Operationalising EO & AI for Early Warning

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CENTAUR Project – In a nutshell

THEMATIC AREAS

Emergency Management

Flood-related threats to population, assets and infrastructures in urban areas.

Security

Water and food insecurity as precursors of political instability, conflict and forced displacement.

OPERATIONAL BENEFITS

Emergency Management

- Including of a prototype urban flood layer within the European Flood Awareness System (EFAS) map viewer.
- Improving early warning Integrating the CEMS mapping portfolio with enhanced products and services for mapping flood extent in urban areas.

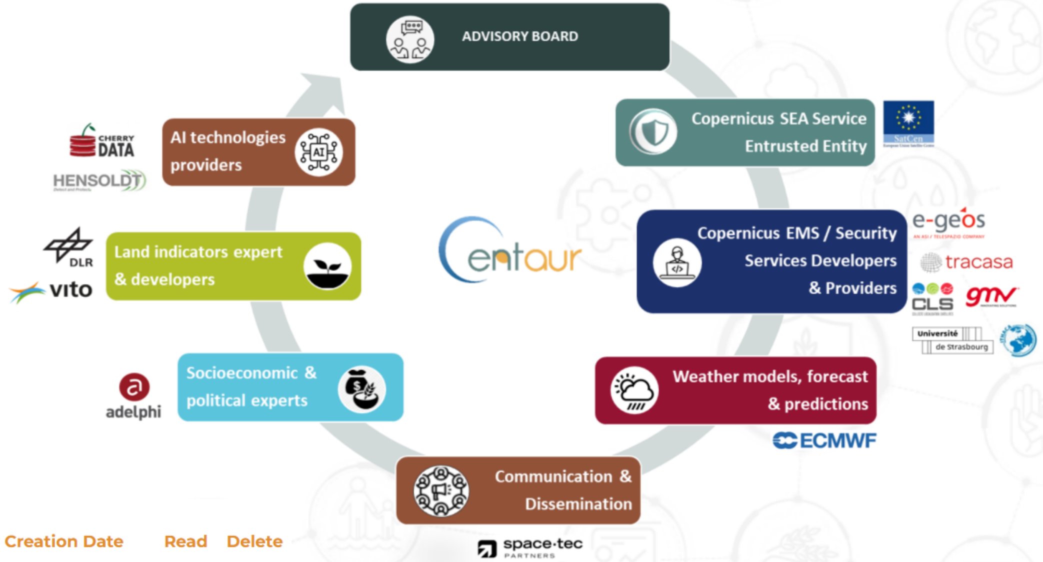
Security

- Enriching the current portfolio by integrating new vulnerability and fragility indexes.
- Reinforcing early warning capacities and pro-active geo-intelligence services for systematic surveillance of early signs and drivers of social unrest, population movements, and conflicts in connection with food and water insecurity

Region	Read Status	Alert Description	Short Description	Alert Level	Creation Date	Read	Delete
Mopti	NOT READ	Agricultural Drought Risk - Cropland - Monthly Update	Mali: Medium Risk (> 0.50, <= 0.75) Agricultural Drought Risk in Mopti for 1-10-2025, refer to Link to product on the CENTAUR platform	Medium Risk (> 0.50, <= 0.75)	Oct. 13, 2025, 2:16 a.m.	Read	Delete

https://centaur-horizon.eu/

Consortium of **14 Partners** led **by e-GEOS**



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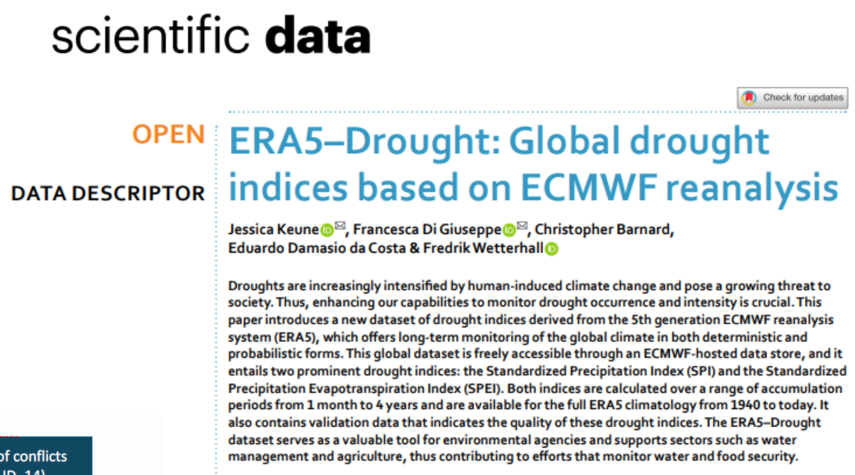
Drought Impact Indicators


scientific **data**

Check for updates

OPEN

DATA DESCRIPTOR

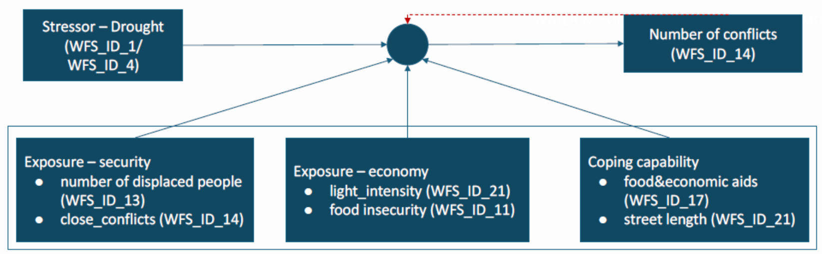
ERA5–Drought: Global drought indices based on ECMWF reanalysis

Jessica Keune, Francesca Di Giuseppe, Christopher Barnard, Eduardo Damasio da Costa & Fredrik Wetterhall

Droughts are increasingly intensified by human-induced climate change and pose a growing threat to society. Thus, enhancing our capabilities to monitor drought occurrence and intensity is crucial. This paper introduces a new dataset of drought indices derived from the 5th generation ECMWF reanalysis system (ERA5), which offers long-term monitoring of the global climate in both deterministic and probabilistic forms. This global dataset is freely accessible through an ECMWF-hosted data store, and it entails two prominent drought indices: the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). Both indices are calculated over a range of accumulation periods from 1 month to 4 years and are available for the full ERA5 climatology from 1940 to today. It also contains validation data that indicates the quality of these drought indices. The ERA5–Drought dataset serves as a valuable tool for environmental agencies and supports sectors such as water management and agriculture, thus contributing to efforts that monitor water and food security.

Meteorological Drought Indicators

- Monitoring (SPI + SPEI)
- Forecasting (SPI + SPEI)



The model also has a feedback loop (dashed line in red), as the number of future conflicts has been found to be influenced by the current conflicts in previous literature. This is a well known concept in the literature, also known as *conflict trap*.

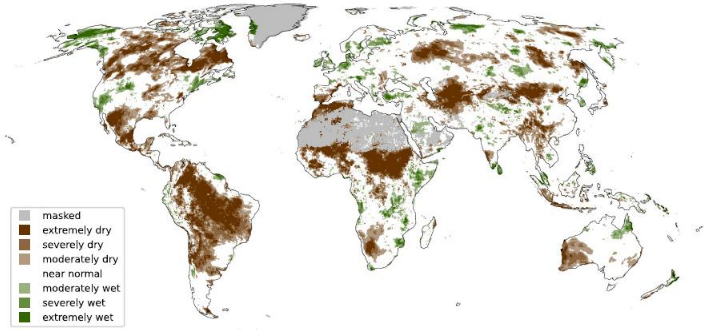
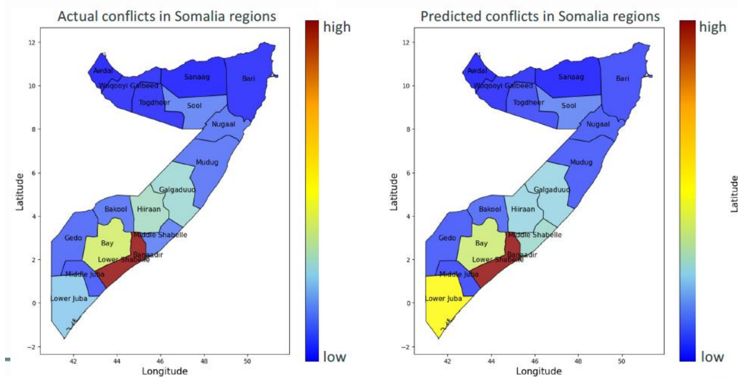


