In [1]:
```
state="TX"
```

In [2]:
```
import pandas as pd
import numpy as np
import sklearn as sk
import matplotlib

import warnings  # Suppress Warnings
warnings.filterwarnings('ignore')

_figsize=(10,7)
```

In [3]:
```
%%time
%run lib/startup.py S
```

```
sc_type= S
10.41.226.243
namespace= skondakindi
driver_host= 10.41.226.243
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
25/06/04 15:37:25 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-java classes where applic
able
sparkContext= <SparkContext master=spark://spark-master-0.spark-headless.skondakindi.svc.cluster.local:7077 appName=myapp>

version of ipwidgets= 8.1.7
parquet_root= /home/skondakindi/public/Data/weather

measurements is a Dataframe (and table) with 12720632 records
stations is a Dataframe (and table) with 119503 records
[Stage 9:====================================================>   (32 + 2) / 34]
weather is a Dataframe (and table) which is a join of measurements and stations with 12720632 records
CPU times: user 587 ms, sys: 105 ms, total: 691 ms
Wall time: 57.1 s
```

In [4]:
```
ms=['SNWD', 'PRCP', 'TOBS']
cms='or\n'.join(['Measurement="%s" '%(m) for m in ms])

##  read all data for state
Query="""
SELECT *
FROM weather
WHERE state="%s" and
(%s)
"""%(state,cms)
```

In [5]:
```
weather_df=sqlContext.sql(Query)
print('number of rows in result=',weather_df.count())
weather_df.show(5)
```

```
number of rows in result= 171400
[Stage 17:>                                                         (0 + 0) / 1]

[Stage 17:>                                                         (0 + 1) / 1]
+-----------+-----------+----+--------------------+--------+---------+---------+----------+--------------------+-----+-------------+
|    Station|Measurement|Year|              Values|latitude|longitude|elevation|dist2coast|                name|state|      country|
+-----------+-----------+----+--------------------+--------+---------+---------+----------+--------------------+-----+-------------+
|US1TXAS0015|       PRCP|2022|[00 00 00 00 00 0...| 30.0341| -96.2209|     79.2|     122.5|  BELLVILLE 6.5 NNE|   TX|United States|
|US1TXBEL009|       PRCP|2022|[00 00 00 00 00 0...| 31.1231| -97.5284|    230.4|    280.75|      BELTON 5.4 NW|   TX|United States|
|US1TXBEL039|       PRCP|2022|[00 00 00 00 00 0...| 31.1861| -97.3422|    242.0|     278.0|     TEMPLE 6.2 NNE|   TX|United States|
|US1TXBEL055|       PRCP|2022|[00 00 00 00 00 0...| 31.1778| -97.3294|    235.0|     278.0|     TEMPLE 5.9 NNE|   TX|United States|
|US1TXBLC034|       PRCP|2022|[00 00 00 00 00 0...| 30.3582|  -98.319|    420.0|   239.375|JOHNSON CITY 7.8 NE|   TX|United States|
+-----------+-----------+----+--------------------+--------+---------+---------+----------+--------------------+-----+-------------+
only showing top 5 rows
```

In [6]:
```
koppen_df = pd.read_csv("../../public/Data/Boosting_HW/Texas_Koppen.csv")
koppen_df
```

Out[6]:

	Unnamed: 0	ID	Latitude	Longitude	Elevation	State	Name	GSN_Flag	HCN_CRN_Flag	WMO_ID	Koppen
0	83933	US1TXAC0002	33.8281	-98.5492	305.7	TX	WICHITA FALLS 5.2 SSW	NaN	NaN	NaN	Cfa
1	83934	US1TXAC0003	33.5838	-98.6298	323.7	TX	ARCHER CITY 0.7 SSW	NaN	NaN	NaN	Cfa
2	83935	US1TXAC0005	33.7762	-98.5350	300.2	TX	WICHITA FALLS 8.5 S	NaN	NaN	NaN	Cfa
3	83936	US1TXAC0009	33.8328	-98.5360	300.5	TX	WICHITA FALLS 4.6 SSW	NaN	NaN	NaN	Cfa
4	83937	US1TXAD0002	32.0533	-102.8796	973.5	TX	ANDREWS 26.7 SW	NaN	NaN	NaN	BSk
...	...	...	...	...	...	...	...	...	...	...	...
5386	117501	USW00093904	32.8167	-97.3500	214.9	TX	FT WORTH MEACHAM FLD NAAF	NaN	NaN	74739.0	Cfa
5387	117508	USW00093914	31.7831	-95.6039	141.7	TX	PALESTINE 2 NE	NaN	NaN	NaN	Cfa
5388	117513	USW00093928	32.7667	-96.7833	195.1	TX	DALLAS WBO	NaN	NaN	NaN	Cfa
5389	117521	USW00093985	32.7817	-98.0603	283.5	TX	MINERAL WELLS AP	NaN	NaN	NaN	Cfa
5390	117523	USW00093987	31.2361	-94.7544	87.8	TX	LUFKIN ANGELINA CO AP	NaN	NaN	NaN	Cfa

5391 rows × 11 columns

In [7]:

```python
spark = (
    SparkSession.builder
        .appName("pandas-to-spark")
        .getOrCreate()
)

spark.conf.set("spark.sql.execution.arrow.pyspark.enabled", "true")

if not hasattr(pd.DataFrame, "iteritems"):
    # monkey-patch brings the alias back
    pd.DataFrame.iteritems = pd.DataFrame.items

koppen_sdf = spark.createDataFrame(koppen_df)

koppen_sdf.show(5)
```

```
[Stage 18:>                                                         (0 + 1) / 1]
+----------+-----------+--------+---------+---------+-----+--------------------+--------+------------+------+------+
|Unnamed: 0|         ID|Latitude|Longitude|Elevation|State|                Name|GSN_Flag|HCN_CRN_Flag|WMO_ID|Koppen|
+----------+-----------+--------+---------+---------+-----+--------------------+--------+------------+------+------+
|     83933|US1TXAC0002| 33.8281| -98.5492|    305.7|   TX|WICHITA FALLS 5.2...|    null|        null|  null|   Cfa|
|     83934|US1TXAC0003| 33.5838| -98.6298|    323.7|   TX| ARCHER CITY 0.7 SSW|    null|        null|  null|   Cfa|
|     83935|US1TXAC0005| 33.7762|  -98.535|    300.2|   TX| WICHITA FALLS 8.5 S|    null|        null|  null|   Cfa|
|     83936|US1TXAC0009| 33.8328|  -98.536|    300.5|   TX|WICHITA FALLS 4.6...|    null|        null|  null|   Cfa|
|     83937|US1TXAD0002| 32.0533|-102.8796|    973.5|   TX|     ANDREWS 26.7 SW|    null|        null|  null|   BSk|
+----------+-----------+--------+---------+---------+-----+--------------------+--------+------------+------+------+
only showing top 5 rows
```

In [8]:

```python
from pyspark.sql.functions import col

weather_df = weather_df.withColumn("Station", col("Station").cast("string"))
koppen_sdf = koppen_sdf.withColumn("ID", col("ID").cast("string"))

weather_df = weather_df.withColumnRenamed("Station", "station_id")
koppen_sdf = koppen_sdf.withColumnRenamed("ID", "station_id")
```

In [9]:

```python
valid_station_ids = koppen_df['ID'].unique().tolist()

tobs_df = weather_df.filter((weather_df.Measurement=="TOBS") & (weather_df.station_id.isin(valid_station_ids)))
snwd_df = weather_df.filter((weather_df.Measurement=="SNWD") & (weather_df.station_id.isin(valid_station_ids)))
prcp_df = weather_df.filter((weather_df.Measurement=="PRCP") & (weather_df.station_id.isin(valid_station_ids)))
```

