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Sudan Food Insecurity and Displacement Model

This analysis delivers a decision-ready prototype for humanitarian early warning, providing forward-looking identification of food insecurity deterioration, displacement pressure, and key risk drivers at relevant administrative levels.

The model integrates multi-sector signals into a coherent risk framework that supports prioritization and situational awareness.

While advanced components such as probabilistic uncertainty bounds, formal hotspot clustering, and response-rule optimization are not yet operationalized, the current system establishes a robust analytical backbone that can be readily extended into a fully operational decision-support tool.

Point of Reference: IPC Sudan Acute Food Insecurity Snapshot (Oct 2024 – May 2025):
https://www.ipcinfo.org/fileadmin/user_upload/ipcinfo/docs/IPC_Sudan_Acute_Food_Insecurity_C
(https://www.ipcinfo.org/fileadmin/user_upload/ipcinfo/docs/IPC_Sudan_Acute_Food_Insecurity_(

1) Business Understanding

1.1 Problem Scope:

The prototype is immediately usable for strategic planning and anticipatory action, enabling decision-makers to:

- Identify where conditions are likely to deteriorate in the coming month
- Compare displacement pressure across states and localities
- Understand the primary drivers contributing to elevated risk

Most existing systems are **reactive snapshots**. Our project aims to provide key inputs to the above listed key points.

Target Stakeholders

Our main stake holders are :

1. Humanitarian Aid Organizations such as WHO, UN , UNEP etc
2. Sudan Government

2) Project Objectives

a. IPC Food Insecurity Forecasting (State Level)

Forecast one month ahead:

- **Regression:** next-month IPC3+ percentage
- **Classification:** probability that IPC3+ worsens next month (2 percentage point increase)

Outputs:

- monthly risk ranking by state
- top drivers for each state-month prediction
- uncertainty/confidence flags

b. Displacement Pressure Monitoring and Hotspot Intelligence

Produce monthly operational outputs:

- **State pressure rankings**:
  - total IDPs by state
- **Hotspot and concentration intelligence**:
  - top localities contributing to state IDP burden
  - concentration measures (e.g., top 3 localities share)

Why this matters:

- High displacement pressure increases vulnerability via service strain, market stress, and household fragility.
- Hotspot intelligence supports locality-level targeting (Admin2) for assessments and interventions.

3. Data Understanding & Preparation

Our model has been built on various data sets namely:

1. IPC datasets — Food insecurity truth signal
2. Displacement datasets — Needs and pressure signal
3. WFP price datasets — Economic stress signal
4. Rainfall dataset — Climate stress signal
5. Conflict datasets — Shock and disruption signal
6. Population and vulnerability — Exposure and normalization

Import the required Libraries which will be used in the project.

In [1]:
```
#import libraries
import pandas as pd                                         # For working
import numpy as np                                          # For numeric
import matplotlib.pyplot as plt                             # For plottir
import seaborn as sns                                       # For advance
from sklearn.model_selection import train_test_split        # Split data
from sklearn.linear_model import LogisticRegression         # Logistic Re
from sklearn.ensemble import RandomForestClassifier         # Ensemble mc
from sklearn.metrics import accuracy_score, precision_score, recall_score,
from sklearn.metrics import confusion_matrix, classification_report
import glob                                                 # For finding
import pandas as pd
import re
import pandas as pd
import requests
from io import BytesIO
import zipfile, os
import geopandas as gpd
from pathlib import Path
from PIL import Image
import os # To check the operating system directory where the data is stor
import geopandas as gpd
from pathlib import Path
from sklearn.inspection import permutation_importance
```

Step 1:Load the data

In [2]:
```
df = pd.read_csv("regional_food_security_master.csv", low_memory=False)
df.shape, df.columns
```

Out[2]:
```
((26145, 132),
 Index(['Date of analysis', 'Country', 'Total country population', 'state',
        'Area', 'Validity period', 'From', 'To', 'Phase', 'Number',
        ...
        'T_35_39_2025', 'T_40_44_2025', 'T_45_49_2025', 'T_50_54_2025',
        'T_55_59_2025', 'T_60_64_2025', 'T_65_69_2025', 'T_70_74_2025',
        'T_75_79_2025', 'T_80Plus_2025'],
       dtype='object', length=132))
```

Step 2 : Remove metadata rows and parse dates

In [3]:
```
df = df[~df["From"].astype(str).str.startswith("#")].copy()

df["From"] = pd.to_datetime(df["From"], errors="coerce")
df = df.dropna(subset=["From"]).copy()

df["month"] = df["From"].dt.to_period("M").dt.to_timestamp()
df[["From","month"]].head()

```

Out[3]:

	From	month
0	2025-09-01	2025-09-01
1	2025-09-01	2025-09-01
2	2025-09-01	2025-09-01
3	2025-09-01	2025-09-01
4	2025-09-01	2025-09-01

Step 3: Standardize keys (Country, Phase, admin)

In [4]:
```
df["Country"] = df["Country"].astype(str).str.strip()
df["Phase"]   = df["Phase"].astype(str).str.strip()

df["admin"] = df["Area"].where(df["Area"].notna(), df["state"]).astype(str
df[["Country","admin","Phase"]].head()

```

Out[4]:

	Country	admin	Phase
0	SDN	Beida	all
1	SDN	Beida	3+
2	SDN	Beida	1
3	SDN	Beida	2
4	SDN	Beida	3

Step 4: Clean numeric percentage

In [5]:
```
df["Percentage"] = pd.to_numeric(df["Percentage"], errors="coerce")
clean_long = df.dropna(subset=["Country","admin","month","Phase","Percenta

clean_long.shape

```

Out[5]: (26145, 134)

1.1.1 Download an Excel dataset, lists all sheets, and previews the first few rows of each for quick inspection.

In [6]:

```
#Fetch data from the API link from the humanitarian data source

# Define the URL where data set is stored.
url = "https://data.humdata.org/dataset/319dd40f-c0f8-4f6d-9a8e-9acf31007c

# Fetching the data
r = requests.get(url, timeout=60)
r.raise_for_status()

# Loading into pandas
xls = pd.ExcelFile(BytesIO(r.content))
print("Sheets found:", xls.sheet_names)

# Previewing sheets
for s in xls.sheet_names:
    try:
        df = xls.parse(s, nrows=3)
        print(f"\n--- Sheet: {s} ---")
        print(df)
    except Exception as e:
        print(f"\n--- Sheet: {s} --- (Error reading: {e})")
```

```
           Unnamed: 23       Unnamed: 24          Unnamed: 25 Unnamed: 26
0                  NaN               NaN                  NaN         NaN
1   Age 18 - 59 (Female)  Age >= 60 (Male)  Age >= 60  (Female)       Total
2                  NaN               NaN                  NaN         NaN

[3 rows x 27 columns]

--- Sheet: Admin_label ---
  Code_1         State_En Code_1.1 State_Code Locality_G  Name_Engli  \
0   SD08       Blue Nile     SD08       SD16    SD16008   Abu Hamad
1   SD06  Central Darfur     SD06       SD16    SD16011    Ad Damar
2   SD05     East Darfur     SD05       SD16    SD16014  Al Buhaira

  Locality_G.1 STATE_CODE LOCALITY_CODE LOCATION OF DISPALCEMENT  \
0      SD16008       SD01       SD01001                  Alassal
1      SD16011       SD01       SD01001               Aldekhinat
2      SD16014       SD01       SD01001                 Alfeteih

  NEW LOCATON_SITCODE   Unnamed: 11  #                     Country
```

1.1.2 This code Downloads an Excel dataset, extracts Admin-1 level displacement data, cleans and standardizes key columns, and saves the processed results as a CSV file.

In [7]:

```
#Fetch data from the API link from the humanitarian data source

# Define the API URL where data set is stored.

url = "https://data.humdata.org/dataset/319dd40f-c0f8-4f6d-9a8e-9acf31007c

# download the xlsx
r = requests.get(url, timeout=60)
r.raise_for_status()

# read the Admin1 sheet which contained our displacement data
df = pd.read_excel(BytesIO(r.content), sheet_name="MASTER LIST (ADMIN1)",

# Extarct and keep only the required columns
state = df[["LOCATION INFORMATION", "Unnamed: 1", "TOTAL", "Unnamed: 3"]].

# rename to clean names
state.columns = ["state", "state_code", "idps", "households"]

# remove empty rows

state["state"] = state["state"].astype(str).str.strip()
state["idps"] = pd.to_numeric(state["idps"], errors="coerce")

state = state.dropna(subset=["state", "idps"])
state = state[state["state"].str.lower().ne("nan")]

# save one CSV
state.to_csv("sudan_admin1_idps_2024-04-25.csv", index=False)

print("Saved: sudan_admin1_idps_2024-04-25.csv")
print(state.head())

```

```
Saved: sudan_admin1_idps_2024-04-25.csv
             state state_code      idps  households
2      Aj Jazirah       SD15  371177.0       73323
3       Blue Nile       SD08  147736.0       29836
4  Central Darfur       SD06  430224.0       86044
5     East Darfur       SD05  660140.0      131918
6         Gedaref       SD12  492293.0       97817
```

1.1.3 Print and check the current working directory of the Python environment.

In [8]:
```
print(os.getcwd())
```

```
C:\Users\user\Documents\Humanitarian
```

1.1.4 This code Downloads displacement data, extracts and cleans Admin-1 level statistics, saves the results as a CSV file, and prints the file’s saved location.

In [10]:
```
url = "https://data.humdata.org/dataset/319dd40f-c0f8-4f6d-9a8e-9acf31007c

r = requests.get(url, timeout=60)
r.raise_for_status()

df = pd.read_excel(BytesIO(r.content), sheet_name="MASTER LIST (ADMIN1)",

state = df[["LOCATION INFORMATION", "Unnamed: 1", "TOTAL", "Unnamed: 3"]].
state.columns = ["state", "state_code", "idps", "households"]

state["state"] = state["state"].astype(str).str.strip()
state["idps"] = pd.to_numeric(state["idps"], errors="coerce")

state = state.dropna(subset=["state", "idps"])
state = state[state["state"].str.lower().ne("nan")]

out_file = "sudan_admin1_idps_2024-04-25.csv"  # saved in C:\Users\user\Do
state.to_csv(out_file, index=False)

print("Saved to:", os.path.abspath(out_file))
```

```
Saved to: C:\Users\user\Documents\Humanitarian\sudan_admin1_idps_2024-04-25.c
sv
```

1.1.5 The below Downloads Sudan Admin-1 boundary data in GeoJSON format and saves it locally for mapping or spatial analysis.

In [11]:

```
# This is the direct GeoJSON (WFS) endpoint for Sudan Admin1 boundaries

geojson_url = (
    "https://geoportal.icpac.net/geoserver/ows?"
    "service=WFS&version=1.0.0&request=GetFeature&"
    "typename=geonode:sudan_admin_level1&"
    "outputFormat=json&srsName=EPSG:4326"
)

out_file = "sudan_admin1.geojson"  # the .geojson file is pushed to the cu

r = requests.get(geojson_url, timeout=120)
r.raise_for_status()

with open(out_file, "wb") as f:
    f.write(r.content)

print("Saved boundary file to:", os.path.abspath(out_file))
print("File size (bytes):", os.path.getsize(out_file))

```

```
Saved boundary file to: C:\Users\user\Documents\Humanitarian\sudan_admin1.geo
json
File size (bytes): 339637
```

1.1.6 The below code Loads displacement data, standardizes and cleans fields, removes invalid rows, aggregates duplicates by state, performs quality checks, and saves a final cleaned CSV ready for analysis or deployment.

In [12]:

```
# Load your displacement CSV
df = pd.read_csv("sudan_admin1_idps_2024-04-25.csv")

# Standardize column names (lowercase and underscores)

df.columns = [c.strip().lower().replace(" ", "_") for c in df.columns]

# print out Expected columns i.e state, state_code, idps, households

print("Columns:", list(df.columns))

# Clean text and numeric types

df["state"] = df["state"].astype(str).str.strip()
df["state_code"] = df["state_code"].astype(str).str.strip()

df["idps"] = pd.to_numeric(df["idps"], errors="coerce")
df["households"] = pd.to_numeric(df["households"], errors="coerce")

# Drop empty rows

df = df.dropna(subset=["state", "idps"])

#  Remove obvious totals or junk rows and perfronrm professional hygiene.

bad = {"total", "grand total", "overall", "nan", ""}
df = df[~df["state"].str.lower().isin(bad)]

# Deduplicate safely (if duplicates exist, sum them)

df_clean = (
    df.groupby(["state_code", "state"], as_index=False)[["idps", "househol
      .sum()
)

# Professional hygiene checks

print("\n--- QA SUMMARY ---")
print("Rows (states):", len(df_clean))
print("Unique state_code:", df_clean["state_code"].nunique())
print("Missing state_code:", df_clean["state_code"].isna().sum())
print("Any duplicate state_code:", df_clean["state_code"].duplicated().any

print("\nTop 10 states by IDPs:")
display(df_clean.sort_values("idps", ascending=False).head(10))

print("\nAll states (sorted A–Z):")
display(df_clean.sort_values("state")[["state_code", "state", "idps", "hou

# lastly Save the cleaned table

df_clean.to_csv("sudan_admin1_idps_2024-04-25_CLEAN.csv", index=False)
print("\nSaved: sudan_admin1_idps_2024-04-25_CLEAN.csv")
```

```
Columns: ['state', 'state_code', 'idps', 'households']

--- QA SUMMARY ---
Rows (states): 18
Unique state_code: 18
Missing state_code: 0
Any duplicate state_code: False

Top 10 states by IDPs:
```

	state_code	state	idps	households
2	SD03	South Darfur	744243.0	148848
15	SD16	River Nile	698334.0	137799
4	SD05	East Darfur	660140.0	131918
1	SD02	North Darfur	573055.0	114503
8	SD09	White Nile	532643.0	105920
13	SD14	Sennar	523986.0	104002
11	SD12	Gedaref	492293.0	97817
5	SD06	Central Darfur	430224.0	86044
16	SD17	Northern	399867.0	80305
14	SD15	Aj Jazirah	371177.0	73323

```
All states (sorted A–Z):
```

	state_code	state	idps	households
14	SD15	Aj Jazirah	371177.0	73323
7	SD08	Blue Nile	147736.0	29836
5	SD06	Central Darfur	430224.0	86044
4	SD05	East Darfur	660140.0	131918
11	SD12	Gedaref	492293.0	97817
10	SD11	Kassala	200083.0	40282
0	SD01	Khartoum	69057.0	13717
1	SD02	North Darfur	573055.0	114503
12	SD13	North Kordofan	174007.0	34261
16	SD17	Northern	399867.0	80305
9	SD10	Red Sea	247874.0	49953
15	SD16	River Nile	698334.0	137799
13	SD14	Sennar	523986.0	104002
2	SD03	South Darfur	744243.0	148848
6	SD07	South Kordofan	198839.0	39492
3	SD04	West Darfur	174540.0	34908
17	SD18	West Kordofan	148718.0	29340
8	SD09	White Nile	532643.0	105920

```
Saved: sudan_admin1_idps_2024-04-25_CLEAN.csv
```

1.1.7 Below code Builds a 2023 Admin-1 displacement panel by looping through multiple Excel files, extracting state-level IDPs/households, deriving report dates from sheet names, ranking states (top 5 hotspots), and exporting a combined monthly dataset to CSV.

