Università di Pisa

Avalanche Danger Level Prediction

FOR DRY-SNOW CONDITIONS

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Data Mining and Machine Learning Course
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INTRODUCTION

IN EUROPE ALONE, EAWS REPORTS AN AVERAGE OF **~100 AVALANCHE FATALITIES PER WINTER** SEASON DESPITE MODERN RESCUE AND SAFETY MEASURES

THE ALPINE REGION HOSTS **~375 MILLION OVERNIGHT STAYS ANNUALLY**: CRITICAL RELIABLE AVALANCHE FORECASTS ARE FOR BOTH LOCAL ECONOMIES AND VISITING SKIERS.

EACH DAY, EAWS FORECASTERS RELEASE A DANGER LEVEL TO **GUIDE PUBLIC AND COMMERCIAL DECISION-MAKING**.

INTRODUCTION

IN EUROPE ALONE, EAWS REPORTS AN AVERAGE OF **~100 AVALANCHE FATALITIES PER WINTER** SEASON DESPITE MODERN RESCUE AND SAFETY MEASURES

TODAY'S BULLETINS DEPEND ON **EXPERT INTERPRETATION** OF SNOWPACK OUTPUTS AND FIELD DATA, INTRODUCING **SUBJECTIVE VARIABILITY**.

MANUAL WORKFLOWS CANNOT SCALE TO HOURLY NOWCASTING AT INDIVIDUAL IMIS STATIONS, DELAYING CRITICAL INFORMATION EXACTLY WHEN IT'S NEEDED MOST.

DATASET ANALYSIS
The Envidat dataset

TARGET:
AVALANCHE DANGER LEVEL RATING

Categorical target variable (1–5) indicating overall snowpack stability, possible triggering events, expected slopes in which the avalanche can be generated. Only **certified** SLF avalanche danger levels.

METEOROLOGICAL VARIABLES
Hourly weather measurements aggregated over 24 h to capture conditions driving snow processes.

SNOWPACK FEATURES
Layer-specific properties extracted from SNOWPACK's detailed snow-cover profiles.

AGGREGATED FEATURES
Aggregated versions of key variables (up to one week earlier).

DERIVED FEATURES
Higher-level summary values condensing complex physical processes.

CONTEXT FEATURES
Localization metadata and station attributes for tracking and grouping observations.

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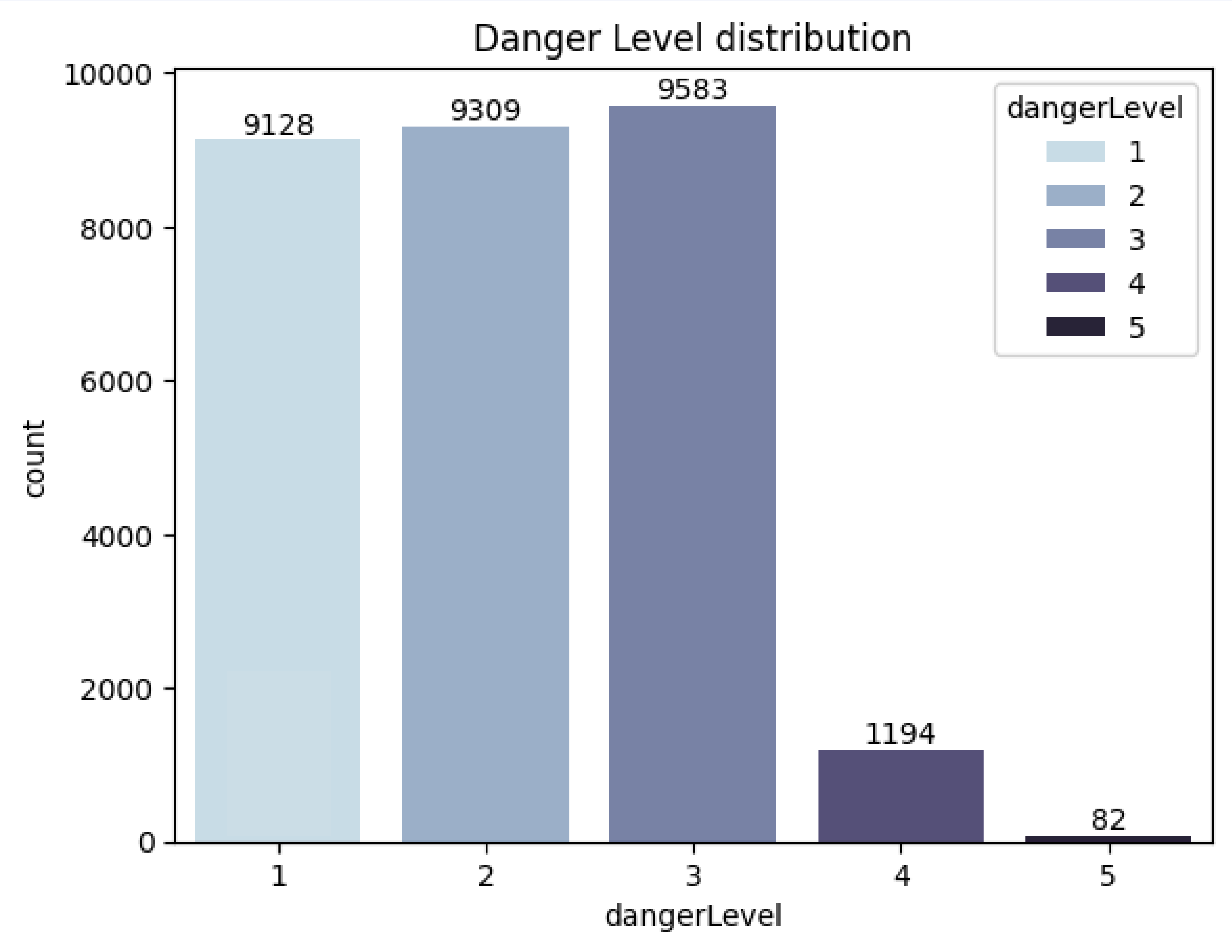
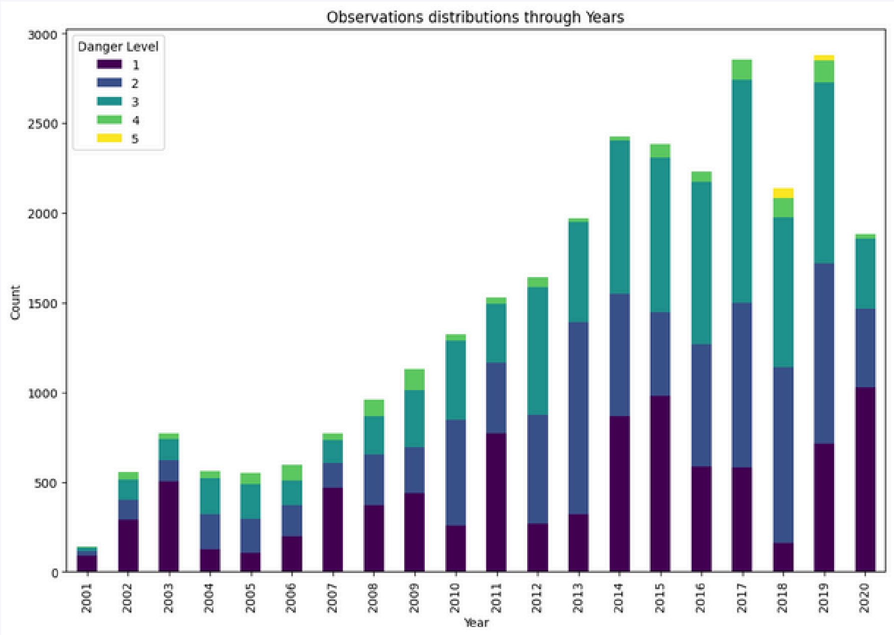
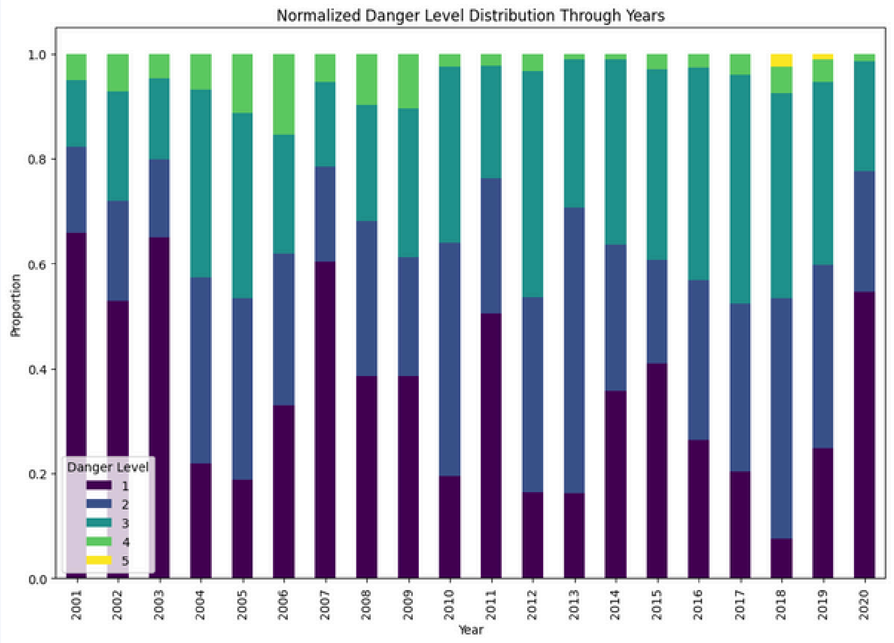
29 296 OBSERVATIONS | 79 FEATURES