In [10]:

```python
from __future__ import annotations
import numpy as np
from typing import Union, ByteString

def decode_and_average(
    data: Union[ByteString, memoryview, np.ndarray],
    *,
    dtype: np.dtype = np.int16,
    low: int = -200,
    high: int = 1000
) -> np.ndarray:
    """
    Decode a raw byte/array payload to `dtype`, clip out-of-range values,
    and return a z-scored NumPy array.

    Parameters
    ----------
    data : bytes | bytearray | memoryview | np.ndarray
        The raw buffer (or already-decoded NumPy array) to process.
    dtype : np.dtype, default ``np.int16``
        Target dtype for decoding.  Must match the true encoding.
    low, high : int, default (-200, 1000)
        Inclusive limits outside of which values are considered invalid.
```

```
    Returns
    -------
    np.ndarray
        *Shape and dtype preserved.*
        • If the entire payload is invalid, an array of zeros is returned.
        • Otherwise the array is mean-centered and scaled to unit variance.
    """
    # Convert to ndarray with **zero copies** when possible
    if isinstance(data, np.ndarray):
        arr = data.astype(dtype, copy=False)
    else:              # bytes, bytearray, memoryview …
        arr = np.frombuffer(data, dtype=dtype)

    # Mask the invalid range
    mask = (arr < low) | (arr > high)
    if mask.all():
        # All values invalid → return zeros (float for downstream math safety)
        return np.zeros(arr.shape, dtype=float)

    # Compute mean & std on the valid slice only
    valid = arr[~mask].astype(float)
    mean = valid.mean()
    std = valid.std()

    # Standardize; fall back to simple centering when std == 0
    result = (arr.astype(float) - mean) if std == 0 else (arr.astype(float) - mean) / std

    # Keep overall shape; preserve NaN for the positions that were masked
    result[mask] = np.nan
    return result
```

In [11]:
```
import numpy as np
from sklearn.decomposition import PCA
from functools import reduce
from typing import Dict, List, Sequence, Tuple

Array  = np.ndarray
Key    = Tuple[str, int]            # (station_id, year)
Matrix = Tuple[List[Key], Array]    # (keys, matrix or pca result)


def _build_matrix(
    spark_df,
    decode_fn,
) -> Matrix:
    """
    → keys  : [(station_id, year), …]     len == n_samples
    → matrix: np.ndarray shape (n_samples, 366)
    """
    rows = (spark_df
            .rdd
            .map(lambda r: (r.station_id, r.Year, decode_fn(r.Values)))
            .collect())

    keys   = [(sid, yr) for sid, yr, _ in rows]
    matrix = np.vstack([vec for _, _, vec in rows])
    matrix = np.nan_to_num(matrix, nan=0.0)          # replace NaNs with 0
    return keys, matrix


def _pca(matrix: Array, n_components: int = 3, *, seed: int = 42) -> Array:
    """Wrapper that always returns a (n_samples, n_components) matrix."""
    return PCA(n_components=n_components, random_state=seed).fit_transform(matrix)


def process_measurement(
    spark_df,
    decode_fn,
    n_components: int = 3,
    *,
    seed: int = 42,
) -> Matrix:
    """Decode, clean, run PCA, return (keys, pca_matrix)."""
    keys, M = _build_matrix(spark_df, decode_fn)
    return keys, _pca(M, n_components, seed=seed)
```

In [12]:
```
joins_tobs, tobs_pca = process_measurement(tobs_df,  decode_and_average)
joins_snwd, snwd_pca = process_measurement(snwd_df,  decode_and_average)
joins_prcp, prcp_pca = process_measurement(prcp_df,  decode_and_average)
```

In [13]:
```
dicts: Sequence[Dict[Key, Array]] = [
    {k: v for k, v in zip(joins_tobs, tobs_pca)},
    {k: v for k, v in zip(joins_snwd, snwd_pca)},
    {k: v for k, v in zip(joins_prcp, prcp_pca)},
]

common_keys = reduce(set.intersection, (set(d) for d in dicts))
n_features  = sum(p.shape[1] for p in (tobs_pca, snwd_pca, prcp_pca))

X = np.empty((len(common_keys), n_features))
for i, key in enumerate(common_keys):
```

```
    X[i] = np.hstack([d[key] for d in dicts])

# keeping the keys for later joins if necessary
final_keys = list(common_keys)
```

In [14]:
```
feature_cols = [f"{m}_{i}"
                for m in ("TOBS", "SNWD", "PRCP")
                for i in range(1, 4)]

df_final = pd.DataFrame(X, columns=feature_cols)

# unpack keys → two extra columns
keys_arr = np.asarray(final_keys, dtype=object)      # shape (n_samples, 2)
df_final["station_id"] = keys_arr[:, 0]
df_final["year"]       = keys_arr[:, 1].astype(int)
```

In [15]:
```
koppen_df_clean = (
    koppen_df[["ID", "Koppen"]]        # keep only what we need
      .rename(columns={"ID": "station_id"})
)

df_final_with_labels = (
    df_final
      .merge(koppen_df_clean, on="station_id", how="inner")
)

print(df_final_with_labels.head())
```

```
     TOBS_1    TOBS_2    TOBS_3    SNWD_1    SNWD_2   SNWD_3    PRCP_1  \
0 -1.214594  0.696746 -1.583781 -0.220516 -0.225016 -0.18624 -0.293254
1 -1.829101  0.148525  2.251975 -0.220516 -0.225016 -0.18624 -0.867830
2 -0.555854  0.665180  1.677259 -0.220516 -0.225016 -0.18624  0.998790
3  8.197500  4.267913 -1.628339 -0.220516 -0.225016 -0.18624 -1.295066
4 -1.488594  2.183347 -0.917223 -0.220516 -0.225016 -0.18624 -0.934946

     PRCP_2    PRCP_3   station_id  year Koppen
0  0.975490  2.433447  USC00415579  2018    BSh
1  0.299103 -0.665492  USC00415579  1965    BSh
2 -1.064510 -0.095306  USC00415579  1941    BSh
3  0.072391  0.048279  USC00415579  1945    BSh
4  0.550973  0.038974  USC00415579  2002    BSh
```

XGBoost

In [26]:
```
f'Version of xgb={xgb.__version__}, should be at least 1.5.1'
```

Out[26]:
```
'Version of xgb=2.1.4, should be at least 1.5.1'
```

Trial 1

In [27]:
```
# Prepare feature matrix X and label vector y

import numpy as np
import xgboost as xgb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# Drop ID columns, extract features and labels
df_ml = df_final_with_labels.drop(columns=["station_id", "year"])
X      = df_ml.drop(columns="Koppen").values         # shape: (n_samples, 9)
y_raw  = df_ml["Koppen"].values                       # string labels

# Encode Köppen strings → integer classes (0, 1, …, C−1)
le = LabelEncoder()
y  = le.fit_transform(y_raw)                          # e.g. ['A','B','C','A'] → [0,1,2,0]

n_classes = len(le.classes_)                          # number of unique Köppen labels
```

In [28]:
```
# Create 50% train, 25% validation, 25% test splits (stratified)

# First split off 50% as “train”, 50% as “temp”
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.50, stratify=y, random_state=42
)

# Now split the “temp” set 50/50 → 25% total each for validation & test
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.50, stratify=y_temp, random_state=42
)

print("Shapes →",
      f"Train:   {X_train.shape}, {y_train.shape};",
      f"Val:     {X_val.shape},   {y_val.shape};",
      f"Test:    {X_test.shape},  {y_test.shape}")
```

```
Shapes → Train:   (13126, 9), (13126,); Val:     (6563, 9),   (6563,); Test:    (6563, 9),  (6563,)
```

In [29]:
```
# Wrap arrays into DMatrix for XGBoost
```

```python
dtrain = xgb.DMatrix(X_train, label=y_train)
dval   = xgb.DMatrix(X_val,   label=y_val)
dtest  = xgb.DMatrix(X_test,  label=y_test)
```