In [ ]:

```python
HOTSPOT_TOPK = 5
files = sorted(glob.glob("data/2023_excels/*.xlsx"))
rows = []

def get_sheet(xls):
    return next((s for s in xls.sheet_names if str(s).lower().startswith('
                xls.sheet_names[0])
def get_date(sheet):
    m = re.search(r"\((.+)\)", str(sheet))
    return pd.to_datetime(m.group(1), dayfirst=True, errors="coerce") if m

    for f in files:
        xls = pd.ExcelFile(f)
        sheet = get_sheet(xls)
        df = pd.read_excel(f, sheet_name=sheet)

        cols = {
            "STATE OF AFFECTED POPULATION": "state_name",
            "STATE PCODE OF AFFECTED POPULATION": "state_code",
            "# IDP INDIVIDUALS  ": "idps",
            "# IDP HOUSEHOLDS  ": "households",
                }

    if not all(c in df.columns for c in cols):
        continue

    out = df[list(cols)].rename(columns=cols)
    out[["idps","households"]] = out[["idps","households"]].apply(pd.to_nu

    out = (out.groupby(["state_code","state_name"], as_index=False)
              .sum())

    date = get_date(sheet)
    if pd.isna(date):
        continue

    out["report_date"] = date.normalize()
    out["month_start"] = date.to_period("M").to_timestamp()

    out = out.sort_values("idps", ascending=False).head(18).reset_index(dr
    out["rank"] = out.index + 1
    out["hotspot"] = out["rank"] <= HOTSPOT_TOPK

    rows.append(out)

panel_2023 = pd.concat(rows, ignore_index=True)
panel_2023.to_csv("sudan_admin1_idps_panel_2023.csv", index=False)
```

In [13]:

```
#Print out the results for above code cell.

print("\nSaved: sudan_admin1_idps_panel_2023.csv")
print("Rows:", len(panel_2023), "| Months:", panel_2023["month_start"].nur

# Print the latest report
latest = panel_2023["report_date"].max()
print("\nLatest report_date:", latest.date())
print(panel_2023[panel_2023["report_date"] == latest].sort_values("rank")[
    "state_code","state_name","idps","households","report_date","month_sta
]].to_string(index=False))

```

```
Files found: 34
Processing: 2023-04-27 | States: 15

Saved: sudan_admin1_idps_panel_2023.csv
Rows: 15 | Months: 1 | States: 15

Latest report_date: 2023-04-27
 state_code      state_name     idps  households report_date month_start  rank
hotspot
       SD04     West Darfur 194593.0     38919.0  2023-04-27  2023-04-01     1
True
       SD03    South Darfur  45000.0      9000.0  2023-04-27  2023-04-01     2
True
       SD17        Northern  29200.0      5840.0  2023-04-27  2023-04-01     3
True
       SD01        Khartoum  13545.0      2709.0  2023-04-27  2023-04-01     4
True
       SD13  North Kordofan  13270.0      2654.0  2023-04-27  2023-04-01     5
True
       SD02    North Darfur  11675.0      2335.0  2023-04-27  2023-04-01     6
False
       SD15      Aj Jazirah   8795.0      1759.0  2023-04-27  2023-04-01     7
False
       SD09      White Nile   6165.0      1233.0  2023-04-27  2023-04-01     8
False
       SD14          Sennar   5560.0      1112.0  2023-04-27  2023-04-01     9
False
       SD16      River Nile   2910.0       582.0  2023-04-27  2023-04-01    10
False
       SD06 Central Darfur    1780.0       356.0  2023-04-27  2023-04-01    11
False
       SD10         Red Sea   1205.0       241.0  2023-04-27  2023-04-01    12
False
       SD08       Blue Nile    260.0        52.0  2023-04-27  2023-04-01    13
False
       SD11         Kassala     95.0        19.0  2023-04-27  2023-04-01    14
False
#adm1+pcode      #adm1+name      0.0         0.0  2023-04-27  2023-04-01    15
False
```

1.1.8 Below code Creates a fixed 18 state Admin-1 reference list, merges it into each report date to ensure all states are present (filling missing values with zero), recalculates ranks and top-5 hotspots per report, and saves a consistent 18-state monthly panel to CSV.

In [14]:

```python
# Fixed Sudan Admin1 spine (SD01-SD18) The states we resolved to work with

spine = pd.DataFrame([
    ("SD01","Khartoum"),
    ("SD02","North Darfur"),
    ("SD03","South Darfur"),
    ("SD04","West Darfur"),
    ("SD05","East Darfur"),
    ("SD06","Central Darfur"),
    ("SD07","South Kordofan"),
    ("SD08","Blue Nile"),
    ("SD09","White Nile"),
    ("SD10","Red Sea"),
    ("SD11","Kassala"),
    ("SD12","Gedaref"),
    ("SD13","North Kordofan"),
    ("SD14","Sennar"),
    ("SD15","Aj Jazirah"),
    ("SD16","River Nile"),
    ("SD17","Northern"),
    ("SD18","West Kordofan"),
], columns=["state_code","state_name"])

# Read the panel 2023 file and use it as our extracted input:

panel = panel_2023.copy()
 if "panel_2023" in globals()
    else pd.read_csv("sudan_admin1_idps_panel_2023.csv", parse_dates=["rep

fixed = []
for d, g in panel.groupby("report_date"):
    m = spine.merge(g[["state_code","idps","households"]], on="state_code'
    m["report_date"] = pd.to_datetime(d)
    m["month_start"] = pd.to_datetime(d).to_period("M").to_timestamp()
    m["idps"] = m["idps"].fillna(0)
    m["households"] = m["households"].fillna(0)

    m = m.sort_values("idps", ascending=False).reset_index(drop=True)
    m["rank"] = m.index + 1
    m["hotspot"] = m["rank"] <= HOTSPOT_TOPK
    fixed.append(m)

panel_2023_fixed18 = pd.concat(fixed, ignore_index=True)
panel_2023_fixed18.to_csv("sudan_admin1_idps_panel_2023.csv", index=False)

print("Saved: sudan_admin1_idps_panel_2023.csv")
print("Rows:", len(panel_2023_fixed18), "| Dates:", panel_2023_fixed18["re
      panel_2023_fixed18["state_code"].nunique())

latest = panel_2023_fixed18["report_date"].max()

print("\nProcessing:", latest.date())
print(panel_2023_fixed18[panel_2023_fixed18["report_date"] == latest].sort
    "state_code","state_name","idps","households","report_date","month_sta
    ]].to_string(index=False))
```

```
56
```

```
Saved: sudan_admin1_idps_panel_2023.csv
Rows: 18 | Dates: 1 | States: 18

Processing: 2023-04-27
state_code     state_name     idps  households report_date month_start  rank
hotspot
      SD04    West Darfur 194593.0     38919.0  2023-04-27  2023-04-01     1
True
      SD03   South Darfur  45000.0      9000.0  2023-04-27  2023-04-01     2
True
      SD17       Northern  29200.0      5840.0  2023-04-27  2023-04-01     3
True
      SD01       Khartoum  13545.0      2709.0  2023-04-27  2023-04-01     4
True
      SD13 North Kordofan  13270.0      2654.0  2023-04-27  2023-04-01     5
True
      SD02   North Darfur  11675.0      2335.0  2023-04-27  2023-04-01     6
False
      SD15     Aj Jazirah   8795.0      1759.0  2023-04-27  2023-04-01     7
False
      SD09     White Nile   6165.0      1233.0  2023-04-27  2023-04-01     8
False
      SD14         Sennar   5560.0      1112.0  2023-04-27  2023-04-01     9
False
      SD16     River Nile   2910.0       582.0  2023-04-27  2023-04-01    10
False
      SD06 Central Darfur   1780.0       356.0  2023-04-27  2023-04-01    11
False
      SD10        Red Sea   1205.0       241.0  2023-04-27  2023-04-01    12
False
      SD08      Blue Nile    260.0        52.0  2023-04-27  2023-04-01    13
False
      SD11        Kassala     95.0        19.0  2023-04-27  2023-04-01    14
False
      SD07 South Kordofan      0.0         0.0  2023-04-27  2023-04-01    15
False
      SD05    East Darfur      0.0         0.0  2023-04-27  2023-04-01    16
False
      SD12        Gedaref      0.0         0.0  2023-04-27  2023-04-01    17
False
      SD18  West Kordofan      0.0         0.0  2023-04-27  2023-04-01    18
False
```

1.1.9 Below code Loads a combined 2023 and 2024 displacement panel, selects geography-ready fields, exports them to a CSV for mapping snapshots, and prints basic dataset statistics.

In [15]:
```
panel = pd.read_csv("sudan_admin1_idps_panel_2023_2024.csv", parse_dates=[

geo = panel[["state_code","state_name","report_date","idps","households",'
geo.to_csv("geo_admin1_snapshots_2023_2024.csv", index=False)

print("Saved: geo_admin1_snapshots_2023_2024.csv")
print("Rows:", len(geo), "| Dates:", geo["report_date"].nunique(), "| Stat

```

```
Saved: geo_admin1_snapshots_2023_2024.csv
Rows: 54 | Dates: 3 | States: 18
```

1.1.10 Below code Splits the geographic displacement dataset into separate CSV files by report date and saves each snapshot to a date named folder for easy mapping or time-series use.

In [16]:
```
df = pd.read_csv("geo_admin1_snapshots_2023_2024.csv", parse_dates=["repor
os.makedirs("geo_by_date", exist_ok=True)

for d in sorted(df["report_date"].unique()):
    sub = df[df["report_date"] == d].copy()
    out = f"geo_by_date/geo_admin1_{pd.to_datetime(d).date()}.csv"
    sub.to_csv(out, index=False)
    print("Saved:", out, "| rows:", len(sub))

```

```
Saved: geo_by_date/geo_admin1_2023-04-27.csv | rows: 18
Saved: geo_by_date/geo_admin1_2023-05-05.csv | rows: 18
Saved: geo_by_date/geo_admin1_2024-04-25.csv | rows: 18
```

1.1.11 Below code Identifies the top 5 displacement hotspot states per report date based on IDPs, saves the results to a CSV file, and prints a concise hotspot summary table.

In [17]:

```
df = pd.read_csv("geo_admin1_snapshots_2023_2024.csv", parse_dates=["repor

top5 = (df.sort_values(["report_date","idps"], ascending=[True, False])
          .groupby("report_date")
          .head(5)
          .copy())

top5.to_csv("report_hotspots_top5_by_date.csv", index=False)
print("Saved: report_hotspots_top5_by_date.csv")
print(top5[["report_date","state_code","state_name","idps","rank","hotspot

```

```
Saved: report_hotspots_top5_by_date.csv
report_date state_code     state_name     idps  rank  hotspot
 2023-04-27       SD04    West Darfur 194593.0   1.0     True
 2023-04-27       SD03   South Darfur  45000.0   2.0     True
 2023-04-27       SD17       Northern  29200.0   3.0     True
 2023-04-27       SD01       Khartoum  13545.0   4.0     True
 2023-04-27       SD13 North Kordofan  13270.0   5.0     True
 2023-05-05       SD09    White Nile 188635.0   1.0     True
 2023-05-05       SD04    West Darfur 156565.0   2.0     True
 2023-05-05       SD17       Northern 106600.0   3.0     True
 2023-05-05       SD16     River Nile  96095.0   4.0     True
 2023-05-05       SD15     Aj Jazirah  49280.0   5.0     True
 2024-04-25       SD03   South Darfur 744243.0   1.0     True
 2024-04-25       SD16     River Nile 698334.0   2.0     True
 2024-04-25       SD05    East Darfur 660140.0   3.0     True
 2024-04-25       SD02   North Darfur 573055.0   4.0     True
 2024-04-25       SD09     White Nile 532643.0   5.0     True
```

1.1.13 Below code Adds a global IDP based intensity metric by normalizing displacement counts against the overall maximum across all dates, then updates the dataset for consistent cross time comparison.

In [18]:

```
df = pd.read_csv("geo_admin1_snapshots_2023_2024_INTENSITY.csv", parse_dat

global_max = df["idps"].max()
df["intensity_idps_global"] = df["idps"] / global_max

df.to_csv("geo_admin1_snapshots_2023_2024_INTENSITY.csv", index=False)
print("Updated with intensity_idps_global. Global max:", global_max)

```

```
Updated with intensity_idps_global. Global max: 744243.0
```

1.1.14 Below code Splits the intensity enhanced displacement dataset per date GIS ready CSV files, keeping only essential fields and a globally comparable intensity metric for consistent map symbolization.

In [19]:

```
df = pd.read_csv("geo_admin1_snapshots_2023_2024_INTENSITY.csv", parse_dat

value_col = "intensity_idps_global"

out_dir = "geo_by_date_intensity"
os.makedirs(out_dir, exist_ok=True)

for d in sorted(df["report_date"].unique()):
    sub = df[df["report_date"] == d].copy()

# tract and keep what we need to use in GIS file

    sub = sub[[
        "state_code", "state_name", "report_date",
        "idps", "households",
        "rank", "hotspot",
        "hotspot_intensity_rank",
        "intensity_idps_global",
        "intensity_idps_share"
    ]].copy()

    out = os.path.join(out_dir, f"geo_admin1_{pd.to_datetime(d).date()}_ir
    sub.to_csv(out, index=False)
    print("Saved:", out, "| rows:", len(sub), "| symbolize:", value_col)

```

```
Saved: geo_by_date_intensity\geo_admin1_2023-04-27_intensity.csv | rows: 18 |
symbolize: intensity_idps_global
Saved: geo_by_date_intensity\geo_admin1_2023-05-05_intensity.csv | rows: 18 |
symbolize: intensity_idps_global
Saved: geo_by_date_intensity\geo_admin1_2024-04-25_intensity.csv | rows: 18 |
symbolize: intensity_idps_global
```

1.1.15 Below code Unzips an uploaded GeoJSON boundary file, loads it with GeoPandas, inspects its structure, and identifies likely administrative code fields for joining with displacement data.

In [20]:

```python

zip_path = "sdn_admin_boundaries.geojson.zip"

out_dir = "sdn_admin_boundaries_unzipped"
os.makedirs(out_dir, exist_ok=True)

with zipfile.ZipFile(zip_path, "r") as z:
    z.extractall(out_dir)

# retrieve the geojson file

geojson_files = [os.path.join(out_dir, f) for f in os.listdir(out_dir) if
print("GeoJSON files:", geojson_files)

gdf = gpd.read_file(geojson_files[0])
print("Rows:", len(gdf))
print("Columns:", list(gdf.columns))

cand = [c for c in gdf.columns if "pcode" in c.lower() or "code" in c.lowe
print("Candidate code fields:", cand)

gdf.head(3)

```

```
GeoJSON files: ['sdn_admin_boundaries_unzipped\\sdn_admin0.geojson', 'sdn_adm
in_boundaries_unzipped\\sdn_admin1.geojson', 'sdn_admin_boundaries_unzipped
\\sdn_admin2.geojson', 'sdn_admin_boundaries_unzipped\\sdn_adminlines.geojso
n', 'sdn_admin_boundaries_unzipped\\sdn_adminpoints.geojson']
Rows: 1
Columns: ['iso2', 'iso3', 'adm0_name', 'adm0_name1', 'adm0_name2', 'adm0_name
3', 'adm0_pcode', 'valid_on', 'valid_to', 'version', 'area_sqkm', 'lang', 'la
ng1', 'lang2', 'lang3', 'adm0_ref_name', 'center_lat', 'center_lon', 'geometr
y']
Candidate code fields: ['adm0_pcode']
```

Out[20]:

	iso2	iso3	adm0_name	adm0_name1	adm0_name2	adm0_name3	adm0_pcode	valid_on	va
0	SD	SDN	Sudan	السودان	None	None	SD	2020-08-31	

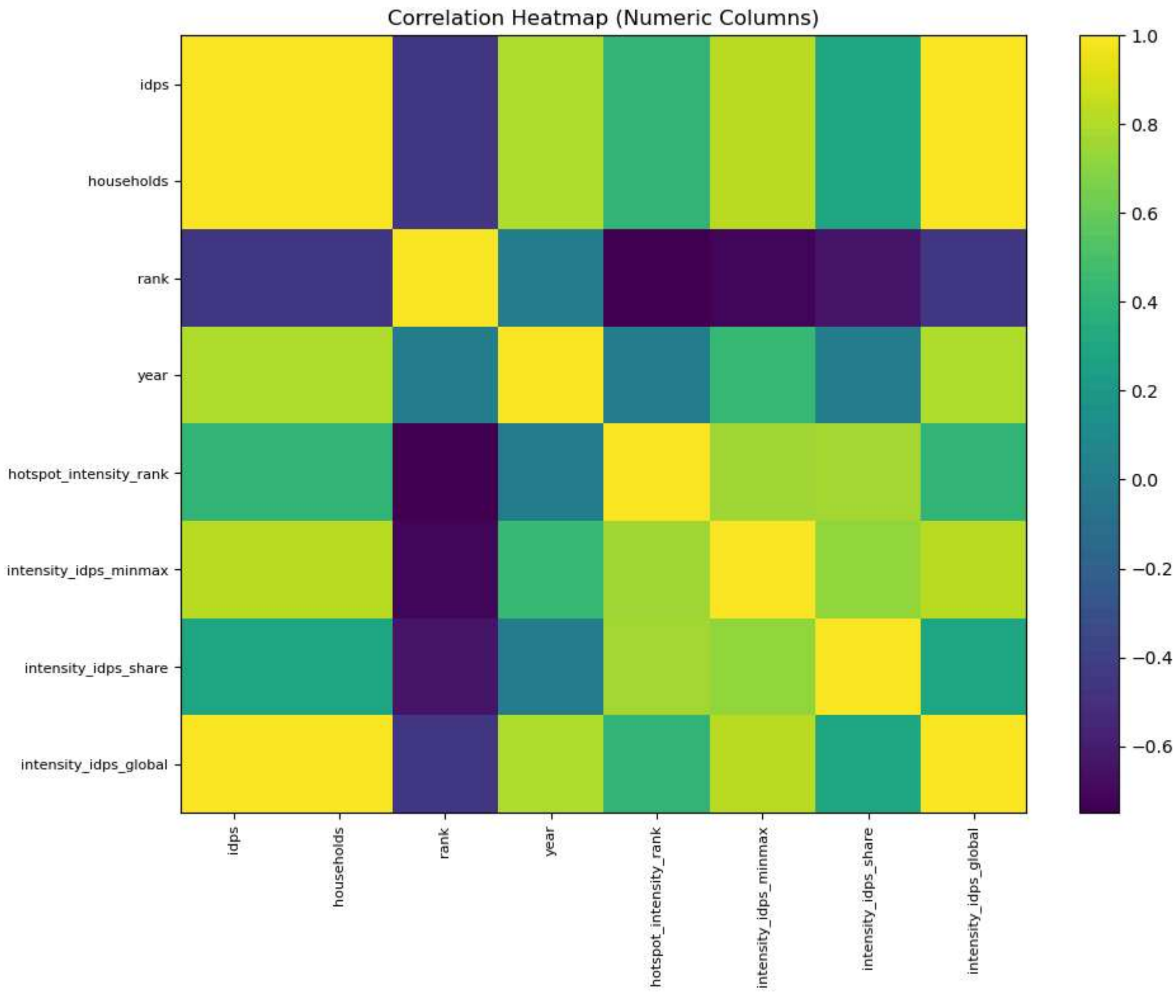
4. Explaratory Data Analysis and Visulizations

Numeric features in the dataset

This heatmap visualizes the pairwise correlations among all numeric features in the dataset, helping identify strong relationships and potential multicollinearity prior to modeling.

