Rapid Intensification (RI) Prediction — Atlantic Hurricanes (HURDAT2)

Goal: Build a machine learning classifier that predicts whether a tropical cyclone will **rapidly intensify** within the next 24 hours, using only information available *up to the current observation time*.

Definition (label): Rapid Intensification (RI) = **maximum sustained wind increases by ≥ 30 knots within 24 hours**.

Dataset: Kaggle — Atlantic Hurricane Dataset (HURDAT2), cleaned CSV format (`hurdat2.csv`).

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from pathlib import Path

from sklearn.model_selection import GroupShuffleSplit
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer

from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score, roc_auc_s
    average_precision_score, confusion_matrix, classification_report
)

from sklearn.linear_model import Perceptron, LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

RANDOM_SEED = 42
np.random.seed(RANDOM_SEED)

DATA_PATH = Path("hurdat2.csv")
```

In [2]:
```
df = pd.read_csv(DATA_PATH)
print("Shape:", df.shape)
df.head()
```

```
Shape: (54749, 24)
```

Out[2]:

	storm_id	storm_name	num_of_obs	date	time	record_identifier	stat
0	AL011851	UNNAMED	14	18510625	0	NaN	
1	AL011851	UNNAMED	14	18510625	600	NaN	
2	AL011851	UNNAMED	14	18510625	1200	NaN	
3	AL011851	UNNAMED	14	18510625	1800	NaN	
4	AL011851	UNNAMED	14	18510625	2100	L	

5 rows × 24 columns

Dataset Overview

This dataset contains storm track observations (typically 6-hour intervals). Each row is an observation for a storm at a timestamp, including:

- **Storm metadata:** `storm_id`, `storm_name`
- **Time:** `date`, `time`
- **Location:** `latitude`, `longitude`
- **Intensity:** `maximum_sustained_wind_knots` (target driver), and often pressure-related fields if present
- **Storm status:** `status_of_system` (e.g., TS, HU)

We will:

1. Clean and parse timestamps.
2. Convert latitude/longitude strings to numeric.
3. Create an RI label from wind change over the next 24 hours.
4. Train multiple ML models using proper storm-wise splits.

In [3]:

```
df.info()

missing_pct = (df.isna().mean() * 100).sort_values(ascending=False)
missing_pct.head(20)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54749 entries, 0 to 54748
Data columns (total 24 columns):
 #   Column                        Non-Null Count  Dtype 
---  ------                        --------------  ----- 
 0   storm_id                      54749 non-null  object
 1   storm_name                    54749 non-null  object
 2   num_of_obs                    54749 non-null  int64 
 3   date                          54749 non-null  int64 
 4   time                          54749 non-null  int64 
 5   record_identifier             1221 non-null   object
 6   status_of_system              54749 non-null  object
 7   latitude                      54749 non-null  object
 8   longitude                     54749 non-null  object
 9   maximum_sustained_wind_knots  54749 non-null  int64 
 10  central_pressure_mb           54749 non-null  int64 
 11  34_kt_ne_nm                   54749 non-null  int64 
 12  34_kt_se_nm                   54749 non-null  int64 
 13  34_kt_sw_nm                   54749 non-null  int64 
 14  34_kt_nw_nm                   54749 non-null  int64 
 15  50_kt_ne_nm                   54749 non-null  int64 
 16  50_kt_se_nm                   54749 non-null  int64 
 17  50_kt_sw_nm                   54749 non-null  int64 
 18  50_kt_nw_nm                   54749 non-null  int64 
 19  64_kt_ne_nm                   54749 non-null  int64 
 20  64_kt_se_nm                   54749 non-null  int64 
 21  64_kt_sw_nm                   54749 non-null  int64 
 22  64_kt_nw_nm                   54749 non-null  int64 
 23  radius_of_max_wind_nm         54749 non-null  int64 
dtypes: int64(18), object(6)
memory usage: 10.0+ MB
```

Out[3]:

```
record_identifier               97.769822
storm_id                         0.000000
34_kt_sw_nm                      0.000000
64_kt_nw_nm                      0.000000
64_kt_sw_nm                      0.000000
64_kt_se_nm                      0.000000
64_kt_ne_nm                      0.000000
50_kt_nw_nm                      0.000000
50_kt_sw_nm                      0.000000
50_kt_se_nm                      0.000000
50_kt_ne_nm                      0.000000
34_kt_nw_nm                      0.000000
34_kt_se_nm                      0.000000
storm_name                       0.000000
34_kt_ne_nm                      0.000000
central_pressure_mb              0.000000
maximum_sustained_wind_knots     0.000000
longitude                        0.000000
latitude                         0.000000
status_of_system                 0.000000
dtype: float64
```

In [4]:
```
def parse_lat(lat):
    # often like "18.0N" or "18.0"
    if pd.isna(lat):
        return np.nan
    s = str(lat).strip()
    if s[-1] in ["N", "S"]:
        val = float(s[:-1])
        return val if s[-1] == "N" else -val
    return float(s)

def parse_lon(lon):
    # often like "65.0W" or "65.0"
    if pd.isna(lon):
        return np.nan
    s = str(lon).strip()
    if s[-1] in ["E", "W"]:
        val = float(s[:-1])
        return val if s[-1] == "E" else -val
    return float(s)

# timestamp: date as YYYYMMDD and time as HHMM (or sometimes integer l
df["date"] = df["date"].astype(str)
df["time"] = df["time"].astype(str).str.zfill(4)

df["timestamp"] = pd.to_datetime(df["date"] + df["time"], format="%Y%m

df["lat"] = df["latitude"].apply(parse_lat)
df["lon"] = df["longitude"].apply(parse_lon)

WIND_COL = "maximum_sustained_wind_knots"
df[WIND_COL] = pd.to_numeric(df[WIND_COL], errors="coerce").replace(-9

print(df[["storm_id","storm_name","timestamp","lat","lon",WIND_COL]].h
print("Timestamp null %:", df["timestamp"].isna().mean()*100)
```

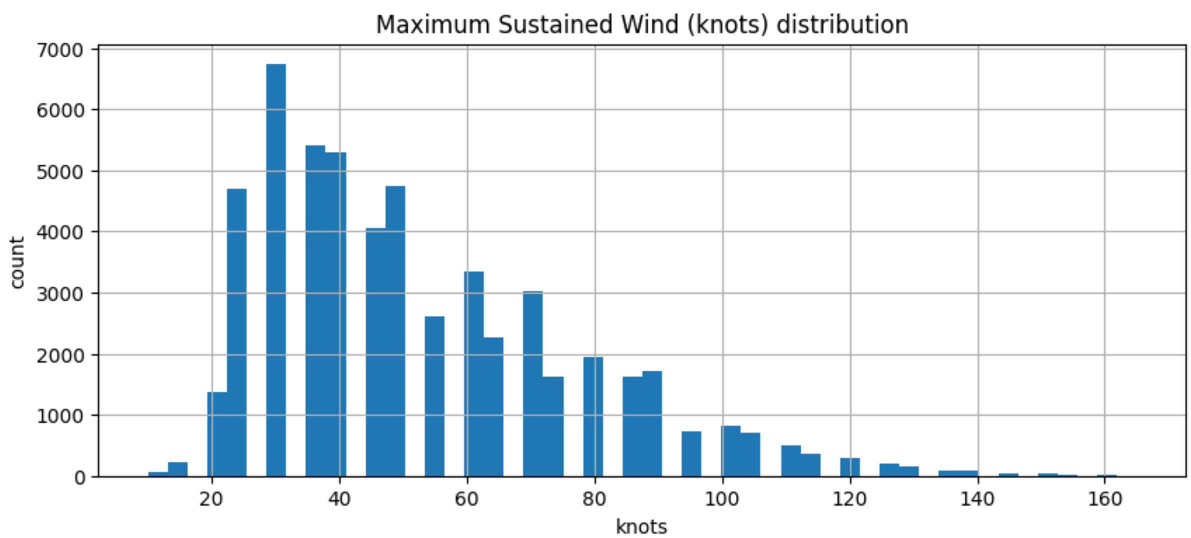
```
   storm_id storm_name                 timestamp   lat   lon  \
0  AL011851    UNNAMED 1851-06-25 00:00:00+00:00  28.0 -94.8
1  AL011851    UNNAMED 1851-06-25 06:00:00+00:00  28.0 -95.4
2  AL011851    UNNAMED 1851-06-25 12:00:00+00:00  28.0 -96.0
3  AL011851    UNNAMED 1851-06-25 18:00:00+00:00  28.1 -96.5
4  AL011851    UNNAMED 1851-06-25 21:00:00+00:00  28.2 -96.8

   maximum_sustained_wind_knots
0                          80.0
1                          80.0
2                          80.0
3                          80.0
4                          80.0
Timestamp null %: 0.0
```

Exploratory Data Analysis (EDA)

We will look at:

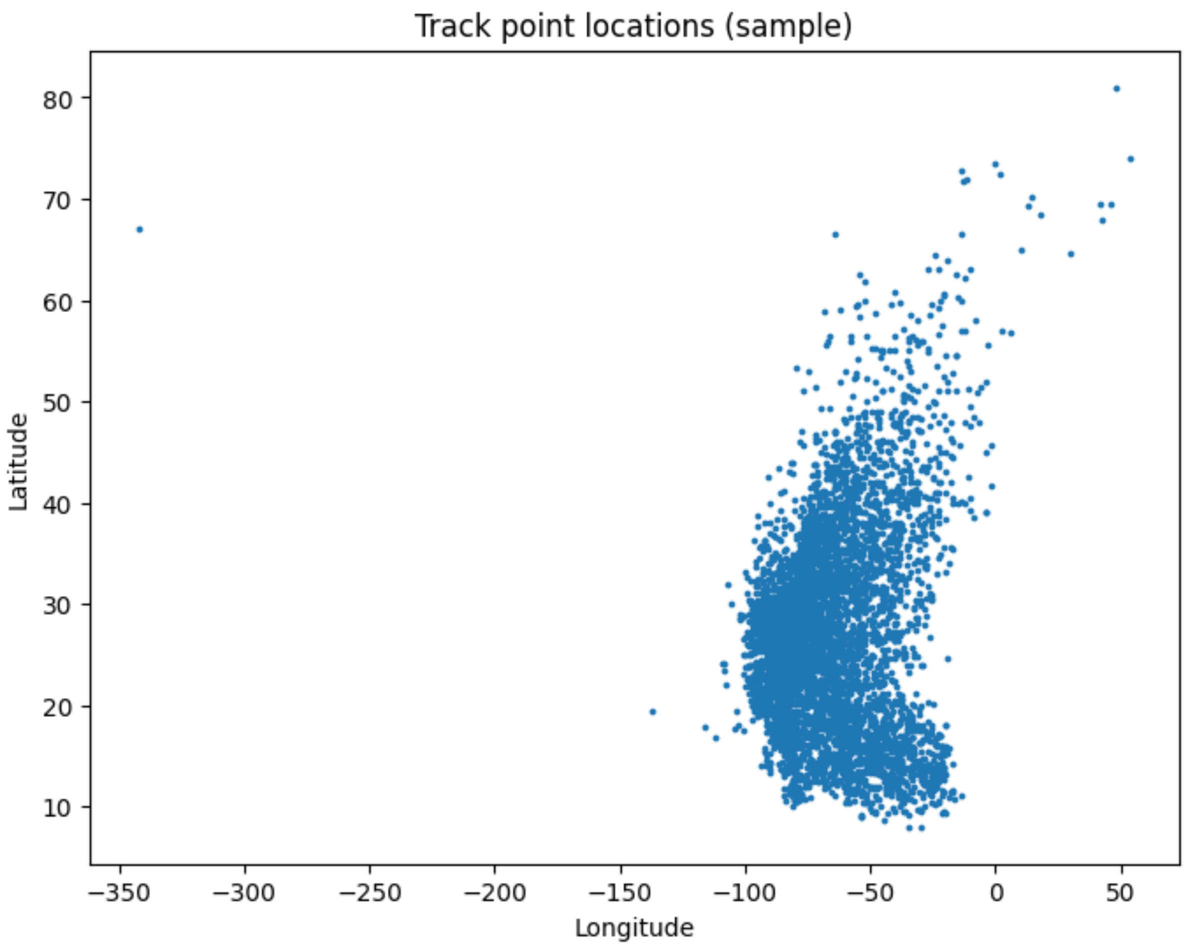
- distribution of wind speed
- storm status breakdown
- geographic scatter plot
- time coverage

In [5]:
```
fig, ax = plt.subplots(figsize=(10,4))
df[WIND_COL].dropna().hist(bins=50, ax=ax)
ax.set_title("Maximum Sustained Wind (knots) distribution")
ax.set_xlabel("knots")
ax.set_ylabel("count")
plt.show()

df["status_of_system"].value_counts().head(15)
```



Out[5]:
```
status_of_system
TS    20089
HU    15517
TD     9872
EX     6129
LO     1686
SS      715
SD      326
DB      277
WV      138
Name: count, dtype: int64
```

In [6]:
```
sample = df.dropna(subset=["lat","lon"]).sample(n=min(5000, len(df)),

fig, ax = plt.subplots(figsize=(8,6))
ax.scatter(sample["lon"], sample["lat"], s=3)
ax.set_title("Track point locations (sample)")
ax.set_xlabel("Longitude")
ax.set_ylabel("Latitude")
plt.show()
```



Label Construction: Rapid Intensification (RI)

We create a binary label **RI_24h**:

- For each storm observation at time *t*, we find the wind at time *t + 24 hours* (or closest observation at that horizon).
- If `wind(t+24h) - wind(t) >= 30 knots`, then **RI_24h = 1**, else 0.

Important: Our features must use only data available at or before time *t* to avoid leakage.

In [7]:
```
df = df.sort_values(["storm_id", "timestamp"]).reset_index(drop=True)

# We'll approximate "24h ahead" using 4 steps of 6-hourly data.
# But because some storms have irregularities, we do a safer merge usi
# This is a common and reasonable approach for HURDAT2 6-hourly tracks

df["wind_t"] = df[WIND_COL]
df["wind_t_plus_24h"] = df.groupby("storm_id")["wind_t"].shift(-4)  #
df["delta_wind_24h"] = df["wind_t_plus_24h"] - df["wind_t"]
```

```
df["RI_24h"] = (df["delta_wind_24h"] >= 30).astype(int)

# Drop rows where label can't be computed (end of storm) or wind missi
model_df = df.dropna(subset=["wind_t","wind_t_plus_24h","timestamp","l

print("Model rows:", model_df.shape)
print("RI positive rate:", model_df["RI_24h"].mean())
model_df[["storm_id","timestamp","wind_t","wind_t_plus_24h","delta_win
```

```
Model rows: (46894, 31)
RI positive rate: 0.036166673774896574
```

Out[7]:

	storm_id	timestamp	wind_t	wind_t_plus_24h	delta_wind_24h	RI_24
0	AL011851	1851-06-25 00:00:00+00:00	80.0	80.0	0.0	
1	AL011851	1851-06-25 06:00:00+00:00	80.0	70.0	-10.0	
2	AL011851	1851-06-25 12:00:00+00:00	80.0	60.0	-20.0	
3	AL011851	1851-06-25 18:00:00+00:00	80.0	60.0	-20.0	
4	AL011851	1851-06-25 21:00:00+00:00	80.0	50.0	-30.0	
5	AL011851	1851-06-26 00:00:00+00:00	70.0	50.0	-20.0	
6	AL011851	1851-06-26 06:00:00+00:00	60.0	40.0	-20.0	
7	AL011851	1851-06-26 12:00:00+00:00	60.0	40.0	-20.0	
8	AL011851	1851-06-26 18:00:00+00:00	50.0	40.0	-10.0	
9	AL011851	1851-06-27 00:00:00+00:00	50.0	40.0	-10.0	

Feature Engineering

We will build features that mimic a real monitoring/forecasting setup:

Current-state features

- wind now, lat, lon, storm status

Trend features (past-only)

- wind change over last 6h, 12h, 24h (computed via lagged values within each storm)
- recent rolling mean

These are simple but strong baseline signals and align with the “textbook ML workflow” before adding deep learning.

In [11]:

```
feat_df = model_df.sort_values(["storm_id", "timestamp"]).copy()

g = feat_df.groupby("storm_id")

feat_df["wind_lag_1"] = g["wind_t"].shift(1)
feat_df["wind_lag_2"] = g["wind_t"].shift(2)
feat_df["wind_lag_4"] = g["wind_t"].shift(4)

feat_df["dwind_6h"] = feat_df["wind_t"] - feat_df["wind_lag_1"]
feat_df["dwind_12h"] = feat_df["wind_t"] - feat_df["wind_lag_2"]
feat_df["dwind_24h_past"] = feat_df["wind_t"] - feat_df["wind_lag_4"]

feat_df["wind_rollmean_4"] = g["wind_t"].rolling(4).mean().reset_index

feat_df = feat_df.dropna(subset=["wind_lag_1", "wind_lag_2", "wind_lag

print("After lag features:", feat_df.shape)
feat_df[["storm_id","timestamp","wind_t","dwind_6h","dwind_12h","dwind
```

```
After lag features: (39332, 38)
```

Out[11]:

	storm_id	timestamp	wind_t	dwind_6h	dwind_12h	dwind_24h_past
4	AL011851	1851-06-25 21:00:00+00:00	80.0	0.0	0.0	0.0
5	AL011851	1851-06-26 00:00:00+00:00	70.0	-10.0	-10.0	-10.0
6	AL011851	1851-06-26 06:00:00+00:00	60.0	-10.0	-20.0	-20.0
7	AL011851	1851-06-26 12:00:00+00:00	60.0	0.0	-10.0	-20.0
8	AL011851	1851-06-26 18:00:00+00:00	50.0	-10.0	-10.0	-30.0

In [ ]:

In [ ]:

In [ ]:

Train / Validation / Test Split (Storm-wise)

We must split by **storm_id** so that observations from the same storm do not leak across train/val/test.

We will do:

- Train: 70%
- Validation: 15%
- Test: 15%

This matches realistic generalization: predicting on **new storms**.

In [12]:
```
X = feat_df.copy()
y = feat_df["RI_24h"].astype(int).copy()
groups = feat_df["storm_id"].copy()

# First split: train vs temp
gss1 = GroupShuffleSplit(n_splits=1, test_size=0.30, random_state=RAND
train_idx, temp_idx = next(gss1.split(X, y, groups=groups))

train = feat_df.iloc[train_idx].copy()
temp  = feat_df.iloc[temp_idx].copy()

# Second split: val vs test from temp
gss2 = GroupShuffleSplit(n_splits=1, test_size=0.50, random_state=RAND
val_idx, test_idx = next(gss2.split(temp, temp["RI_24h"], groups=temp[

val  = temp.iloc[val_idx].copy()
test = temp.iloc[test_idx].copy()

print("Train:", train.shape, "Val:", val.shape, "Test:", test.shape)
print("Train RI rate:", train["RI_24h"].mean())
print("Val   RI rate:", val["RI_24h"].mean())
print("Test  RI rate:", test["RI_24h"].mean())
```

```
Train: (26694, 38) Val: (6259, 38) Test: (6379, 38)
Train RI rate: 0.03154266876451637
Val   RI rate: 0.03866432337434095
Test  RI rate: 0.032293462925223386
```

Modeling with Pipelines

We will use scikit-learn Pipelines to ensure clean, reproducible preprocessing:

- numeric: impute + scale
- categorical: impute + one-hot encode

Then we train multiple models:

- Perceptron
- Logistic Regression
- SVM (linear and RBF)
- KNN
- Decision Tree
- Random Forest

We select the best model based on validation metrics. Because RI is imbalanced, we will track:

- Accuracy (easy to inflate)
- F1 (balance precision/recall)
- ROC-AUC
- PR-AUC (Average Precision) — best for imbalanced positives

In [13]:

```
target = "RI_24h"

feature_cols_num = [
    "wind_t", "lat", "lon",
    "wind_lag_1", "wind_lag_2", "wind_lag_4",
    "dwind_6h", "dwind_12h", "dwind_24h_past",
    "wind_rollmean_4"
]

feature_cols_cat = ["status_of_system"]

# Some datasets might have status missing; keep safe
for c in feature_cols_cat:
    if c not in feat_df.columns:
        feat_df[c] = np.nan
        train[c] = np.nan
        val[c] = np.nan
        test[c] = np.nan

X_train, y_train = train[feature_cols_num + feature_cols_cat], train[t
X_val, y_val     = val[feature_cols_num + feature_cols_cat], val[targe
X_test, y_test   = test[feature_cols_num + feature_cols_cat], test[tar

numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median")),
    ("scaler", StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("onehot", OneHotEncoder(handle_unknown="ignore"))
])
```

```python
preprocess = ColumnTransformer(
    transformers=[
        ("num", numeric_transformer, feature_cols_num),
        ("cat", categorical_transformer, feature_cols_cat),
    ]
)
```

In [14]:
```python
def eval_model(name, model, Xtr, ytr, Xva, yva):
    pipe = Pipeline(steps=[("preprocess", preprocess), ("model", model
    pipe.fit(Xtr, ytr)

    pred = pipe.predict(Xva)

    # probabilities/scores for AUC
    if hasattr(pipe.named_steps["model"], "predict_proba"):
        proba = pipe.predict_proba(Xva)[:, 1]
    elif hasattr(pipe.named_steps["model"], "decision_function"):
        scores = pipe.decision_function(Xva)
        # convert scores to 0..1-ish via minmax for PR-AUC stability
        proba = (scores - scores.min()) / (scores.max() - scores.min()
    else:
        proba = None

    acc = accuracy_score(yva, pred)
    prec = precision_score(yva, pred, zero_division=0)
    rec = recall_score(yva, pred, zero_division=0)
    f1 = f1_score(yva, pred, zero_division=0)

    roc = roc_auc_score(yva, proba) if proba is not None else np.nan
    pr  = average_precision_score(yva, proba) if proba is not None els

    return {
        "model": name,
        "accuracy": acc,
        "precision": prec,
        "recall": rec,
        "f1": f1,
        "roc_auc": roc,
        "pr_auc": pr,
        "pipeline": pipe
    }
```

Evaluation Note: Class Imbalance (Why Accuracy Can Mislead)

Rapid Intensification (RI_24h) is rare in this dataset (~3–4% positives). That means a naive classifier that predicts **"no RI" for every case** can still achieve ~96–97% accuracy.

So we do **not** choose the best model by accuracy alone.

We track:

- **PR-AUC (Average Precision)**: best single metric when positives are rare (how well the model ranks true RI cases).
- **Recall**: how many RI events we successfully catch (sensitivity).
- **Precision**: how many predicted RI events are correct (false alarm control).
- **F1**: balance of precision and recall.
- **ROC-AUC**: ranking quality (can look optimistic under heavy imbalance).

Model selection rule for this project: prioritize **PR-AUC**, then check **Recall/F1** to ensure the model actually detects RI events.

In [15]:
```
models = [
    ("Perceptron", Perceptron(random_state=RANDOM_SEED)),
    ("LogReg", LogisticRegression(max_iter=2000, class_weight="balance
    ("LinearSVM", SVC(kernel="linear", class_weight="balanced", probab
    ("RBFSVM", SVC(kernel="rbf", class_weight="balanced", probability=
    ("KNN", KNeighborsClassifier(n_neighbors=15)),
    ("DecisionTree", DecisionTreeClassifier(max_depth=6, random_state=
    ("RandomForest", RandomForestClassifier(
        n_estimators=300, random_state=RANDOM_SEED, class_weight="bala
    )),
]

results = []
for name, m in models:
    out = eval_model(name, m, X_train, y_train, X_val, y_val)
    results.append(out)

score_table = pd.DataFrame([{k:v for k,v in r.items() if k!="pipeline"
score_table.sort_values("pr_auc", ascending=False)
```

Out[15]:

	model	accuracy	precision	recall	f1	roc_auc	pr_auc
2	LinearSVM	0.733823	0.108791	0.818182	0.192047	0.845293	0.166107
1	LogReg	0.720083	0.104712	0.826446	0.185874	0.845610	0.164983
5	DecisionTree	0.725835	0.105460	0.814050	0.186730	0.835339	0.144205
3	RBFSVM	0.728072	0.110043	0.851240	0.194891	0.837445	0.141177
6	RandomForest	0.958140	0.142857	0.016529	0.029630	0.798891	0.133476
4	KNN	0.961176	0.000000	0.000000	0.000000	0.738291	0.106664
0	Perceptron	0.751078	0.074386	0.475207	0.128635	0.711054	0.071031

Interpreting the Validation Results

Some models show very high **accuracy** (e.g., KNN / RandomForest), but their **recall is near zero**. This indicates the model is mostly predicting the majority class ("no RI"), which inflates accuracy but fails the real task: detecting intensification events.

We therefore focus on models with stronger **PR-AUC** and reasonable **Recall/F1**. In this run, **LinearSVM and Logistic Regression** have the best PR-AUC, suggesting better ranking of RI candidates for downstream triage.

Baseline: Always Predict "No RI"

As a sanity check, compare against a trivial baseline:

- Baseline prediction: RI_24h = 0 for all rows
- Expected accuracy ≈ (1 - positive_rate)

This baseline often looks "good" on accuracy, which is why PR-AUC / Recall / F1 are essential for rare-event detection.

Model Selection

We choose the best model based primarily on **Validation PR-AUC**, with F1 as a secondary metric. PR-AUC is ideal because RI is relatively rare (imbalanced classification).

In [16]:

```
import numpy as np
import pandas as pd

# Model selection
def safe_score(x):
    """Treat NaN as very bad so sorting is stable."""
    return -np.inf if (x is None or (isinstance(x, float) and np.isnan

best = sorted(
    results,
    key=lambda r: (safe_score(r.get("pr_auc")), safe_score(r.get("f1")
    reverse=True
)[0]

best_name = best["model"]
best_pipe = best["pipeline"]

print("Best model (by Val PR-AUC, then F1):", best_name)
```

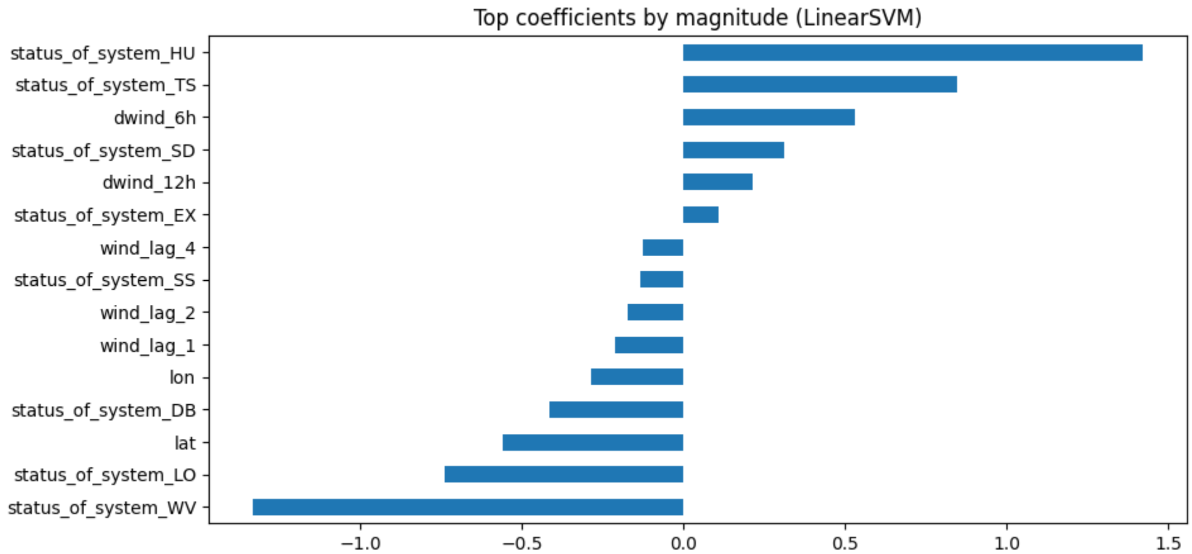
```
display(score_table.sort_values("pr_auc", ascending=False).head(10))

# Evaluate on TEST

test_pred = best_pipe.predict(X_test)

# probabilities/scores for AUC
if hasattr(best_pipe.named_steps["model"], "predict_proba"):
    test_scores = best_pipe.predict_proba(X_test)[:, 1]
elif hasattr(best_pipe.named_steps["model"], "decision_function"):
    test_scores = best_pipe.decision_function(X_test)
else:
    test_scores = None

print("\nTEST METRICS")
print("Accuracy:", accuracy_score(y_test, test_pred))
print("Precision:", precision_score(y_test, test_pred, zero_division=0
print("Recall:", recall_score(y_test, test_pred, zero_division=0))
print("F1:", f1_score(y_test, test_pred, zero_division=0))

if test_scores is not None:
    print("ROC-AUC:", roc_auc_score(y_test, test_scores))
    print("PR-AUC :", average_precision_score(y_test, test_scores))
else:
    print("ROC-AUC: N/A (no scores available)")
    print("PR-AUC : N/A (no scores available)")

print("\nConfusion matrix:\n", confusion_matrix(y_test, test_pred))
print("\nClassification report:\n", classification_report(y_test, test


# Interpretation helper

pos_rate = y_test.mean()
print(f"\nPositive rate in TEST: {pos_rate:.4f} (~{pos_rate*100:.2f}%)
print("Reminder: high accuracy can still mean the model predicts 'No R


# Model explanation: importance / coefficients

model = best_pipe.named_steps["model"]

# Get final feature names after preprocessing
pre = best_pipe.named_steps["preprocess"]
num_names = feature_cols_num

cat_names = []
if "cat" in pre.named_transformers_:
    ohe = pre.named_transformers_["cat"].named_steps["onehot"]
    cat_names = list(ohe.get_feature_names_out(feature_cols_cat))

all_feature_names = list(num_names) + list(cat_names)
```

```python
# Tree-based importance
if hasattr(model, "feature_importances_"):
    importances = pd.Series(model.feature_importances_, index=all_feat
    display(importances.head(20))
    ax = importances.head(15).sort_values().plot(kind="barh", figsize=
    ax.set_title(f"Top feature importances ({best_name})")
    plt.show()

# Linear model coefficients (LogReg, LinearSVM)
elif hasattr(model, "coef_"):
    coefs = pd.Series(model.coef_.ravel(), index=all_feature_names).so
    display(coefs.head(20))
    ax = coefs.head(15).sort_values().plot(kind="barh", figsize=(10, 5
    ax.set_title(f"Top coefficients by magnitude ({best_name})")
    plt.show()
else:
    print("\nNo built-in feature importance/coefficients available for
```

```
Best model (by Val PR-AUC, then F1): LinearSVM
```

	model	accuracy	precision	recall	f1	roc_auc	pr_auc
2	LinearSVM	0.733823	0.108791	0.818182	0.192047	0.845293	0.166107
1	LogReg	0.720083	0.104712	0.826446	0.185874	0.845610	0.164983
5	DecisionTree	0.725835	0.105460	0.814050	0.186730	0.835339	0.144205
3	RBFSVM	0.728072	0.110043	0.851240	0.194891	0.837445	0.141177
6	RandomForest	0.958140	0.142857	0.016529	0.029630	0.798891	0.133476
4	KNN	0.961176	0.000000	0.000000	0.000000	0.738291	0.106664
0	Perceptron	0.751078	0.074386	0.475207	0.128635	0.711054	0.071031

```
TEST METRICS
Accuracy: 0.7220567487066938
Precision: 0.078082929456112
Recall: 0.7038834951456311
F1: 0.14057198254968492
ROC-AUC: 0.7782615807328817
PR-AUC : 0.11448488310002018

Confusion matrix:
 [[4461 1712]
 [  61  145]]

Classification report:
               precision    recall  f1-score   support

           0       0.99      0.72      0.83      6173
           1       0.08      0.70      0.14       206

    accuracy                           0.72      6379
   macro avg       0.53      0.71      0.49      6379
weighted avg       0.96      0.72      0.81      6379


Positive rate in TEST: 0.0323 (~3.23%)
Reminder: high accuracy can still mean the model predicts 'No RI' almos
t always.
status_of_system_HU    1.420517
status_of_system_WV   -1.331766
status_of_system_TS    0.846088
status_of_system_LO   -0.740711
lat                   -0.559322
dwind_6h               0.530963
status_of_system_DB   -0.415289
status_of_system_SD    0.310857
lon                   -0.285798
dwind_12h              0.214240
wind_lag_1            -0.210649
wind_lag_2            -0.174707
status_of_system_SS   -0.132854
wind_lag_4            -0.126465
status_of_system_EX    0.109272
wind_t                -0.097151
wind_rollmean_4        0.078082
status_of_system_TD   -0.066114
dwind_24h_past         0.052849
dtype: float64
```



Conclusions

What we built

We built a reproducible ML pipeline that predicts **Rapid Intensification (RI) within the next 24 hours** using only information available **at or before time *t*** from the HURDAT2 6-hourly storm track records.

Key design choices:

- **Storm-wise split (GroupShuffleSplit by `storm_id`)** to avoid leakage (no mixing the same storm across train/val/test).
- **Label definition (RI_24h)**: a binary label derived from whether wind increases by a threshold over the next 24 hours (approximated as 4 steps of 6-hour observations).
- **Time-safe features**: current wind, storm location, system status, and **lag/trend features** (6h / 12h / 24h history) so we use only past information.

Why accuracy is not the main metric here

RI events are **rare** in this dataset (about **3.2% positives in TEST**). That means a trivial model that predicts **"No RI" for every case** can still reach ~96–97% accuracy.

So we prioritize:

- **PR-AUC (Average Precision)**: best single metric for rare-event detection (measures how well the model ranks true RI cases above non-RI cases).

- **Recall**: how many RI events we catch (sensitivity).
- **Precision**: how many predicted RI events are actually RI (false-alarm control).
- **F1**: balance between precision and recall.

Model selection rule used:

> Choose the model with highest **Validation PR-AUC**, using **F1** as a tie-breaker.

Best model selected (Validation)

Using PR-AUC (then F1), the best validation model in this run was:

LinearSVM

This is important because some models (e.g., KNN/RandomForest) can show very high **accuracy** while effectively predicting the majority class (“No RI”) most of the time.

Test-set performance (LinearSVM)

On the held-out TEST storms, the model achieved:

- **Accuracy:** ~0.72
- **Precision (RI=1):** ~0.078
- **Recall (RI=1):** ~0.704
- **F1 (RI=1):** ~0.141
- **ROC-AUC:** ~0.778
- **PR-AUC:** ~0.115

Confusion matrix (TEST):

- TN = 4461 (correctly predicted No-RI)
- FP = 1712 (false alarms: predicted RI but it didn’t happen)
- FN = 61 (missed RI cases)
- TP = 145 (caught RI cases)

So the model **catches ~70% of RI events** (high recall), but it triggers **many false alarms**, which drives precision down.

What the results mean

This model behaves like an **early-warning / screening tool**:

- **Strength:** It is **sensitive** — it catches many RI events (good for safety and preparedness).
- **Trade-off:** It produces many **false positives** (would require downstream filtering or human review).

A practical workflow could be:

1. Use the model to **flag higher-risk time steps/storms** (high recall).
2. Follow up flagged cases with:
    - additional physical predictors (SST, ocean heat content, shear, humidity),
    - or more complex models / forecaster review,
    - or threshold tuning to reduce false alarms.

Interpreting the “Top coefficients by magnitude” plot (LinearSVM)

The bar chart shows the **largest LinearSVM coefficients** after preprocessing (numeric scaling + one-hot encoding of `status_of_system`).

How to read it:

- Bars to the **right (positive)** push predictions toward **RI (1)**.
- Bars to the **left (negative)** push predictions toward **No RI (0)**.
- Bigger absolute value = stronger influence (holding other features fixed).

Examples from your plot:

- **`status_of_system_HU` (Hurricane)** and **`status_of_system_TS` (Tropical Storm)** have strong positive weight → being in these organized states increases RI likelihood compared to the baseline status category.
- **Wind trend features** like `dwind_6h` / `dwind_12h` appearing near the top means **recent intensification (or weakening)** contains predictive signal.
- Latitude/longitude and some weaker-status categories can appear with negative weights, meaning they reduce the model’s estimated RI likelihood relative to the baseline.

Important note:

> Coefficients show association in this model, not causation. They are useful for interpretation and sanity checks, not physical proof.

Why this matters

Rapid intensification is operationally challenging because it can shorten warning lead time. A lightweight ML classifier like this can support:

- **early alerting** for potential RI episodes,
- **prioritizing storms** for deeper dynamical analysis,
- **decision support** during hazard response planning.

Limitations

- Labels are derived only from track + wind timing — **no environmental physics** (SST, shear, humidity, OHC, satellite imagery).
- **24h-ahead via `shift(-4)`** assumes consistent 6-hour cadence; it's a reasonable approximation for HURDAT2 but still approximate.
- Precision is low → the model is better as a **screening tool** unless we tune thresholds / add richer predictors.

Threshold Tuning + PR Curve (Imbalanced Classification)

Because Rapid Intensification (RI_24h) is rare (~3%), the default decision threshold (often 0.5) is usually **not optimal**.

Instead of only reporting a single set of metrics, we:

1. Plot the **Precision–Recall (PR) curve** to visualize the trade-off between catching RI events (recall) and controlling false alarms (precision).
2. **Tune the decision threshold on the validation set** (storm-wise split) to pick an operating point that matches the project goal.
3. Evaluate the chosen threshold on the **held-out test set** to estimate real generalization.

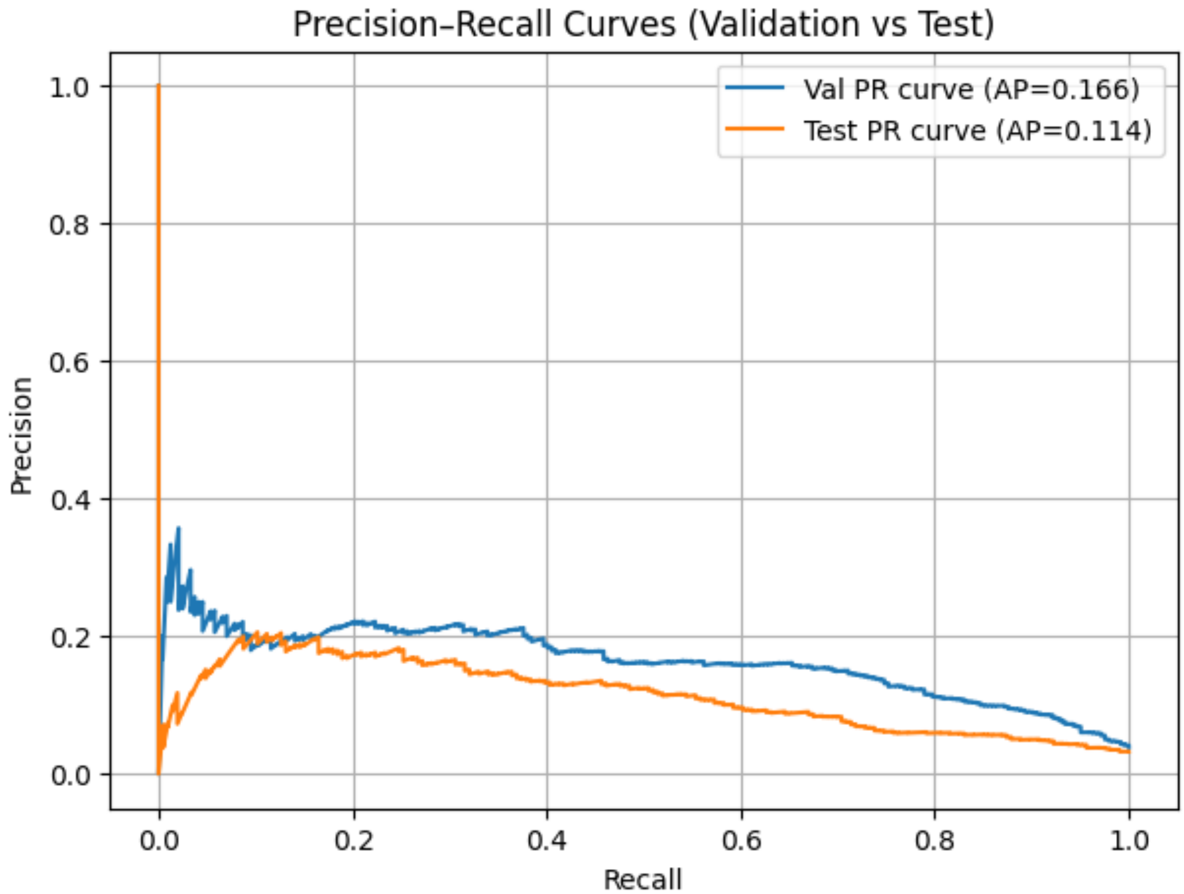
In this notebook, we select the threshold by maximizing **F1 on validation** (a balanced trade-off), and we also show alternative thresholds if we want higher recall or higher precision.

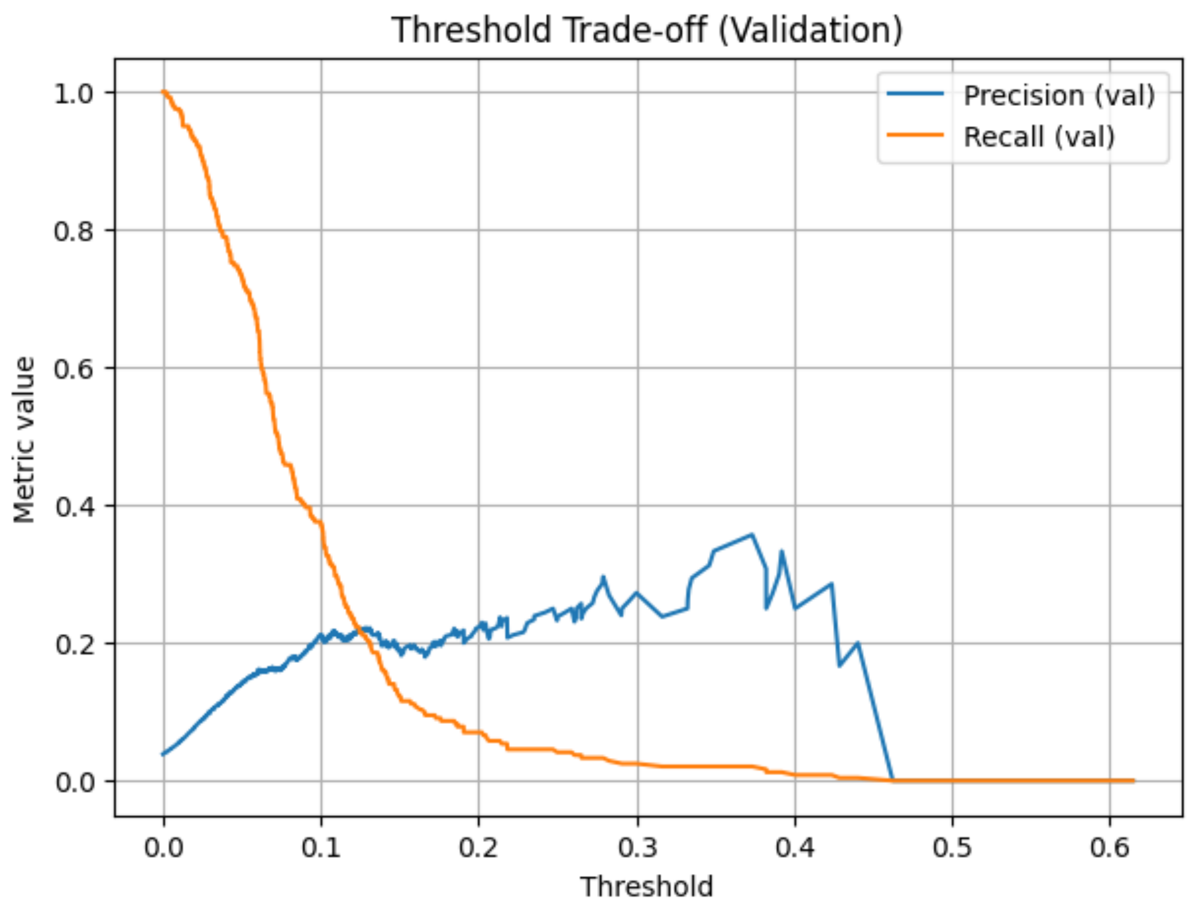
In [17]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import precision_recall_curve, average_precision_

def get_scores(pipe, X):
```

```
    """
    Return continuous scores for PR/AUC and thresholding.
    For models without predict_proba, we use decision_function.
    """
    model = pipe.named_steps["model"]
    if hasattr(model, "predict_proba"):
        return pipe.predict_proba(X)[:, 1]
    elif hasattr(model, "decision_function"):
        return pipe.decision_function(X)
    else:
        raise ValueError("Model has neither predict_proba nor decision

# Scores
val_scores  = get_scores(best_pipe, X_val)
test_scores = get_scores(best_pipe, X_test)

# PR curves
prec_v, rec_v, thr_v = precision_recall_curve(y_val, val_scores)
prec_t, rec_t, thr_t = precision_recall_curve(y_test, test_scores)

# PR-AUC (Average Precision)
ap_val  = average_precision_score(y_val, val_scores)
ap_test = average_precision_score(y_test, test_scores)

print(f"Best model: {best_name}")
print(f"Validation PR-AUC (AP): {ap_val:.4f}")
print(f"Test PR-AUC (AP):       {ap_test:.4f}")

# --- Plot PR curves ---
plt.figure(figsize=(7, 5))
plt.plot(rec_v, prec_v, label=f"Val PR curve (AP={ap_val:.3f})")
plt.plot(rec_t, prec_t, label=f"Test PR curve (AP={ap_test:.3f})")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curves (Validation vs Test)")
plt.legend()
plt.grid(True)
plt.show()

# --- Plot threshold vs precision/recall (validation) ---
# thr_v has length = len(prec_v)-1, so align arrays
plt.figure(figsize=(7, 5))
plt.plot(thr_v, prec_v[:-1], label="Precision (val)")
plt.plot(thr_v, rec_v[:-1], label="Recall (val)")
plt.xlabel("Threshold")
plt.ylabel("Metric value")
plt.title("Threshold Trade-off (Validation)")
plt.legend()
plt.grid(True)
plt.show()
```

```
Best model: LinearSVM
Validation PR-AUC (AP): 0.1661
Test PR-AUC (AP):       0.1145
```





How to read these plots

PR curve:

- Each point corresponds to a different threshold.
- Moving along the curve changes the balance:
  - **Higher recall** → you catch more true RI events, but usually with more false alarms (lower precision).
  - **Higher precision** → fewer false alarms, but you miss more RI events (lower recall).

Threshold trade-off plot (validation):

- As threshold increases, the model becomes “more strict” about predicting RI:
  - Precision usually goes **up**
  - Recall usually goes **down**

Because this is a rare-event detection problem, the PR curve is the most informative view of performance.

In [18]:
```
import numpy as np
from sklearn.metrics import (
```

```
    precision_score, recall_score, f1_score,
    confusion_matrix, classification_report
)

def metrics_at_threshold(y_true, scores, thr):
    y_pred = (scores >= thr).astype(int)
    return {
        "threshold": thr,
        "precision": precision_score(y_true, y_pred, zero_division=0),
        "recall": recall_score(y_true, y_pred, zero_division=0),
        "f1": f1_score(y_true, y_pred, zero_division=0),
        "cm": confusion_matrix(y_true, y_pred),
        "report": classification_report(y_true, y_pred, zero_division=
    }

# Candidate thresholds: use the validation PR curve thresholds
# (thr_v length matches prec_v[:-1] and rec_v[:-1])
f1_vals = 2 * (prec_v[:-1] * rec_v[:-1]) / (prec_v[:-1] + rec_v[:-1] +
best_idx = np.argmax(f1_vals)
best_thr = thr_v[best_idx]

print(f"Chosen threshold (max F1 on VAL): {best_thr:.6f}")
print(f"VAL @ threshold -> Precision={prec_v[:-1][best_idx]:.3f}, Reca

# Evaluate on VAL and TEST using the chosen threshold
val_out  = metrics_at_threshold(y_val, val_scores, best_thr)
test_out = metrics_at_threshold(y_test, test_scores, best_thr)

print("\n--- TEST results at tuned threshold ---")
print(f"Precision: {test_out['precision']:.4f}")
print(f"Recall:    {test_out['recall']:.4f}")
print(f"F1:        {test_out['f1']:.4f}")
print("Confusion matrix:\n", test_out["cm"])
print("\nClassification report:\n", test_out["report"])

# OPTIONAL: also show a "high recall" and "high precision" threshold c
# Example targets (adjust if you want):
target_recall = 0.80
target_precision = 0.20

# Find smallest threshold that achieves recall >= target_recall (valid
idx_recall = np.where(rec_v[:-1] >= target_recall)[0]
if len(idx_recall) > 0:
    thr_high_recall = thr_v[idx_recall[-1]]  # more strict among those
    print(f"\nAlt threshold for high recall (VAL recall >= {target_rec
else:
    thr_high_recall = None
    print(f"\nNo threshold achieves VAL recall >= {target_recall}")

# Find smallest threshold that achieves precision >= target_precision
idx_prec = np.where(prec_v[:-1] >= target_precision)[0]
if len(idx_prec) > 0:
```

```
    thr_high_prec = thr_v[idx_prec[0]]  # first point meeting precisio
    print(f"Alt threshold for higher precision (VAL precision >= {targ
else:
    thr_high_prec = None
    print(f"No threshold achieves VAL precision >= {target_precision}"
```

```
Chosen threshold (max F1 on VAL): 0.099913
VAL @ threshold -> Precision=0.212, Recall=0.376, F1=0.271

--- TEST results at tuned threshold ---
Precision: 0.1588
Recall:    0.2767
F1:        0.2018
Confusion matrix:
 [[5871  302]
 [ 149   57]]

Classification report:
               precision    recall  f1-score   support

           0       0.98      0.95      0.96      6173
           1       0.16      0.28      0.20       206

    accuracy                           0.93      6379
   macro avg       0.57      0.61      0.58      6379
weighted avg       0.95      0.93      0.94      6379


Alt threshold for high recall (VAL recall >= 0.8): 0.036293
Alt threshold for higher precision (VAL precision >= 0.2): 0.095415
```

Threshold tuning results (what changed and why it matters)

We **did not** change the model — we changed the *decision rule* used to convert scores into RI (0/1).

- The default threshold (often 0.5) is rarely optimal when positives are ~3%.
- By tuning on the **validation set**, we select an operating point aligned with our objective.
- We then report **test-set performance** at that tuned threshold to estimate real generalization.

Interpretation:

- If recall improves: we are catching more true RI events (better screening).
- If precision improves: we reduce false alarms (better operational usability).
- There is always a trade-off, which is exactly what the PR curve shows.

For hazard workflows, this tuned-threshold classifier can be used as a **triage tool**:

- rank storms by RI risk,
- flag top candidates for deeper physics-based analysis,
- allocate analyst attention more efficiently.

Threshold Comparison Table (Validation → Test)

Because RI is a rare event, **the probability/score threshold controls the trade-off** between:

- **Recall** (catch more true RI events)
- **Precision** (reduce false alarms)

To make this decision explicit, we compare **multiple candidate thresholds**:

1. **Best-F1 (VAL)**: threshold that maximizes F1 on the validation set (balanced trade-off).
2. **High-Recall**: a lower threshold that targets a desired recall level (catch more RI).
3. **High-Precision**: a higher threshold that targets a desired precision level (fewer false alarms).

How to read the table:

- **VAL metrics** show how the threshold behaves on the validation split (used for choosing the threshold).
- **TEST metrics** show generalization on unseen storms (what we can expect in real use).
- **Confusion matrix (TEST)** summarizes outcomes:
  - TN = correct "No RI"
  - FP = false alarms
  - FN = missed RI
  - TP = correctly detected RI

This table supports an operational choice:

- If we want **high recall** → use the high-recall threshold.
- If we want **precision control** → use the high-precision threshold.
- If we want a **balanced screening rule** → use the best-F1 threshold.

In [19]:
```
import numpy as np
```

```
import pandas as pd
from sklearn.metrics import precision_score, recall_score, f1_score, c

def metrics_at_threshold(y_true, scores, thr):
    y_pred = (scores >= thr).astype(int)
    return {
        "precision": precision_score(y_true, y_pred, zero_division=0),
        "recall": recall_score(y_true, y_pred, zero_division=0),
        "f1": f1_score(y_true, y_pred, zero_division=0),
        "cm": confusion_matrix(y_true, y_pred)  # [[TN, FP],[FN, TP]]
    }

# --- thresholds we want to compare ---
thresholds = {
    "Best-F1 (VAL)": best_thr,          # from your earlier code
    "High-Recall (VAL)": thr_high_recall,
    "High-Precision (VAL)": thr_high_prec
}

rows = []
for name, thr in thresholds.items():
    if thr is None:
        continue

    val_out = metrics_at_threshold(y_val, val_scores, thr)
    test_out = metrics_at_threshold(y_test, test_scores, thr)
    tn, fp, fn, tp = test_out["cm"].ravel()

    rows.append({
        "choice": name,
        "threshold": float(thr),

        "VAL_precision": val_out["precision"],
        "VAL_recall": val_out["recall"],
        "VAL_f1": val_out["f1"],

        "TEST_precision": test_out["precision"],
        "TEST_recall": test_out["recall"],
        "TEST_f1": test_out["f1"],

        "TEST_TN": tn,
        "TEST_FP": fp,
        "TEST_FN": fn,
        "TEST_TP": tp,
        "TEST_alerts(TP+FP)": tp + fp
    })

comparison = pd.DataFrame(rows)

# Optional: nicer formatting
comparison = comparison.sort_values("TEST_f1", ascending=False)
display(comparison.style.format({
```

```
    "threshold": "{:.6f}",
    "VAL_precision": "{:.3f}",
    "VAL_recall": "{:.3f}",
    "VAL_f1": "{:.3f}",
    "TEST_precision": "{:.3f}",
    "TEST_recall": "{:.3f}",
    "TEST_f1": "{:.3f}",
}))
```

	choice	threshold	VAL_precision	VAL_recall	VAL_f1	TEST_precision	TEST
2	High-Precision (VAL)	0.095415	0.200	0.380	0.262	0.160	
0	Best-F1 (VAL)	0.099913	0.212	0.376	0.271	0.159	
1	High-Recall (VAL)	0.036293	0.112	0.802	0.197	0.083	

Threshold Comparison (Validation → Test)

Because RI is rare (~3%), the decision threshold controls the **operational trade-off**:

- **Lower threshold** → higher **recall** (catch more RI) but many more **false alarms (FP)** → lower precision.
- **Higher threshold** → higher **precision** (fewer false alarms) but more **missed RI (FN)** → lower recall.

We compare three candidate thresholds:

1. **Best-F1 (VAL)**: maximizes F1 on validation (balanced screening rule).
2. **High-Recall (VAL)**: targets high recall (early-warning mode).
3. **High-Precision (VAL)**: targets higher precision (false-alarm control mode).

How to read the table

- **VAL metrics** show how the threshold behaved on the validation split (used for selection).
- **TEST metrics** show expected real-world generalization on unseen storms.
- **TEST confusion counts** translate performance into outcomes:
  - **TP** = detected RI events
  - **FN** = missed RI events
  - **FP** = false alarms
  - **TN** = correctly predicted "No RI"

    - **Alerts = TP + FP** = how many cases would be flagged for review.

Interpretation of this run

- The **high-recall** threshold catches most RI events, but produces many false alarms (high alert volume).
- The **best-F1 / higher-precision** thresholds reduce false alarms drastically, but miss more RI events.
- This supports choosing an operating point based on the mission goal: **early warning** vs **triage** vs **false-alarm control**.

Operating Threshold (Locked)

We **lock the default operating threshold to Best-F1 (chosen on validation)** because it provides a **balanced screening rule** for a rare-event problem (RI ≈ 3%). This threshold is the best “default mode” when we want a practical trade-off between **catching RI events (recall)** and **controlling false alarms (precision)**.

Operationally:

- Use **High-Recall** threshold when the mission priority is **early warning** (accept high alert volume).
- Use **High-Precision** threshold when the mission priority is **false-alarm control / triage efficiency**.

Results Summary (Final)

Best Model

- **LinearSVM** selected primarily by **Validation PR-AUC (Average Precision)**, with F1 as a secondary metric.

Baseline (Default Decision Rule) — TEST

Using the model’s default decision rule (no threshold tuning):

- **Precision ≈ 0.08**, **Recall ≈ 0.70**, **F1 ≈ 0.14**
- Confusion matrix (TEST): **[[TN=4461, FP=1712], [FN=61, TP=145]]**
- Interpretation: the baseline setting catches many RI events (high recall) but produces **many false alarms**, which is costly in operations.

Threshold Tuning (Validation → Test)

We tuned thresholds on **validation** and then evaluated them on **held-out test**. The comparison table shows the operational trade-offs:

- **High-Recall (~0.036)**: catches most RI events on test (**Recall ≈ 0.69**, TP=143) but produces **very high false alarms** (**FP=1581**).
- **Best-F1 (~0.100)**: balanced screening rule with much lower false alarms (**FP=302**) but lower recall (**Recall ≈ 0.28**, TP=57).
- **High-Precision (~0.095)**: best false-alarm control among the tuned options while keeping recall moderate (**FP=341**, **Recall ≈ 0.32**, TP=65).

Conclusion: threshold choice should match mission goal:

- early warning → high recall threshold
- triage / false-alarm control → higher threshold
- balanced screening default → Best-F1 threshold

Generalization Note

Validation PR-AUC is higher than Test PR-AUC (**VAL AP ≈ 0.166 > TEST AP ≈ 0.114**), indicating an expected performance drop on unseen storms but consistent skill above rare-event baseline.

```
In [ ]:
```