In [30]:
```python
# Sweep tree depths 1 → 4, use early stopping on validation logloss

depth_results = {}
num_round       = 1000      # upper bound on # of trees
early_stop_rounds = 25      # if no improvement in 25 rounds on validation

for depth in [1, 2, 3, 4]:
    print(f"\nTree Depth {depth}")

    # Define parameters (multi-class)
    param = {
        'max_depth':   depth,
        'eta':         0.3,                     # shrinkage
        'verbosity':   0,                       # 0 = silent
        'objective':   'multi:softprob',        # multi-class logloss
        'num_class':   n_classes,
        'eval_metric': 'mlogloss',
        'nthread':     7
    }

    # Train with early stopping on validation
    evals = [(dtrain, 'train'), (dval, 'validation')]

    bst = xgb.train(
        params                 = param,
        dtrain                 = dtrain,
        num_boost_round        = num_round,
        evals                   = evals,
        early_stopping_rounds  = early_stop_rounds,
        verbose_eval          = False       # suppress per-iteration prints
    )

    # 4c)  Record best iteration and accuracies
    best_iter = bst.best_iteration
    # Predict class labels on train & val
    y_train_pred = np.argmax(bst.predict(dtrain), axis=1)
    y_val_pred   = np.argmax(bst.predict(dval),   axis=1)
    train_acc    = accuracy_score(y_train, y_train_pred)
    val_acc      = accuracy_score(y_val,   y_val_pred)

    depth_results[depth] = {
        'model':     bst,
        'best_iter': best_iter,
        'train_acc': train_acc,
        'val_acc':   val_acc
    }

    print(f"  → Best Iteration: {best_iter:3d};  "
          f"Train Acc = {train_acc:.3f};  Val Acc = {val_acc:.3f}")
```

```
Tree Depth 1
  → Best Iteration: 216;  Train Acc = 0.725;  Val Acc = 0.724

Tree Depth 2
  → Best Iteration: 127;  Train Acc = 0.744;  Val Acc = 0.732

Tree Depth 3
  → Best Iteration:  69;  Train Acc = 0.757;  Val Acc = 0.733

Tree Depth 4
  → Best Iteration:  55;  Train Acc = 0.777;  Val Acc = 0.732
```

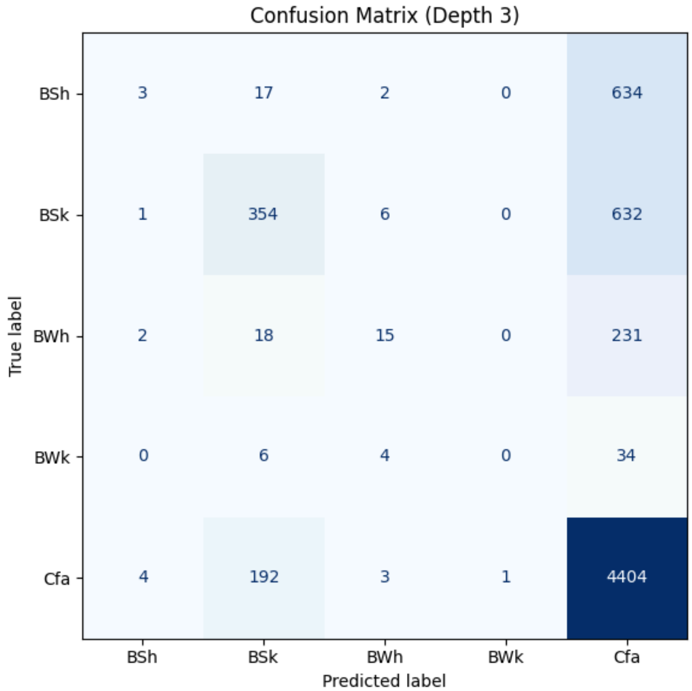
In [31]:
```python
# Choose the depth with highest validation accuracy (tie → smaller depth)

best_depth = max(
    depth_results,
    key=lambda d: (depth_results[d]['val_acc'], -d)
)
best_model = depth_results[best_depth]['model']

print(f"\nSelected tree depth = {best_depth} "
      f"(val_acc = {depth_results[best_depth]['val_acc']:.3f})")
```

```
Selected tree depth = 3 (val_acc = 0.733)
```