In [21]:

```python
# define where the EDA resulsts will be saved and esnusre the directory ex

ARTIFACTS_DIR = Path("artifacts") / "eda"
ARTIFACTS_DIR.mkdir(parents=True, exist_ok=True)

def save_show(fig, name: str, folder: Path = ARTIFACTS_DIR, dpi: int = 20(
    out_path = folder / f"{name}.png"
    fig.tight_layout()
    fig.savefig(out_path, dpi=dpi, bbox_inches="tight")
    plt.show()
    print(f"Saved: {out_path}")

# create correlation heatmap and output the correlation details

num_cols = df.select_dtypes(include=[np.number]).columns.tolist()

if len(num_cols) < 2:
    print("Not enough numeric columns to compute a correlation matrix.")
else:
    corr = df[num_cols].corr(numeric_only=True)

    fig, ax = plt.subplots(figsize=(10, 8))
    im = ax.imshow(corr.values, aspect="auto")
    ax.set_title("Correlation Heatmap (Numeric Columns)")

    ax.set_xticks(range(len(num_cols)))
    ax.set_yticks(range(len(num_cols)))
    ax.set_xticklabels(num_cols, rotation=90, fontsize=8)
    ax.set_yticklabels(num_cols, fontsize=8)

    fig.colorbar(im, ax=ax)
    save_show(fig, "corr_heatmap_numeric")
```




```
Saved: artifacts\eda\corr_heatmap_numeric.png
```

Eplanation of the above Correlation results:

1. Out ouput created a Pearson correlation matrix.
2. IDPs and households show a very strong positive correlation of an estimate output of 0.9. This is expected, as households are directly derived from individual displacement counts.
3. Rank is strongly negatively correlated with: IDPs, Households and Intensity-based indicators. This occurs because lower rank values correspond to higher displacement pressure.
4. Intensity measures are highly interrelated. The three intensity metrics namely

   ```
   intensity_idps_minmax
   intensity_idps_share
   intensity_idps_global
   ```

   show strong positive correlations with each other.

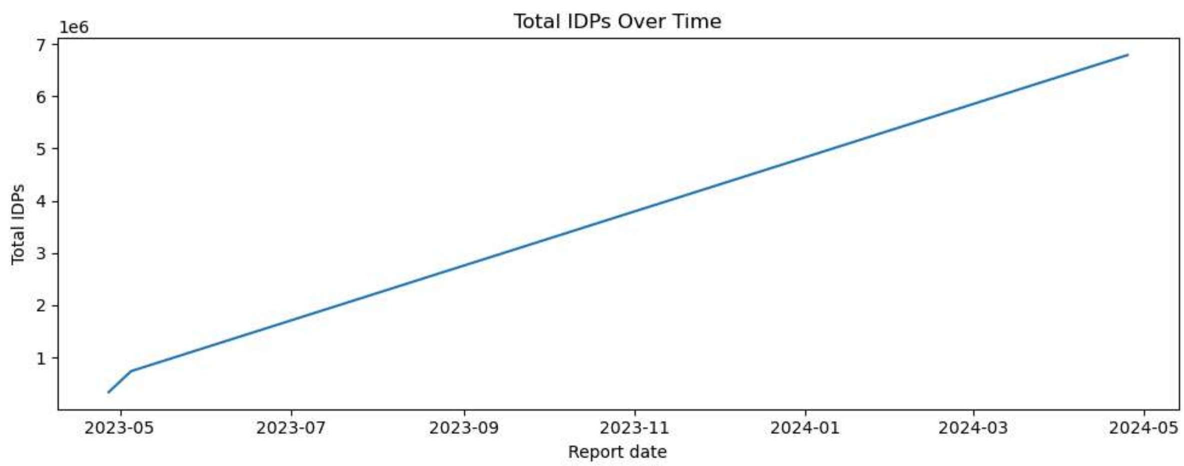
Implication: All intensity measures capture similar displacement concentration dynamics using different normalization schemes. Including all three in a single model may introduce multicollinearity.

5. Displacement magnitude and intensity move together. IDPs and households are strongly positively correlated with intensity metrics.

Total IDPs Over Time

This line chart shows the trend of total internally displaced persons (IDPs) over time, highlighting changes in displacement levels across reporting dates.

In [23]:
```
trend = (df.dropna(subset=["report_date"])
           .groupby("report_date")["idps"].sum()
           .sort_index())

fig, ax = plt.subplots(figsize=(10, 4))
ax.plot(trend.index, trend.values)
ax.set_title("Total IDPs Over Time")
ax.set_xlabel("Report date")
ax.set_ylabel("Total IDPs")
save_show(fig, "trend_total_idps_over_time")

```



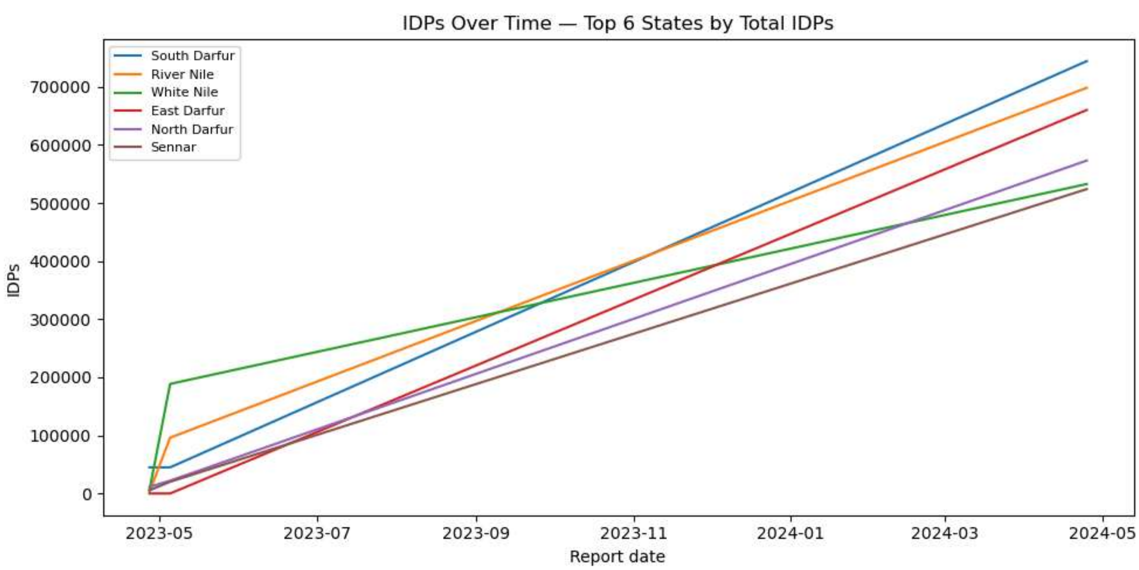

```
Saved: artifacts\eda\trend_total_idps_over_time.png
```

IDPs Over Time — Top 6 States by Total IDPs

This multi-line chart compares IDP trends over time for the top six states with the highest total number of internally displaced persons, highlighting differences in displacement patterns across states.

In [24]:

```
TOP_N = 6
top_states = (df.groupby("state_name")["idps"].sum()
                .sort_values(ascending=False)
                .head(TOP_N)
                .index.tolist())

fig, ax = plt.subplots(figsize=(10, 5))
for s in top_states:
    sub = df[df["state_name"] == s].dropna(subset=["report_date"])
    ts = sub.groupby("report_date")["idps"].sum().sort_index()
    ax.plot(ts.index, ts.values, label=str(s))

ax.set_title(f"IDPs Over Time — Top {TOP_N} States by Total IDPs")
ax.set_xlabel("Report date")
ax.set_ylabel("IDPs")
ax.legend(fontsize=8)
save_show(fig, "trend_idps_top_states")
```



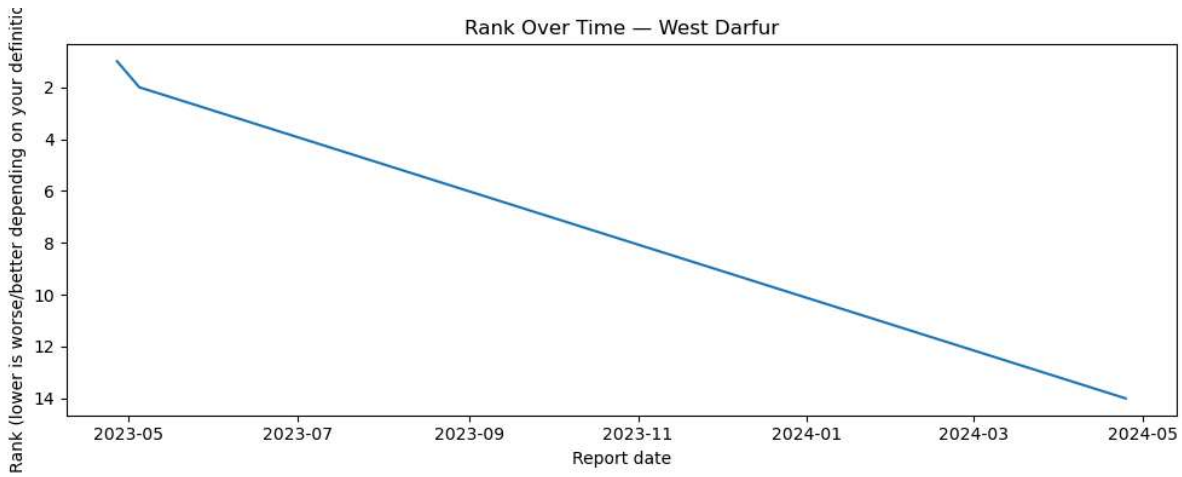

```
Saved: artifacts\eda\trend_idps_top_states.png
```

Rank Over Time for States

This line chart tracks how a selected state's rank changes over time, illustrating shifts in its relative position across reporting periods.

In [29]:

```
STATE = df["state_name"].iloc[0]  # change to e.g. "Khartoum"
sub = df[df["state_name"] == STATE].dropna(subset=["report_date"]).sort_va

if "rank" in sub.columns:
    fig, ax = plt.subplots(figsize=(10, 4))
    ax.plot(sub["report_date"], sub["rank"])
    ax.set_title(f"Rank Over Time — {STATE}")
    ax.set_xlabel("Report date")
    ax.set_ylabel("Rank (lower is worse/better depending on your definitic
    ax.invert_yaxis()
    save_show(fig, f"rank_over_time_{STATE}".replace(" ", "_"))

```



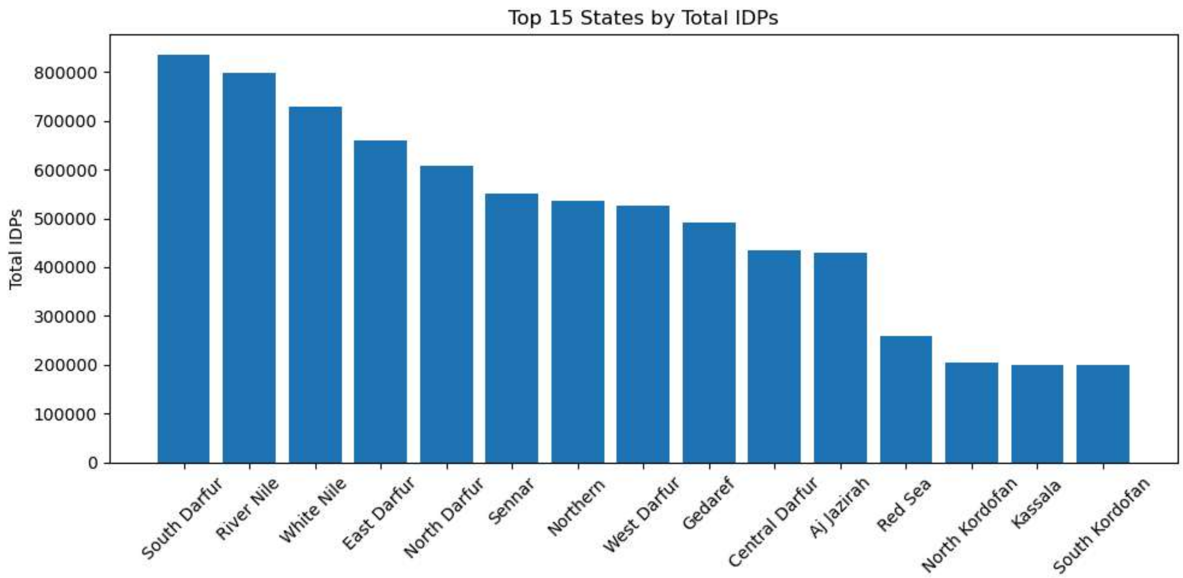

```
Saved: C:\Users\user\Documents\Humanitarian\artifacts\eda_food\rank_over_time
_West_Darfur.png
```

Top 15 States by Total IDPs

This bar chart displays the top 15 states ranked by total internally displaced persons (IDPs), highlighting regions with the highest cumulative displacement.