WHERE: forecasted from different meteorological stations in Switzerland
WHEN: winter periods between 2001 and 2020

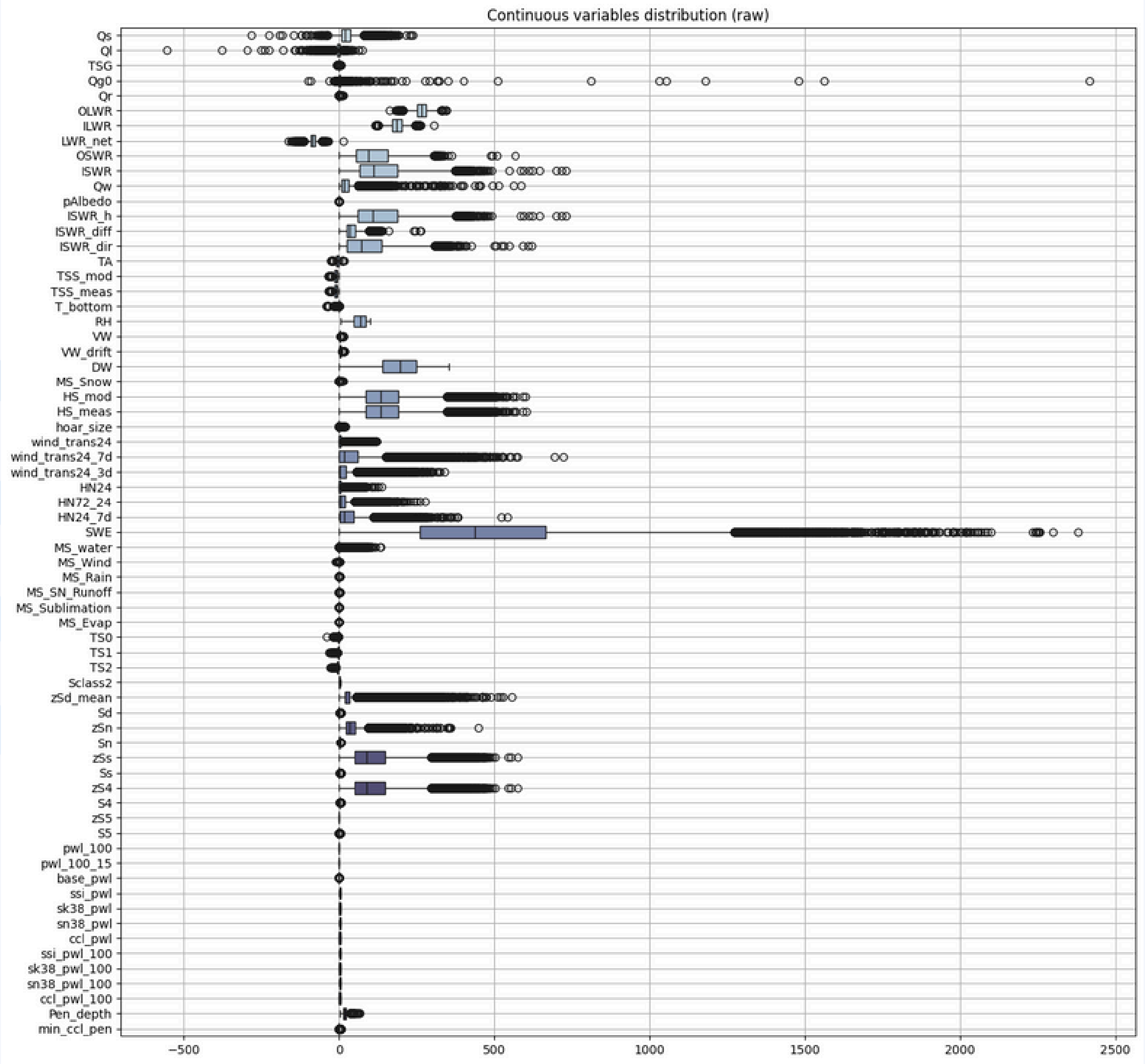
DATASET ANALYSIS
EDA - Target distribution

