Predicting Flood Responses from Spatial Rainfall Variability and Basin Morphology through Machine Learning

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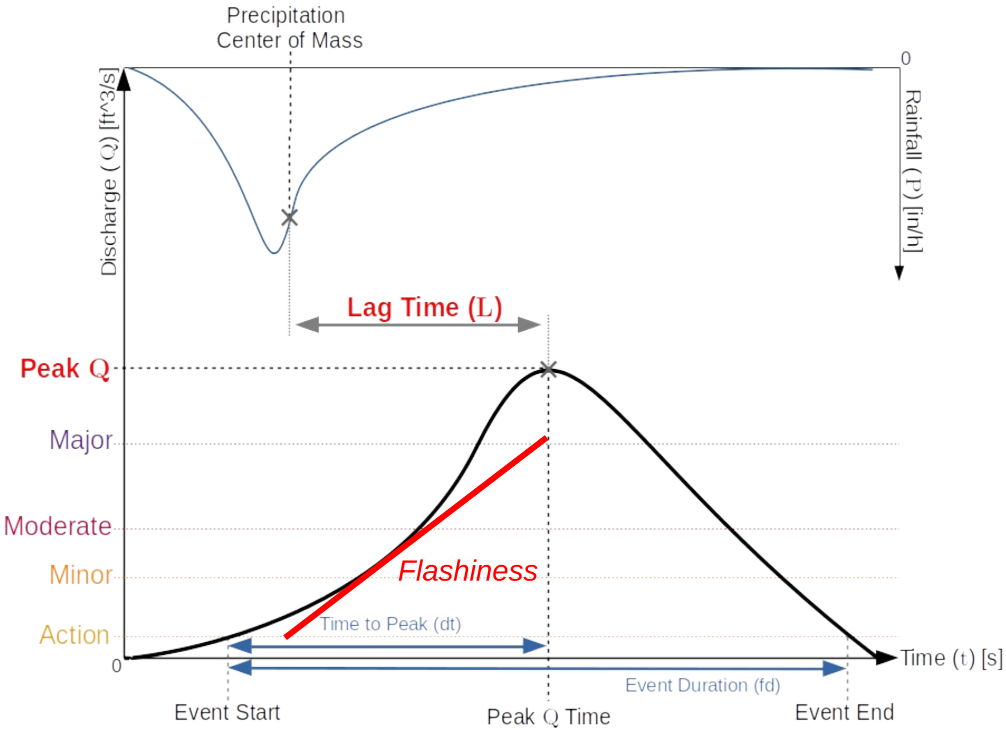
Flood Response Characterization



Detailed flow response measures and characteristics

- Characterize flood-generating flow responses with respect to:
  - Causating rainfall event:
    - Lag Time
  - Pre-defined discharge thresholds:
    - Flood Stage Threshold Exceedance (NWS)
- Information for Flash Flood Forecasting
- Flashiness relates closely to basin morphology

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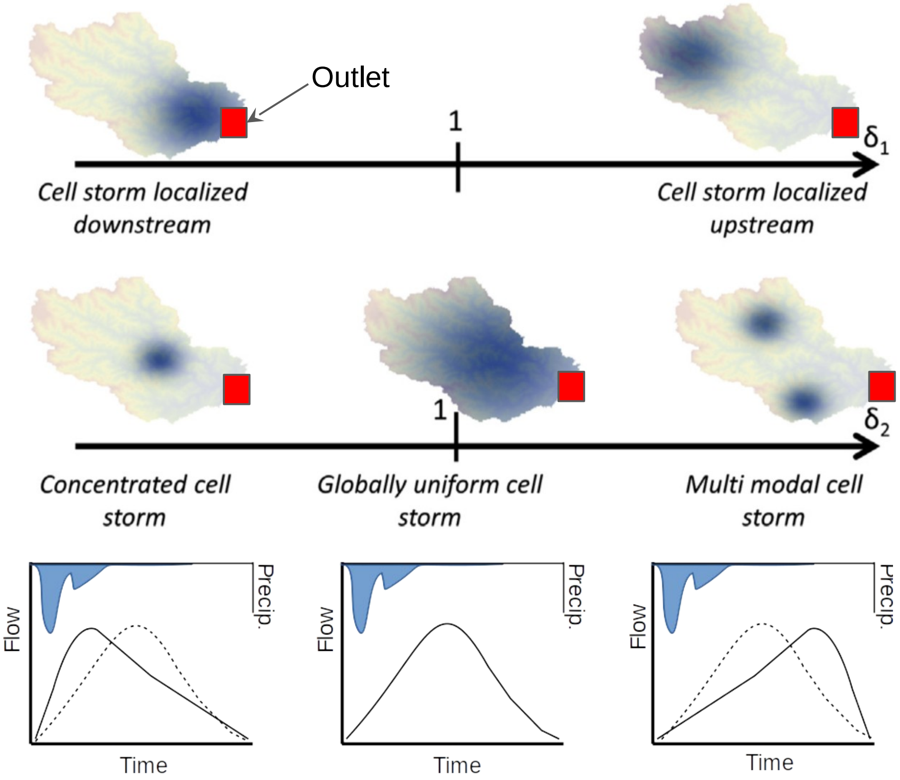
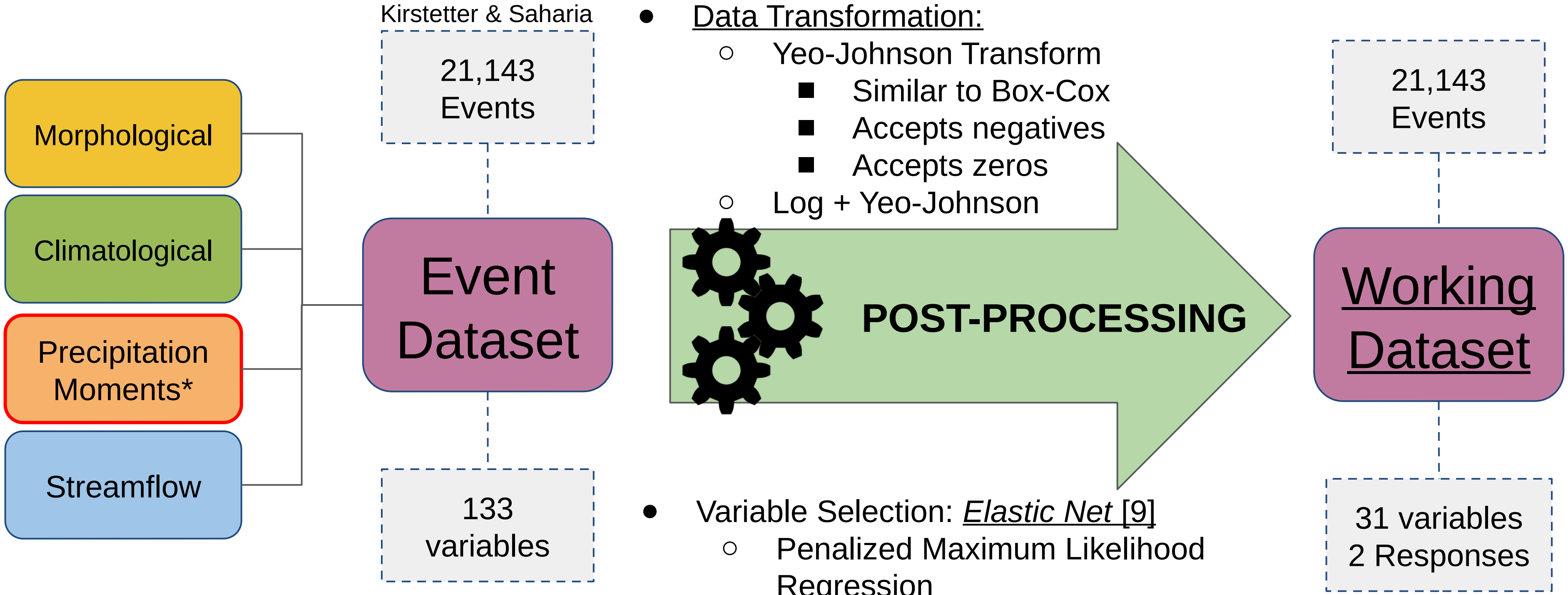
Precipitation Spatial Variability



Rainfall Spatial Variability Characterization [5]

- <u>Rainfall spatial variability influences basin response</u> [1,5,6,7,8].
- Spatial rainfall moments:
  - Dimensionless indices
  - Based on precipitation location.
  - Based on *flow distance.*
  - ➡ Describe the behavior of the storm event, relative to the basin.
- Statistical Moments:
  - Mean, Variance, Skewness...
  - Single and cross-moments.

Data Set



- Data Transformation:
  - Yeo-Johnson Transform
    - Similar to Box-Cox
    - Accepts negatives
    - Accepts zeros
  - Log + Yeo-Johnson
- Variable Selection: *Elastic Net* [9]
  - Penalized Maximum Likelihood Regression
  - Selection such that Error is within 1SE of optimum (minimum)

Some Variable Examples

Climatological

- Flashiness
- Mean Diurnal Temperature Range
- Mean Temp. of Warmest Quarter
- Isothermality (Mean Diurnal Range / Annual Range)
- Precip. Of Warmest Quarter
- Annual Mean Temperature

Morphological

- Outlet Slope
- Curve Number
- River Length
- Basin Imperviousness
- Slope Index

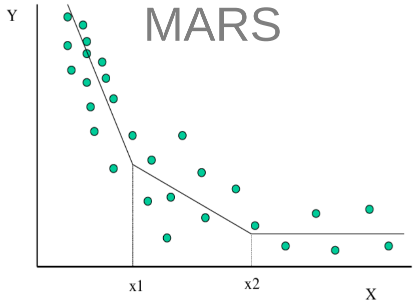
Precip. Moments

- Precipitation Mean
- Precip. Std. Deviation
- Precip. Skewness
- Flow Distance Mean
- Flow Dist. Std. Deviation
- Flow Dist. Skewness
- Precipitation x Flow Dist. Mean
- Precip. x Flow Dist. Std. Deviation
- Precip. x Flow Dist. Skewness
- Precip. x Flow Dist. Kurtosis

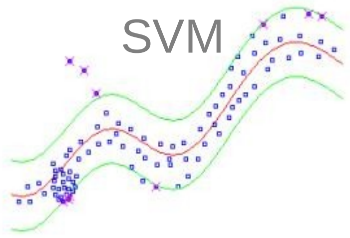
Response Modeling

- Dataset divided randomly into 75% - 25% training and validation subsets:
  - Both subsets showed similar distributions for the data.
  - Preserved representativeness in both subsets.
- Three different approaches:
  - MARS: Multidimensional piecewise linear fits.
  - Support Vector Machines: Kernel-based spatial transformations (radial basis function).
  - Random Forest: Randomized, bagged tree ensemble.
- All training subject <u>10 x 10-fold cross-validation</u>.
- Validation with unseen data **v.s.** cross-validated training.
- <u>Variable importance analysis</u> performed on models.

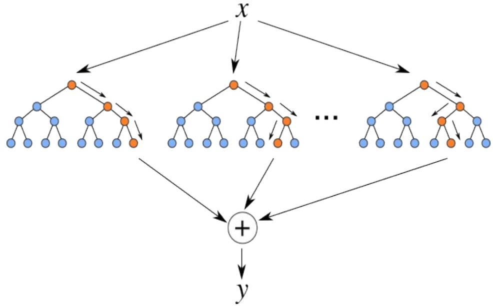
MARS



SVM



Random Forests



Images taken from [2, 3, 4]

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Results - Training Times

	MARS	Random Forest	Support Vector Machines
Lag Time	1.76 hours	8.20 hours	**<u>344.13 hours</u>**
Flood Stage Threshold Exceedance	9.5 hours	3.0 hours	<u>~150 hours</u>

- What are the relationships and trade-offs between ML technique, training time and performance?

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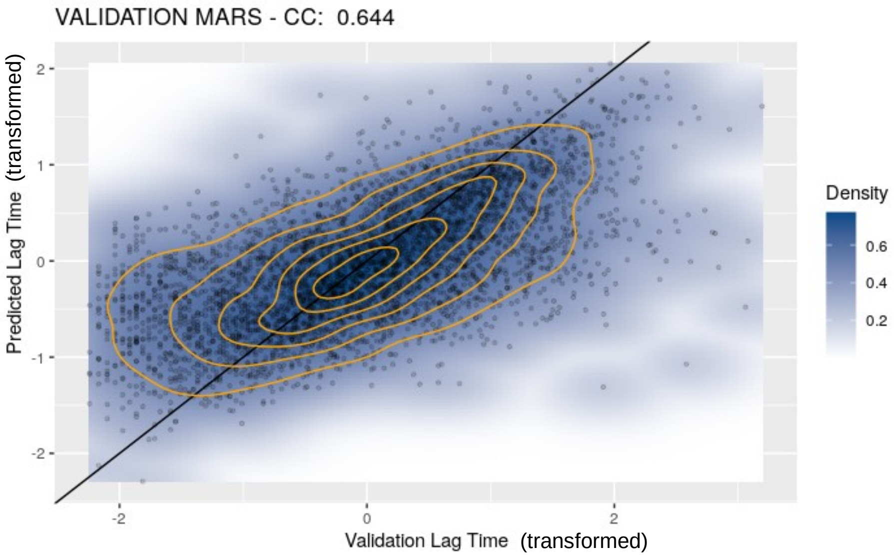
MARS Results - Validation

Lag Time



VALIDATION		TRAINING
"CC 0.64"	V.S.	"CC 0.66"

- Performance remains consistent between training and validation, for both responses.

Flood Stage Threshold Exceedance

Prediction	Reference				
	No Action	**Action**	**Minor**	**Moderate**	**Major**
No Action	**5**	5	0	3	0
Action	13	**123**	45	35	16
Minor	1	5	**21**	16	8
Moderate	2	30	86	**164**	86
Major	0	14	55	238	**3258**

VALIDATION		TRAINING
"ACCURACY 0.84" “KAPPA 0.58”	V.S.	"ACCURACY 0.85" "KAPPA 0.5288"

- Class imbalance - favors **Major** events.
- Sensitive to **Action** and **Major** events

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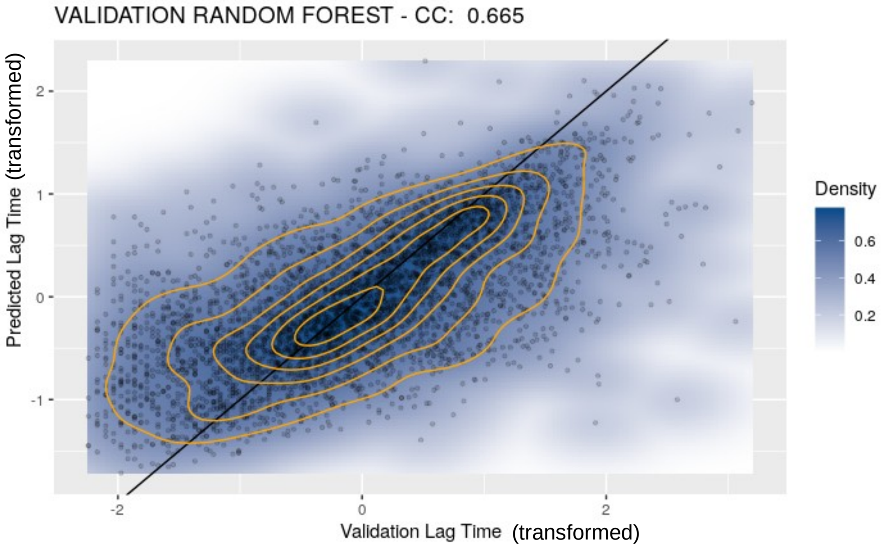
RF Results - Validation

Lag Time



VALIDATION
"CC 0.67"

V.S.

TRAINING
"CC 0.96"

- Performance lost between training and validation, for both responses.
  - ➡ Even <u>using 10 x 10-fold CV</u>!

Flood Stage Threshold Exceedance

Prediction	**Reference**				
	No Action	**Action**	**Minor**	**Moderate**	**Major**
No Action	**9**	7	0	0	0
Action	12	**132**	63	33	28
Minor	0	16	**56**	30	13
Moderate	0	16	65	**210**	109
Major	0	6	23	183	**3218**

VALIDATION
"ACCURACY 0.86"
"KAPPA 0.58"

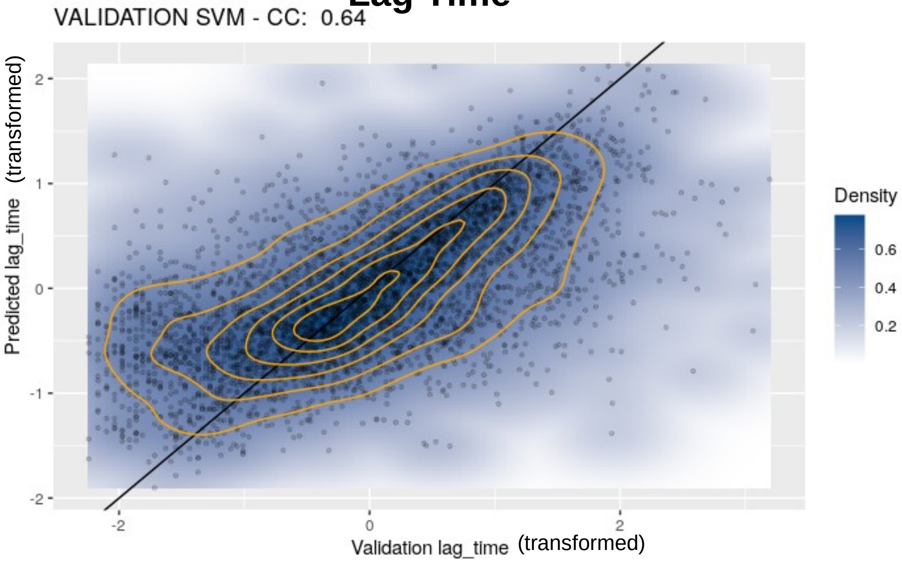
V.S.