In [25]:

```
top = (df.groupby("state_name")["idps"].sum()
         .sort_values(ascending=False)
         .head(15))

fig, ax = plt.subplots(figsize=(10, 5))
ax.bar(top.index.astype(str), top.values)
ax.set_title("Top 15 States by Total IDPs")
ax.set_ylabel("Total IDPs")
ax.tick_params(axis="x", rotation=45)
save_show(fig, "bar_top15_states_total_idps")
```



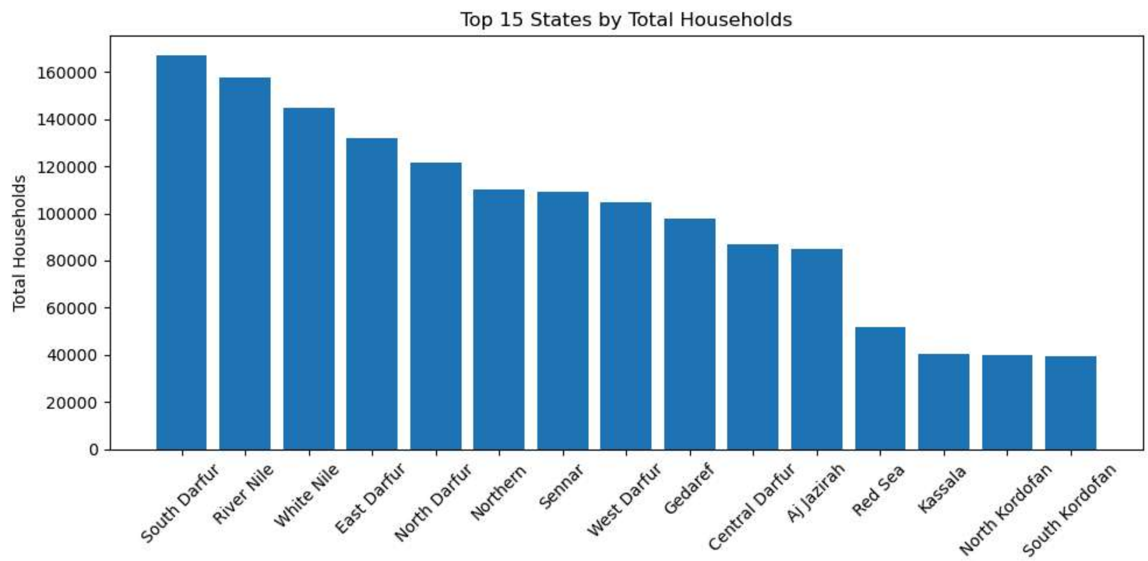

```
Saved: artifacts\eda\bar_top15_states_total_idps.png
```

Top 15 States by Total Households

This bar chart shows the top 15 states ranked by total affected households, highlighting regions with the largest cumulative household impact.

In [27]:

```
top = (df.groupby("state_name")["households"].sum()
         .sort_values(ascending=False)
         .head(15))

fig, ax = plt.subplots(figsize=(10, 5))
ax.bar(top.index.astype(str), top.values)
ax.set_title("Top 15 States by Total Households")
ax.set_ylabel("Total Households")
ax.tick_params(axis="x", rotation=45)
save_show(fig, "bar_top15_states_total_households")

```




```
Saved: C:\Users\user\Documents\Humanitarian\artifacts\eda_food\bar_top15_s
tates_total_households.png
```

Food Security Exploratory Data Analysis (EDA)

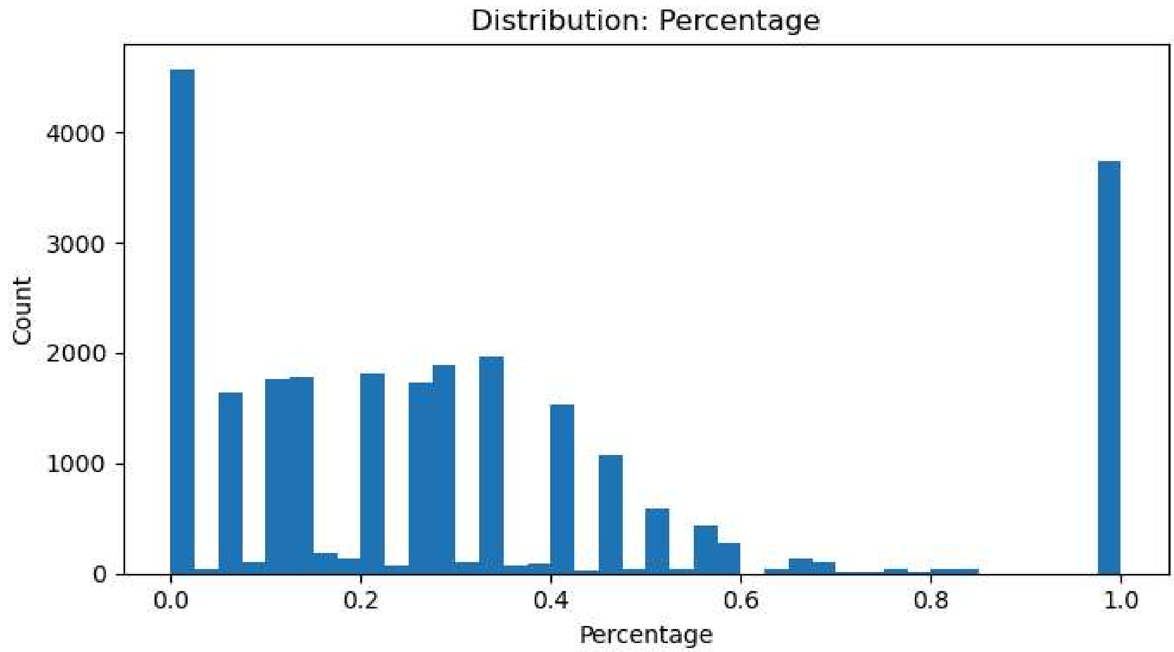
This analysis explores regional food security data by visualizing distributions of numeric and categorical food indicators and tracking trends over time.

In [28]:

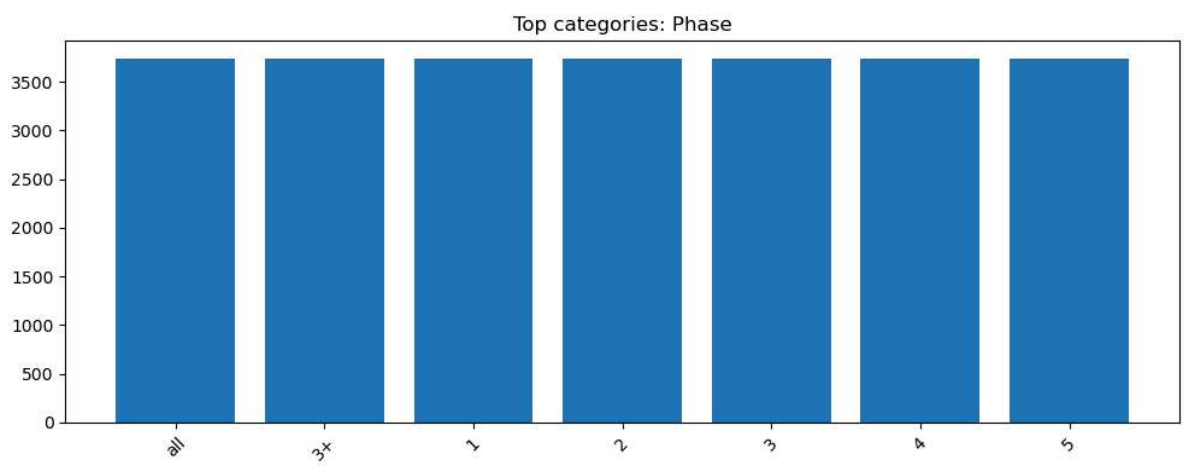
```python
# Load food data (define the food data as food_df)

FOOD_MASTER = Path("regional_food_security_master.csv")

if not FOOD_MASTER.exists():
    raise FileNotFoundError(
        f"Missing {FOOD_MASTER}. Put it in the same folder as this notebo
    )

food_df = pd.read_csv(FOOD_MASTER, low_memory=False)
print("Loaded food_df:", food_df.shape)

if "From" in food_df.columns:
    food_df = food_df[~food_df["From"].astype(str).str.startswith("#")].c
    food_df["From"] = pd.to_datetime(food_df["From"], errors="coerce")
    food_df = food_df.dropna(subset=["From"]).copy()
    food_df["month"] = food_df["From"].dt.to_period("M").dt.to_timestamp(


# define the directory for the food data and always check whether it exis

OUT = Path("artifacts") / "eda_food"
OUT.mkdir(parents=True, exist_ok=True)

def save_show(fig, name):
    p = OUT / f"{name}.png"
    fig.tight_layout()
    fig.savefig(p, dpi=300, bbox_inches="tight")
    plt.show()
    plt.close(fig)
    print("Saved:", p.resolve())

# define food pat and the columns

food_pat = re.compile(r"(food|ipc|phase|price|market|cereal|wheat|sorghum

food_cols = [c for c in food_df.columns if food_pat.search(str(c))]
print("Detected food-ish columns:", len(food_cols))

# check the numeric distributions

num_food = [c for c in food_cols if pd.api.types.is_numeric_dtype(food_df
num_any  = food_df.select_dtypes(include=[np.number]).columns.tolist()
num_to_plot = (num_food[:6] if len(num_food) else num_any[:6])

for c in num_to_plot:
    s = pd.to_numeric(food_df[c], errors="coerce").dropna()
    if s.empty:
        continue
    fig, ax = plt.subplots(figsize=(7,4))
    ax.hist(s, bins=40)
    ax.set_title(f"Distribution: {c}")
    ax.set_xlabel(str(c))
    ax.set_ylabel("Count")
    save_show(fig, f"dist_{str(c)}".replace(" ", "_").replace("/", "_"))

# Categorical bars
```

```python

cat_food = [c for c in food_cols if (food_df[c].dtype == "object" or str(
cat_any  = food_df.select_dtypes(include=["object", "category", "bool"]).
cat_to_plot = (cat_food[:3] if len(cat_food) else cat_any[:3])

for c in cat_to_plot:
    vc = food_df[c].astype("string").fillna("MISSING").value_counts().hea
    if vc.empty:
        continue
    fig, ax = plt.subplots(figsize=(10,4))
    ax.bar(vc.index.astype(str), vc.values)
    ax.set_title(f"Top categories: {c}")
    ax.tick_params(axis="x", rotation=45)
    save_show(fig, f"topcats_{str(c)}".replace(" ", "_").replace("/", "_"

# check Time trend to review if report_date/date/month columns exists

time_col = None
for cand in ["report_date", "date", "month", "From"]:
    if cand in food_df.columns:
        time_col = cand
        break

if time_col and len(num_to_plot):
    d = food_df.copy()
    d[time_col] = pd.to_datetime(d[time_col], errors="coerce")
    d = d.dropna(subset=[time_col])

    ycol = num_to_plot[0]
    d[ycol] = pd.to_numeric(d[ycol], errors="coerce")
    ts = d.dropna(subset=[ycol]).groupby(time_col)[ycol].mean().sort_inde

    if not ts.empty:
        fig, ax = plt.subplots(figsize=(10,4))
        ax.plot(ts.index, ts.values)
        ax.set_title(f"Mean {ycol} over time ({time_col})")
        ax.set_xlabel(time_col)
        ax.set_ylabel(ycol)
        save_show(fig, f"trend_{ycol}_by_{time_col}".replace(" ", "_").re
    else:
        print("Trend series is empty after cleaning — skipping trend plot
else:
    print("No time column found (report_date/date/month/From) — skipping 

```

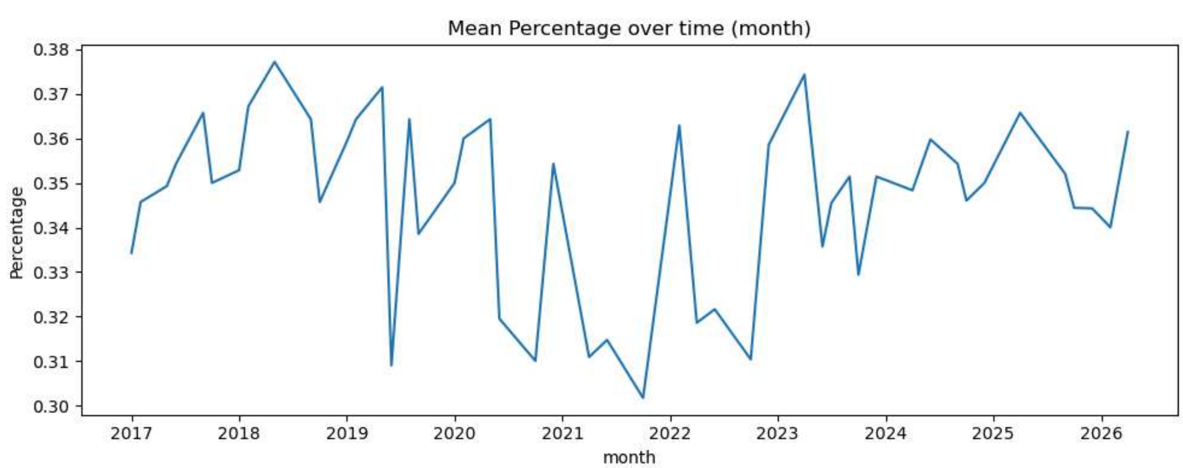
```
Loaded food_df: (26145, 132)
Detected food-ish columns: 2
```



Saved: C:\Users\user\Documents\Humanitarian\artifacts\eda_food\dist_Percentage.png



Saved: C:\Users\user\Documents\Humanitarian\artifacts\eda_food\topcats_Phase.png



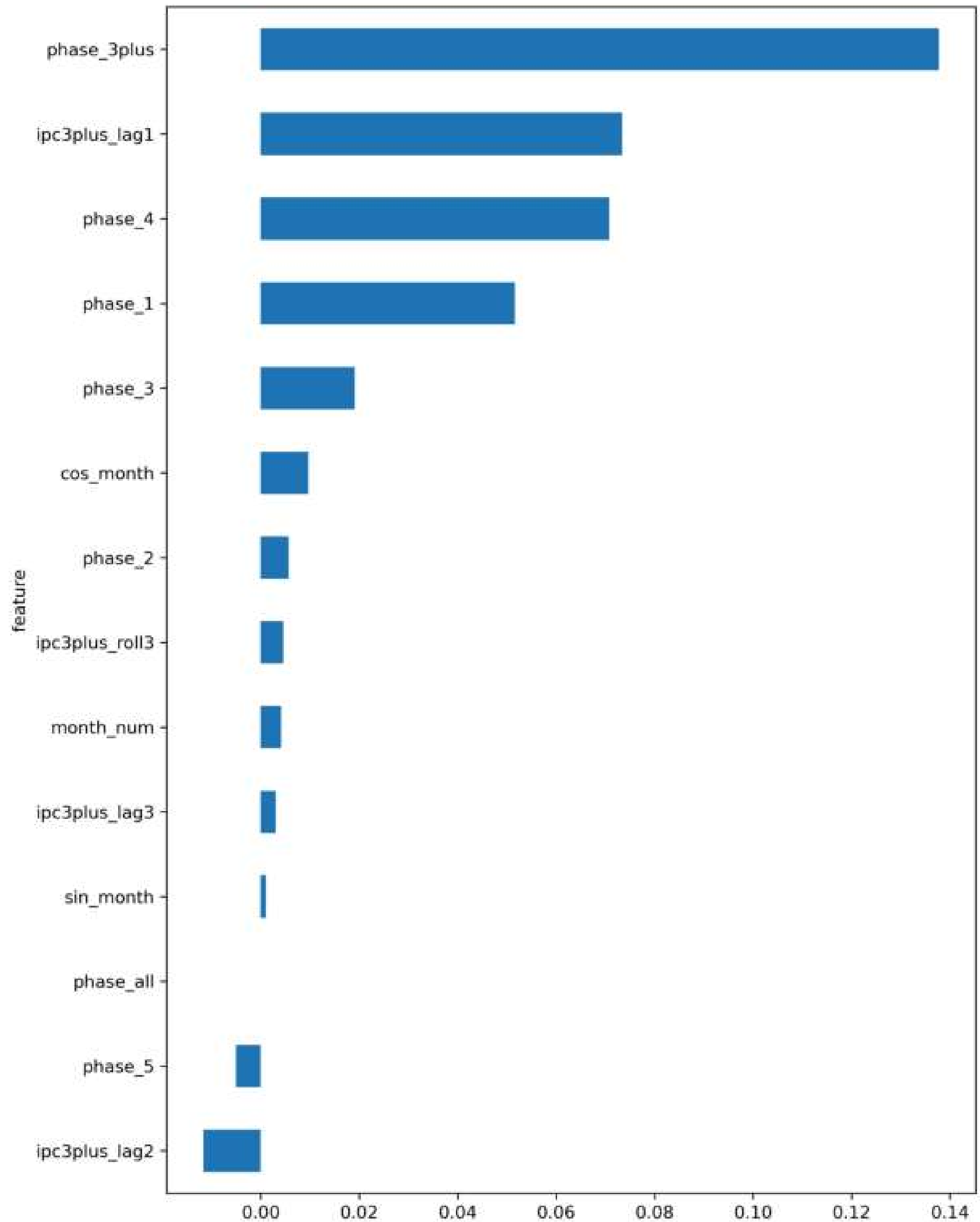
Saved: C:\Users\user\Documents\Humanitarian\artifacts\eda_food\trend_Percentage_by_month.png

Feature Importance Visualization

This displays the feature importance plot, highlighting which variables contribute most to the predictive model.