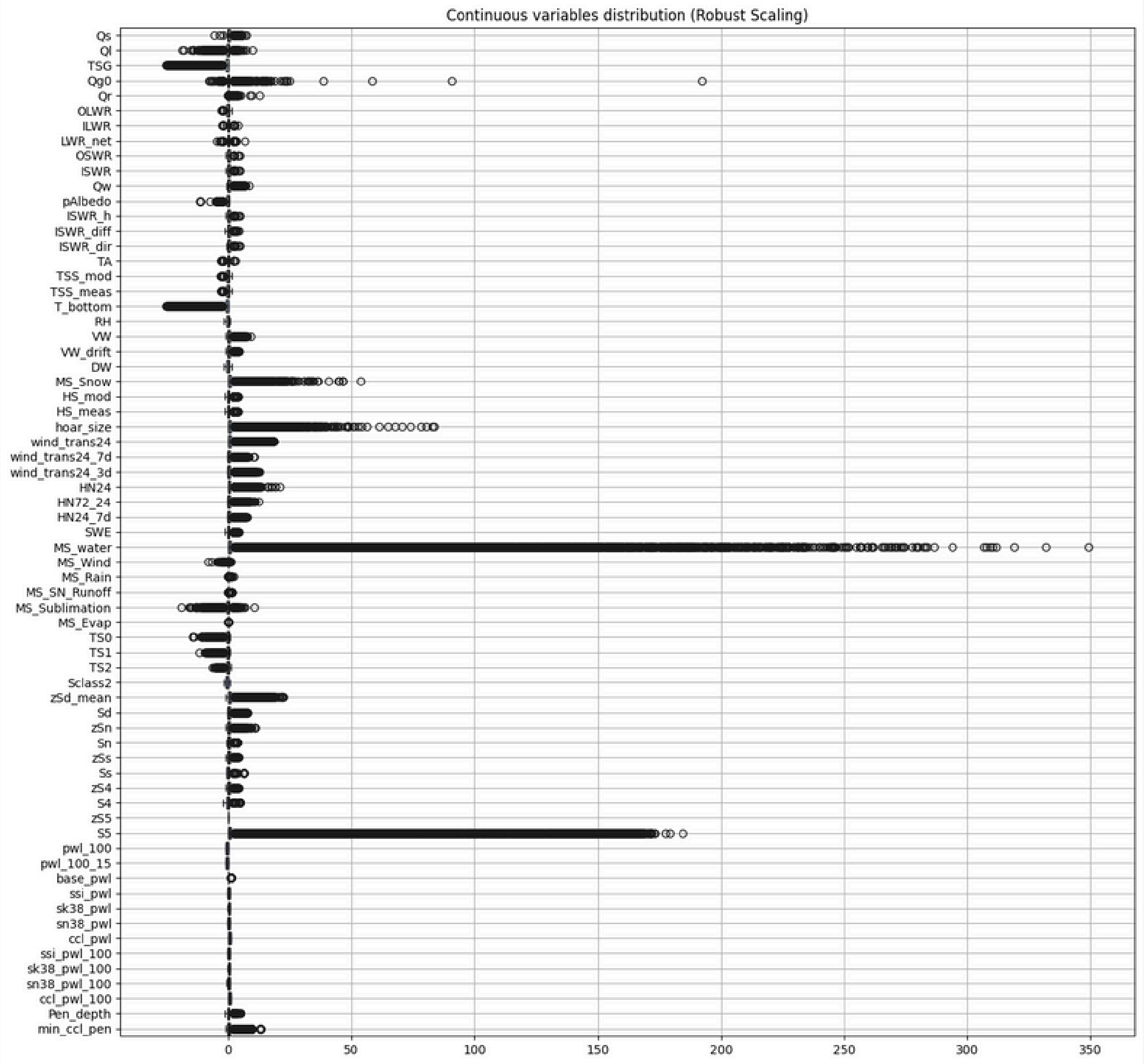






DATASET ANALYSIS
EDA - Data variety





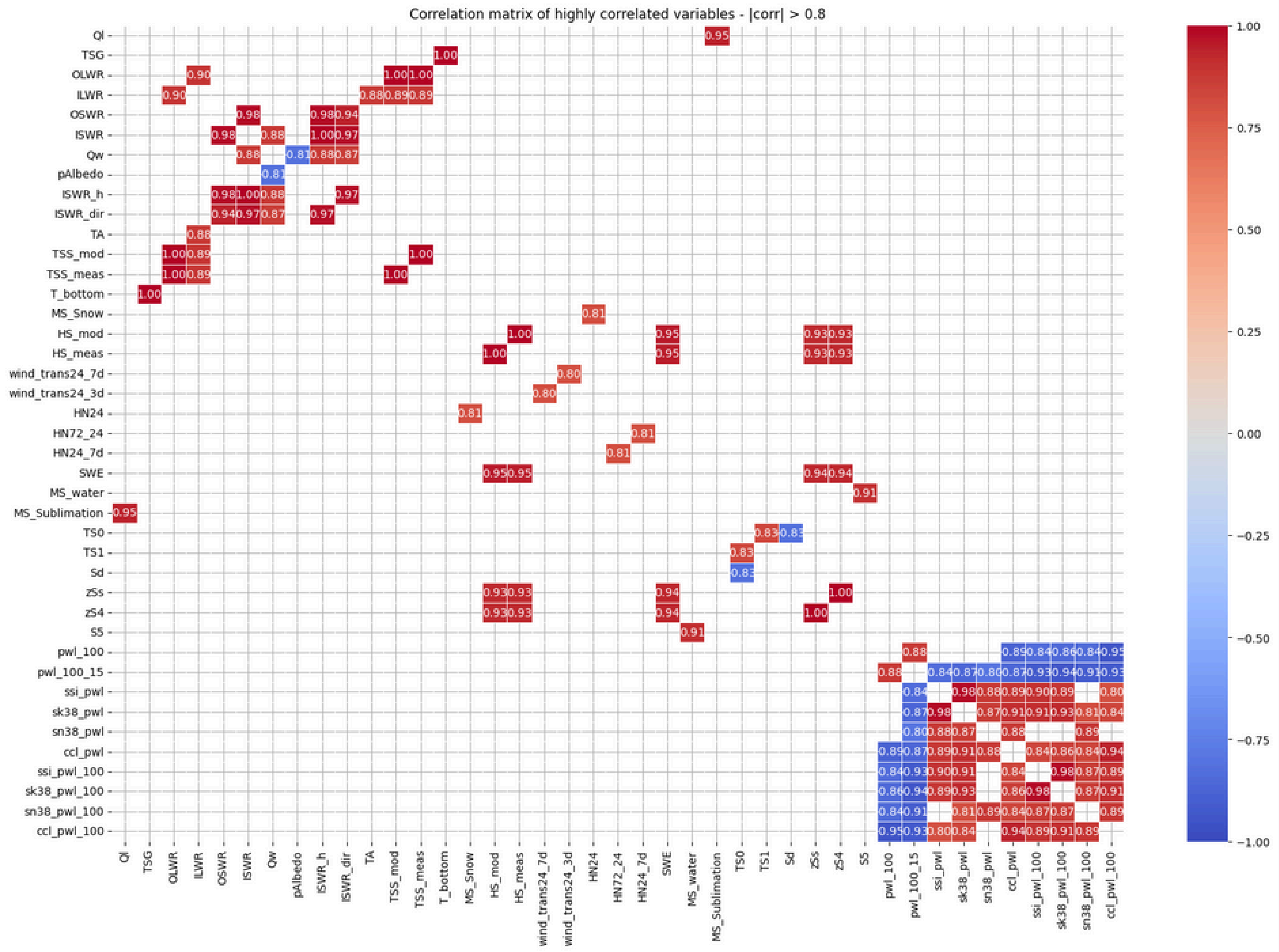
5 EMPTY FEATURES

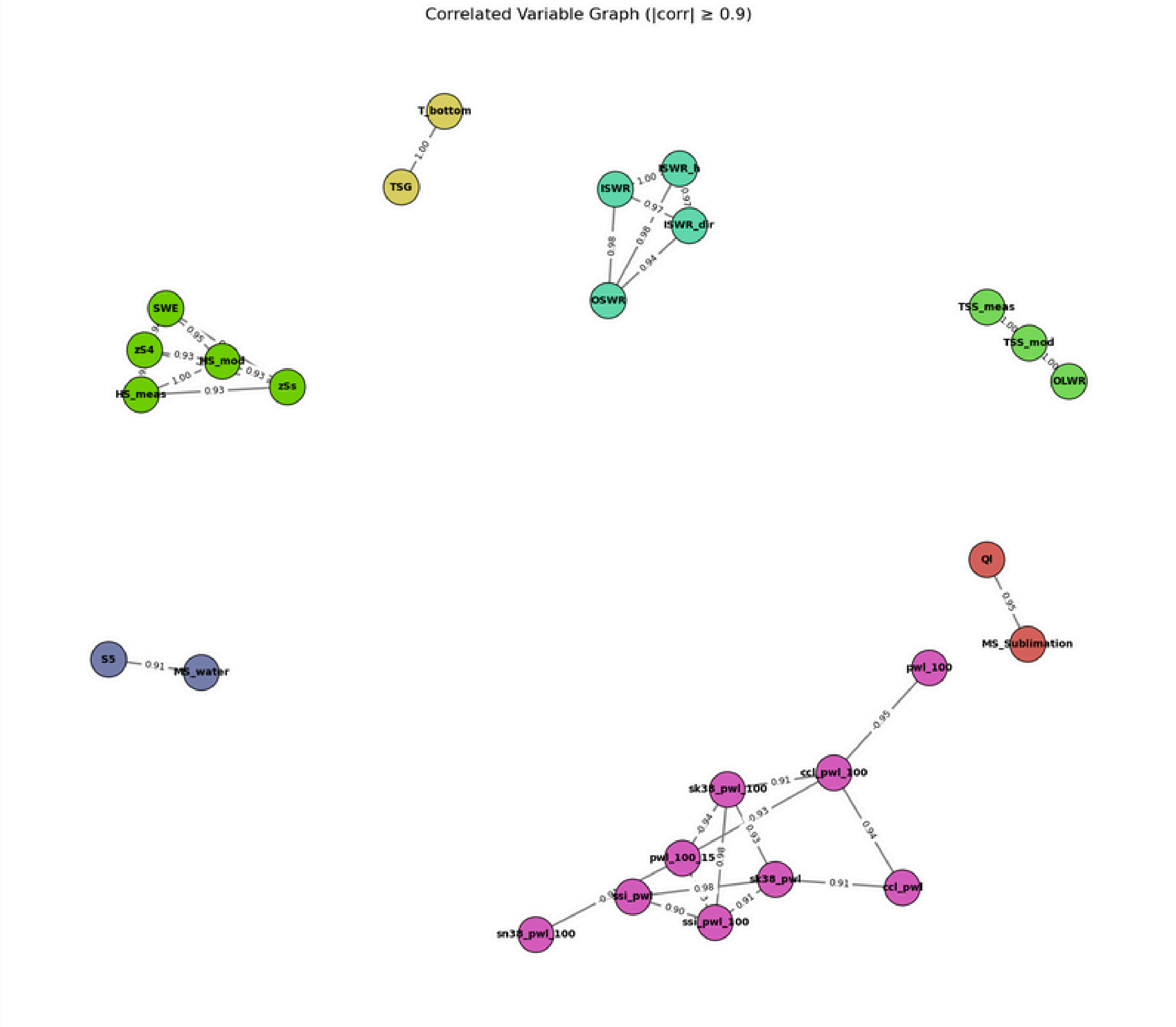
1 CONSTANT FEATURE

77% OBSERVATIONS WITHOUT MISSING VALUES

DATASET ANALYSIS

EDA - Features Correlation





7 GROUPS OF HIGHLY (>0.9) CORRELATED FEATURES

~30 COMPONENTS NEEDED TO REACH 0.95 C.V. USING STANDARD SCALING

DATASET ANALYSIS
Preprocessing

29 296 OBSERVATIONS
79 FEATURES
1-5 CLASS TARGET

FEATURE PRUNING

- Removed empty and constant features
- dropped metadata to avoid bias
- kept datnum for chronological splits

MISSING-VALUES REMOVAL

Deleted all records with any missing values, without altering target-class balance.

CLASS MERGING

Combined danger levels 4 and 5 to increase sample size and reduce rare-class instability.

22 601 OBSERVATIONS
68 FEATURES
1-4 CLASS TARGET

DATASET ANALYSIS
Splitting

Outer Hold-Out Split

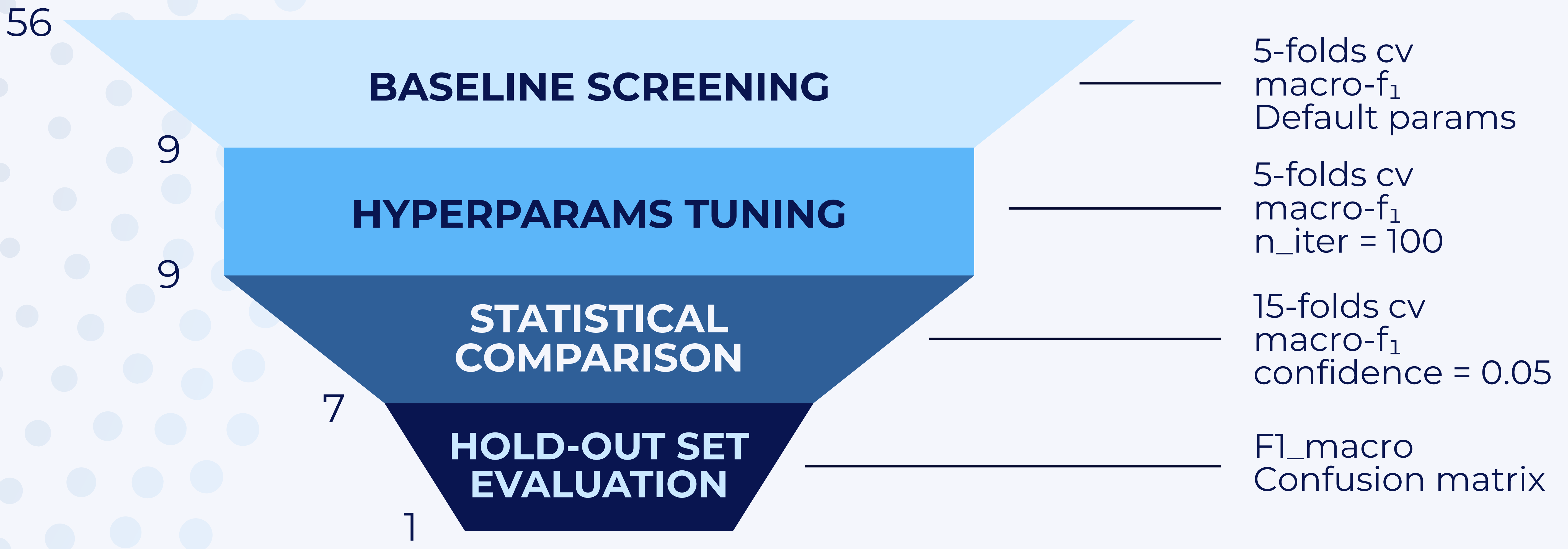
Inner K-Fold CV

1. **GROUP** OBSERVATIONS BY WINTER SEASON (NOV–MAR)
2. **SEASONS 2017–2019** OUT-OF-TIME TEST SET.
3. **SEASONS 2001–2016** TRAINS ON SEASONS ≤ Y AND VALIDATES ON SEASON Y+1.

