KAL: Kernel Atmospheric Learner

Operational QPE in Radar-Absent Basins via MSG SEVIRI & Machine Learning on the European Weather Cloud

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Official EWC Use Case [Ref. 50]

Organisations

University of Ioannina

University of Ioannina, Department of Agriculture (Lead Organization)

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AGRICULTURAL UNIVERSITY OF ATHENS

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Supported

HNMS
Hellenic National Meteorological Service

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EUMETSAT

European Organisation for the Exploitation of Meteorological Satellites

Region introduction – and operational targets

PART 1

Area Characteristics

Epirus receives >1,000 mm/yr of rain

Mediterranean climate

Proximity to mountainous complexity

Intensive irrigation agriculture

Flood-prone & environmentally sensitive basin

UOI Research Operational Targets

Delivering reliable daily Delivering reliable daily QPE / rainfall estimates

1. For water management

2. Post-event damage assessment
(insurance & compensation auditing), and regional policy planning

* No forecast

Area of study – Epirus region – west Greece

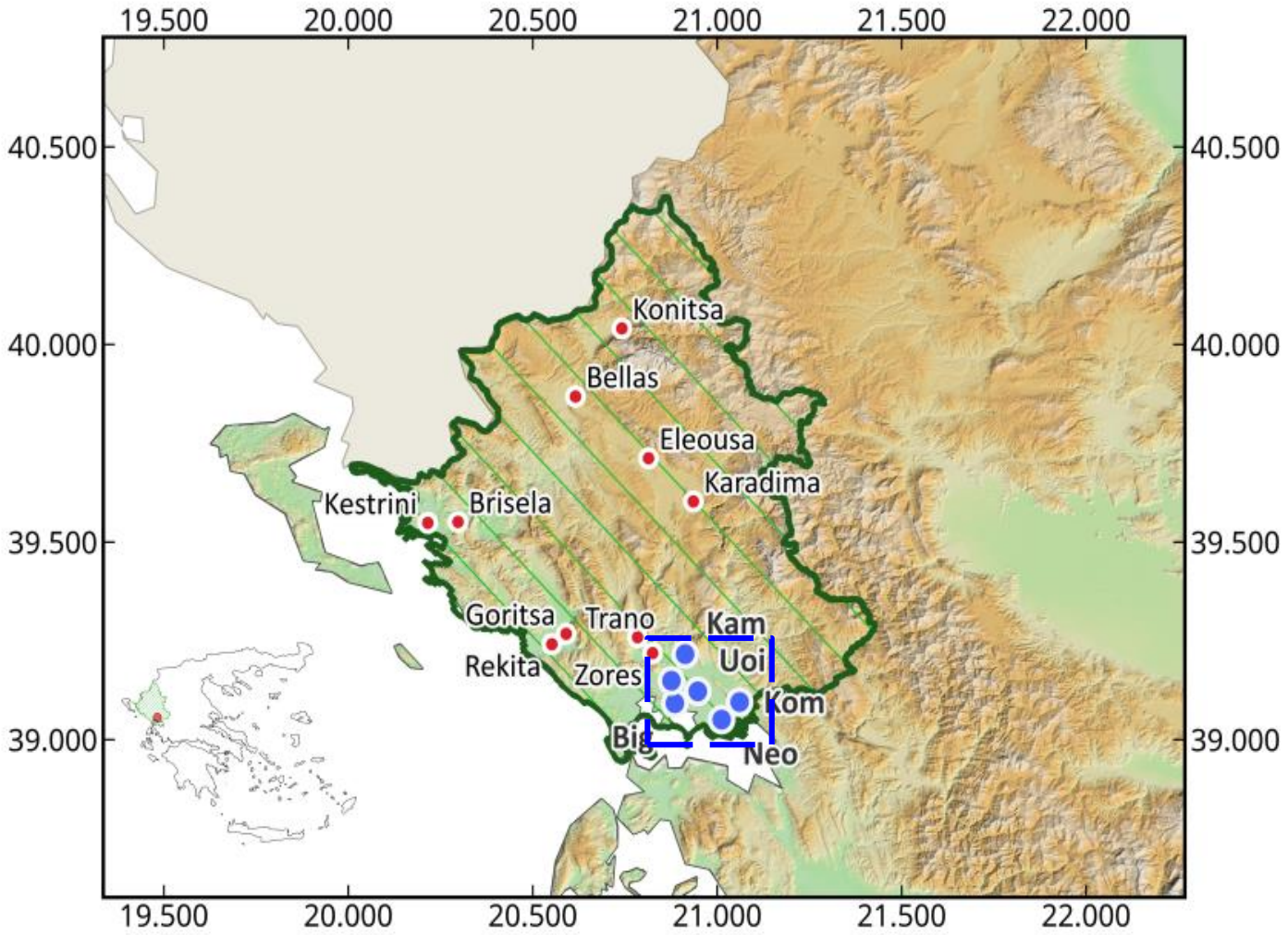