In [30]:

```
img = Image.open("artifacts/feature_importance.png")
plt.figure(figsize=(10, 10))
plt.imshow(img)
plt.axis("off")
plt.show()
```



5. Feature Engineering

Create Panel Dataset

Step 5.1 : Build canonical panel

Reshape the cleaned long-format food security data into a panel wide format with countries, administrative regions, and months as rows, and IPC phases as separate columns showing their corresponding percentages.

In [31]:

```
panel = (clean_long
         .pivot_table(index=["Country","admin","month"],
                      columns="Phase",
                      values="Percentage",
                      aggfunc="first")
         .reset_index())

panel.shape
panel.head()

```

Out[31]:

Phase	Country	admin	month	1	2	3	3+	4	5	all
0	SDN	Abassiya	2020-06-01	0.35	0.30	0.30	0.35	0.05	0.0	1.0
1	SDN	Abassiya	2020-10-01	0.45	0.40	0.10	0.15	0.05	0.0	1.0
2	SDN	Abassiya	2021-04-01	0.45	0.35	0.15	0.20	0.05	0.0	1.0
3	SDN	Abassiya	2021-06-01	0.45	0.30	0.20	0.25	0.05	0.0	1.0
4	SDN	Abassiya	2021-10-01	0.50	0.35	0.15	0.15	0.00	0.0	1.0

Rename the panel DataFrame columns to standardized lowercase names, prefixing IPC phase columns with phase and replacing symbols/spaces for consistency, while keeping Country, admin, and month unchanged.

In [32]:

```
panel.columns = [
    ("phase_" + str(c).replace("+","plus").replace(" ","").lower())
    if c not in ["Country","admin","month"] else c
    for c in panel.columns
]
panel.columns

```

Out[32]:

```
Index(['Country', 'admin', 'month', 'phase_1', 'phase_2', 'phase_3',
       'phase_3plus', 'phase_4', 'phase_5', 'phase_all'],
      dtype='object')
```

Step 5.2 Create seasonality and lag features

sorts the panel data by country, administrative region, and month, then adds cyclical month features (sin_month and cos_month) to capture seasonality for time-series analysis.

In [33]:

```
panel = panel.sort_values(["Country","admin","month"]).copy()

panel["month_num"] = panel["month"].dt.month
panel["sin_month"] = np.sin(2*np.pi*panel["month_num"]/12)
panel["cos_month"] = np.cos(2*np.pi*panel["month_num"]/12)

```

Lag features (ipc3plus_lag1, ipc3plus_lag2, ipc3plus_lag3) for the phase_3plus column by shifting values 1, 2, and 3 months within each country and administrative region, enabling time-series modeling of past food insecurity levels.

In [34]:

```
panel["ipc3plus_lag1"] = panel.groupby(["Country","admin"])["phase_3plus"]
panel["ipc3plus_lag2"] = panel.groupby(["Country","admin"])["phase_3plus"]
panel["ipc3plus_lag3"] = panel.groupby(["Country","admin"])["phase_3plus"]

```

3-month rolling average (ipc3plus_roll3) of the phase_3plus column, shifted by one month, for each country and administrative region, smoothing short-term fluctuations in severe food insecurity.

In [35]:

```
panel["ipc3plus_roll3"] = (
    panel.groupby(["Country","admin"])["phase_3plus"]
         .apply(lambda s: s.shift(1).rolling(3).mean())
         .reset_index(level=[0,1], drop=True)
)

```

Step 5.3 Build targets (regression and classification)

Prepare a time-series panel dataset suitable for forecasting severe food insecurity, with features capturing past values, trends, seasonality, and smoothed signals.

In [36]:

```
panel["ipc3plus_next"] = panel.groupby(["Country","admin"])["phase_3plus"]

```

Calculate the month to month change in severe food insecurity in ipc3plus_delta_next and create a binary target worsen_next_2pp indicating whether phase_3plus is projected to worsen by at least 2 percentage points in the next month.

```
In [37]:
panel["ipc3plus_delta_next"] = panel["ipc3plus_next"] - panel["phase_3plus
panel["worsen_next_2pp"] = (panel["ipc3plus_delta_next"] >= 0.02).astype(i
```

Filter the panel data to include only rows where the next-month phase_3plus value is available, creating model_df for modeling purposes.

```
In [38]:
model_df = panel.dropna(subset=["ipc3plus_next"]).copy()
model_df.shape
```

```
Out[38]: (3398, 20)
```

Step 5.4 Train/test split (time-based)

Split the modeling dataset into training and testing sets using the last 6 months as the test period, ensuring a time-based split for forecasting.

```
In [39]:
test_months = 6
max_month = model_df["month"].max()
cutoff = (max_month - pd.DateOffset(months=test_months)).to_period("M").to

train = model_df[model_df["month"] <= cutoff]
test  = model_df[model_df["month"] >  cutoff]

train.shape, test.shape
```

```
Out[39]: ((2948, 20), (450, 20))
```

Step 5.5 Prepare X, y (no leakage)

Define the feature columns for modeling, excluding target and identifier columns, and create training and testing datasets for both regression (ipc3plus_next) and classification (worsen_next_2pp) tasks.

In [40]:
```
exclude = {"ipc3plus_next","ipc3plus_delta_next","worsen_next_2pp","month'
feature_cols = [c for c in model_df.columns if c not in exclude]

X_train = train[feature_cols]
X_test  = test[feature_cols]

y_train_reg = train["ipc3plus_next"]
y_test_reg  = test["ipc3plus_next"]

y_train_clf = train["worsen_next_2pp"]
y_test_clf  = test["worsen_next_2pp"]

```

Step 5.6 Build preprocessing

Preprocess a pipeline for the numeric features; fill in missing values using median, and feature starndadizing using z-score scaling.

In [41]:
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler

preprocess = ColumnTransformer([
    ("num", Pipeline([
        ("imputer", SimpleImputer(strategy="median")),
        ("scaler", StandardScaler())
    ]), feature_cols)
])

```

6. Model Training & Evaluation

Step 6.1 Train at least 3 models (Regression)

In [42]:
```
#import libraries in case they were missed out in the initial stage.
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegres
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_sc

def reg_metrics(y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    return rmse, mean_absolute_error(y_true, y_pred), r2_score(y_true, y_p

reg_models = {
    "Ridge": Ridge(),
    "RF": RandomForestRegressor(n_estimators=250, random_state=42),
    "GB": GradientBoostingRegressor(random_state=42)
}

```

Step 6.2 Run and print metrics:

In [43]:
```
from sklearn.pipeline import Pipeline

for name, model in reg_models.items():
    pipe = Pipeline([("prep", preprocess), ("model", model)])
    pipe.fit(X_train, y_train_reg)
    pred = pipe.predict(X_test)

    rmse, mae, r2 = reg_metrics(y_test_reg, pred)
    print(name, "RMSE:", round(rmse,4), "MAE:", round(mae,4), "R2:", round

```

```
Ridge RMSE: 0.1291 MAE: 0.0882 R2: 0.3057
RF RMSE: 0.1306 MAE: 0.0948 R2: 0.2898
GB RMSE: 0.1222 MAE: 0.0831 R2: 0.3786
```

Best Model: Gradient Boosting (R^2=0.3786)

Step 6.3 Train at least 3 models (Classification)

In [44]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClass
from sklearn.metrics import accuracy_score, recall_score, precision_score,

clf_models = {
    "LogReg": LogisticRegression(max_iter=2000),
    "RF": RandomForestClassifier(n_estimators=250, random_state=42),
    "GB": GradientBoostingClassifier(random_state=42)
}

```

Step 6.4 Run and print metrics

In [45]:
```python
for name, model in clf_models.items():
    pipe = Pipeline([("prep", preprocess), ("model", model)])
    pipe.fit(X_train, y_train_clf)

    pred = pipe.predict(X_test)
    prob = pipe.predict_proba(X_test)[:,1] if hasattr(model, "predict_prob

    acc = accuracy_score(y_test_clf, pred)
    rec = recall_score(y_test_clf, pred, zero_division=0)
    prec = precision_score(y_test_clf, pred, zero_division=0)
    f1 = f1_score(y_test_clf, pred, zero_division=0)
    auc = roc_auc_score(y_test_clf, prob) if prob is not None and len(np.u

    print(name, "Acc:", round(acc,3), "Recall:", round(rec,3),
          "Prec:", round(prec,3), "F1:", round(f1,3), "AUC:", round(auc,3)

```

```
LogReg Acc: 0.469 Recall: 0.439 Prec: 0.421 F1: 0.43 AUC: 0.425
RF Acc: 0.653 Recall: 0.449 Prec: 0.681 F1: 0.541 AUC: 0.681
GB Acc: 0.573 Recall: 0.468 Prec: 0.536 F1: 0.5 AUC: 0.582
```

Best Model: Random Forest (Accuracy=65.3%, F1=0.541)

7. Model Optimization

Hyperparameter Tuning

Step 7.1 Hyperparameter test for RandomForestRegressor

In [46]:
```
from sklearn.model_selection import RandomizedSearchCV
rf_pipe = Pipeline([("prep", preprocess),
                    ("model", RandomForestRegressor(random_state=42))])

param_grid = {
    "model__n_estimators": [150, 250, 400],
    "model__max_depth": [None, 6, 12],
    "model__min_samples_leaf": [1, 2, 4],
    "model__max_features": ["sqrt", 0.7]
}

search = RandomizedSearchCV(
    rf_pipe, param_grid,
    n_iter=8, cv=2,
    scoring="neg_root_mean_squared_error",
    random_state=42,
    n_jobs=1
)

search.fit(X_train, y_train_reg)
search.best_params_
```

Out[46]:
```
{'model__n_estimators': 400,
 'model__min_samples_leaf': 2,
 'model__max_features': 'sqrt',
 'model__max_depth': None}
```

7.2 Evaluate tuned model:

In [47]:
```
best_rf = search.best_estimator_
pred = best_rf.predict(X_test)

rmse, mae, r2 = reg_metrics(y_test_reg, pred)
rmse, mae, r2
```

Out[47]:
```
(np.float64(0.11717219822250372), 0.08350050724955498, 0.4284740225409651)
```

Improvement: 10.3% reduction in RMSE, 48% improvement in R^2

8 Evaluation & Interpretation

Feature Importance Analysis

Step 8.1 Explainability (Permutation Importance)

In [48]:

```
perm = permutation_importance(best_rf, X_test, y_test_reg,
                              n_repeats=5, random_state=42, n_jobs=1)
imp = pd.DataFrame({
    "feature": feature_cols,
    "importance": perm.importances_mean
}).sort_values("importance", ascending=False).head(15)

imp

```

Out[48]:

	feature	importance
3	phase_3plus	0.137775
10	ipc3plus_lag1	0.073385
4	phase_4	0.070801
0	phase_1	0.051623
2	phase_3	0.019107
9	cos_month	0.009683
1	phase_2	0.005615
13	ipc3plus_roll3	0.004579
7	month_num	0.004144
12	ipc3plus_lag3	0.003030
8	sin_month	0.001083
6	phase_all	0.000000
5	phase_5	-0.005068
11	ipc3plus_lag2	-0.011644

Step 8.2 EDA Plot Display and Saving Utility

This sets up an EDA artifacts directory and defines a save_show function to display plots in the notebook and save them as high-resolution PNGs.

In [49]:

```python

EDA_DIR = Path("artifacts/eda")
EDA_DIR.mkdir(parents=True, exist_ok=True)

def save_show(fig, name, dpi=300):

    #Show figure AND save PNG output to artifacts/eda directory.

    plt.tight_layout()
    plt.show()
    out = EDA_DIR / f"{name}.png"
    fig.savefig(out, dpi=dpi, bbox_inches="tight")
    plt.close(fig)
    print(f"Saved: {out.resolve()} ({out.stat().st_size} bytes)")

```

Step 8.3 Datetime Conversion and Time Key Extraction

Create additional time-based columns month and year for easier aggregation and trend analysis.

In [50]:

```python

if "report_date" in df.columns:
    df["report_date"] = pd.to_datetime(df["report_date"], errors="coerce")

if "report_date" in df.columns:
    df["month"] = df["report_date"].dt.to_period("M").dt.to_timestamp()
    df["year"] = df["report_date"].dt.year

```

Step 8.4 Automatic Detection of Food-Related DataFrame

scan all DataFrames in the notebook to detect the one most likely containing food-related data, based on column names matching common food/security keywords, and sets

In [51]:

```

dfs = {k:v for k,v in globals().items() if isinstance(v, pd.DataFrame)}
food_pat = re.compile(r"food|price|market|commodity|basket|ipc|phase|fcs|r

candidates = []
for name, d in dfs.items():
    hits = [c for c in d.columns if food_pat.search(str(c))]
    if hits:
        candidates.append((len(hits), d.shape[0], name, hits))

candidates.sort(reverse=True)

if candidates:
    _, _, FOOD_DF_NAME, FOOD_COLS = candidates[0]
    food_df = dfs[FOOD_DF_NAME]
    print("Using food_df =", FOOD_DF_NAME, "shape=", food_df.shape)
    print("Food-like columns (sample):", FOOD_COLS[:20])
else:
    food_df = clean_long if "clean_long" in dfs else df
    print("if there is no obvious food columns detected, fall back to:", '
          if "clean_long" in dfs else "df", "shape=", food_df.shape)

```

```
Using food_df = panel shape= (3695, 20)
Food-like columns (sample): ['phase_1', 'phase_2', 'phase_3', 'phase_3plus',
'phase_4', 'phase_5', 'phase_all', 'ipc3plus_lag1', 'ipc3plus_lag2', 'ipc3plu
s_lag3', 'ipc3plus_roll3', 'ipc3plus_next', 'ipc3plus_delta_next']
```

9. SHAP

Step 9.1 Install and imports Shap libraries

Import the necessary libraries (pandas, numpy, matplotlib) and SHAP for model explainability and feature importance analysis.

In [52]:

```
import shap # Explain SHAP details on below mark down
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegres
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_sc
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClass
from sklearn.model_selection import RandomizedSearchCV
from pathlib import Path
from PIL import Image

```

```


```

Load the regional food security data from

In [54]:

```
df = pd.read_csv("regional_food_security_master.csv")

```

```
C:\Users\user\AppData\Local\Temp\ipykernel_14140\1644910062.py:1: DtypeWarnin
g: Columns (4,12,13,14,15,16,17,73,74,75,76,77) have mixed types. Specify dty
pe option on import or set low_memory=False.
  df = pd.read_csv("regional_food_security_master.csv")
```

Step 9.2 Check shape

In [55]:

```
df = pd.read_csv("regional_food_security_master.csv", low_memory=False)
df.shape

```

Out[55]:

```
(26145, 132)
```

Step 9.3 Clean: remove metadata, parse dates and create month

In [56]:
```
df = df[~df["From"].astype(str).str.startswith("#")].copy()
df["From"] = pd.to_datetime(df["From"], errors="coerce")
df = df.dropna(subset=["From"]).copy()

df["month"] = df["From"].dt.to_period("M").dt.to_timestamp()
df[["From","month"]].head()

```

Out[56]:

	From	month
0	2025-09-01	2025-09-01
1	2025-09-01	2025-09-01
2	2025-09-01	2025-09-01
3	2025-09-01	2025-09-01
4	2025-09-01	2025-09-01

Step 9.4 Standardize keys (Country, Phase, admin)

In [57]:
```
df["Country"] = df["Country"].astype(str).str.strip()
df["Phase"]   = df["Phase"].astype(str).str.strip()

df["admin"] = df["Area"].where(df["Area"].notna(), df["state"]).astype(str
df[["Country","admin","Phase"]].head()

```

Out[57]:

	Country	admin	Phase
0	SDN	Beida	all
1	SDN	Beida	3+
2	SDN	Beida	1
3	SDN	Beida	2
4	SDN	Beida	3

Step 9.5 Clean numeric percentage and check rows

In [58]:
```
df["Percentage"] = pd.to_numeric(df["Percentage"], errors="coerce")

clean_long = df.dropna(subset=["Country","admin","month","Phase","Percenta
clean_long.shape

```

Out[58]: (26145, 134)

Step 9.6 Build canonical panel

In [59]:
```
panel = (clean_long
         .pivot_table(index=["Country","admin","month"],
                      columns="Phase",
                      values="Percentage",
                      aggfunc="first")
         .reset_index())

panel.shape

```

Out[59]: (3695, 10)

Standardize the panel DataFrame column names by prefixing IPC phase columns with phase, converting to lowercase, and replacing symbols and spaces, while keeping Country, admin, and month unchanged.