Fig. 2 Example from the data record. Global snapshot of the SPEI-12 at the end of December 2023. The global map shows regions that have experienced dry (brown) and wet (green) conditions in 2023 according to the SPEI, i.e. the difference between precipitation and atmospheric water demand (expressed as potential evapotranspiration). The intensity of the dry and wet conditions is categorized as moderate, severe, and extreme and is shown as different shadings of brown and green, respectively. The intensity is evaluated with respect to the reference period 1991–2020. This map highlights the vast long-term drought that extends over large parts of South America that has been affecting people living in Brazil and neighbouring countries in the last years. However, also other countries in Africa and Central America, Canada, and Central Asia have experienced severe drought conditions. Regions without vegetation (deserts and polar regions) or insufficient quality are masked grey.

Agricultural Drought ImpactIndicators (Earth Observation)

- Monitoring (NRT)
- Forecasting



Impact-related Indicators

- Food/Water Security
- #Displaced people
- #Violent Conflicts
- …

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Agricultural Drought Forecasting

Integrating EO and forecasting techniques in a pre-operational setting

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Monitoring

Agricultural Drought

Soil Moisture

Soil Moisture Anomaly
Evapotranspiration Deficit Index
Soil Moisture Deficit Index
Soil Water Storage

Vegetation Condition

Enhanced Vegetation Index
Evaporative Stress Index
Normalized Difference Vegetation Index
Temperature Condition Index
Vegetation Condition Index
Vegetation Drought Response Index
Vegetation Health Index
Water Requirement Satisfaction Index
Normalized Difference Water Index
Land Surface Water Index
Soil Adjusted Vegetation Index

Implemented and combined by many systems

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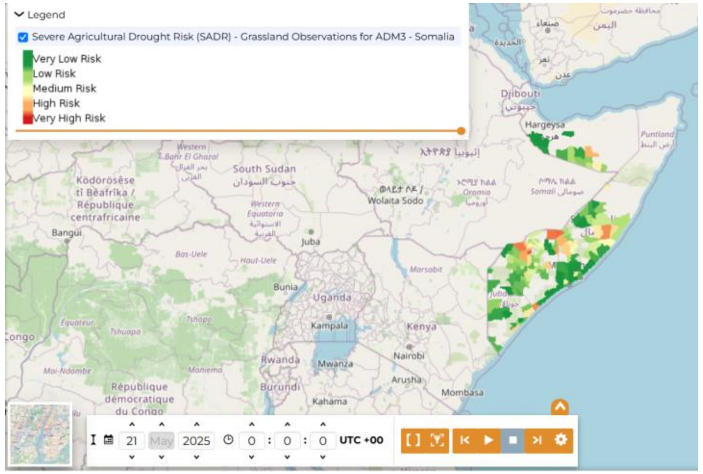
Agricultural Drought Forecasting

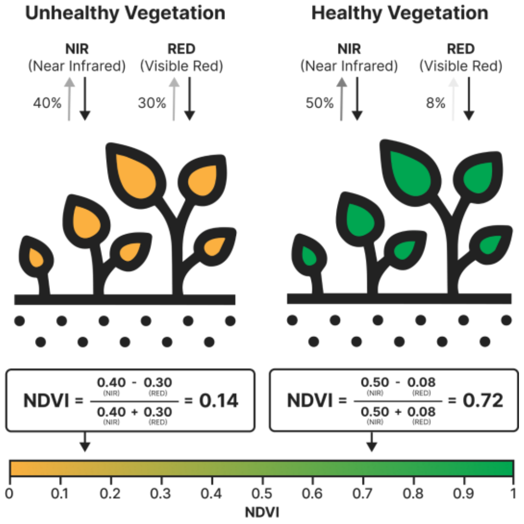
Step 1: Take a simple but meaningful indicator

$NDVIA$ → Per-pixel NDVI anomaly calculated against a historical time series

$$ADR = \frac{\#pixels\ in\ growing\ season\ with\ NDVIA\ below\ p15}{\#pixels\ in\ growing\ season}$$



$$NDVI = \frac{NIR - RED}{NIR + RED}$$



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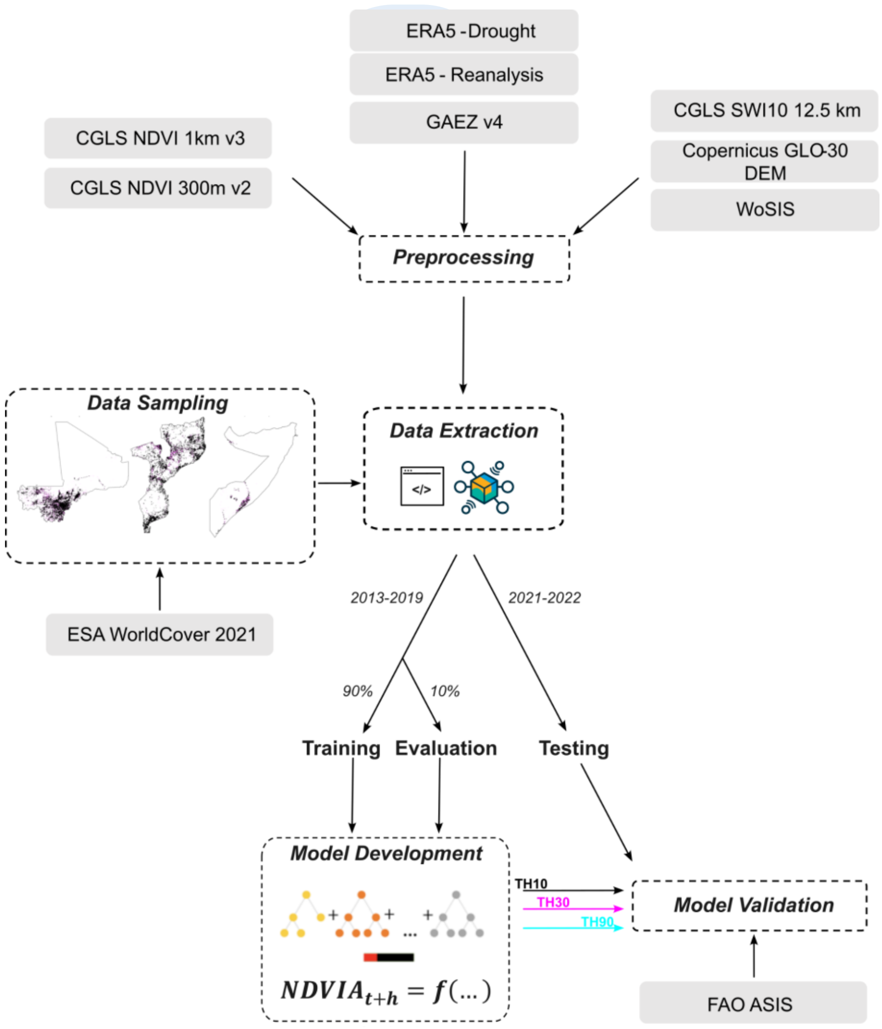
Agricultural Drought Forecasting

Step 2: Build a modelling setup to replicate this indicator

= Machine Learning Model that integrates
- NRT EO Data (NDVIA + Soil Moisture)
- Meteorological Forecasts (SPI + SPEI)
- Environmental Data (slope, topography, soil)

→ Per-pixel (1km), making it flexible

→ To aggregate at any spatial level
→ To mask specific areas / land use of interest



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Agricultural Drought Forecasting

Step 3: Validate the predicted indicator

→ Test in a re-forecasting setting

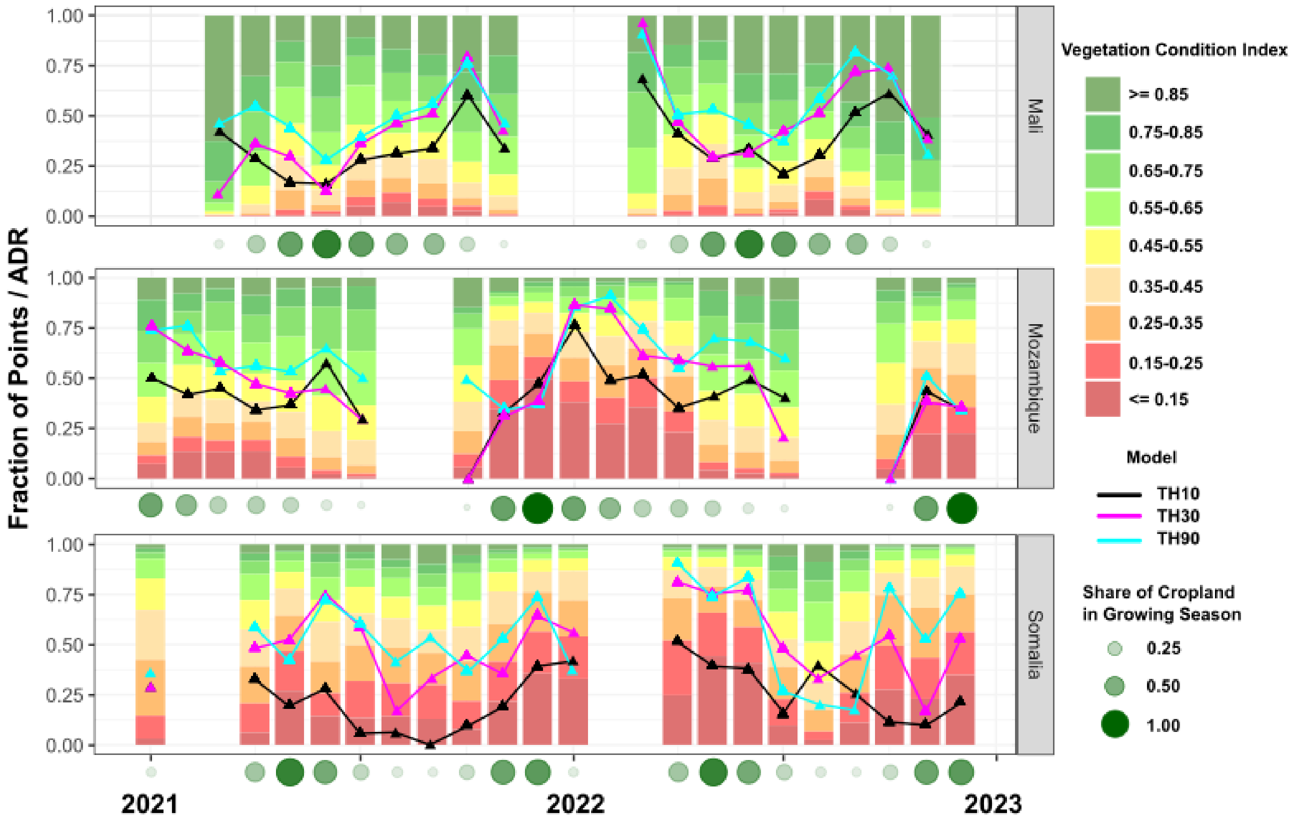
→ Understand the impact of lead time

→ Compare to Existing operational indicators

→ Benchmark against the “status quo”

$$RMSE_{model,h} = RMSE\left(NDVIA_{i,t+h}^{predicted} - NDVIA_{i,t+h}^{monitored}\right)$$

$$RMSE_{baseline,h} = RMSE\left(NDVIA_{i,t}^{monitored} - NDVIA_{i,t+h}^{monitored}\right)$$



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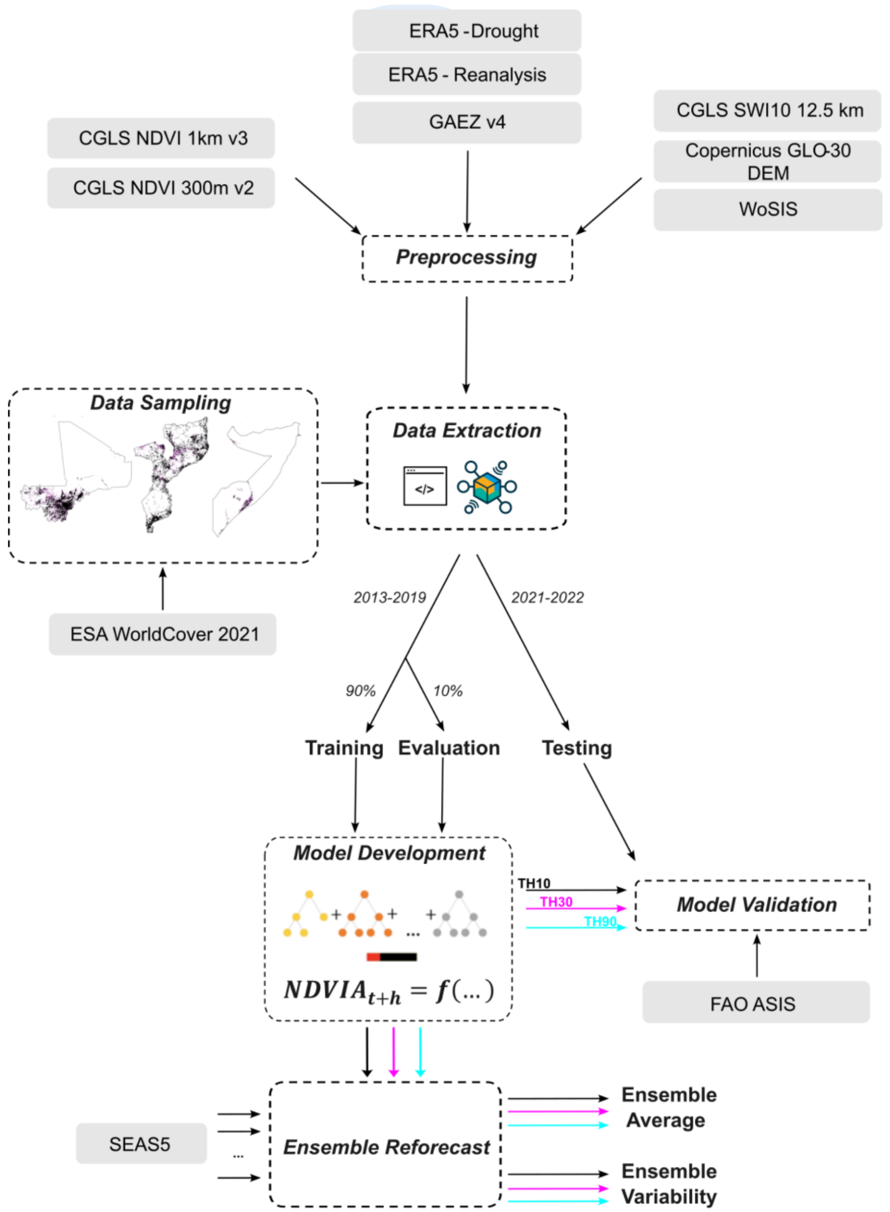
Agricultural Drought Forecasting

Step 4: Adapt to a *pre*-operational setting

- Use actual forecasts
  - 10 days
  - 1 month
  - 3 months

- Automize processing chains



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Intrigued?

Come speak to me!

Read the scientific paper

ELSEVIER

Remote Sensing of Environment

Volume 330, 1 December 2025, 114980

Predicting below-average NDVI anomalies for agricultural drought impact forecasting

Koen De Vos [a], Sarah Gebruers [a], Jeroen Degerickx [a], Marian-Daniel Iordache [a], Jessica Keune [b], Francesca Di Giuseppe [b], Francisco Vilela Pereira [a], Hendrik Wouters [a], Else Swinnen [a], Koen Van Rossum [a], Laurent Tits [a]

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https://doi.org/10.1016/j.rse.2025.114980

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