Problems to overcome

- **The Radar-Void Problem:**
Radar coverage / beam blockage

- **Global Model Limitations:**
Delayed publication (> 24h)
Ignore local climate.

- **Cost efficiency**
Fast, cheap and reliable systems
Low maintenance
Independence

- **Risky project**
topology of weather station network
computational resources / data bottlenecks
ML implementation strategy



Agro-meteorological network of UoI

KAL Kernel Atmospheric Learner model

PART 2

- **Philosophy: “Do one (simple) thing and make it good”***

- **A flexible, small and scalable**

Rather than a generic regional model -> one flexible framework was chosen

1. Adaptable to topography and microclimate.
2. Transferable to other areas – scalable.
3. Retraining friendly.
4. Low computation requirements**
5. Input independent as possible.
6. Rely to open European infrastructure.

*The phrase "do one thing and make it good" (more commonly stated as "make each program do one thing well") is a core tenet of the Unix/Linux philosophy introduced by Doug McIlroy in 1976

** training KAL its hard but execution its fast

Methodology: KAL ML model (2 stage hurdle & LoSo)

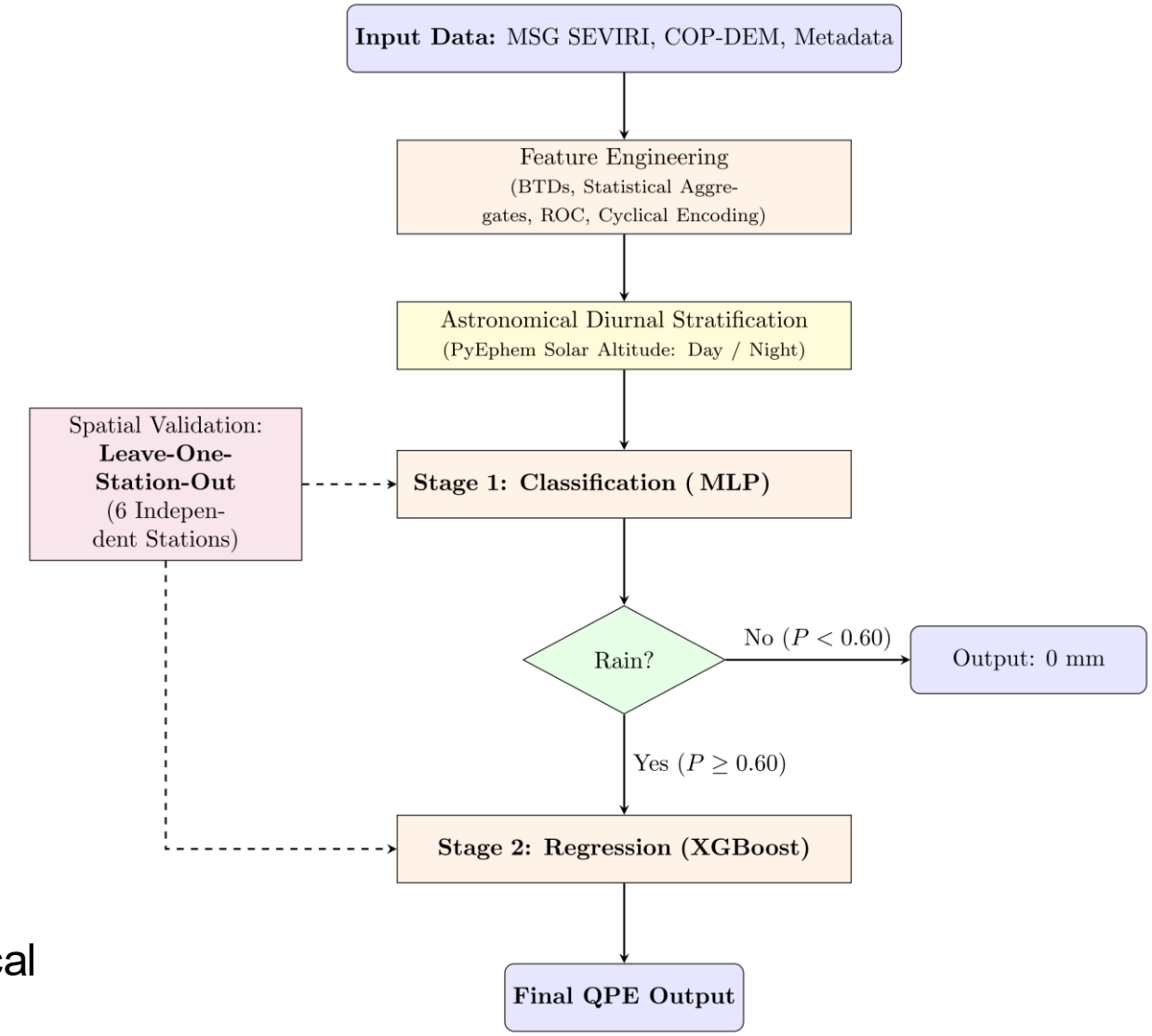
- **Severe Zero-Inflation:**
Mediterranean climate exhibits 83% dry vs. 17% rain periods.