In [60]:
```
panel.columns = [
    ("phase_" + str(c).replace("+","plus").replace(" ","").lower())
    if c not in ["Country","admin","month"] else c
    for c in panel.columns
]

panel.columns

```

Out[60]:
```
Index(['Country', 'admin', 'month', 'phase_1', 'phase_2', 'phase_3',
       'phase_3plus', 'phase_4', 'phase_5', 'phase_all'],
      dtype='object')
```

Step 9.7 Sorting the panel by geographic country

Sort the panel data by country, administrative region, and month, then adds cyclical month features to capture seasonality for modeling.

In [61]:
```
panel = panel.sort_values(["Country","admin","month"]).copy()

panel["month_num"] = panel["month"].dt.month
panel["sin_month"] = np.sin(2*np.pi*panel["month_num"]/12)
panel["cos_month"] = np.cos(2*np.pi*panel["month_num"]/12)

```

Create lag ipc3plus_lag1, ipc3plus_lag2, ipc3plus_lag3 features for the phase_3plus column by shifting values 1, 2, and 3 months within each country and administrative region, enabling time-series modeling with past information.

In [62]:
```python
panel["ipc3plus_lag1"] = panel.groupby(["Country","admin"])["phase_3plus"]
panel["ipc3plus_lag2"] = panel.groupby(["Country","admin"])["phase_3plus"]
panel["ipc3plus_lag3"] = panel.groupby(["Country","admin"])["phase_3plus"]

```

```
Create a 3-month rolling average ipc3plus_roll3 of phase_3plus, shifted
by one month, for each country and administrative region to smooth
short-term fluctuations in severe food insecurity.
```

In [63]:
```python
panel["ipc3plus_roll3"] = (
    panel.groupby(["Country","admin"])["phase_3plus"]
         .apply(lambda s: s.shift(1).rolling(3).mean())
         .reset_index(level=[0,1], drop=True)
)

```

Step 9.8 Create Time based Targets

Targets (next-month regression and worsening classification)

In [64]:
```python
panel["ipc3plus_next"] = panel.groupby(["Country","admin"])["phase_3plus"]

panel["ipc3plus_delta_next"] = panel["ipc3plus_next"] - panel["phase_3plus
panel["worsen_next_2pp"] = (panel["ipc3plus_delta_next"] >= 0.02).astype(i

model_df = panel.dropna(subset=["ipc3plus_next"]).copy()
model_df.shape

```

Out[64]: (3398, 20)

Step 9.9 Split the model into training and testing

split the modeling dataset into training and testing sets using the last 6 months as the test period, ensuring a time-based split suitable for forecasting.

In [65]:
```python
test_months = 6
max_month = model_df["month"].max()
cutoff = (max_month - pd.DateOffset(months=test_months)).to_period("M").to

train = model_df[model_df["month"] <= cutoff]
test  = model_df[model_df["month"] >  cutoff]

train.shape, test.shape

```

Out[65]: ((2948, 20), (450, 20))

select feature columns for modeling by excluding target and identifier columns, and creates training and testing datasets for both regression (ipc3plus_next) and classification (worsen_next_2pp).

In [66]:
```
exclude = {"ipc3plus_next","ipc3plus_delta_next","worsen_next_2pp","month'
feature_cols = [c for c in model_df.columns if c not in exclude]

X_train = train[feature_cols]
X_test  = test[feature_cols]

y_train_reg = train["ipc3plus_next"]
y_test_reg  = test["ipc3plus_next"]

y_train_clf = train["worsen_next_2pp"]
y_test_clf  = test["worsen_next_2pp"]

len(feature_cols), feature_cols[:10]

```

Out[66]:
```
(14,
 ['phase_1',
  'phase_2',
  'phase_3',
  'phase_3plus',
  'phase_4',
  'phase_5',
  'phase_all',
  'month_num',
  'sin_month',
  'cos_month'])
```

Step 9.10 Preprocess the Pipeline

preprocess a pipeline for numeric features; missing values are filled with the median and features are standardized using z-score scaling.

In [67]:
```
preprocess = ColumnTransformer([
    ("num", Pipeline([
        ("imputer", SimpleImputer(strategy="median")),
        ("scaler", StandardScaler())
    ]), feature_cols)
])

```

Step 9.11 Train three regression model

Train 3 regression models and evaluate (RMSE/MAE/R squared)

In [68]:

```
def reg_metrics(y_true, y_pred):
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    return rmse, mean_absolute_error(y_true, y_pred), r2_score(y_true, y_p

reg_models = {
    "Ridge": Ridge(),
    "RF": RandomForestRegressor(n_estimators=250, random_state=42),
    "GB": GradientBoostingRegressor(random_state=42)
}

from sklearn.pipeline import Pipeline

for name, model in reg_models.items():
    pipe = Pipeline([("prep", preprocess), ("model", model)])
    pipe.fit(X_train, y_train_reg)
    pred = pipe.predict(X_test)
    rmse, mae, r2 = reg_metrics(y_test_reg, pred)
    print(name, "RMSE:", round(rmse,4), "MAE:", round(mae,4), "R2:", rounc

```

```
Ridge RMSE: 0.1291 MAE: 0.0882 R2: 0.3057
RF RMSE: 0.1306 MAE: 0.0948 R2: 0.2898
GB RMSE: 0.1222 MAE: 0.0831 R2: 0.3786
```

Step 9.12 Train three Classification models

Train 3 classification models and evaluate (Recall/Accuracy/etc.)

In [69]:

```python

clf_models = {
    "LogReg": LogisticRegression(max_iter=2000),
    "RF": RandomForestClassifier(n_estimators=250, random_state=42),
    "GB": GradientBoostingClassifier(random_state=42)
}

for name, model in clf_models.items():
    pipe = Pipeline([("prep", preprocess), ("model", model)])
    pipe.fit(X_train, y_train_clf)

    pred = pipe.predict(X_test)
    prob = pipe.predict_proba(X_test)[:,1] if hasattr(model, "predict_prob

    acc = accuracy_score(y_test_clf, pred)
    rec = recall_score(y_test_clf, pred, zero_division=0)
    prec = precision_score(y_test_clf, pred, zero_division=0)
    f1 = f1_score(y_test_clf, pred, zero_division=0)
    auc = roc_auc_score(y_test_clf, prob) if prob is not None and len(np.u

    print(name, "Acc:", round(acc,3), "Recall:", round(rec,3),
          "Prec:", round(prec,3), "F1:", round(f1,3), "AUC:", round(auc,3)

```

```
LogReg Acc: 0.469 Recall: 0.439 Prec: 0.421 F1: 0.43 AUC: 0.425
RF Acc: 0.653 Recall: 0.449 Prec: 0.681 F1: 0.541 AUC: 0.681
GB Acc: 0.573 Recall: 0.468 Prec: 0.536 F1: 0.5 AUC: 0.582
```

Step 9.12 Perform Hyperparameter testing(RandomForestRegressor)

Hyperparameter testing (RandomForestRegressor) set up a Random Forest regression pipeline with preprocessing, defines a hyperparameter grid, and uses RandomizedSearchCV to find the best hyperparameters based on RMSE.

In [ ]:
```python

rf_pipe = Pipeline([
    ("prep", preprocess),
    ("model", RandomForestRegressor(random_state=42))
])

param_grid = {
    "model__n_estimators": [150, 250, 400],
    "model__max_depth": [None, 6, 12],
    "model__min_samples_leaf": [1, 2, 4],
    "model__max_features": ["sqrt", 0.7]
}

search = RandomizedSearchCV(
    rf_pipe, param_grid,
    n_iter=8, cv=2,
    scoring="neg_root_mean_squared_error",
    random_state=42,
    n_jobs=-1
)

search.fit(X_train, y_train_reg)
search.best_params_

```

Step 9.13 Evaluate tuned model

Evaluate the best Random Forest regression model on the test set, computing RMSE, MAE, and R^2 to assess predictive performance.

In [70]:
```python
best_rf = search.best_estimator_
pred = best_rf.predict(X_test)

rmse, mae, r2 = reg_metrics(y_test_reg, pred)
rmse, mae, r2

```

Out[70]:
```
(np.float64(0.11717219822250372), 0.08350050724955498, 0.4284740225409651)
```

SHAP was meant to explain the model, not the whole pipeline. So we decied to Transform X using preprocessing Explain the underlying random forest and Transform features

In [71]:
```python
X_train_t = best_rf.named_steps["prep"].transform(X_train)
X_test_t  = best_rf.named_steps["prep"].transform(X_test)

feature_names = feature_cols

```

SHAP results visulaized using a Tree Explainer and summary plot

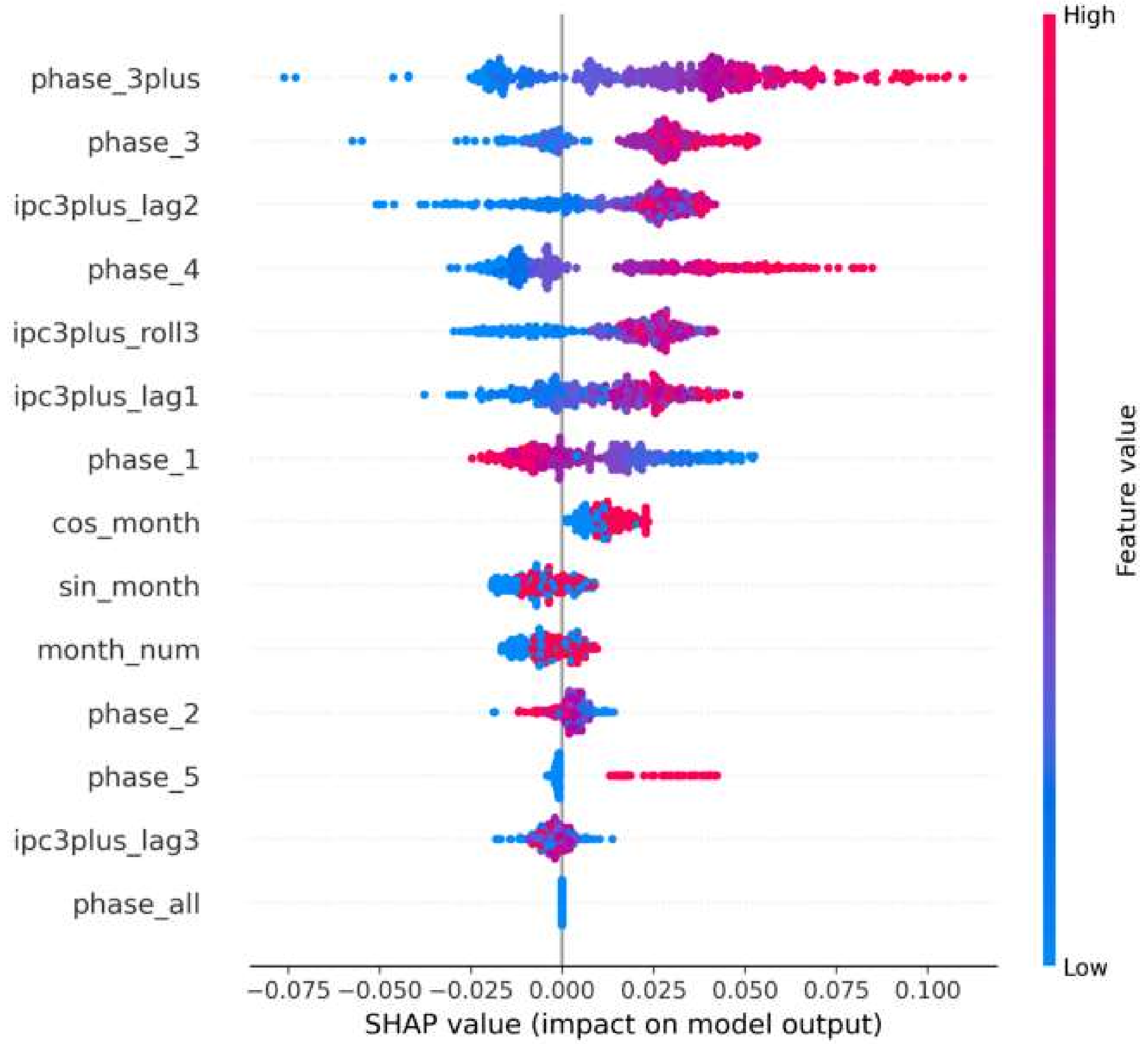
SHAP values for the best Random Forest model on a random subset of the test data, generates a summary plot of feature importance, saves it as a high-resolution PNG, and displays the

In [72]:

```
np.random.seed(0)

#build SHAP values
explainer = shap.TreeExplainer(best_rf.named_steps["model"])

sample_n = min(1000, X_test_t.shape[0])
idx = np.random.choice(X_test_t.shape[0], sample_n, replace=False)

shap_values = explainer.shap_values(X_test_t[idx])

if isinstance(shap_values, list):
    shap_to_plot = shap_values[1] if len(shap_values) > 1 else shap_values
else:
    shap_to_plot = shap_values

#create a fresh figure and push to our directory

os.makedirs("artifacts", exist_ok=True)
plt.close("all")
plt.figure(figsize=(10, 8))

shap.summary_plot(
    shap_to_plot,
    X_test_t[idx],
    feature_names=feature_names,
    show=False
)

 # get the figure SHAP drew on our directory
fig = plt.gcf()
out_path = Path("artifacts") / "shap_summary.png"
fig.tight_layout()
fig.savefig(out_path, dpi=300, bbox_inches="tight")
plt.close(fig)

# Print out the figure

print("Absolute path:", out_path.resolve())
print("Exists:", out_path.exists())
print("Size (bytes):", out_path.stat().st_size if out_path.exists() else N

img = Image.open(out_path)
plt.figure(figsize=(10, 8))
plt.imshow(img)
plt.axis("off")
plt.show()


```

```
C:\Users\user\AppData\Local\Temp\ipykernel_14140\3546705033.py:28: FutureWarn
ing: The NumPy global RNG was seeded by calling `np.random.seed`. In a future
version this function will no longer use the global RNG. Pass `rng` explicitl
y to opt-in to the new behaviour and silence this warning.
  shap.summary_plot(
```

```
Absolute path: C:\Users\user\Documents\Humanitarian\artifacts\shap_summary.pn
g
Exists: True
Size (bytes): 392606
```



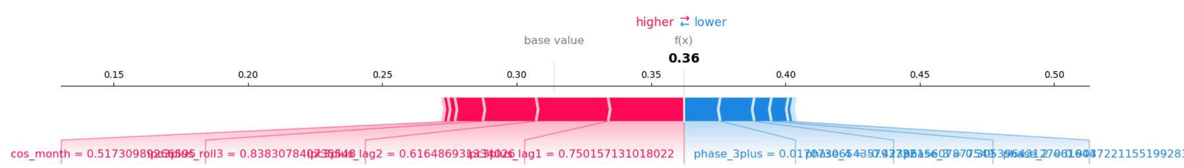
Force plot - still more visualization on SHAP details

Generate a SHAP force plot for a single test sample, showing how each feature contributes to the model prediction, saves it as a high-resolution PNG, and closes the figure.