In [32]:
```python
# Final evaluation on the TEST set

# Predict on test
y_test_pred = np.argmax(best_model.predict(dtest), axis=1)
test_acc    = accuracy_score(y_test, y_test_pred)
test_error  = 1.0 - test_acc

print(f"Test Accuracy = {test_acc:.3f}   →   Test Error = {test_error:.3f}")

# 6b)  Confusion matrix
cm = confusion_matrix(y_test, y_test_pred, labels=range(n_classes))
fig, ax = plt.subplots(figsize=(6, 6))
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=le.classes_)
disp.plot(ax=ax, cmap="Blues", colorbar=False)
```

```
plt.title(f"Confusion Matrix (Depth {best_depth})")
plt.tight_layout()
plt.show()
```

```
Test Accuracy = 0.728   →   Test Error = 0.272
```



Trial 2

In [33]:
```
df_ml = df_final_with_labels.drop(columns=["station_id", "year"])
X      = df_ml.drop(columns="Koppen").values                      # (n_samples, 9)
y_raw  = df_ml["Koppen"].values

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = le.fit_transform(y_raw)                                       # int-encoded labels
```

In [34]:
```
from sklearn.model_selection import train_test_split

X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.50, stratify=y, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.50, stratify=y_temp, random_state=42
)
```

In [35]:
```
import xgboost as xgb
from sklearn.metrics import accuracy_score

depth_results = {}

for depth in [1, 2, 3, 4]:
    clf = xgb.XGBClassifier(
        objective       = "multi:softprob",
        num_class       = len(le.classes_),
        max_depth       = depth,
        learning_rate   = 0.10,
        n_estimators    = 1_000,
        eval_metric     = "mlogloss",
        random_state    = 42,
        n_jobs          = -1,
    )

    clf.fit(
        X_train, y_train,
        eval_set              = [(X_train, y_train), (X_val, y_val)],
        verbose               = False,
    )

    depth_results[depth] = {
        "model"          : clf,
        "train_acc"      : accuracy_score(y_train, clf.predict(X_train)),
        "val_acc"        : accuracy_score(y_val,   clf.predict(X_val)),
    }

    print(f"Depth {depth:>2} | "
```

```python
          f"train_acc={depth_results[depth]['train_acc']:.3f} | "
          f"val_acc={depth_results[depth]['val_acc']:.3f}")
```

```
Depth  1 | train_acc=0.726 | val_acc=0.724
Depth  2 | train_acc=0.757 | val_acc=0.731
Depth  3 | train_acc=0.810 | val_acc=0.730
Depth  4 | train_acc=0.879 | val_acc=0.728
```

In [36]:
```python
best_depth = max(depth_results, key=lambda d: (depth_results[d]["val_acc"], -d))
best_clf   = depth_results[best_depth]["model"]

print(f"\n Chosen depth = {best_depth} "
      f"with validation accuracy {depth_results[best_depth]['val_acc']:.3f}")
```

```
 Chosen depth = 2 with validation accuracy 0.731
```

In [37]:
```python
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt
import numpy as np

y_test_pred = best_clf.predict(X_test)
test_acc    = accuracy_score(y_test, y_test_pred)

print(f"Test accuracy = {test_acc:.3f}  (error rate = {1-test_acc:.3f})")

cm = confusion_matrix(y_test, y_test_pred, labels=range(len(le.classes_)))
fig, ax = plt.subplots(figsize=(6, 6))
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=le.classes_)
disp.plot(ax=ax, cmap="Blues", colorbar=False)
plt.title(f"Confusion Matrix — depth {best_depth}")
plt.tight_layout()
plt.show()
```

```
Test accuracy = 0.727  (error rate = 0.273)
```