METHODOLOGY
Model Training

PIPELINES

1. **Sampling**: RandomOverSampler, SMOTE, None
2. **Scaling**: RobustScaler, StandardScaler, None
3. **Dimensionality red.**: PCA, Local-PCA, None
4. **Classifier**: RandomForest, XGBoost, SVM



D-OUT SET
ALUATION

METHODOLOGY

Model Optimization

REMOVING LESS-IMPORTANT, HIGHLY CORRELATED FEATURES	DETERMINING MINIMAL FEATURE SUBSET SIZE	RFE	RE-TUNING	STATISTICAL COMPARISON	FINAL HOLD-OUT EVALUATION
Drop low-rank features with $\|\rho\|>0.90$ to retain only top informative ones	Identify smallest k whose macro-F_1 matches full set (Wilcoxon)	Use RFE to select k features and update pipeline	Run randomized search over reduced pipeline	Compare 15-fold CV macro-F_1 scores via Wilcoxon test	Retrain on 2001–2016 and test on 2017–2019, reporting metrics

METHODOLOGY
Discriminating Class 5

Brief **Second-stage** analysis on discriminating **Class 5**:

Margin Analysis

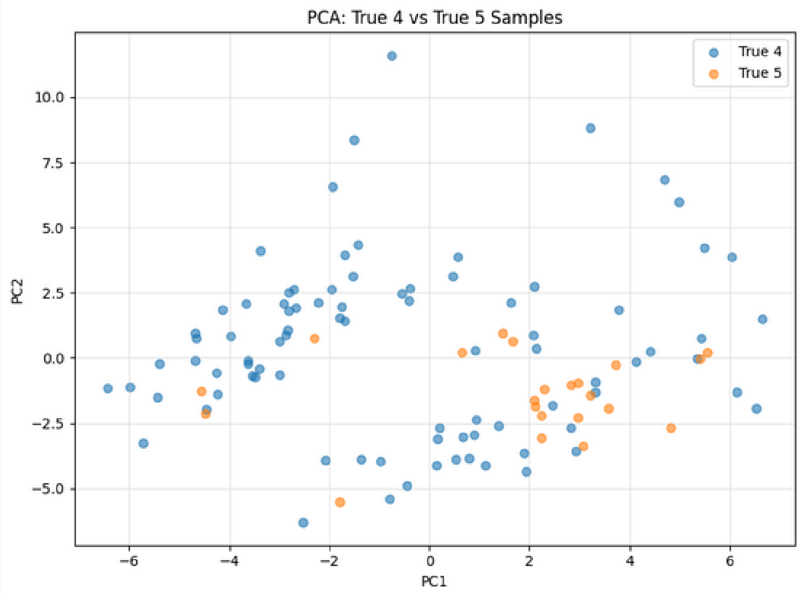
1. Compute $p_4 - p_3$ for true 4/5 samples
2. Rank by this margin
3. Find the threshold that maximizes F_1

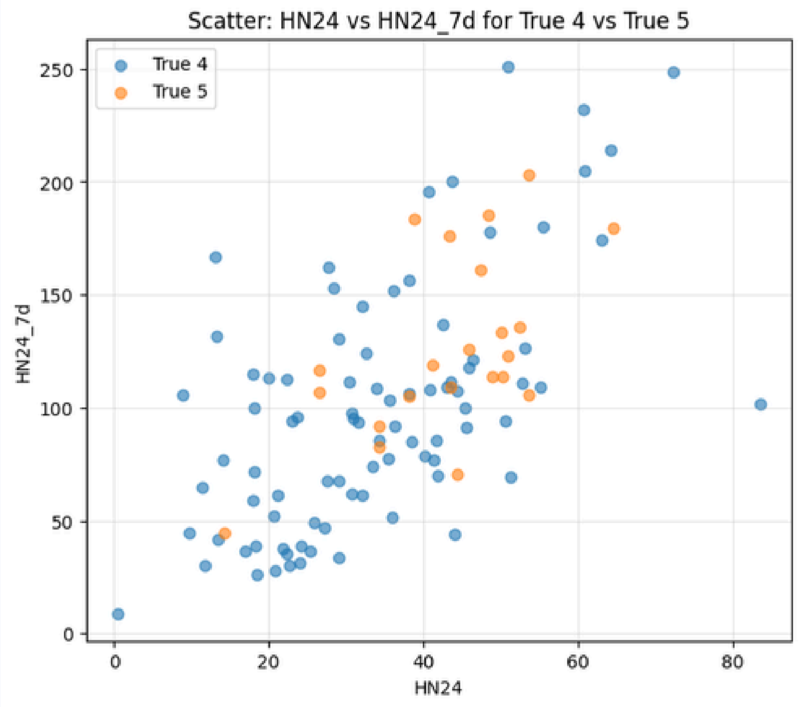
Logistic Meta-Classifier

1. Logistic regression on $\{p_4, p_4 - p_3\}$ from true 4/5 training data
2. Map its binary output to 4 or 5 at test time

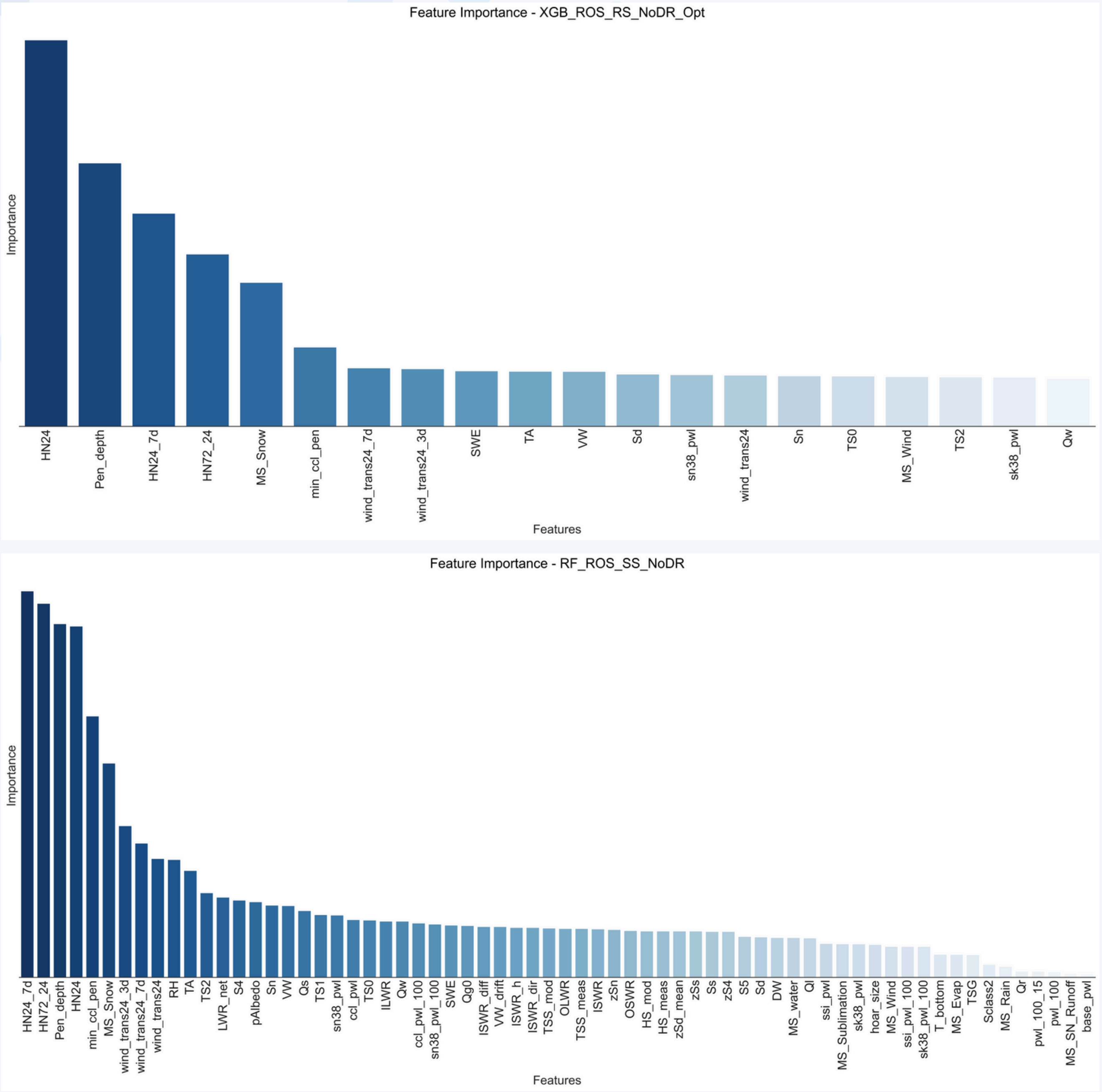
IsolationForest Outlier Detection

1. Fit an IsolationForest on true 4s (contamination = class 5 fraction)
2. Label test points with negative anomaly scores as 5

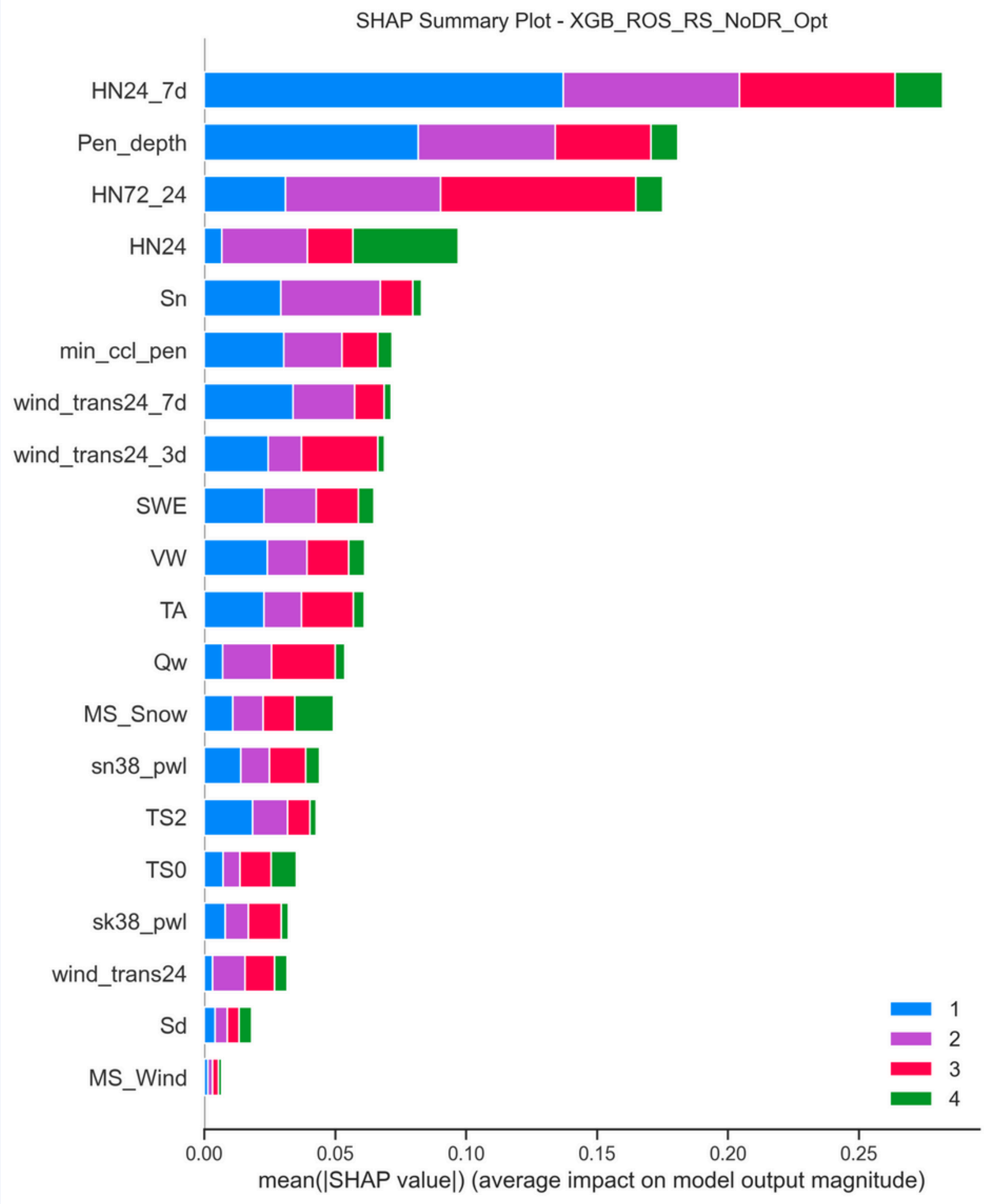




EXPLAINABILITY
Global



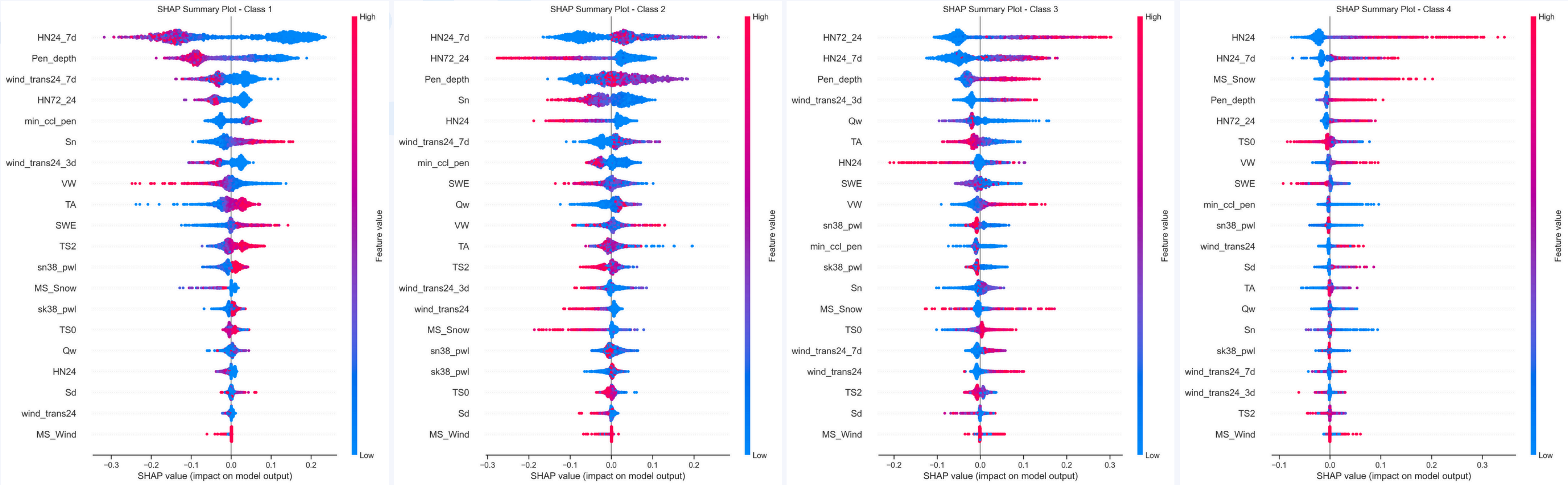
FEATURE IMPORTANCE

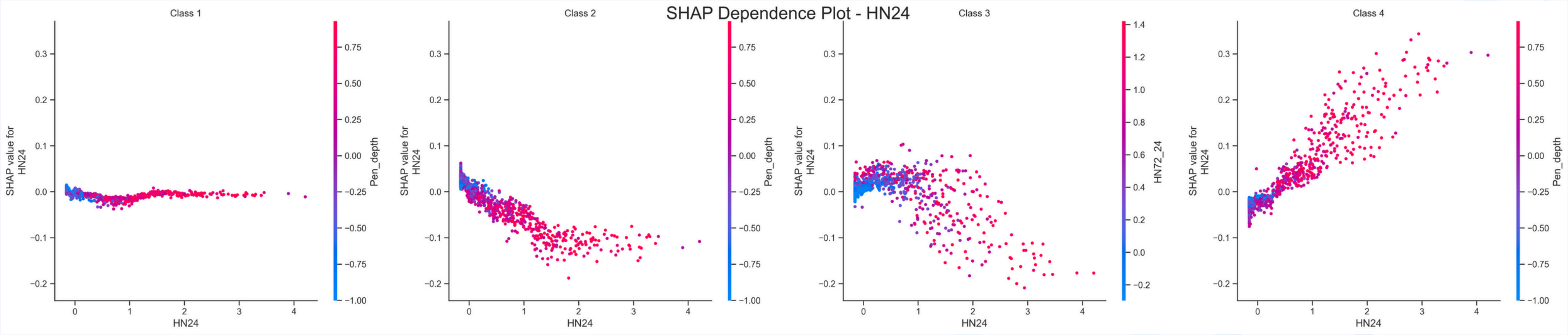


SHAP SUMMARY

EXPLAINABILITY
Global

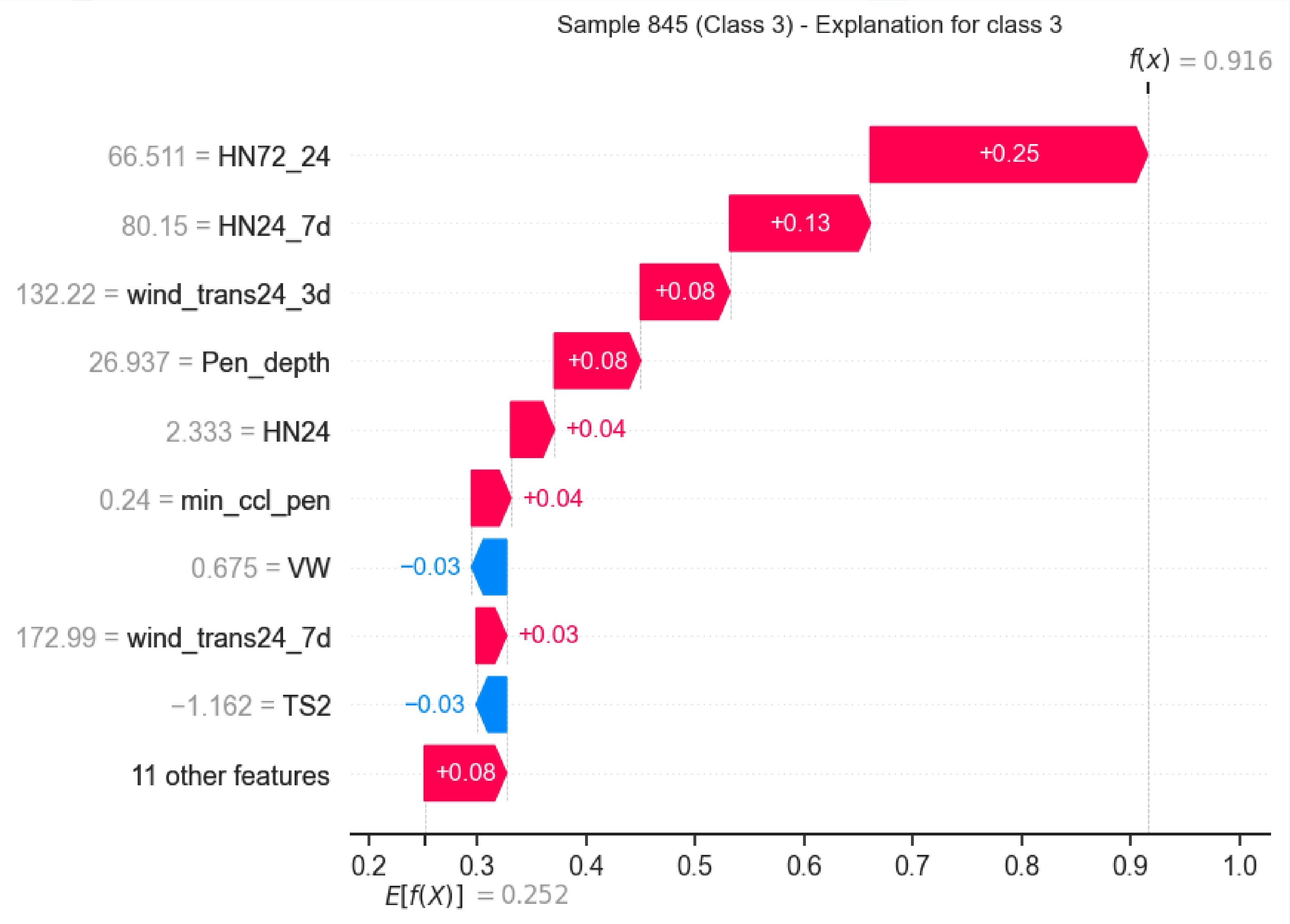
SHAP SUMMARY FOR EACH CLASS

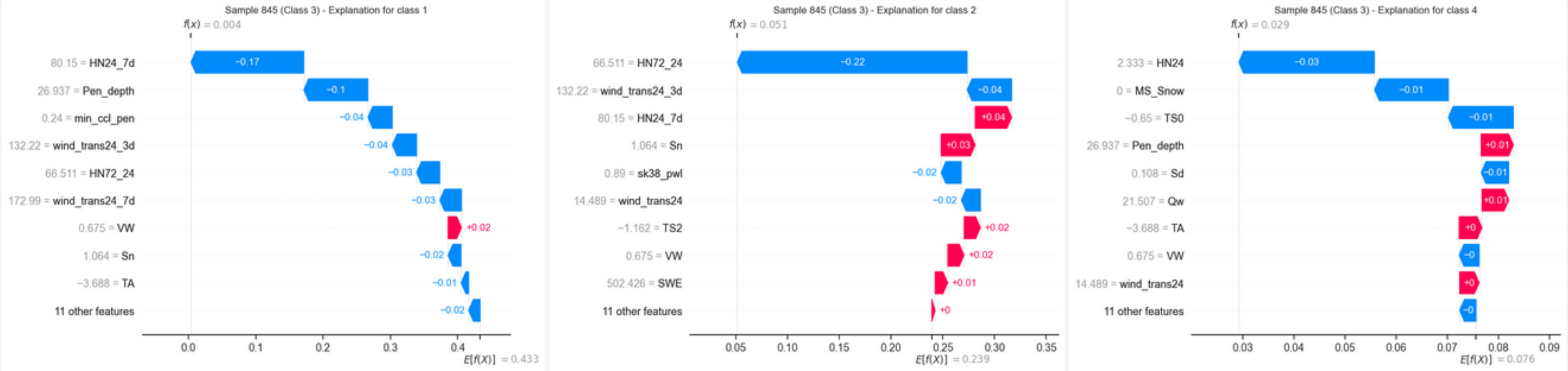




DEPENDENCE PLOT

EXPLAINABILITY
Local





IMPORTANCE OF LOCAL EXPLAINABILITY
Break down individual predictions to show how feature values drive the model’s decision for each observation.

PRACTICAL EXAMPLE (WATERFALL PLOT)
Class 3 sample to visualize each feature’s positive or negative contribution to the prediction score across all classes.

IMPACT OF PIPELINE DESIGN CHOICES

Model choice: Decision-tree methods outperforms others by capturing non-linear interactions and tolerating redundant features.

Oversampling: RandomOverSampler consistently beat SMOTE, likely because SMOTE creates unrealistic synthetic meteorological samples.

Scaling: No clear pattern, since tree-based models (RF, XGB) performances were not influenced by this step.

Dimensionality reduction: Pipelines without DR often performed best; group-wise PCA outperforms global PCA when used.

Pipeline	Accuracy	F_1-macro	Balanced Acc.	MCC
RF_ROS_RS_NoDR	0.754209	**0.710624**	0.698313	0.641582
RF_ROS_SS_NoDR	**0.754563**	0.710500	0.697977	**0.642067**
RF_SMOTE_NoS_L-PCA	0.742867	0.686936	0.682776	0.626233
XGB_NoR_RS_NoDR	0.739677	0.661388	0.645076	0.618530
XGB_NoR_NoS_L-PCA	0.745880	0.657204	0.641983	0.627126
XGB_ROS_RS_NoDR	0.742158	0.700881	**0.706312**	0.627547
Paper_Optimized	*0.748361*	*0.722989*	*0.731236*	*0.636519*

RESULTS

PERFORMANCES CONSIDERATIONS

XGB_ROS_RS_NoDR: achieved >50 % recall on class 4 in hold-out. ROC-AUC=0.94 but threshold sweeps (F_1-, precision-, recall-optimized) failed to yield an unbiased production rule

Model optimization:

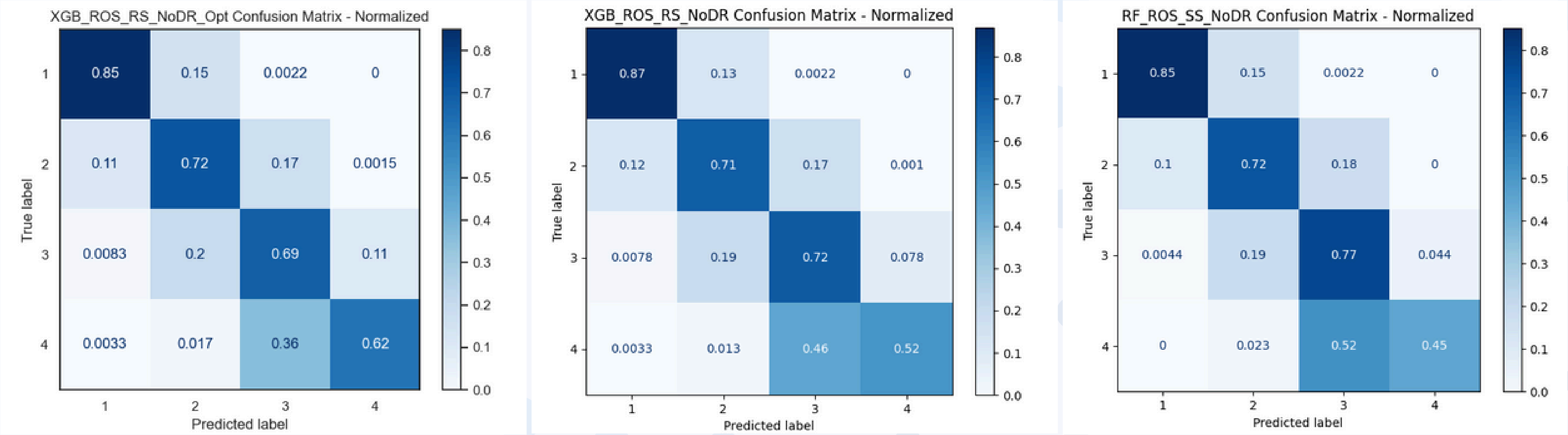
↑ Balanced accuracy, recall on class 4

↓ Overall accuracy, F_1-macro, MCC

Accepting minor overall performance drop may be worthwhile to **better detect high-risk days**.

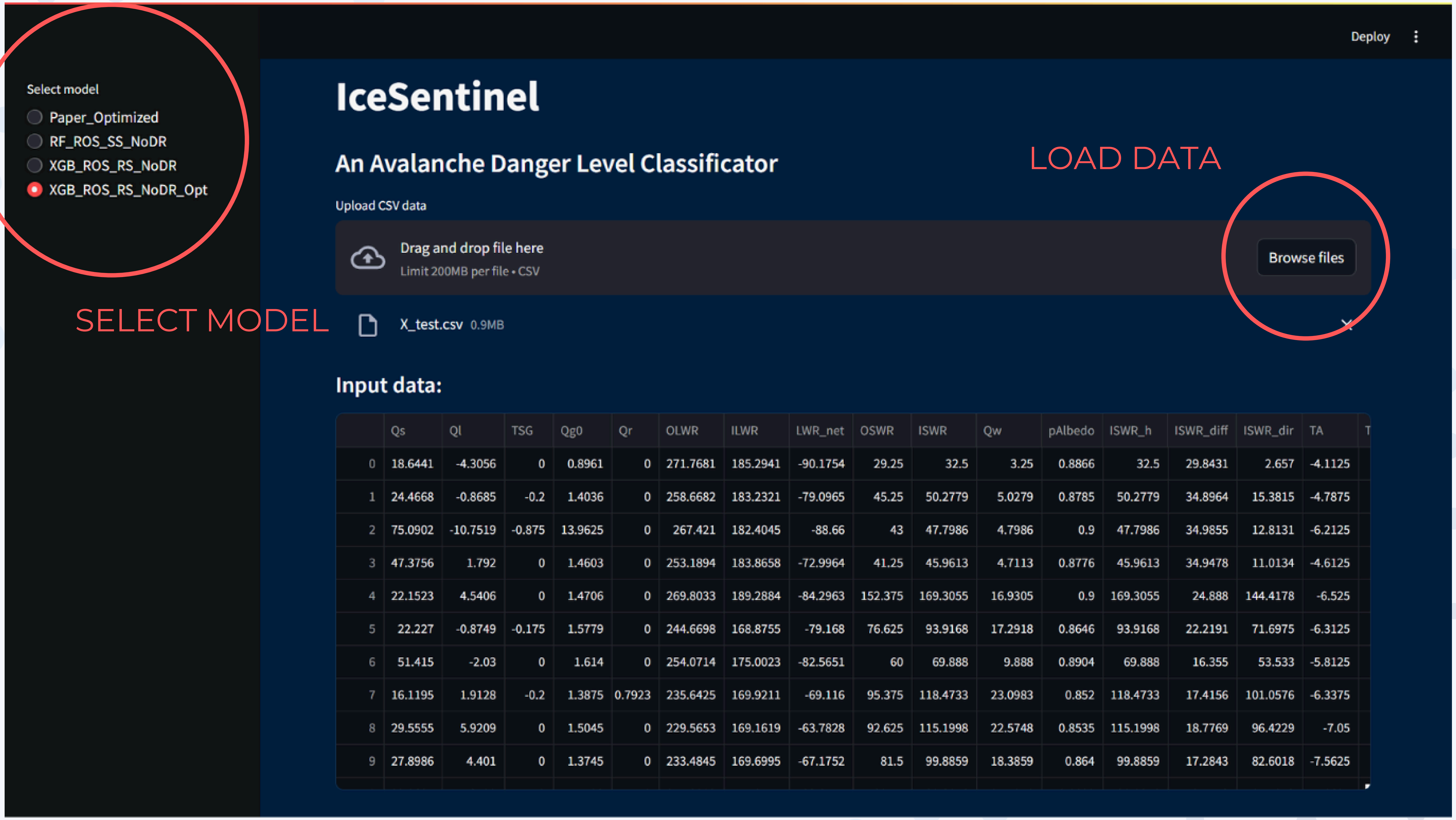
Class 5 discrimination:

True-5 samples are too similar to true-4 in feature space; probability- or outlier-based methods cannot reliably separate them.



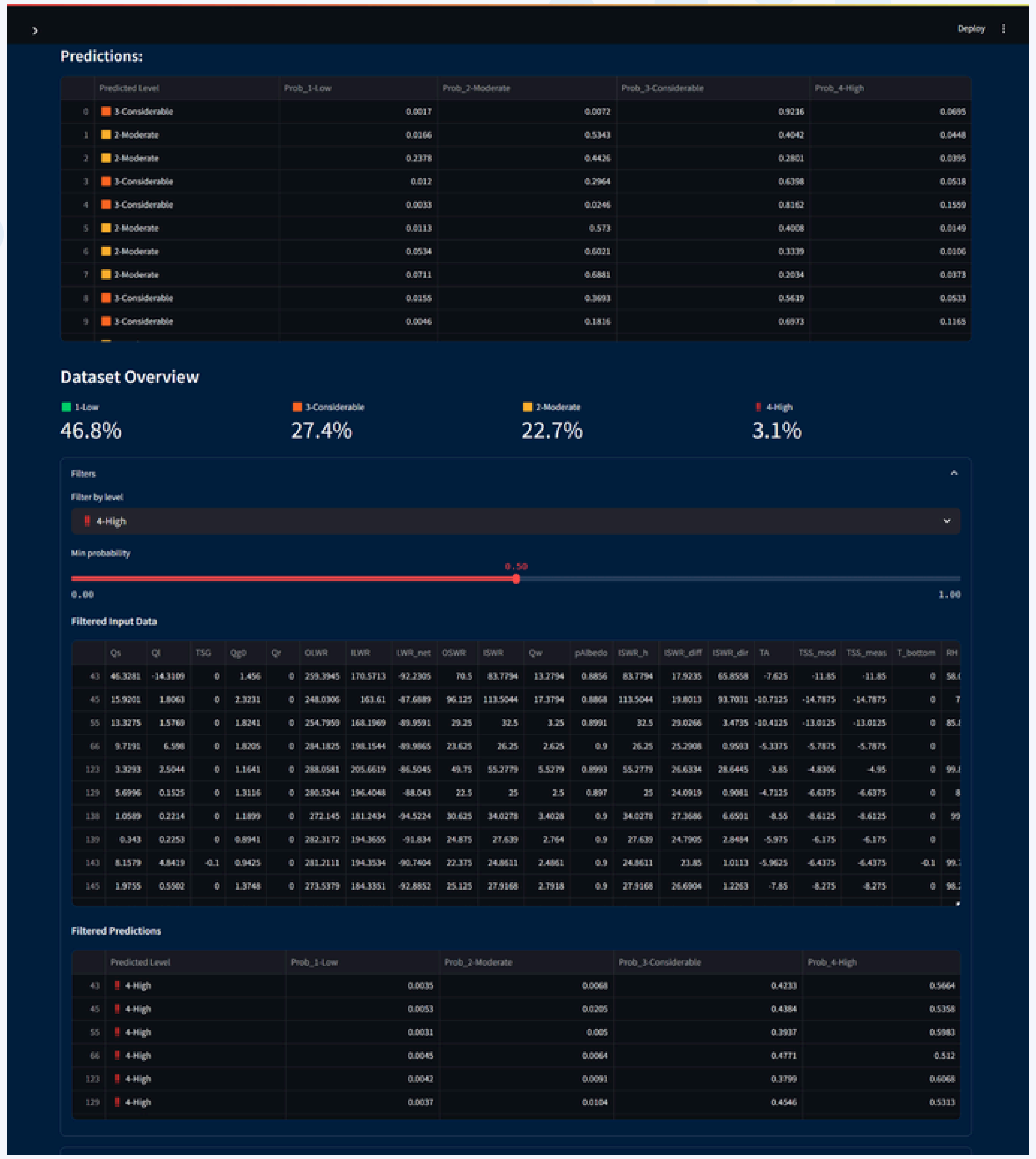
Pipeline	Accuracy	F_1-macro	Balanced Acc.	MCC
XGB_ROS_RS_NoDR_Opt	0.734361	0.700612	**0.720076**	0.618952
XGB_ROS_RS_NoDR	0.742158	0.700881	0.706312	0.627547
RF_ROS_SS_NoDR	**0.754563**	**0.710500**	0.697977	**0.642067**