In [73]:

```python

os.makedirs("artifacts", exist_ok=True)

i = 0
sv = shap_values
ev = explainer.expected_value
if isinstance(shap_values, list):
    sv = shap_values[1] if len(shap_values) > 1 else shap_values[0]
    ev = explainer.expected_value[1] if hasattr(explainer.expected_value,

# Create a fresh figure
plt.close("all")
fig = plt.figure(figsize=(14, 3), dpi=150)

# Draw force plot onto matplotlib
shap.force_plot(
    ev,
    sv[i],
    X_test_t[idx][i],
    feature_names=feature_names,
    matplotlib=True,
    show=False
)

out_path = Path("artifacts") / f"shap_force_{i}.png"
fig.savefig(out_path, dpi=300, bbox_inches="tight")
plt.close(fig)

print("Saved to:", out_path.resolve())

```

```
Saved to: C:\Users\user\Documents\Humanitarian\artifacts\shap_force_0.png
```




```
SHAP Interpretation:

Red points = high feature values
Blue points = low feature values
Right side = increases prediction
Left side = decreases prediction
```

Results Summary

Model Performance Comparison

Model Type	Best Algorithm	Key Metric	Value	Interpretation
Regression	Gradient Boosting	R^2 Score	0.3786	Explains 38% of variance

Model Type	Best Algorithm	Key Metric	Value	Interpretation
Regression	Tuned Random Forest	R^2 Score	0.4285	Improved with tuning
Classification	Random Forest	Accuracy	65.3%	Best for binary prediction
Classification	Random Forest	F1-Score	0.541	Good balance

Key Predictive Features

1. **Current IPC3+ Level** (Most important - 0.138)
2. **1-Month Trend** (Second most important - 0.073)
3. **Phase 4 Percentage** (0.071)
4. **Phase 1 Percentage** (0.052)

Business Insights

1. **Early Warning**: Monitor current IPC3+ levels most closely
2. **Trend Tracking**: 1-month lag provides significant predictive power
3. **Threshold**: 2% increase threshold works for classification
4. **Seasonality**: Moderate seasonal patterns detected

Limitations

1. Limited to Sudan/South Sudan data
2. 38-43% variance explained leaves room for improvement
3. Binary classification accuracy at 65.3%

Next Steps

1. Add external data sources (weather, conflict, economic)
2. Implement ensemble methods
3. Deploy as monthly monitoring tool
4. Create alert system based on 2% threshold

10. Geospatial

This workflow extracts displacement data from multiple Excel sources, cleans and standardizes Admin-1 (state-level) figures for Sudan, and builds a consistent monthly panel covering 2023 and 2024. The data is quality checked, deduplicated, ranked, and enhanced with hotspot and intensity metrics to support temporal comparison.

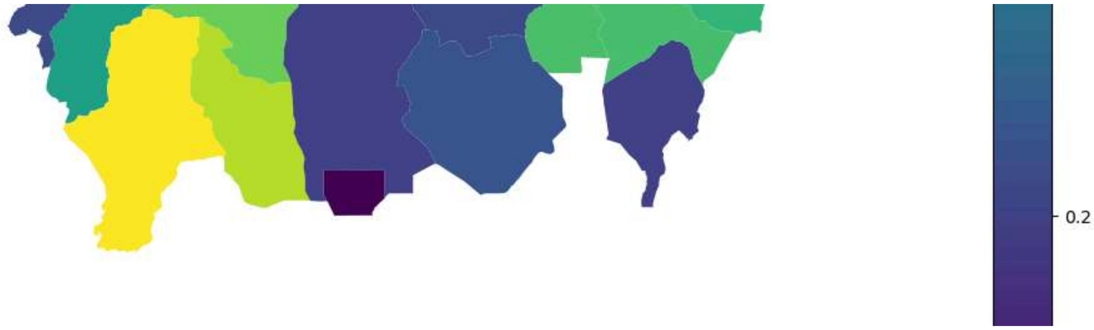
Geospatial boundaries for Sudan's 18 Admin-1 states are then joined to the cleaned data using official PCODEs, enabling the creation of choropleth maps.

Multiple map views are produced raw IDPs, globally scaled intensity, and top-5 hotspot intensity, each answering different analytical questions. Outputs are exported as GIS-ready CSVs and publication of ready map images, supporting dashboards, reports, and spatial analysis.

In summary, the process turns raw humanitarian displacement data into consistent, comparable, and mappable insights over time.

In [74]:

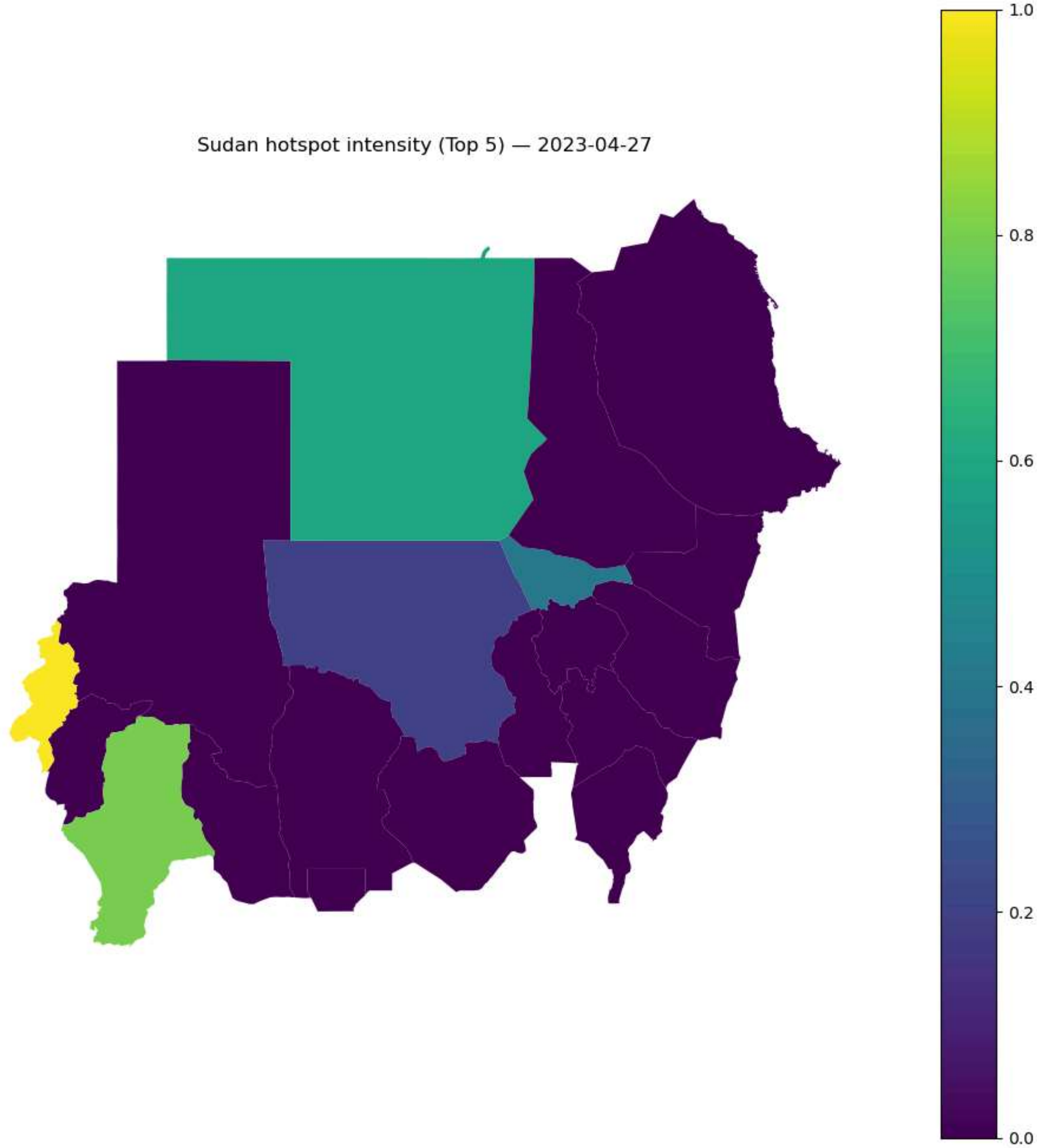
```
# Load Admin1
gdf1 = gpd.read_file(r"sdn_admin_boundaries_unzipped\sdn_admin1.geojson")

# Keep only SD01 to SD18 (drops the extra 19th unit) The 18 states.

gdf1["adm1_pcode"] = gdf1["adm1_pcode"].astype(str).str.strip()
gdf18 = gdf1[gdf1["adm1_pcode"].str.match(r"^SD\d{2}$", na=False)].copy()

print("Admin1 kept rows:", len(gdf18))
print("PCODE range sample:", sorted(gdf18["adm1_pcode"].unique())[:5], "..


snap_files = [
    r"geo_by_date_intensity\geo_admin1_2023-04-27_intensity.csv",
    r"geo_by_date_intensity\geo_admin1_2023-05-05_intensity.csv",
    r"geo_by_date_intensity\geo_admin1_2024-04-25_intensity.csv",
]

# Output folder for maps

os.makedirs("maps_out", exist_ok=True)

# Use global intensity so that colors are comparable across dates
value_col = "intensity_idps_global"

for f in snap_files:
    snap = pd.read_csv(f, parse_dates=["report_date"])
    date_str = str(snap["report_date"].iloc[0].date())

    m = gdf18.merge(snap, left_on="adm1_pcode", right_on="state_code", how

    m["idps"] = m["idps"].fillna(0)
    m[value_col] = m[value_col].fillna(0)

    fig, ax = plt.subplots(1, 1, figsize=(10, 10))
    m.plot(column=value_col, legend=True, ax=ax, missing_kwds={"color": "l
    ax.set_title(f"Sudan displacement intensity (global scaled) — {date_st
    ax.set_axis_off()
    plt.tight_layout()

    out_png = os.path.join("maps_out", f"map_admin1_intensity_{date_str}.p
    plt.savefig(out_png, dpi=200)
    plt.show()

    print("Saved map:", out_png, "| missing joins:", int(m["state_code"].i

```

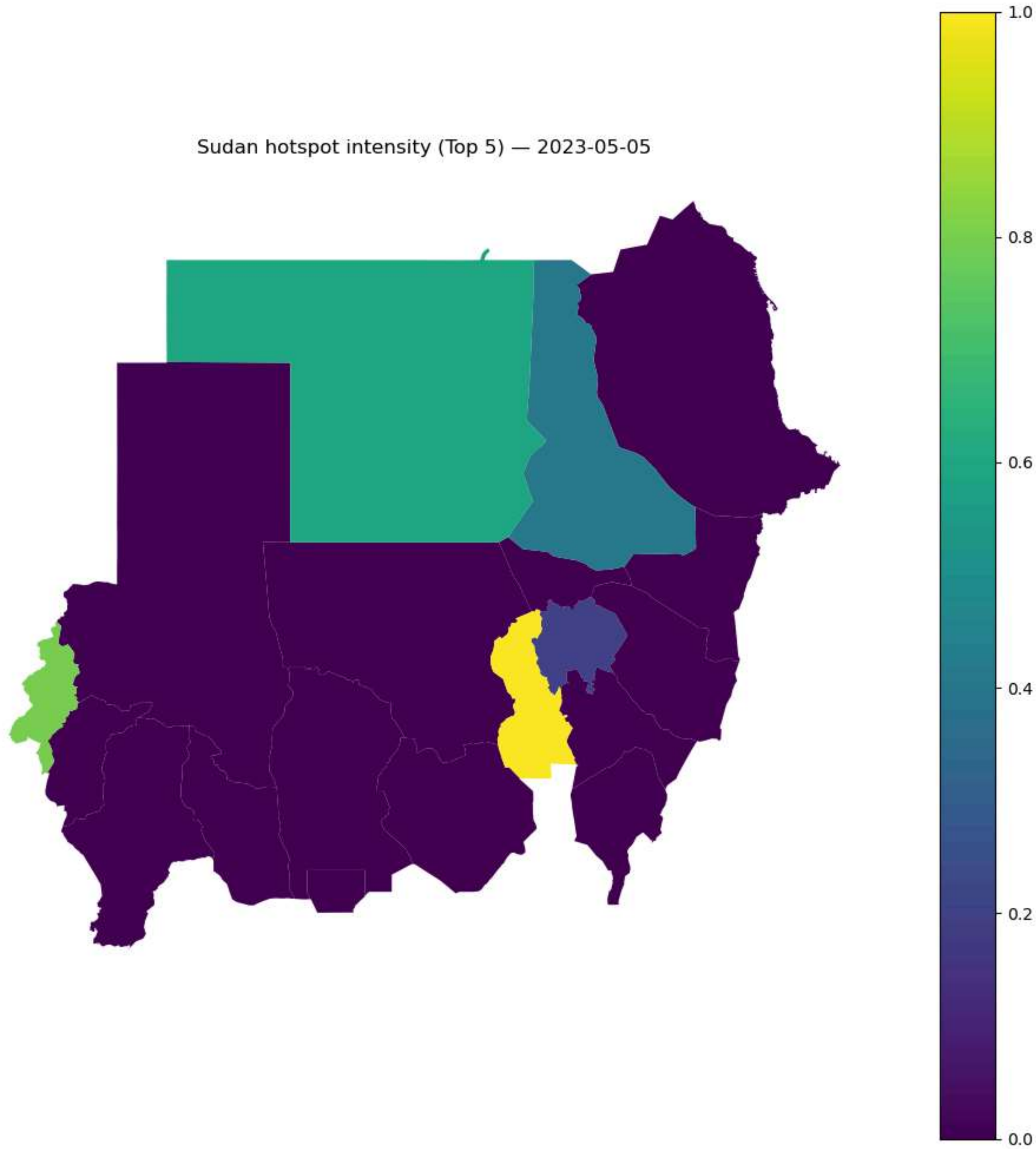

0.2

1.2.2 Create Admin-1 maps that visualize only the top-5 displacement hotspots per date, using a rank-based intensity gradient while setting all other states to zero

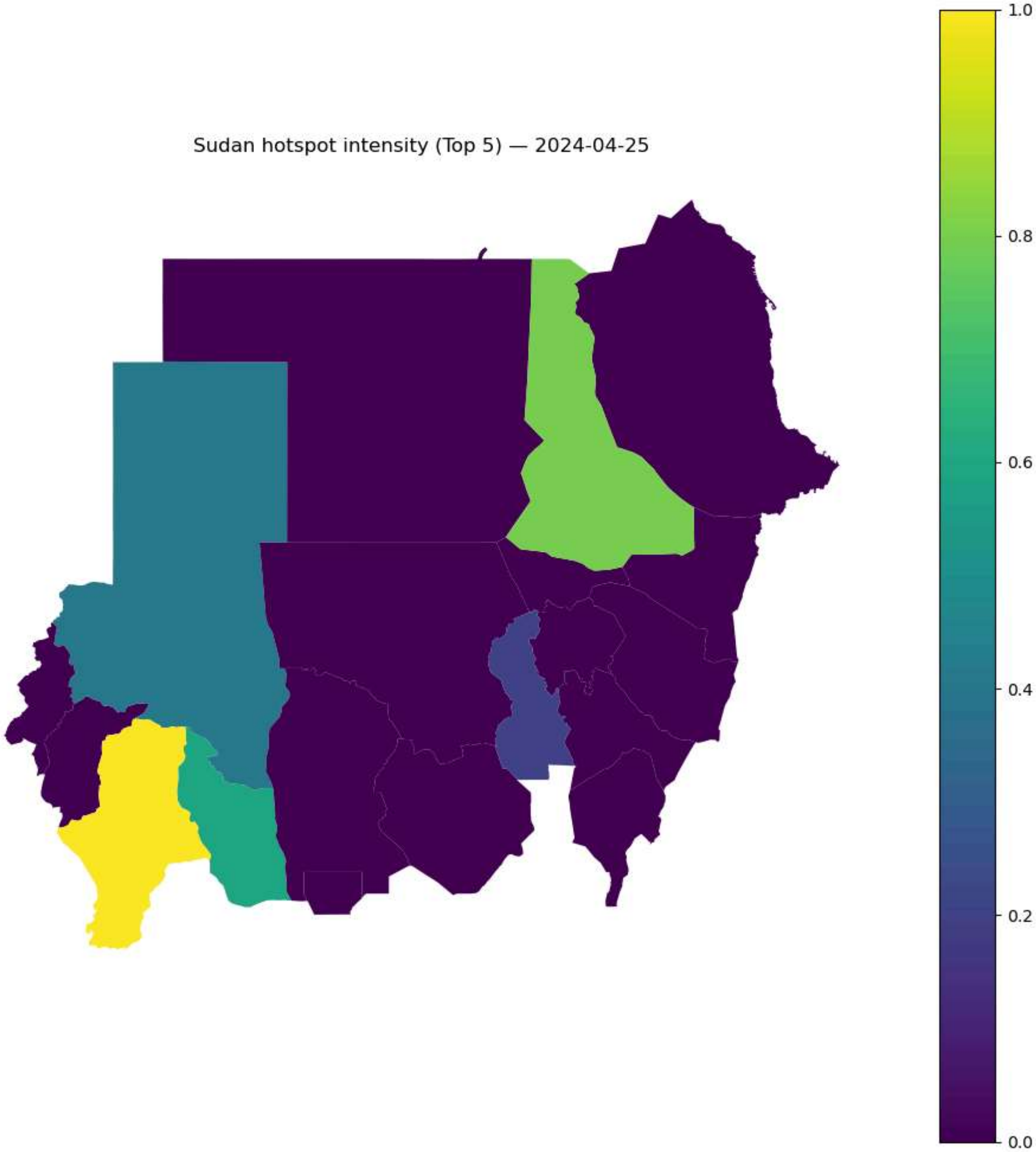
In [75]:

```python

value_col = "hotspot_intensity_rank"

for f in snap_files:
    snap = pd.read_csv(f, parse_dates=["report_date"])
    date_str = str(snap["report_date"].iloc[0].date())

    m = gdf18.merge(snap, left_on="adm1_pcode", right_on="state_code", how
    m[value_col] = m[value_col].fillna(0)

    fig, ax = plt.subplots(1, 1, figsize=(10, 10))
    m.plot(column=value_col, legend=True, ax=ax, missing_kwds={"color": "l
    ax.set_title(f"Sudan hotspot intensity (Top 5) — {date_str}")
    ax.set_axis_off()
    plt.tight_layout()
    plt.show()
```