- **Stage 1 (Detection):**
3-layer MLP Neural Network (Keras) with class weighting.
Applied classification threshold = 0.60.

- **Stage 2 (Quantification):**
XGBoost Regressor trained strictly on positive rain events to accurately capture peak intensities.

- **Diurnal Stratification:** Astronomical zenith angle (PyEphem)

Historical 10-Year (2015-2025) Feature Engineering:
Processing 380,000 SEVIRI slots to extract 300+ physical predictors, BTDs, and Rate-of-Change in parallel.



KAL ML block diagram

KAL ML model results

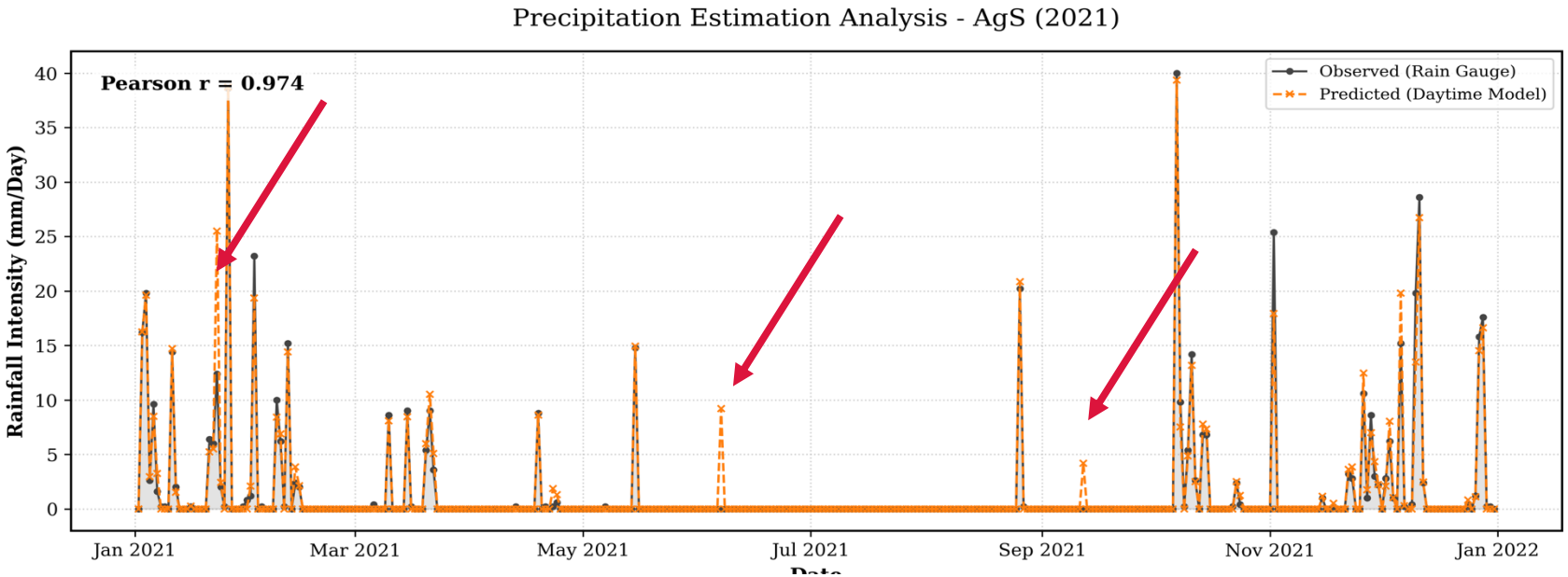
- **Leave-One-Station-Out:** Strict spatial cross-validation prevents spatial autocorrelation leakage; tests true transferability to ungauged basins.
- **Diagnostic Performance:** High sensitivity and discrimination: Night F1 = 0.786 (CSI: 0.652); Day F1 = 0.774 (CSI: 0.631).
- **Hydrological Fidelity:** Mean KGE = 0.658 (night) / 0.629 (day) with near-zero Mean Error (ME <= 0.10 mm/h).
- **50% FAR Reduction:** Decoupled Hurdle cut False Alarm Ratio by more than 50% compared to conventional single-stage models.

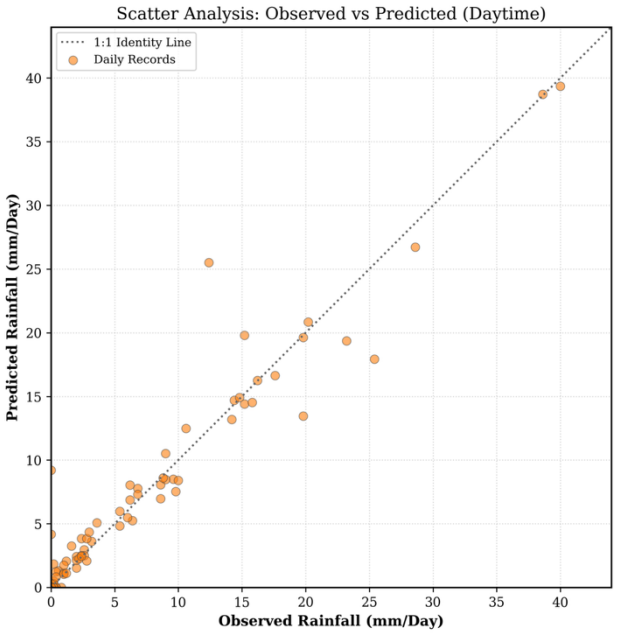
Model Configuration	F1-Score	CSI	POD	FAR	RMSE (mm/h)	ME (mm/h)	KGE
Night-time Regime							
Single-Stage XGBoost (Baseline)	0.557	0.387	**0.920**	0.600	3.45	**+0.06**	0.644
Proposed Hybrid Hurdle	**0.786**	**0.652**	0.868	**0.278**	3.46	+0.10	**0.658**
Relative Difference (Δ%)	*+41.1%*	*+68.5%*	*−5.7%*	*−53.7%*	*+0.3%*	–	*+2.2%*
Day-time Regime							
Single-Stage XGBoost (Baseline)	0.548	0.379	**0.912**	0.612	3.42	**+0.05**	0.618
Proposed Hybrid Hurdle	**0.774**	**0.631**	0.851	**0.287**	**3.40**	+0.09	**0.629**
Relative Difference (Δ%)	*+41.2%*	*+66.5%*	*−6.7%*	*−53.1%*	*−0.6%*	–	*+1.8%*

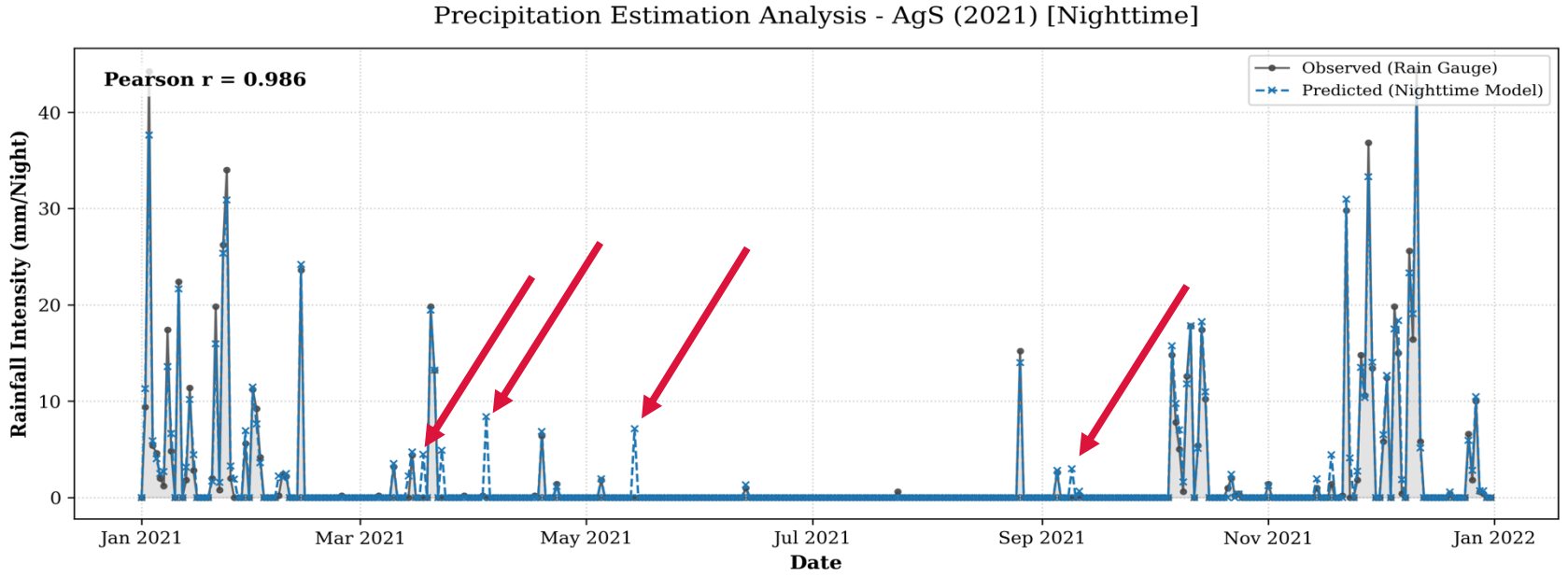
Note: Evaluated on strictly matched populations across all six test stations under identical LOSO splits.

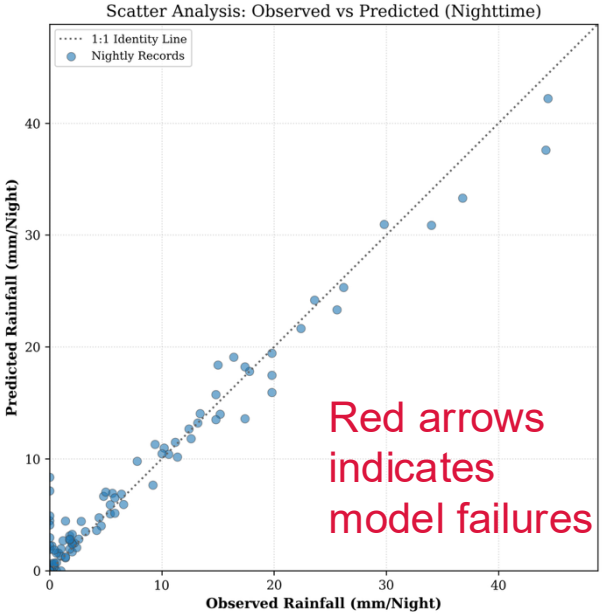
*All technical and scientific results and methodology will be available soon on paper publication / or please contact the KAL team