INTERFACE

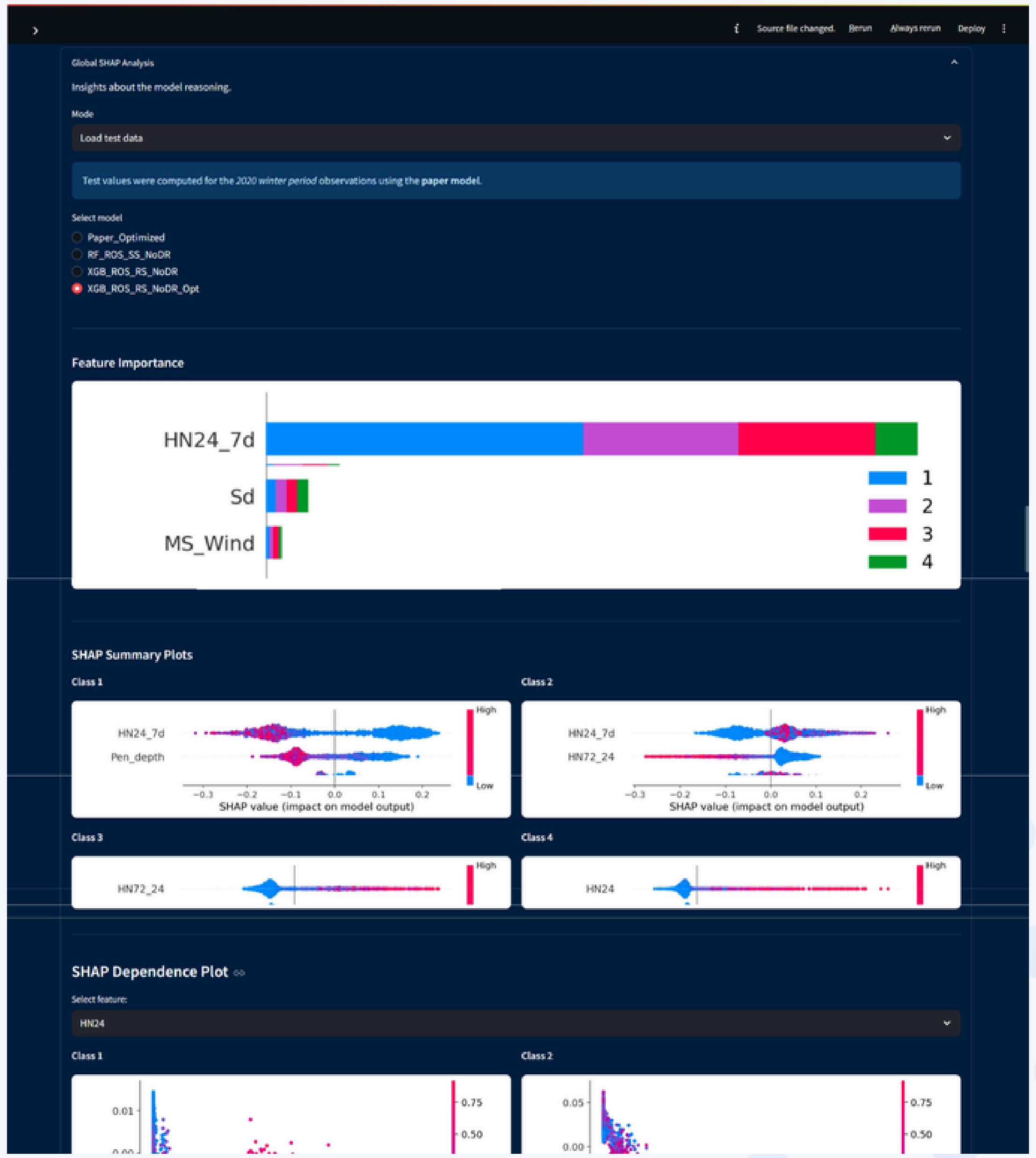


	Qs	Ql	TSG	Qg0	Qr	OLWR	ILWR	LWR_net	OSWR	ISWR	Qw	pAlbedo	ISWR_h	ISWR_diff	ISWR_dir	TA	T
0	18.6441	-4.3056	0	0.8961	0	271.7681	185.2941	-90.1754	29.25	32.5	3.25	0.8866	32.5	29.8431	2.657	-4.1125	
1	24.4668	-0.8685	-0.2	1.4036	0	258.6682	183.2321	-79.0965	45.25	50.2779	5.0279	0.8785	50.2779	34.8964	15.3815	-4.7875	
2	75.0902	-10.7519	-0.875	13.9625	0	267.421	182.4045	-88.66	43	47.7986	4.7986	0.9	47.7986	34.9855	12.8131	-6.2125	
3	47.3756	1.792	0	1.4603	0	253.1894	183.8658	-72.9964	41.25	45.9613	4.7113	0.8776	45.9613	34.9478	11.0134	-4.6125	
4	22.1523	4.5406	0	1.4706	0	269.8033	189.2884	-84.2963	152.375	169.3055	16.9305	0.9	169.3055	24.888	144.4178	-6.525	
5	22.227	-0.8749	-0.175	1.5779	0	244.6698	168.8755	-79.168	76.625	93.9168	17.2918	0.8646	93.9168	22.2191	71.6975	-6.3125	
6	51.415	-2.03	0	1.614	0	254.0714	175.0023	-82.5651	60	69.888	9.888	0.8904	69.888	16.355	53.533	-5.8125	
7	16.1195	1.9128	-0.2	1.3875	0.7923	235.6425	169.9211	-69.116	95.375	118.4733	23.0983	0.852	118.4733	17.4156	101.0576	-6.3375	
8	29.5555	5.9209	0	1.5045	0	229.5653	169.1619	-63.7828	92.625	115.1998	22.5748	0.8535	115.1998	18.7769	96.4229	-7.05	
9	27.8986	4.401	0	1.3745	0	233.4845	169.6995	-67.1752	81.5	99.8859	18.3859	0.864	99.8859	17.2843	82.6018	-7.5625	

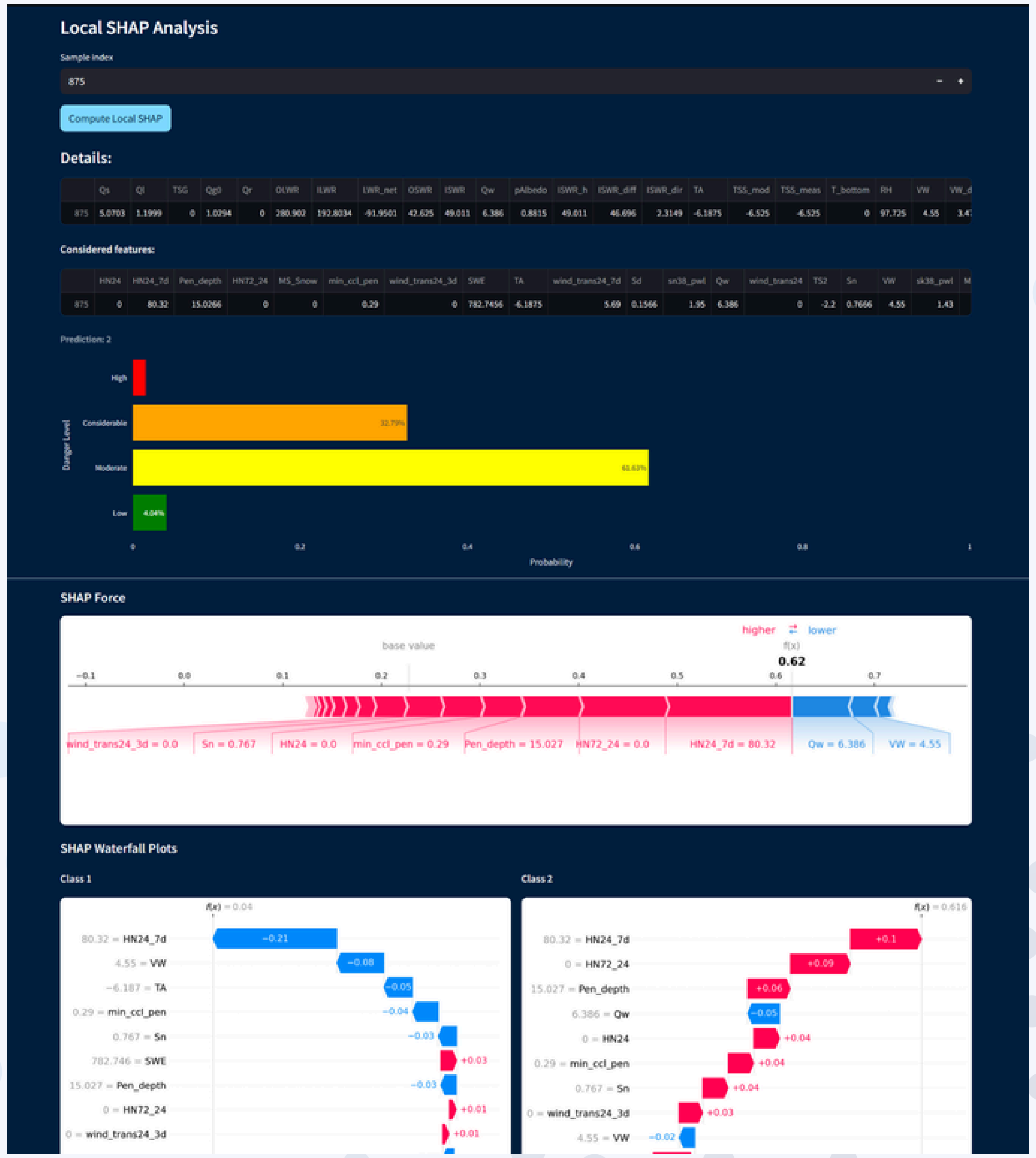
INTERFACE



PREDICTIONS



GLOBAL EXPLANATIONS



LOCAL EXPLANATIONS

Main References

Pérez-Guillén, C., Techel, F., Hendrick, M., Volpi, M., van Herwijnen, A., Olevski, T., Obozinski, G., Pérez-Cruz, F., and Schweizer, J.: **Data-driven automated predictions of the avalanche danger level for dry-snow conditions in Switzerland**, Nat. Hazards Earth Syst. Sci., 22, 2031–2056, 2022. https://doi.org/10.5194/nhess-22-2031-2022

Pérez-Guillén, C., Techel, F., Volpi, M., and van Herwijnen, A.: **Assessing the performance and explainability of an avalanche danger forecast model**, Nat. Hazards Earth Syst. Sci., 25, 1331–1351, 2025. https://doi.org/10.5194/nhess-25-1331-2025

Pérez-Guillén, C., Techel, F., Hendrick, M., Volpi, M., van Herwijnen, A., Olevski, T., Obozinski, G., Pérez-Cruz, F., Schweizer, J. (2022). **Weather, snowpack and danger ratings data for automated avalanche danger level predictions**. EnviDat. https://www.doi.org/10.16904/envidat.330

THANK YOU