TRAINING
"ACCURACY 0.94"
"KAPPA 0.83"

- Class imbalance - favors **Major** events.
- Sensitive to **Action** and **Major** events
- Better "understanding" of **Moderate** events than <u>MARS</u>

SVM Results - Validation

Lag Time



VALIDATION
"CC 0.64"

V.S.

TRAINING
"CC 0.82"

- Performance lost between training and validation, for both responses.
  - ➡ Even using 10 x 10-fold CV!

Flood Stage Threshold Exceedance

Prediction	**Reference**				
	No Action	**Action**	**Minor**	**Moderate**	**Major**
No Action	**4**	4	0	1	0
Action	5	**61**	19	11	6
Minor	0	8	**27**	17	9
Moderate	0	11	35	**97**	43
Major	12	93	126	330	**3310**

VALIDATION
"ACCURACY 0.83"
“KAPPA 0.35”

V.S.

TRAINING
"ACCURACY 0.98"
"KAPPA 0.95"

- Class imbalance - favors **Major** events.
- Sensitive ONLY to **Major** events

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Results - Summary

	MARS		Random Forest		Support Vector Machines	
Lag Time	1.76 hours	CC - 0.64	8.20 hours	CC - 0.66	344.13 hours	CC - 0.64
Flood Stage Threshold Exceedance	9.5 hours	ACC. - 0.84 K - 0.50	3.0 hours	ACC. - 0.85 K - 0.57	~150 hours	ACC. - 0.82 K - 0.34

- Class imbalance makes it difficult to provide accurate predictions for intermediate flood stage thresholds.
  - ➡ Prediction skill for of **Major** events.
- All models exhibit comparable skill levels.
  - ➡ MARS performs consistently across all data, and requires less training time for Lag Time.
  - ➡ RF overfits training data, but performs comparably.
  - ➡ SVM requires extensive parameter tuning and training times, no drastic performance gains.

Lag Time - Variable Importance Ranking

	MARS	Random Forest	Support Vector Machines
Lag Time	**1. Flashiness** **2. Precipitation Mean** **3. Precip. X Flow Dist. Mean** 4. Diurnal Temp. Range Mean 5. Precipitation. Std. Dev.	**1. Flashiness** **2. Precip. X Flow Dist. Mean** 3. Precip. X Flow Dist. Skewness 4. Precip. X Flow Dist. Std. Dev. **5. Precipitation Mean**	**1. Precip. X Flow Dist. Mean** 2. Precip. X Flow Dist. Std. Dev. **3. Precipitation Mean** 4. Precipitation Std. Dev. **5. Flashiness**

- Precipitation moments as well as flashiness appear to play a decisive role across all three algorithms.
  - ➡ Flashiness as an abstracted measure of morphological and climatological information.
- Models consistently rank Precip. x Flow Dist. Mean, Precipitation Mean and Flashiness as significant variables.
- Differences in variable ranking order imply that the choice of ML approach potentially impacts the underlying understanding of the processes being modeled.

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Flood Stages - Variable Ranking

	MARS	**Random Forest**	**Support Vector Machines**
Flood Stage Threshold Exceedance	1. Flashiness 2. Precip. X Flow Dist. Mean 3. Outlet Slope 4. Mean Temp. of Warm. Qt. 5. Basin Imperviousness	1. Curve Number 2. Flow Distance Mean 3. River Length 4. Flow Dist. Std. Deviation 5. Annual Mean Temperature	1. River Length 2. Flow Distance Mean 3. Flow Dist. Std. Deviation 4. Slope Index 5. Annual Precipitation

- Both precipitation moments and morphological variables appear to hold relevance in performing classification.
  - ➡ Thresholds are directly related to morphology and may be influenced by climatology.
- Climatological variables appear as well, most notably measures of temperature and precipitation.
- Differences in variable importance and ranking order imply that the choice of ML approach impacts the underlying understanding of modeled processes.

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Conclusions

- Characterization of floods was achieved by training machine learning models.
  - Data-driven approach for variable selection using Elastic Net.
- Catchment-scale precipitation moments were effectively used to model Lag Time and Flood Stage Threshold Exceedance.
- Variable importance showed relevant factors that contribute to characterizing both responses:
  - Rainfall moments and flashiness lead the ranking for Lag Time.
  - Aside from moments, there is an intrinsic dependence on morphology and climatology for flood stage thresholds.
- MARS was the most consistent performer of all three approaches, and the best at predicting Lag Time.
- RF is more efficient at classification, but overfitting affects consistency.

Thank you!

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Image Sources and References

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