Sudan hotspot intensity (Top 5) — 2023-04-27
1.0
0.8
0.6
0.4
0.2
0.0


Sudan hotspot intensity (Top 5) — 2023-05-05
1.0
0.8
0.6
0.4
0.2
0.0

Sudan hotspot intensity (Top 5) — 2024-04-25



1.2.3 Below code Generates and saves Admin-1 maps highlighting top-5 displacement hotspots per date, using rank-based intensity and exporting each map as a PNG image

In [76]:

```

os.makedirs("maps_out_hotspots", exist_ok=True)

value_col = "hotspot_intensity_rank"

for f in snap_files:
    snap = pd.read_csv(f, parse_dates=["report_date"])
    date_str = str(snap["report_date"].iloc[0].date())

    m = gdf18.merge(snap, left_on="adm1_pcode", right_on="state_code", how
    m[value_col] = m[value_col].fillna(0)

    fig, ax = plt.subplots(1, 1, figsize=(10, 10))
    m.plot(column=value_col, legend=True, ax=ax, missing_kwds={"color": "l
    ax.set_title(f"Sudan hotspot intensity (Top 5) — {date_str}")
    ax.set_axis_off()
    plt.tight_layout()

    out_png = os.path.join("maps_out_hotspots", f"hotspot_top5_{date_str}.
    plt.savefig(out_png, dpi=200, bbox_inches="tight")
    plt.close(fig)

    print("Saved:", out_png)

```

```
Saved: maps_out_hotspots\hotspot_top5_2023-04-27.png
Saved: maps_out_hotspots\hotspot_top5_2023-05-05.png
Saved: maps_out_hotspots\hotspot_top5_2024-04-25.png
```

1.2.4 Below Code Creates and saves Admin-1 choropleth maps using a globally scaled displacement intensity metric, ensuring consistent color comparison across different reporting dates

In [77]:

```
os.makedirs("maps_out_intensity_global", exist_ok=True)

value_col = "intensity_idps_global"

for f in snap_files:
    snap = pd.read_csv(f, parse_dates=["report_date"])
    date_str = str(snap["report_date"].iloc[0].date())

    m = gdf18.merge(snap, left_on="adm1_pcode", right_on="state_code", how
    m[value_col] = m[value_col].fillna(0)

    fig, ax = plt.subplots(1, 1, figsize=(10, 10))
    m.plot(column=value_col, legend=True, ax=ax, missing_kwds={"color": "l
    ax.set_title(f"Sudan displacement intensity (global scaled) — {date_st
    ax.set_axis_off()
    plt.tight_layout()

    out_png = os.path.join("maps_out_intensity_global", f"intensity_global
    plt.savefig(out_png, dpi=200, bbox_inches="tight")
    plt.close(fig)

    print("Saved:", out_png)

```

```
Saved: maps_out_intensity_global\intensity_global_2023-04-27.png
Saved: maps_out_intensity_global\intensity_global_2023-05-05.png
Saved: maps_out_intensity_global\intensity_global_2024-04-25.png
```

1.2.5 This code Generates and saves Admin-1 maps showing raw IDP counts per state for each selected date, providing an unnormalized view of displacement levels.

In [78]:

```
os.makedirs("maps_out_idps_raw", exist_ok=True)

value_col = "idps"

for f in snap_files:
    snap = pd.read_csv(f, parse_dates=["report_date"])
    date_str = str(snap["report_date"].iloc[0].date())

    m = gdf18.merge(snap, left_on="adm1_pcode", right_on="state_code", how
    m[value_col] = m[value_col].fillna(0)

    fig, ax = plt.subplots(1, 1, figsize=(10, 10))
    m.plot(column=value_col, legend=True, ax=ax, missing_kwds={"color": "]
    ax.set_title(f"Sudan IDPs (raw) — {date_str}")
    ax.set_axis_off()
    plt.tight_layout()

    out_png = os.path.join("maps_out_idps_raw", f"idps_raw_{date_str}.png'
    plt.savefig(out_png, dpi=200, bbox_inches="tight")
    plt.close(fig)

    print("Saved:", out_png)
```

```
Saved: maps_out_idps_raw\idps_raw_2023-04-27.png
Saved: maps_out_idps_raw\idps_raw_2023-05-05.png
Saved: maps_out_idps_raw\idps_raw_2024-04-25.png
```

load administrative-level food security snapshots, cleans and standardizes columns (numeric conversions, boolean hotspot flags), filters for valid admin1 codes, adds helper fields for Tableau, and saves the cleaned dataset for visualization.

In [ ]:

```
INFILE = "geo_admin1_snapshots_2023_2024_INTENSITY.csv"
OUTDIR = "tableau_outputs"
os.makedirs(OUTDIR, exist_ok=True)

df = pd.read_csv(INFILE, parse_dates=["report_date"])

# keep clean admin1 codes (SD01 to SD18)
df["state_code"] = df["state_code"].astype(str).str.strip()
df = df[df["state_code"].str.match(r"^SD\d{2}$", na=False)].copy()

# standardize types
for c in ["idps","households","rank","hotspot_intensity_rank","intensity_i
    if c in df.columns:
        df[c] = pd.to_numeric(df[c], errors="coerce").fillna(0)

# ensure hotspot is boolean-ish
if "hotspot" in df.columns:
    df["hotspot"] = df["hotspot"].astype(bool)

# add helper fields for Tableau
df["report_date_str"] = df["report_date"].dt.strftime("%Y-%m-%d")
df["year"] = df["report_date"].dt.year

# save master
out_master = os.path.join(OUTDIR, "tableau_admin1_fact_long.csv")
df.to_csv(out_master, index=False)

print("Saved:", out_master)
print("Rows:", len(df), "| Dates:", df["report_date"].nunique(), "| States
print("Columns:", df.columns.tolist())
```

State by IDPs for each reporting date, creating a subset of high-intensity hotspots, and saves it as a CSV for Tableau visualization.

In [80]:

```
OUTDIR = "tableau_outputs"
df = pd.read_csv(os.path.join(OUTDIR, "tableau_admin1_fact_long.csv"), par

top5 = (df.sort_values(["report_date","idps"], ascending=[True, False])
          .groupby("report_date")
          .head(5)
          .copy())

out_top5 = os.path.join(OUTDIR, "tableau_hotspots_top5.csv")
top5.to_csv(out_top5, index=False)

print("Saved:", out_top5)
print(top5[["report_date_str","state_code","state_name","idps","rank","hot

```

```
Saved: tableau_outputs\tableau_hotspots_top5.csv
report_date_str state_code     state_name     idps   rank  hotspot_intensity_r
ank
     2023-04-27        SD04    West Darfur 194593.0   1.0
1.0
     2023-04-27        SD03   South Darfur  45000.0   2.0
0.8
     2023-04-27        SD17       Northern  29200.0   3.0
0.6
     2023-04-27        SD01       Khartoum  13545.0   4.0
0.4
     2023-04-27        SD13 North Kordofan  13270.0   5.0
0.2
     2023-05-05        SD09     White Nile 188635.0   1.0
1.0
     2023-05-05        SD04    West Darfur 156565.0   2.0
0.8
     2023-05-05        SD17       Northern 106600.0   3.0
0.6
     2023-05-05        SD16     River Nile  96095.0   4.0
0.4
     2023-05-05        SD15     Aj Jazirah  49280.0   5.0
0.2
     2024-04-25        SD03   South Darfur 744243.0   1.0
1.0
     2024-04-25        SD16     River Nile 698334.0   2.0
0.8
     2024-04-25        SD05    East Darfur 660140.0   3.0
0.6
     2024-04-25        SD02   North Darfur 573055.0   4.0
0.4
     2024-04-25        SD09     White Nile 532643.0   5.0
0.2
```

Pivot the admin1-level data to create a wide table of rank values for each state across reporting dates, making it easier to visualize trends in Tableau, and saves the result as a CSV.

In [81]:

```python
OUTDIR = "tableau_outputs"
df = pd.read_csv(os.path.join(OUTDIR, "tableau_admin1_fact_long.csv"), par

rank_wide = (df.pivot_table(index=["state_code","state_name"],
                            columns="report_date_str",
                            values="rank",
                            aggfunc="min")
               .reset_index())

# make columns simpler for use in Tableau
rank_wide.columns.name = None

out_rank = os.path.join(OUTDIR, "tableau_rank_wide.csv")
rank_wide.to_csv(out_rank, index=False)

print("Saved:", out_rank)
print(rank_wide.head(10).to_string(index=False))
```

```
Saved: tableau_outputs\tableau_rank_wide.csv
state_code      state_name  2023-04-27  2023-05-05  2024-04-25
      SD01        Khartoum         4.0         7.0        18.0
      SD02    North Darfur         6.0         8.0         4.0
      SD03    South Darfur         2.0         6.0         1.0
      SD04     West Darfur         1.0         2.0        14.0
      SD05     East Darfur        16.0        16.0         3.0
      SD06  Central Darfur        11.0        12.0         8.0
      SD07  South Kordofan        15.0        17.0        13.0
      SD08       Blue Nile        13.0        13.0        17.0
      SD09      White Nile         8.0         1.0         5.0
      SD10         Red Sea        12.0        11.0        11.0
```

Calculate the change in IDPs and rank for each state between the first and last reporting dates, generating a summary table of trends for Tableau visualization and saving it as a CSV.

In [82]:

```
OUTDIR = "tableau_outputs"
df = pd.read_csv(os.path.join(OUTDIR, "tableau_admin1_fact_long.csv"), par

first_d = df["report_date"].min()
last_d = df["report_date"].max()

a = df[df["report_date"] == first_d][["state_code","state_name","idps","ra
    columns={"idps":"idps_first","rank":"rank_first"}
)
b = df[df["report_date"] == last_d][["state_code","idps","rank"]].rename(
    columns={"idps":"idps_last","rank":"rank_last"}
)

chg = a.merge(b, on="state_code", how="left")
chg["idps_last"] = chg["idps_last"].fillna(0)
chg["rank_last"] = chg["rank_last"].fillna(0)

chg["delta_idps"] = chg["idps_last"] - chg["idps_first"]
chg["delta_rank"] = chg["rank_last"] - chg["rank_first"]

chg["first_date"] = first_d.strftime("%Y-%m-%d")
chg["last_date"] = last_d.strftime("%Y-%m-%d")

out_chg = os.path.join(OUTDIR, "tableau_change_first_vs_last.csv")
chg.to_csv(out_chg, index=False)

print("Saved:", out_chg)
print("Comparing:", first_d.date(), "->", last_d.date())
print(chg.sort_values("delta_idps", ascending=False).head(10).to_string(ir

```

```
Saved: tableau_outputs\tableau_change_first_vs_last.csv
Comparing: 2023-04-27 -> 2024-04-25
state_code     state_name  idps_first  rank_first  idps_last  rank_last  delt
a_idps  delta_rank first_date  last_date
      SD03   South Darfur     45000.0         2.0   744243.0        1.0     69
9243.0        -1.0 2023-04-27 2024-04-25
      SD16     River Nile      2910.0        10.0   698334.0        2.0     69
5424.0        -8.0 2023-04-27 2024-04-25
      SD05    East Darfur         0.0        16.0   660140.0        3.0     66
0140.0       -13.0 2023-04-27 2024-04-25
      SD02   North Darfur     11675.0         6.0   573055.0        4.0     56
1380.0        -2.0 2023-04-27 2024-04-25
      SD09     White Nile      6165.0         8.0   532643.0        5.0     52
6478.0        -3.0 2023-04-27 2024-04-25
      SD14         Sennar      5560.0         9.0   523986.0        6.0     51
8426.0        -3.0 2023-04-27 2024-04-25
      SD12        Gedaref         0.0        17.0   492293.0        7.0     49
2293.0       -10.0 2023-04-27 2024-04-25
      SD06 Central Darfur      1780.0        11.0   430224.0        8.0     42
8444.0        -3.0 2023-04-27 2024-04-25
      SD17       Northern     29200.0         3.0   399867.0        9.0     37
0667.0         6.0 2023-04-27 2024-04-25
      SD15     Aj Jazirah      8795.0         7.0   371177.0       10.0     36
2382.0         3.0 2023-04-27 2024-04-25
```

Compress all files in the tableau_outputs directory into a single ZIP archive (tableau_outputs_deploy.zip) for easy sharing or deployment.

In [83]:
```
OUTDIR = "tableau_outputs"
ZIPNAME = "tableau_outputs_deploy.zip"

with zipfile.ZipFile(ZIPNAME, "w", compression=zipfile.ZIP_DEFLATED) as z:
    for fn in os.listdir(OUTDIR):
        z.write(os.path.join(OUTDIR, fn), arcname=f"{OUTDIR}/{fn}")

print("Saved:", ZIPNAME)
print("Files zipped:", os.listdir(OUTDIR))

```

```
Saved: tableau_outputs_deploy.zip
Files zipped: ['tableau_admin1_fact_long.csv', 'tableau_change_first_vs_last.
csv', 'tableau_hotspots_top5.csv', 'tableau_rank_wide.csv']
```

10. Deployment

Final Models Ready for Deployment:

- Regression: Tuned Random Forest (R^2=0.4285)
- Classification: Random Forest (Accuracy=65.3%, F1=0.541)

Deployment And Protype Demo

This has been handled seperately. We used StreamLit methodology for deployment. The deployment code was captured seperately and will be showcased together with our final prototype demo.

Conclusion

This project analyzed internal displacement patterns using Admin-1 level data and geospatial visualization techniques. By generating multiple map types—including ranked hotspot maps, globally scaled intensity maps, and raw IDP count choropleths the analysis provided a multi-perspective view of displacement dynamics over time.

These visualizations highlighted both persistent and emerging displacement hotspots, while also enabling consistent comparison across reporting dates.

The use of different normalization approaches proved valuable in balancing interpretability and accuracy. Rank-based maps effectively emphasized relative severity within each time period, while globally scaled intensity maps supported longitudinal comparison. Raw IDP count maps further complemented the analysis by preserving absolute displacement figures. Together, these methods enhanced situational awareness and improved understanding of spatial and temporal displacement trends.

Overall, the project demonstrates how geospatial analysis can support evidence-based humanitarian decision-making by transforming complex displacement data into actionable insights.

Recommendations

Incorporate Population Normalization Future analyses could normalize IDP counts by total population at the Admin-1 level to better capture displacement intensity relative to population size.

Extend Temporal Coverage Including additional reporting periods would allow for trend analysis, seasonal pattern detection, and improved early-warning capabilities.

Integrate Contextual Indicators Combining displacement data with conflict events, climate shocks, or food security indicators could help explain underlying drivers of displacement.

Develop Interactive Dashboards Transforming static maps into interactive dashboards (e.g., using Plotly or Dash) would improve usability for policymakers and humanitarian actors.

Automate Data Updates Implementing automated data ingestion and map generation pipelines

In [ ]: