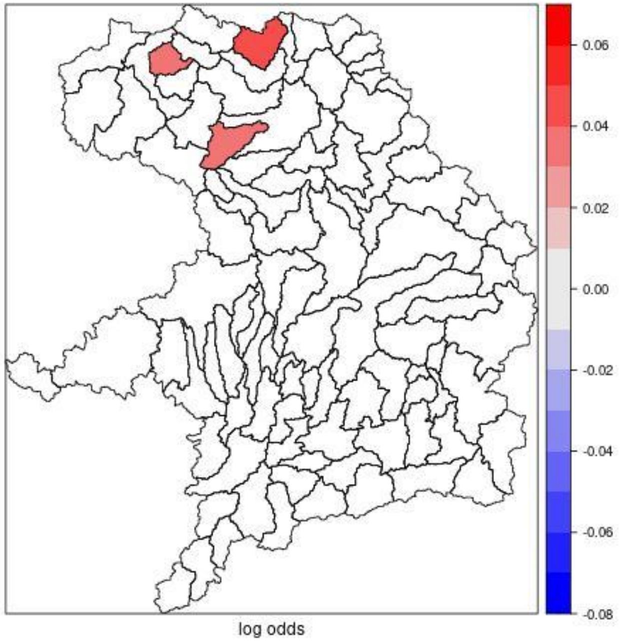
- Average annual temperature calculated for each member
- Boxplot over 10 calculated averages

Results

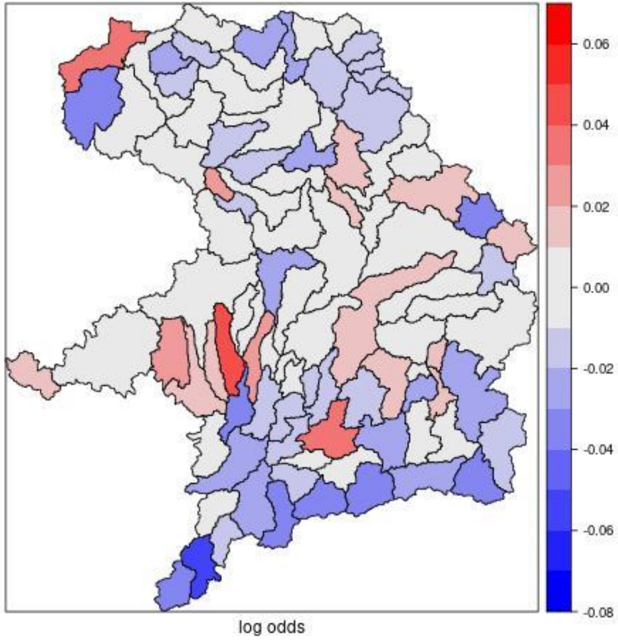
Interaction effect of temperature and precipitation in summer



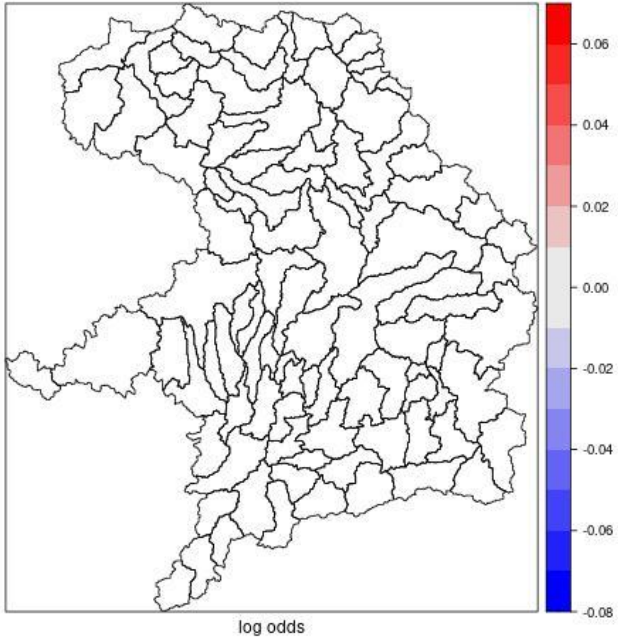
significant effects



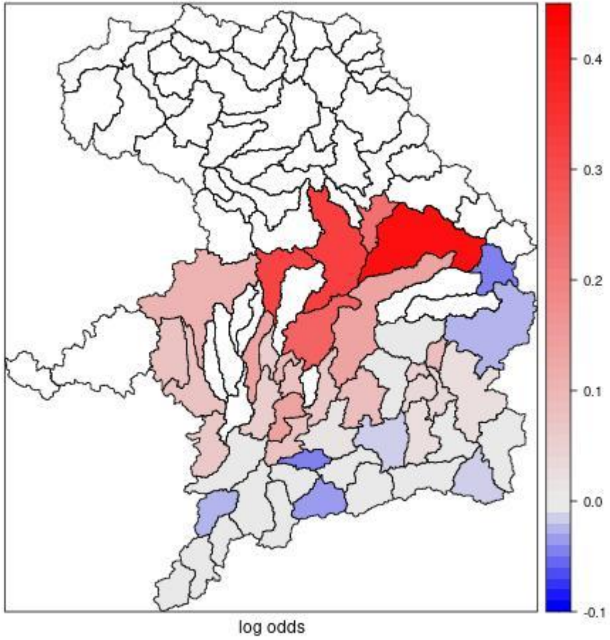
Interaction effect of temperature and precipitation in winter



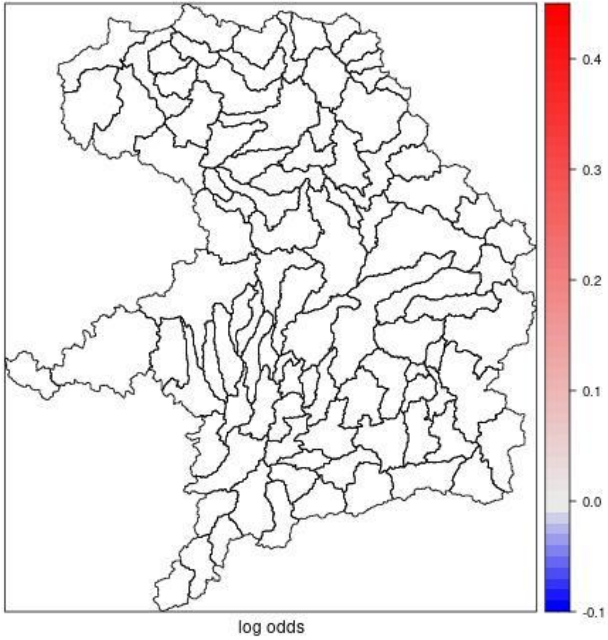
significant effects



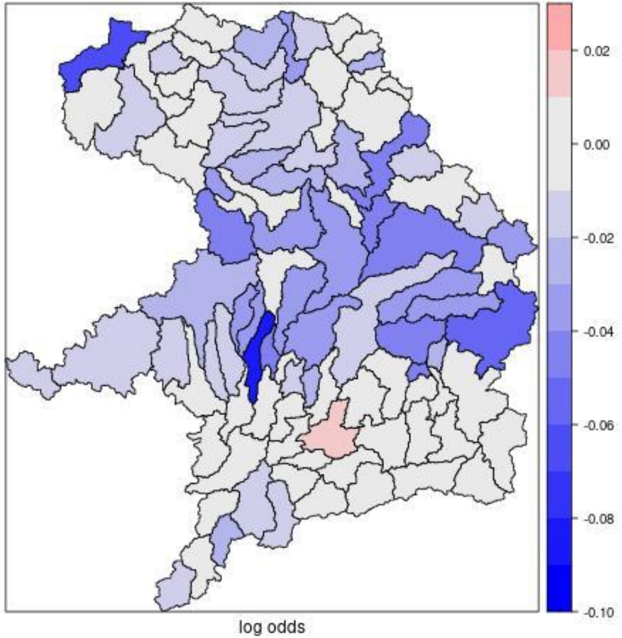
Interaction effect of temperature and snow storage in summer



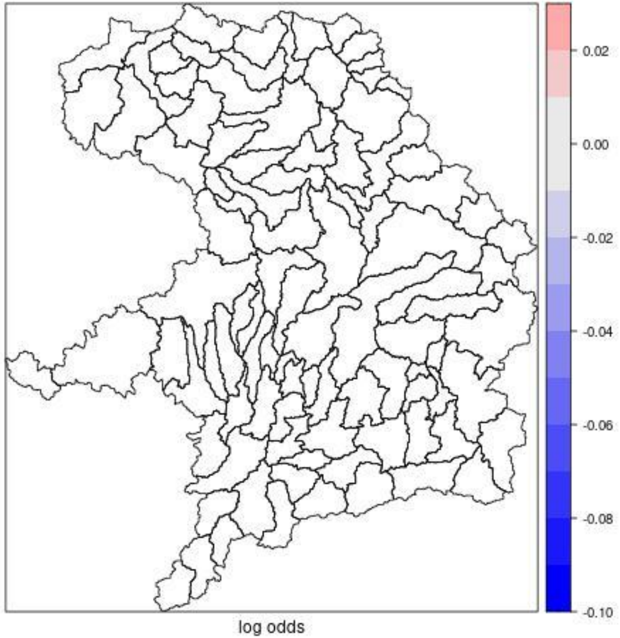
significant effects



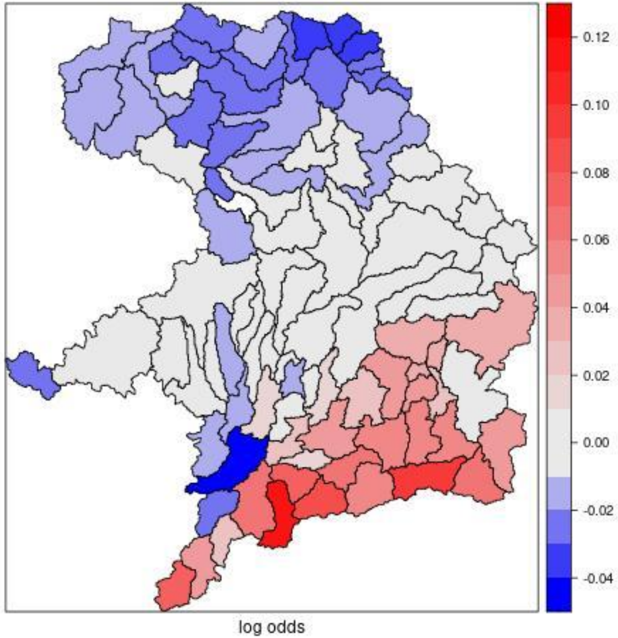
Interaction effect of temperature and snow storage in winter



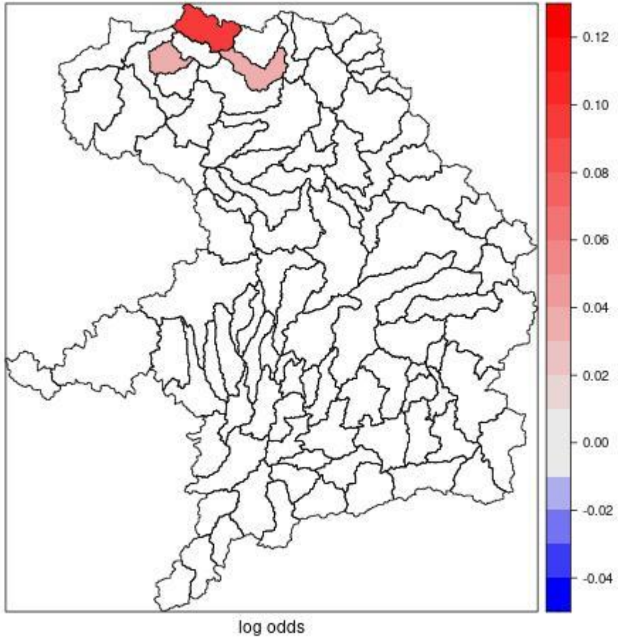
significant effects



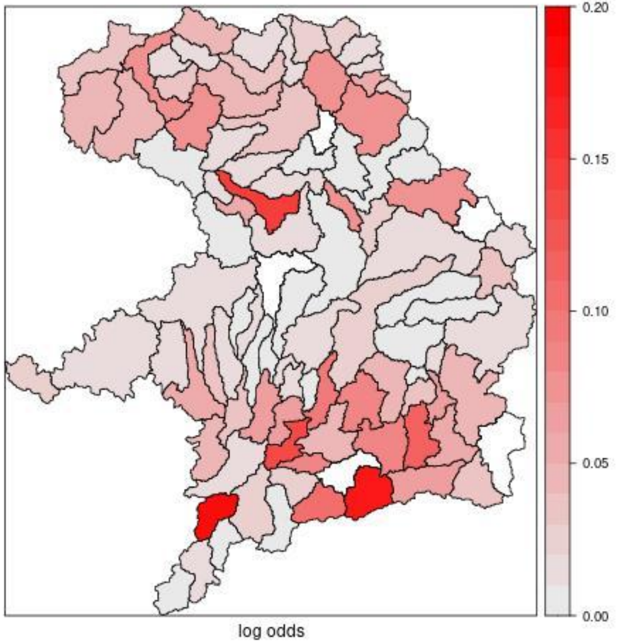
Interaction effect of temperature and soil water in summer



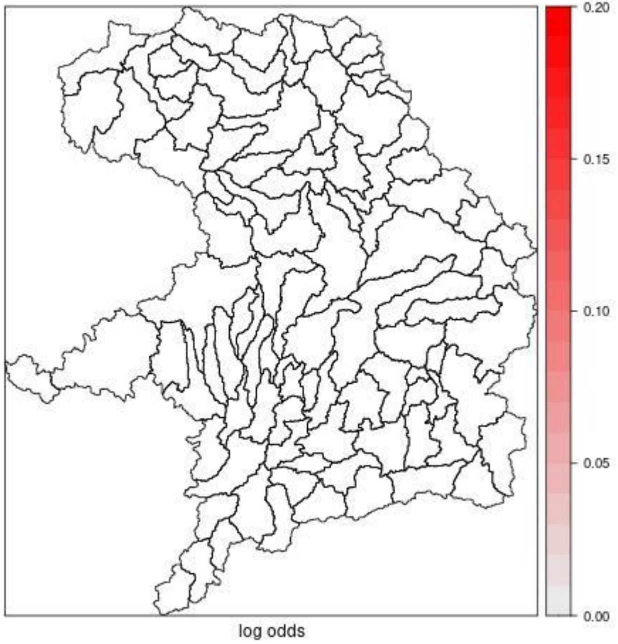
significant effects



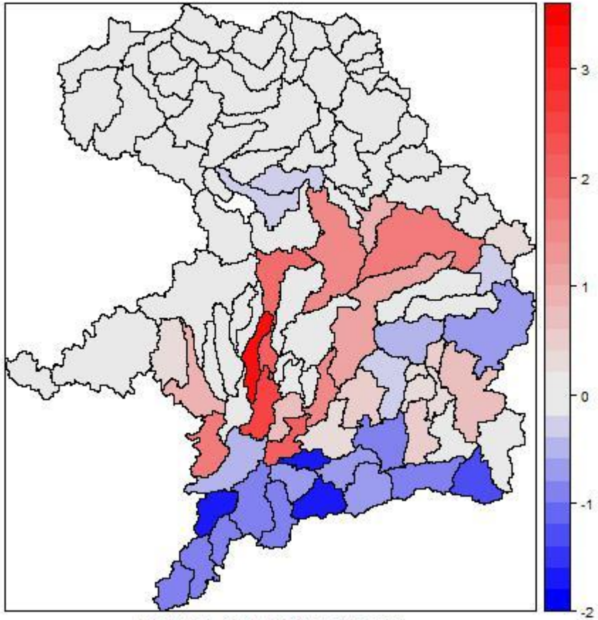
Interaction effect of temperature and soil water in winter



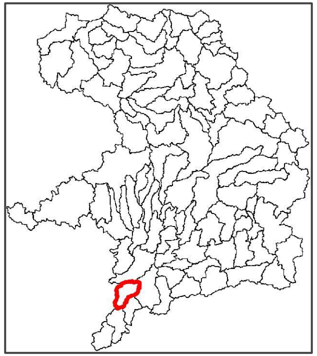
significant effects



Effect of Temperature for Sanna-Landeck-Bruggen



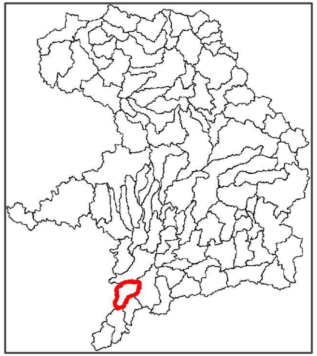
log odds - temperature - summer

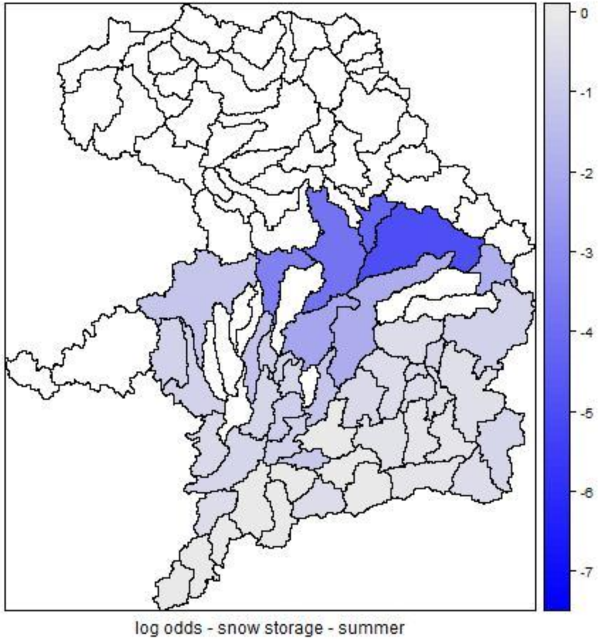


Keeping all other variables constant, for average precipitation, snow storage and soil water, increasing the 7-day mean of temperature by one degree, the log-odds of occurring low flow that day decrease by 1.67 additively on average.

→ the odds of occurring low flow decrease by exp(-1.67) = 0.19 multiplicatively

Effect of Snow Storage for Sanna-Landeck-Bruggen

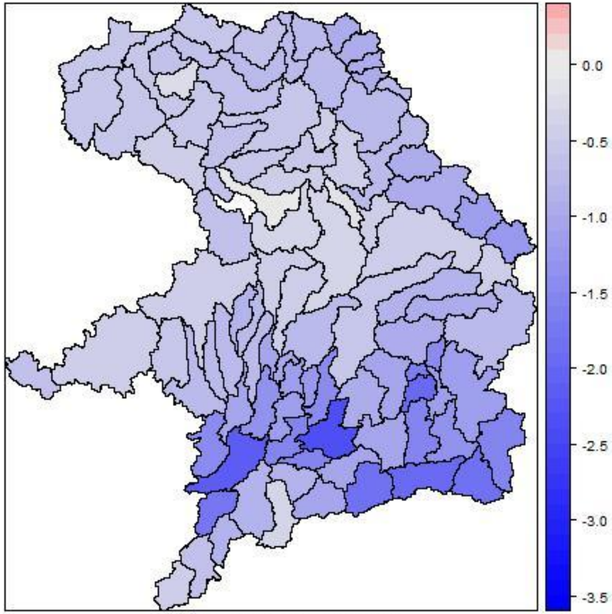




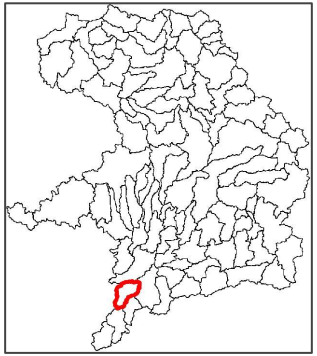
Keeping all other variables constant, for average temperature, increasing the 30-day mean of snow storage by one millimeter, the log-odds of occurring low flow that day decrease by -0.47 additively on average.

→ the odds of occurring low flow decrease by exp(-0.47) = 0.62 multiplicatively

Effect of Soil Water for Sanna-Landeck-Bruggen



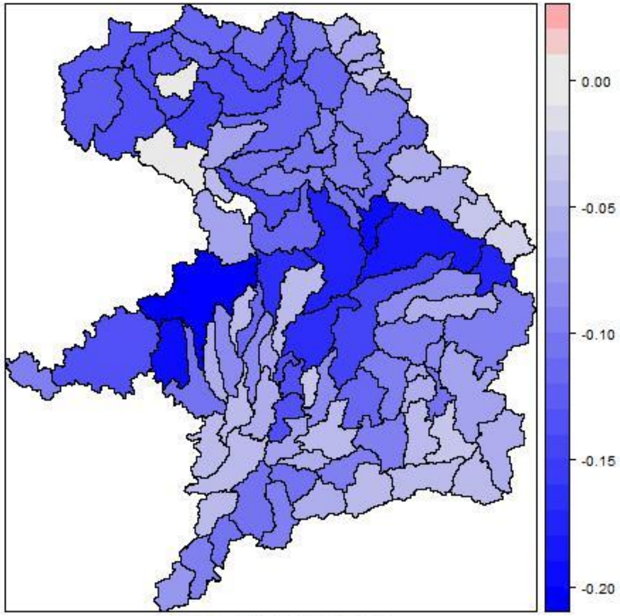
log odds - soil water - summer



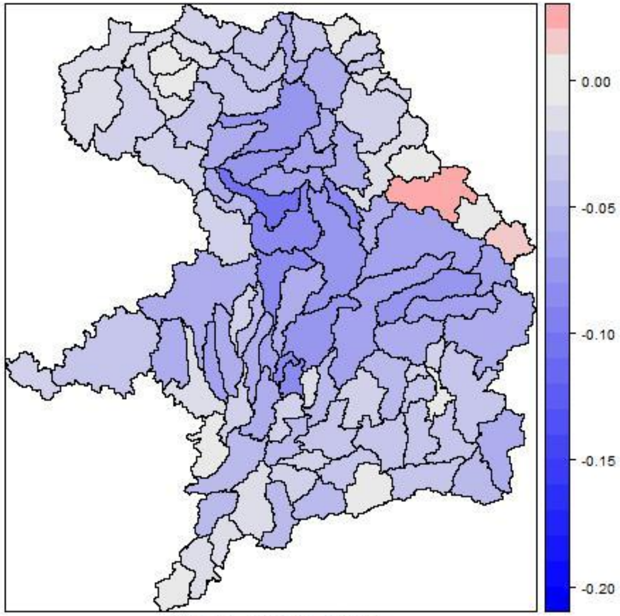
Keeping all other variables constant, for average temperature, increasing the 60-day mean of soil water by one millimeter, the log-odds of occurring low flow that day decrease by 1.72 additively on average.

→ the odds of occurring low flow decrease by exp(-1.72) = 0.18 multiplicatively

Effect of humidity

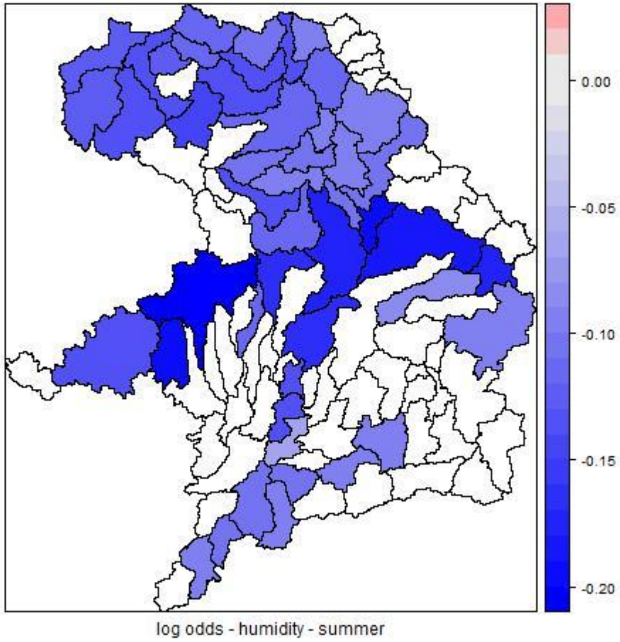


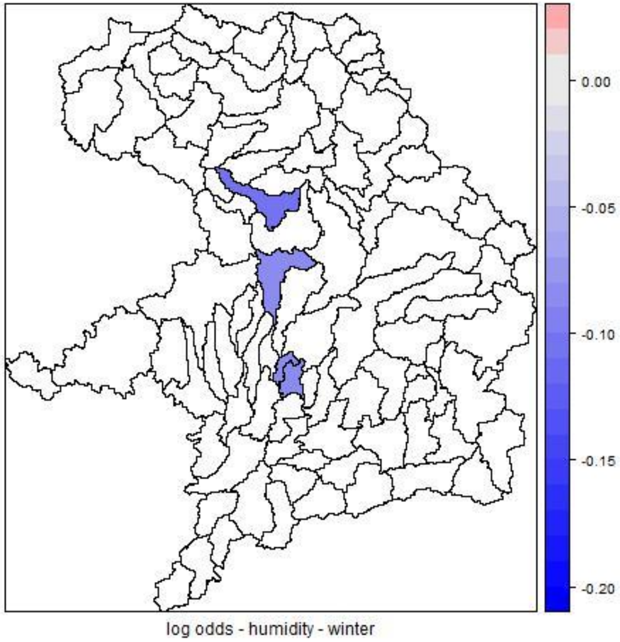
log odds - humidity - summer



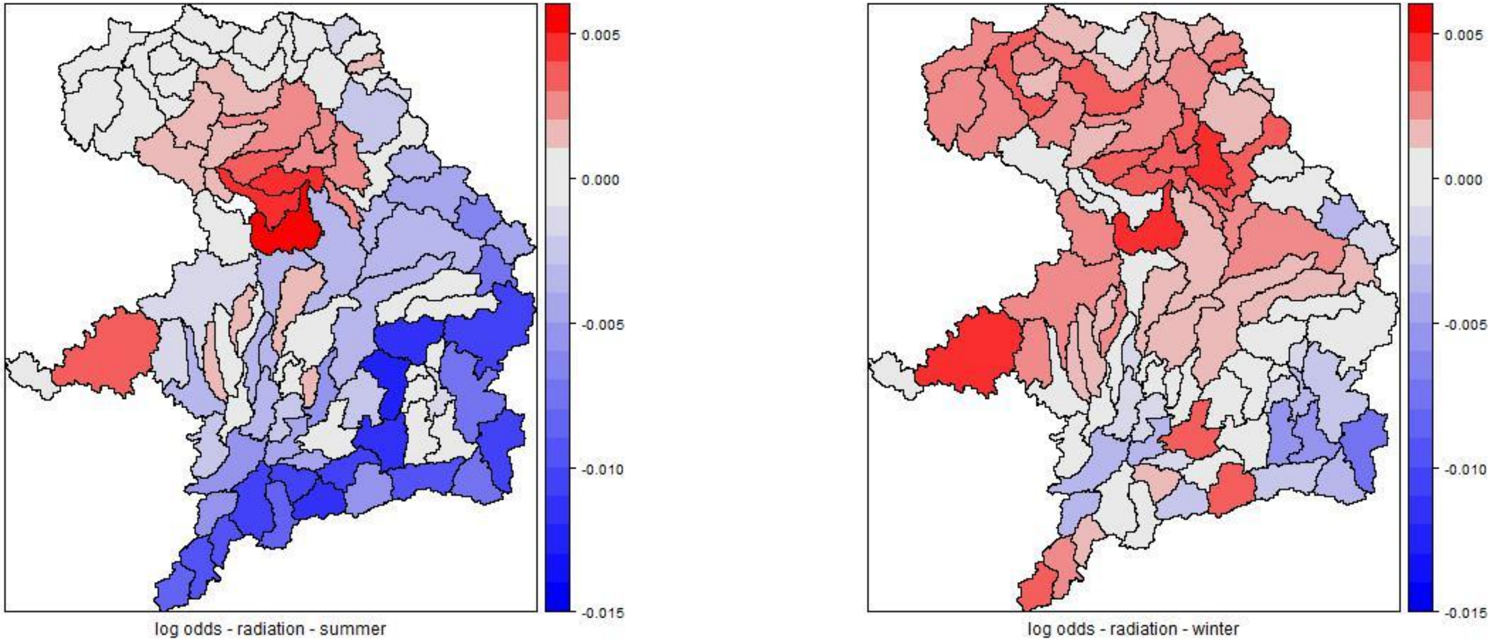
log odds - humidity - winter

Significance of humidity

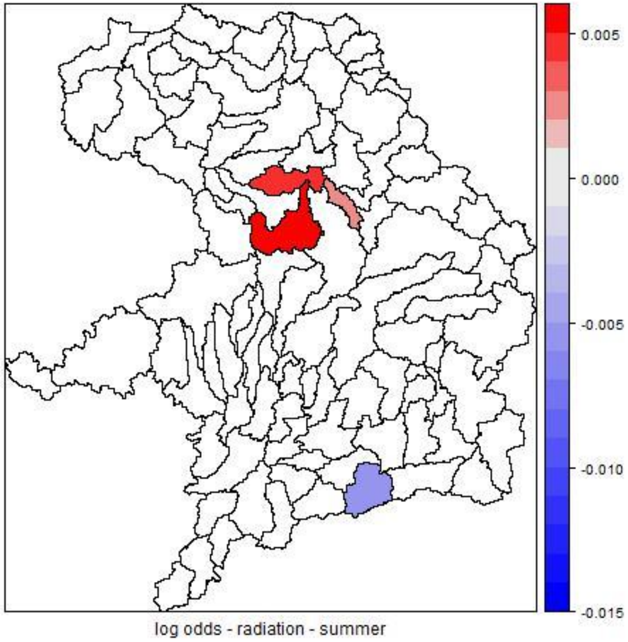


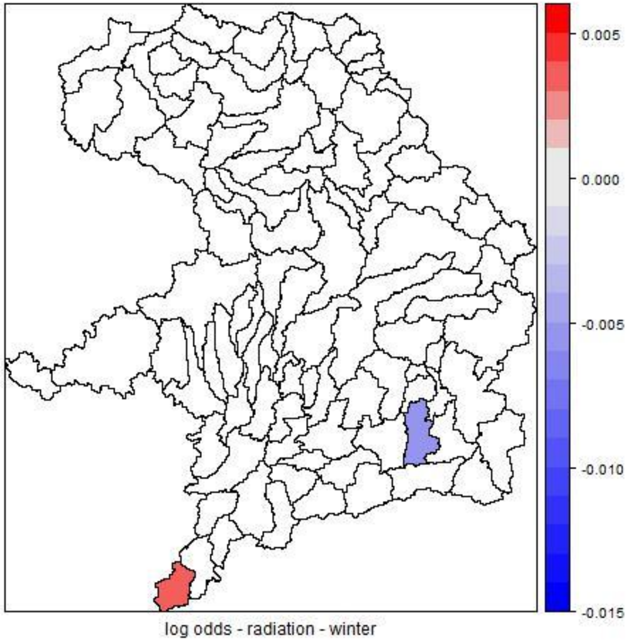


Effect of radiation

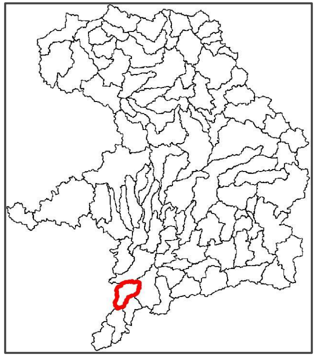


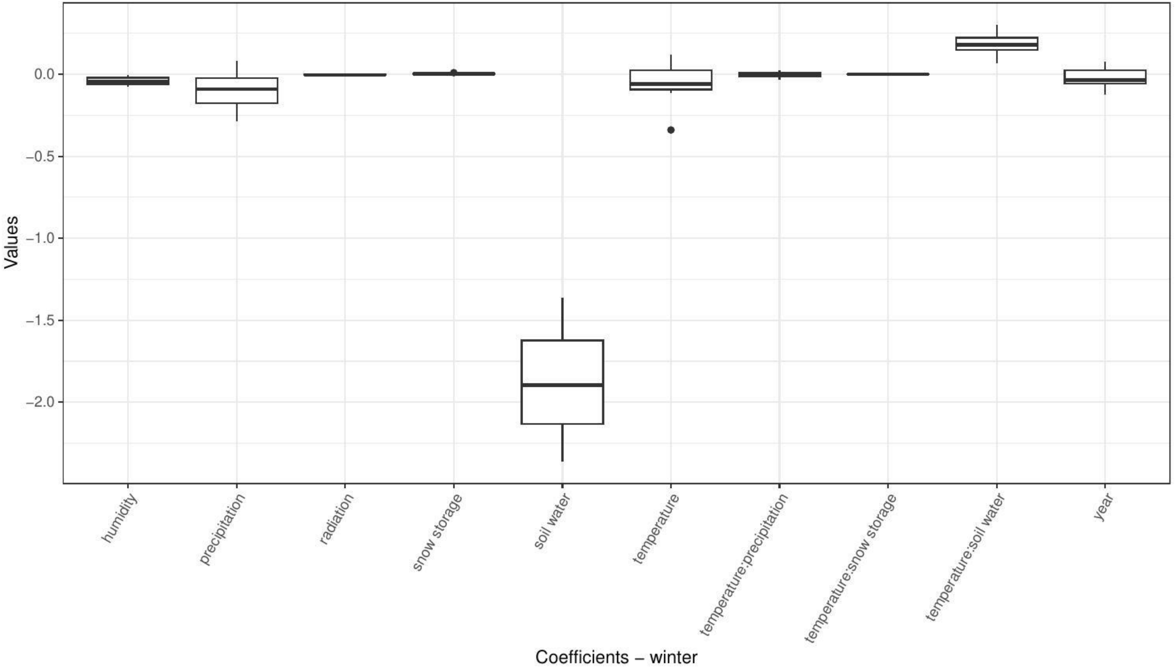
Significance of radiation





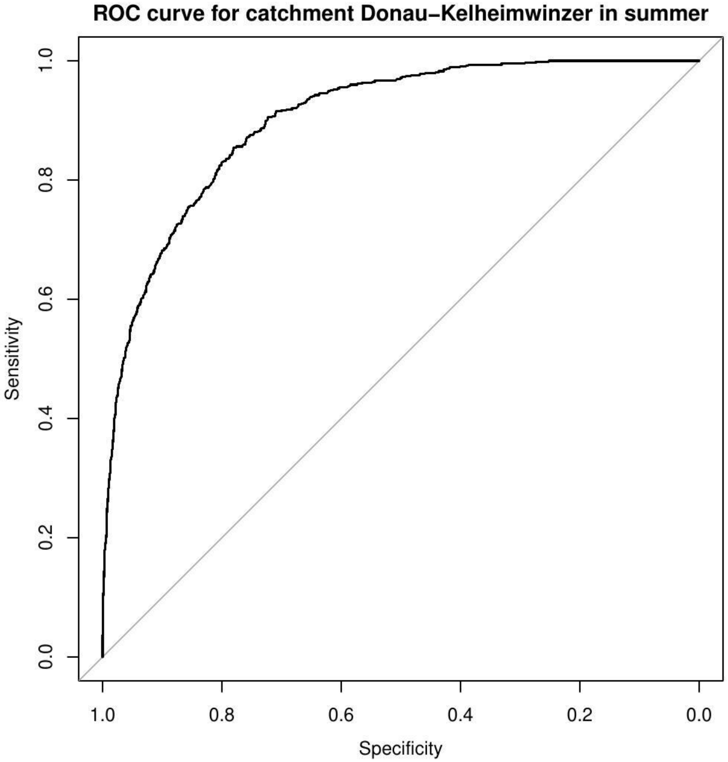
Differences Between Members for Sanna-Landeck-Bruggen





ROC-Analysis

ROC-Curve for One Example Model



Model:

- Catchment: Donau-Kelheimwinzer
- Season: summer
- Trained on member “kbe”
- Tested on member “kby”

Area under the curve (AUC): 0.9012

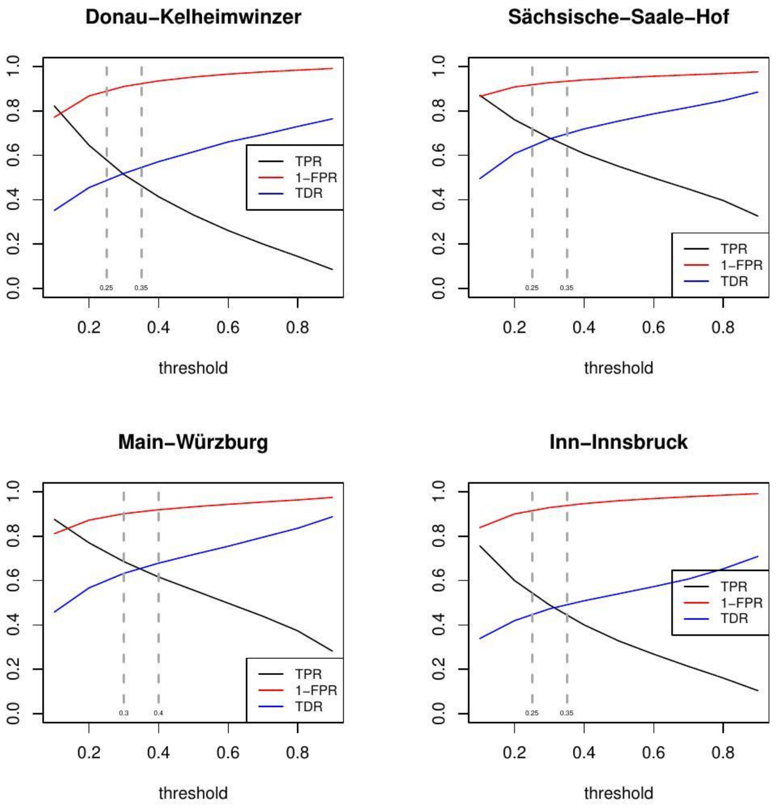
ROC-Analysis for winter

ROC Analysis for Winter Models

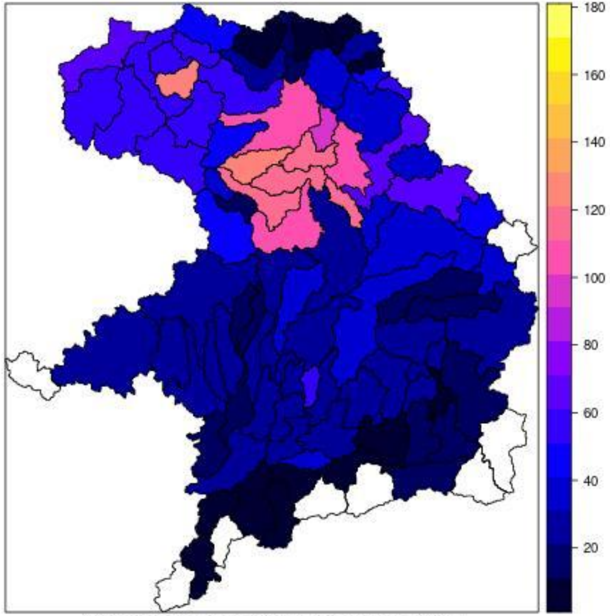
1) Train model on specific member and evaluate TPR, FPR and TDR on all other members for different thresholds

2) Average over all members for each catchment

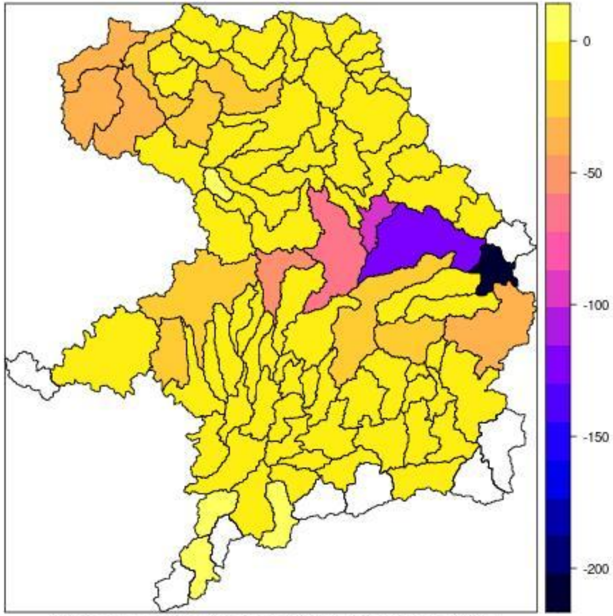
3) Look for intersections points



Analysis of Thresholds for Winter 2020 and One Member



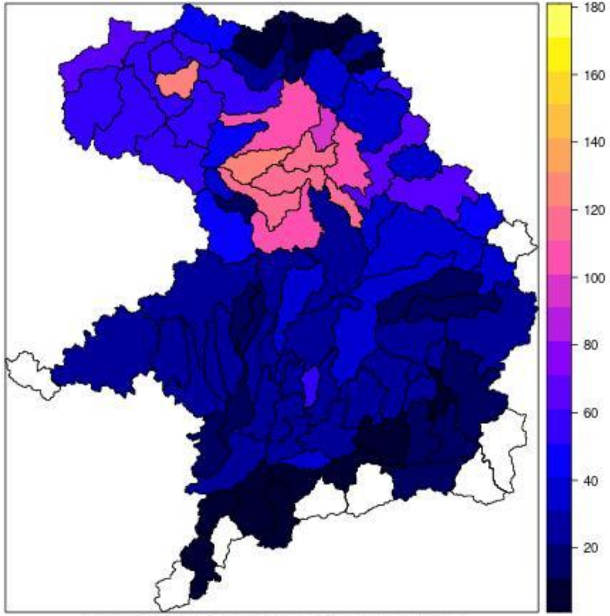
True number of days of low flow in winter of 2020



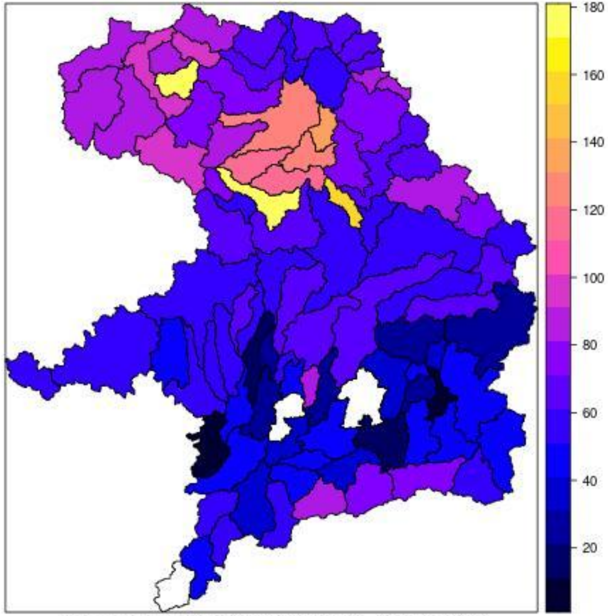
Maximal Intensity of true days of low flow in winter of 2020

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



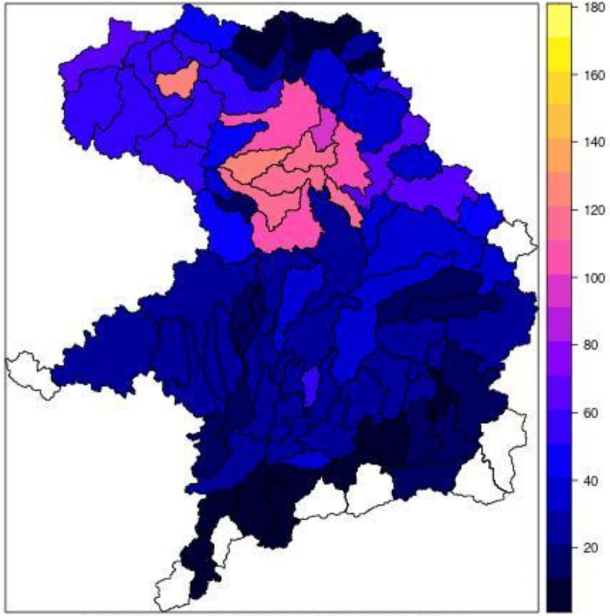
True number of days of low flow in winter of 2020



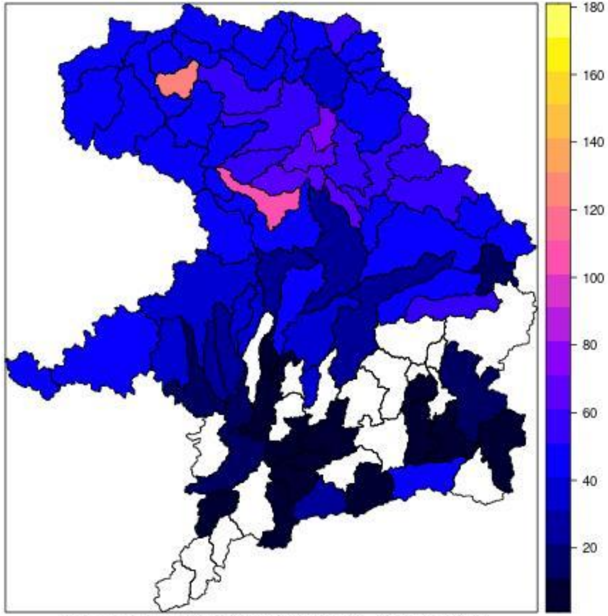
Days of predicted low flow - Winter 2020 - Threshold 0.1

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



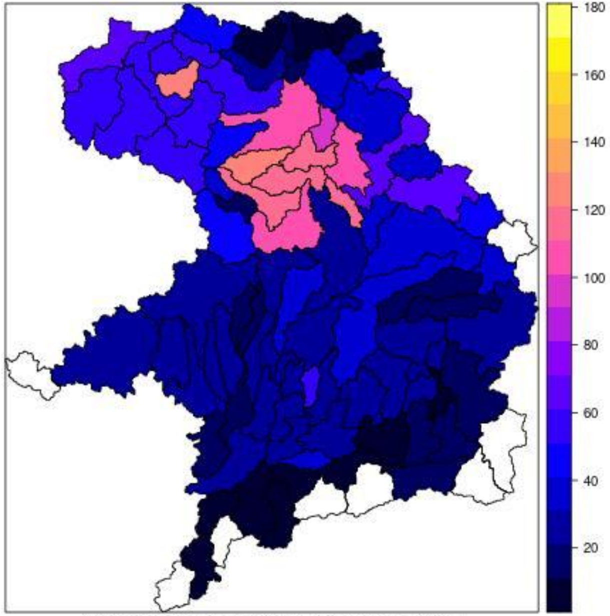
True number of days of low flow in winter of 2020



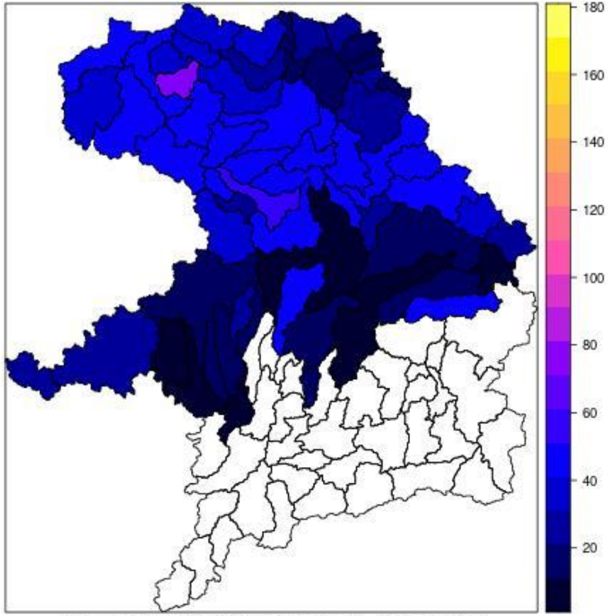
Days of predicted low flow - Winter 2020 - Threshold 0.2

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



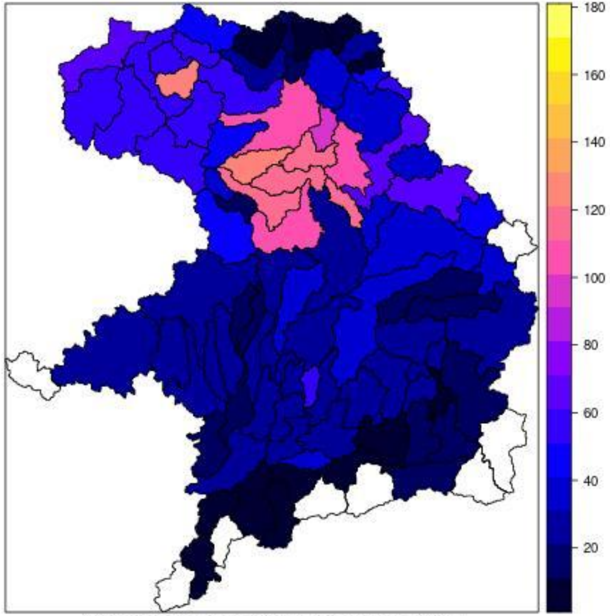
True number of days of low flow in winter of 2020



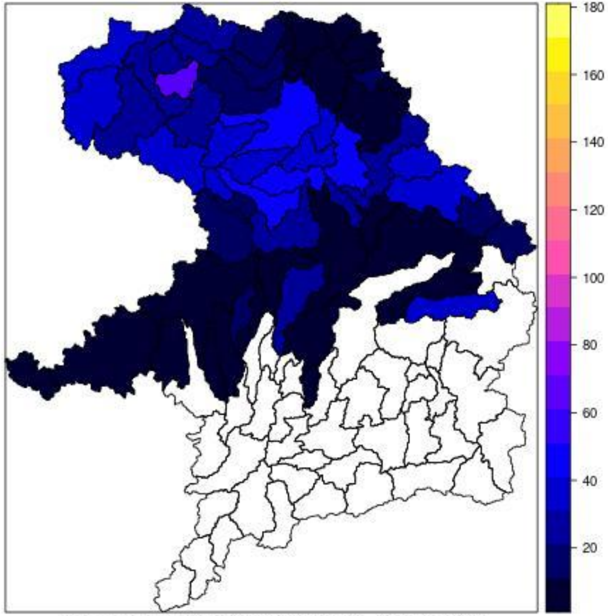
Days of predicted low flow - Winter 2020 - Threshold 0.3

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



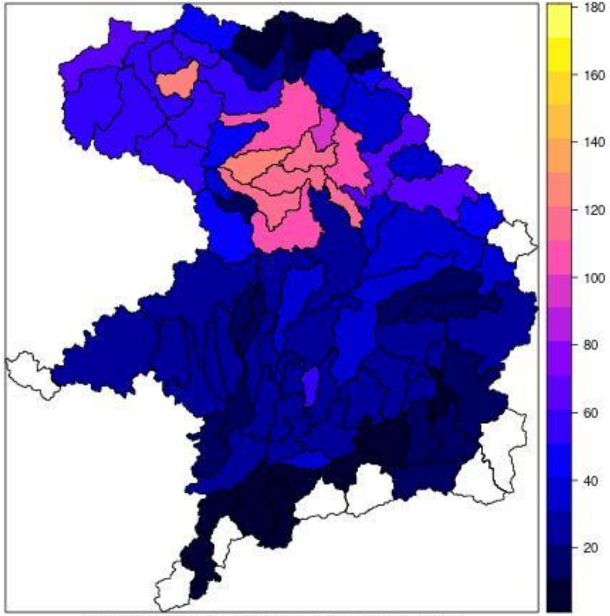
True number of days of low flow in winter of 2020



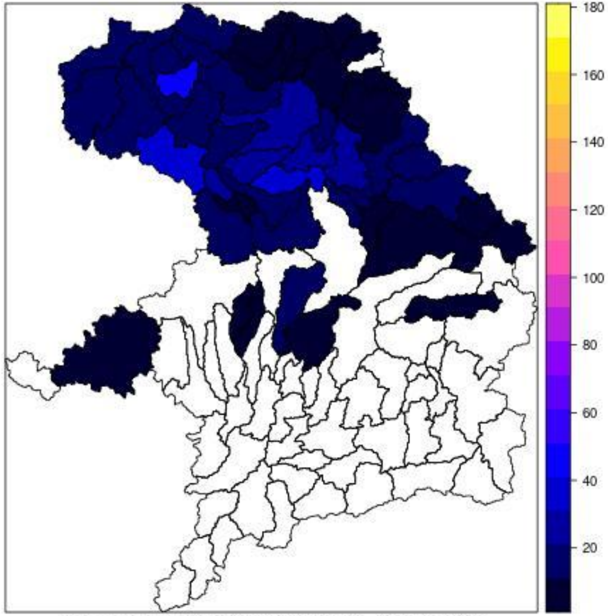
Days of predicted low flow - Winter 2020 - Threshold 0.4

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



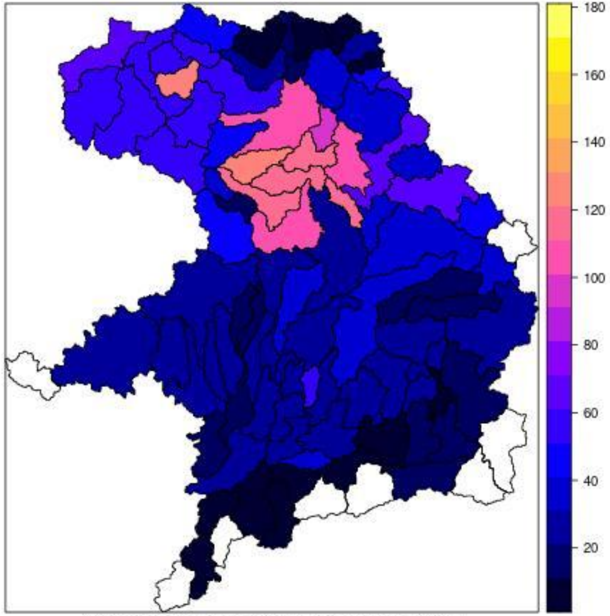
True number of days of low flow in winter of 2020



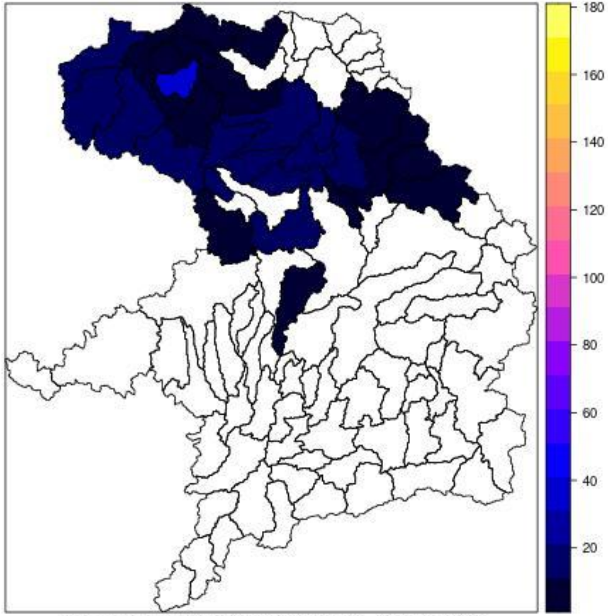
Days of predicted low flow - Winter 2020 - Threshold 0.5

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



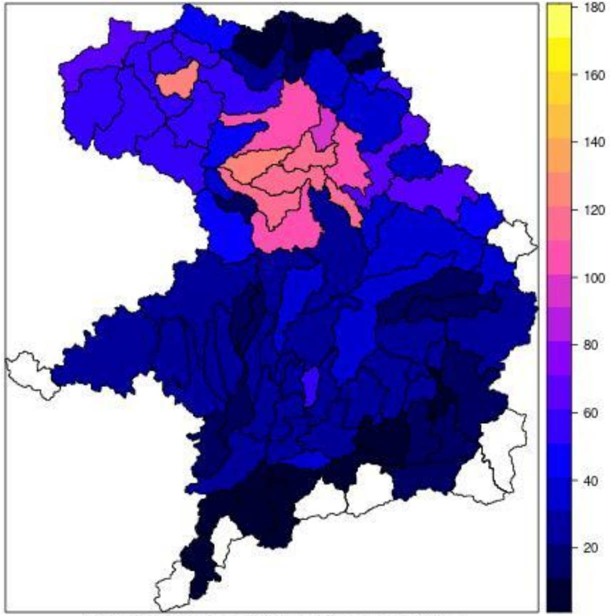
True number of days of low flow in winter of 2020



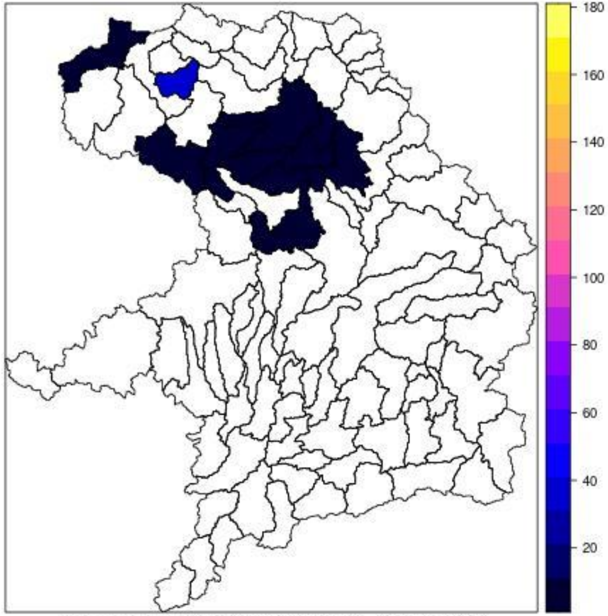
Days of predicted low flow - Winter 2020 - Threshold 0.6

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



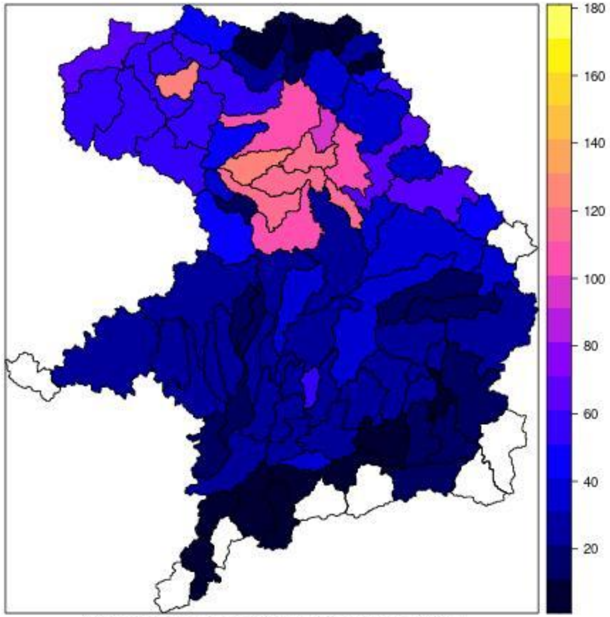
True number of days of low flow in winter of 2020



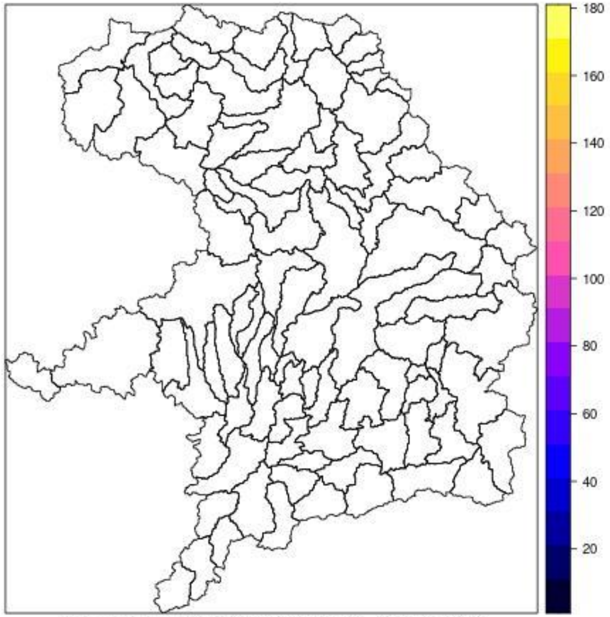
Days of predicted low flow - Winter 2020 - Threshold 0.7

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



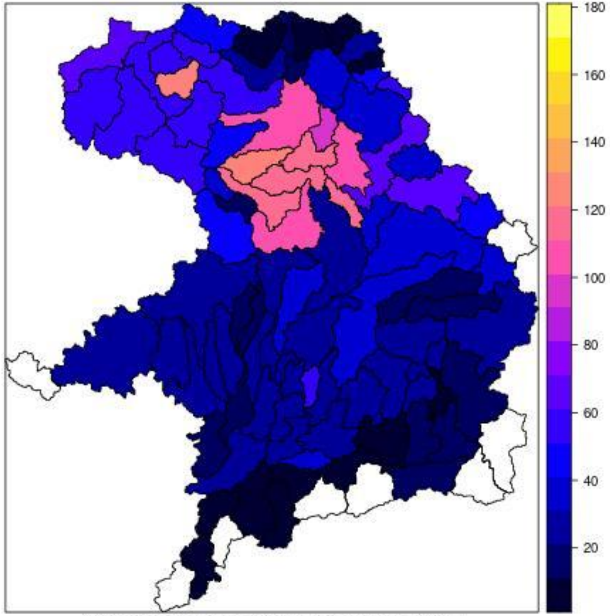
True number of days of low flow in winter of 2020



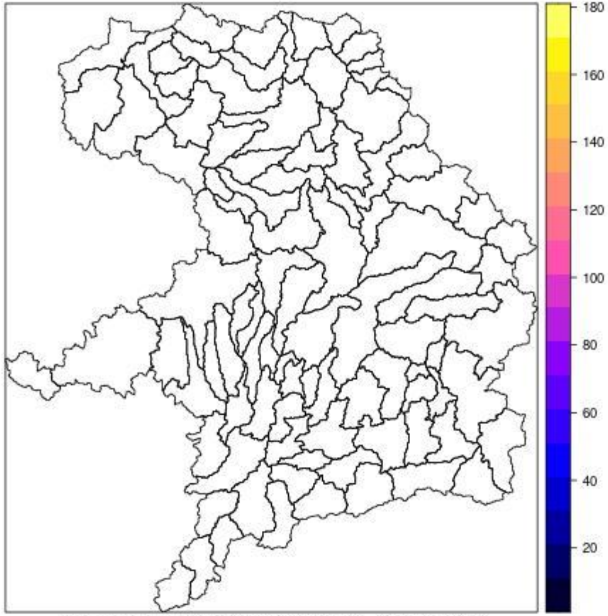
Days of predicted low flow - Winter 2020 - Threshold 0.8

For member “kbt”

Analysis of Thresholds for Winter 2020 and One Member



True number of days of low flow in winter of 2020



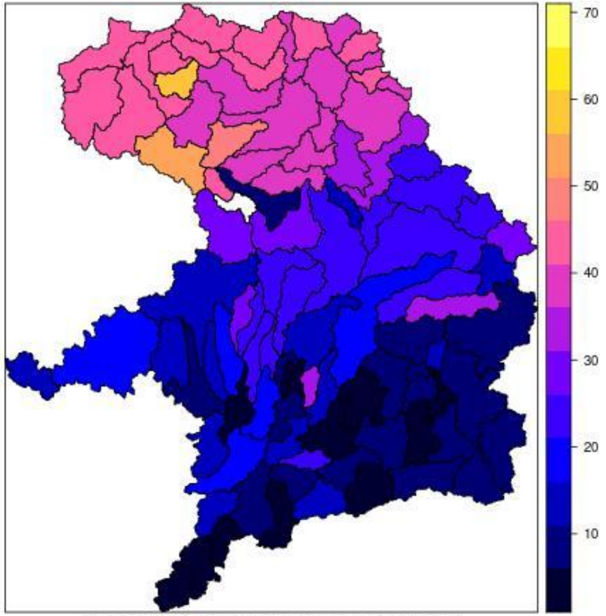
Days of predicted low flow - Winter 2020 - Threshold 0.9

For member “kbt”

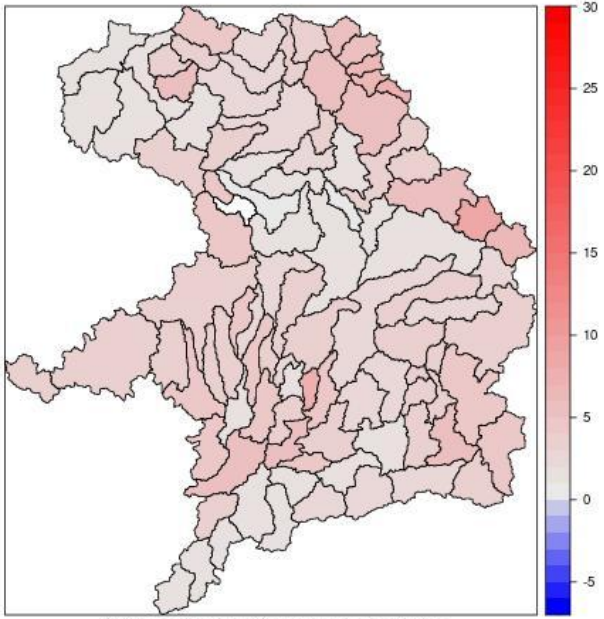
Intermediate Scenarios

Scenarios Summer

Difference Between Predictions for Original Data & less precipitation

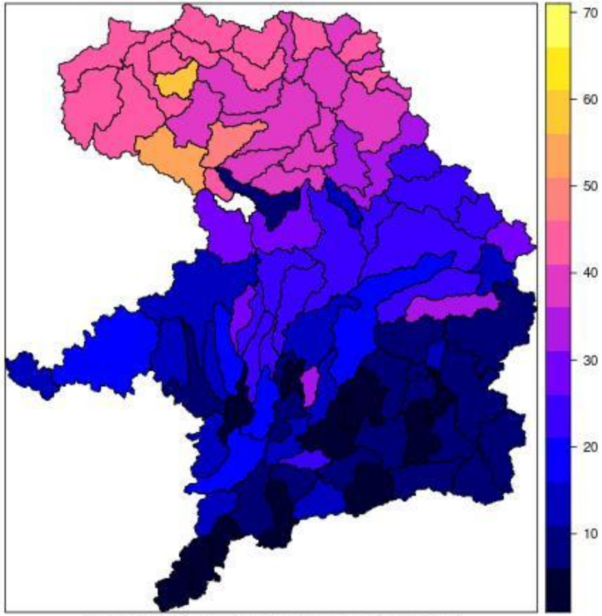


Days of low flow in summer 2010 for original data

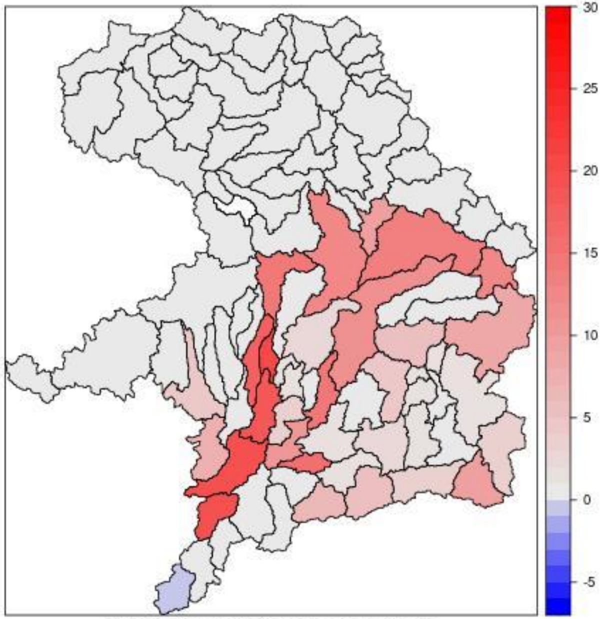


Difference to predicitions: -50% precipitation

Difference Between Predictions for Original Data & no snow storage

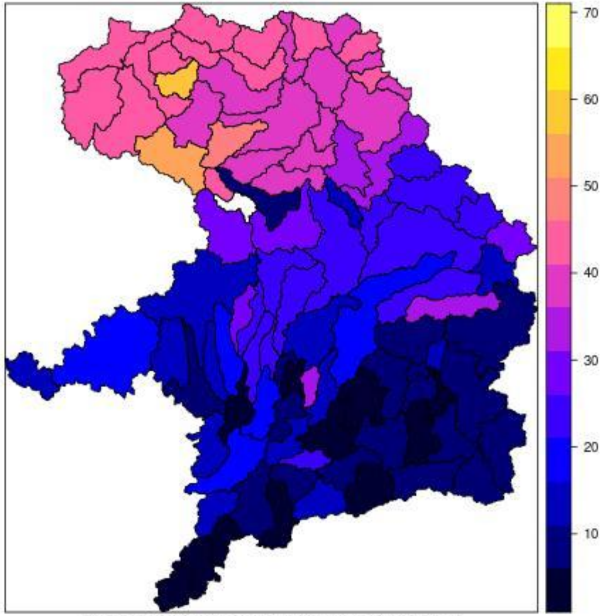


Days of low flow in summer 2010 for original data

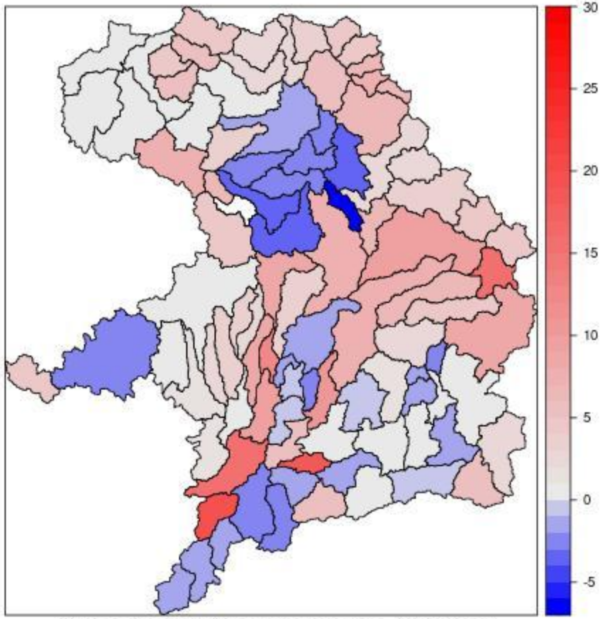


Difference to predicitions: no snow storage

Difference Between Predictions for Original Data & no snow storage and 3°C warmer

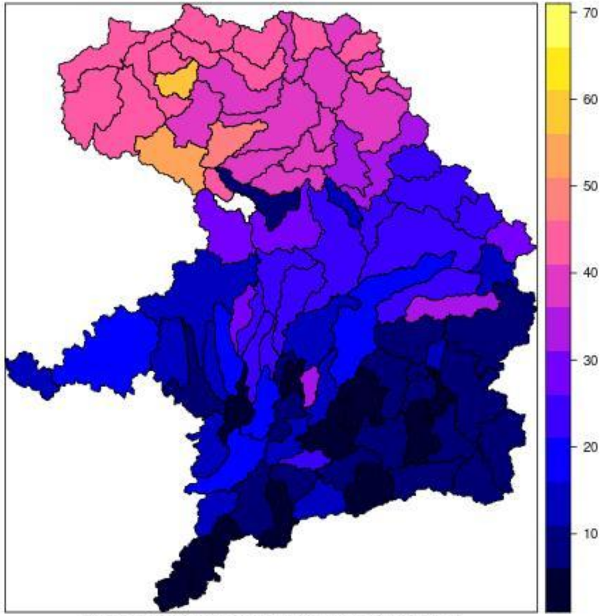


Days of low flow in summer 2010 for original data

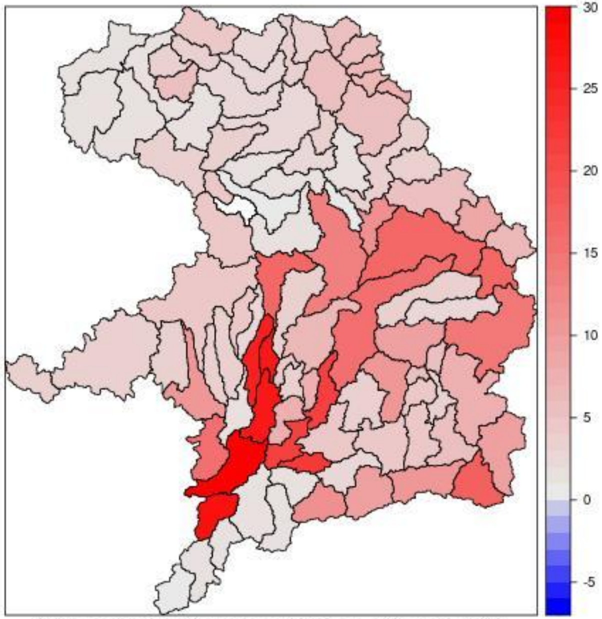


Difference to predicitions: no snow storage, +3°C warmer

Difference Between Predictions for Original Data & no snow storage and less precipitation



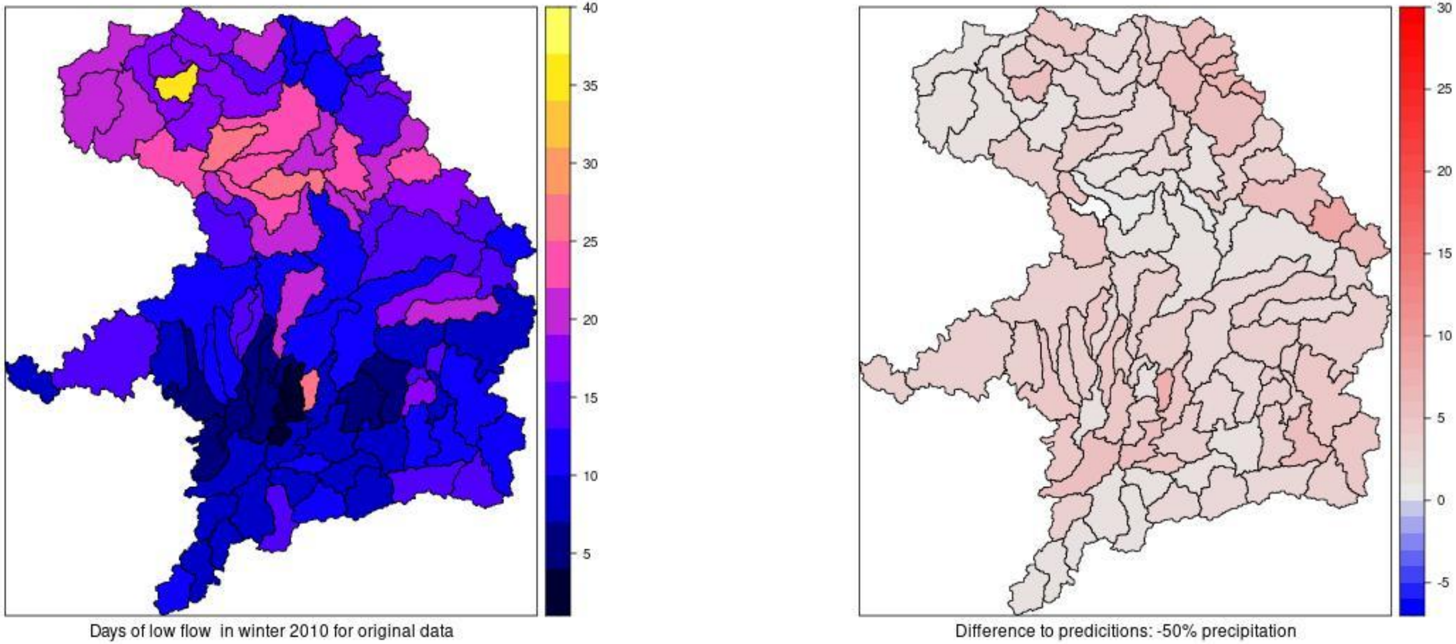
Days of low flow in summer 2010 for original data



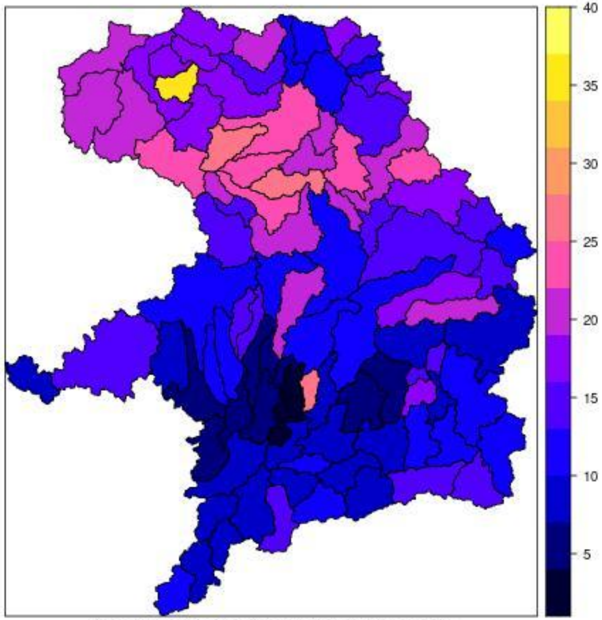
Difference to predicitions: no snow storage, -50% precipitation

Scenarios Winter

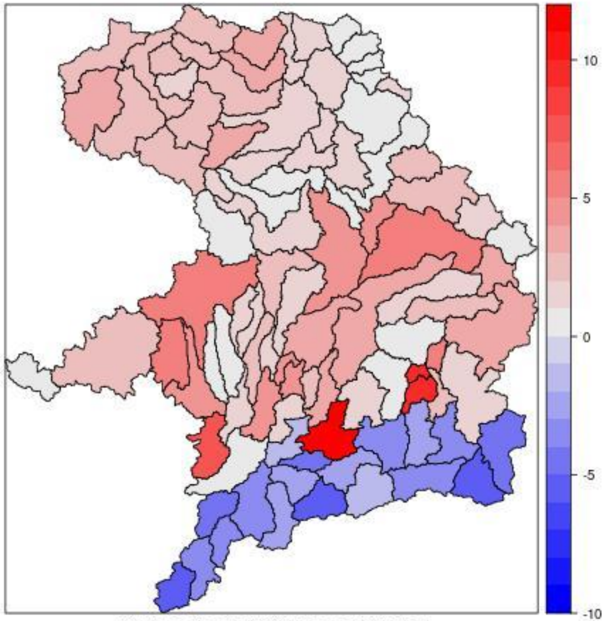
Difference Between Predictions for Original Data & more precipitation



Difference Between Predictions for Original Data & no snow storage

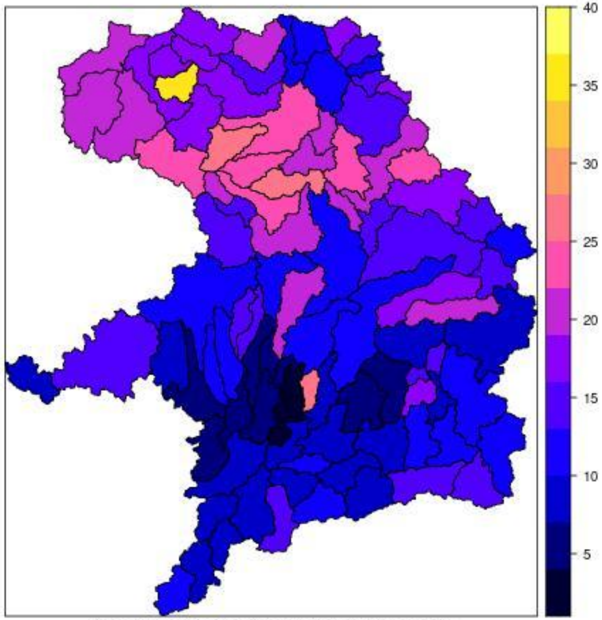


Days of low flow in winter 2010 for original data

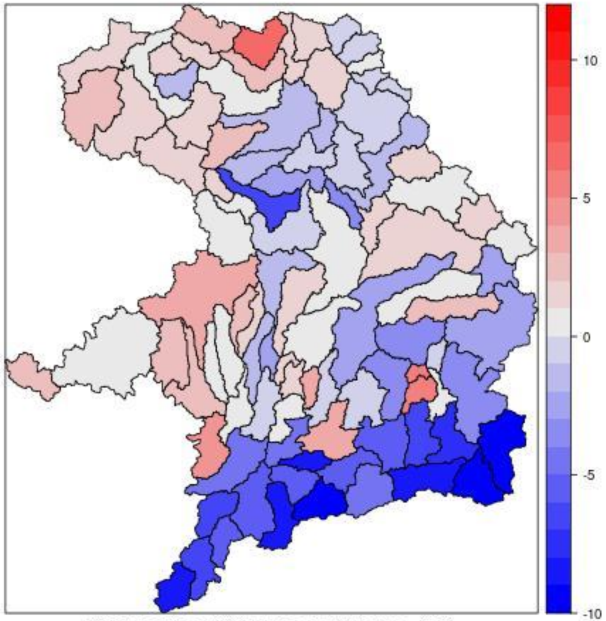


Difference to predicition: no snow storage

Difference Between Predictions for Original Data & no snow storage and 3°C warmer

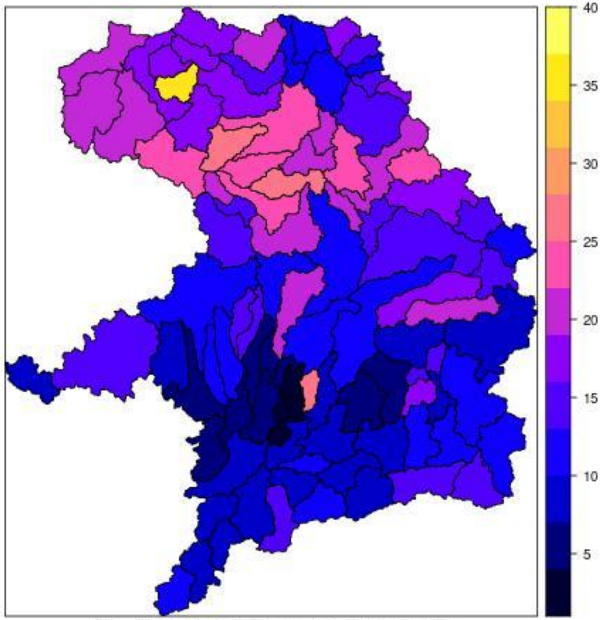


Days of low flow in winter 2010 for original data

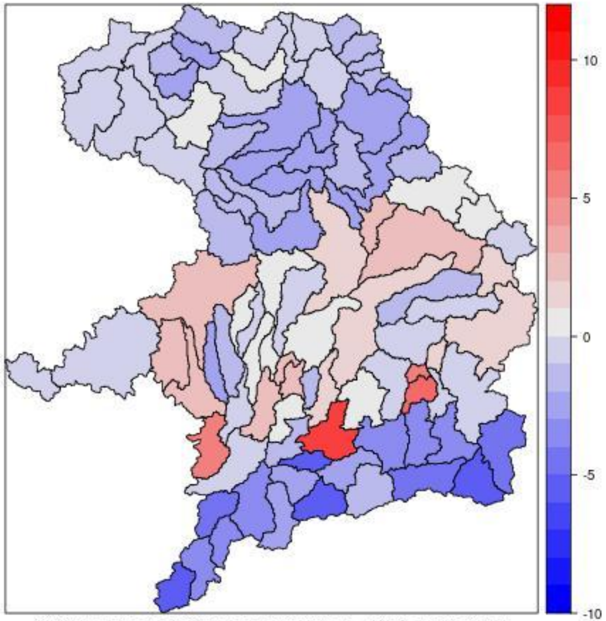


Difference to predicition: no snow storage, +3°C

Difference Between Predictions for Original Data & no snow storage and more precipitation



Days of low flow in winter 2010 for original data

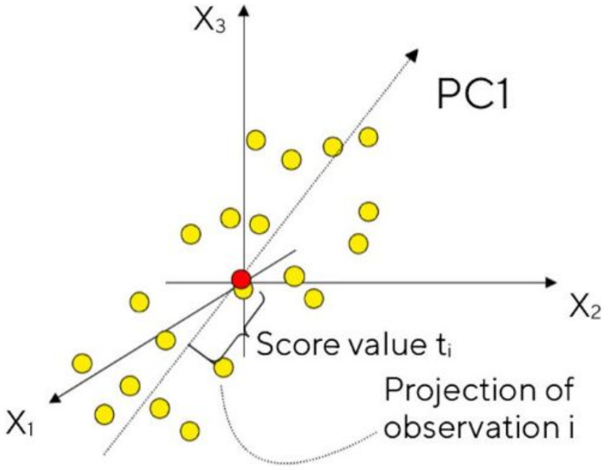


Difference to predicition: no snow storage, +50% precipitation

Clustering

Principal Component Analysis

- Dimension reduction technique
- Beneficial for data sets with lots of variables
- Orthogonal linear transformation of data → new coordinate system → x-axis; greatest variance by some scalar projection
- Principal component = maximum variance direction in the data (unit vectors)



https://www.sartorius.com/en/knowledge/science-snippets/what-is-principal-component-analysis-pca-and-how-it-is-used-507186