ML Results - 2021 Daily Precipitation - LoSo method

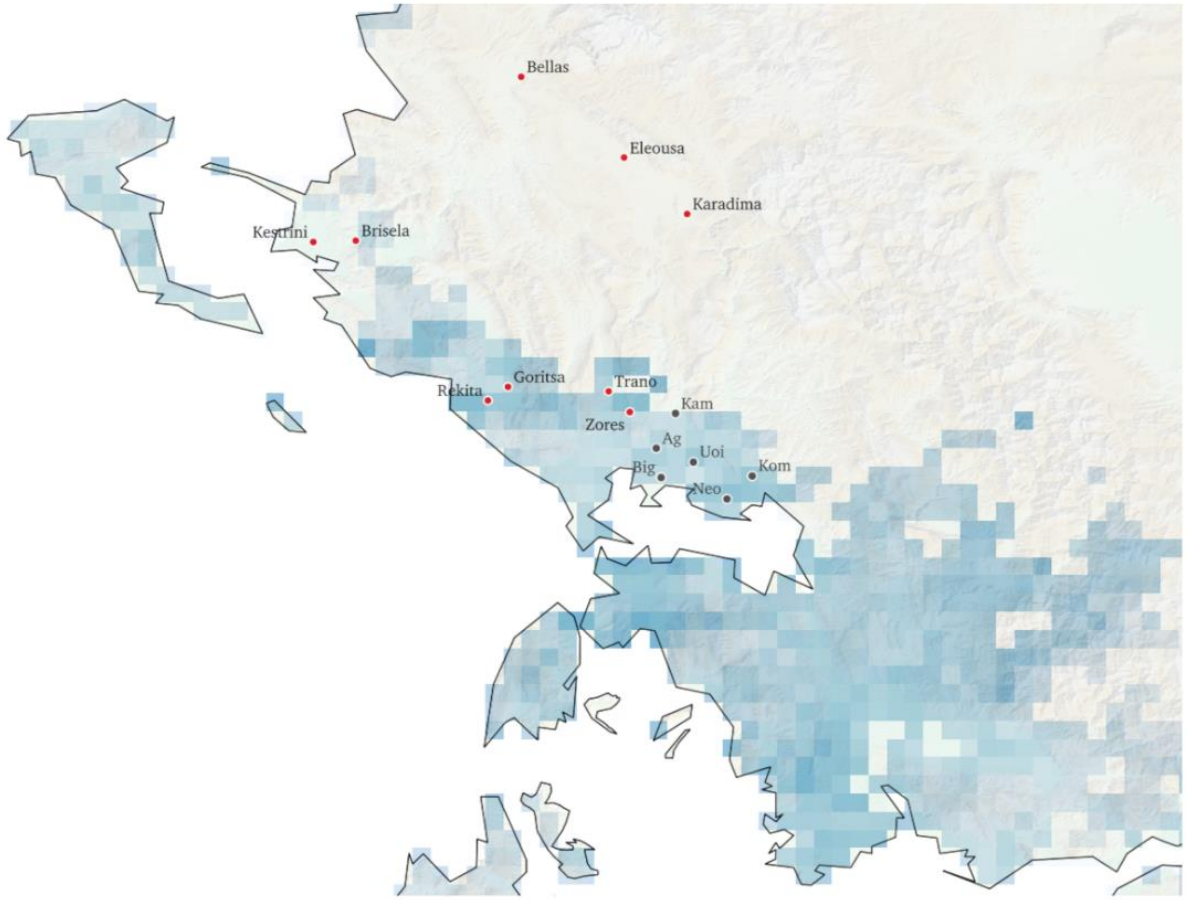








KAL under evaluation: Extreme Storm Case Study



(a)

(b)

Qualitative spatial consistency check and independent extrapolation for the extreme precipitation event of December 4, 2025.

(a) Proposed Hybrid Framework (MLP-XGBoost)

(b) EUMETSAT H-SAF (H90 Product).

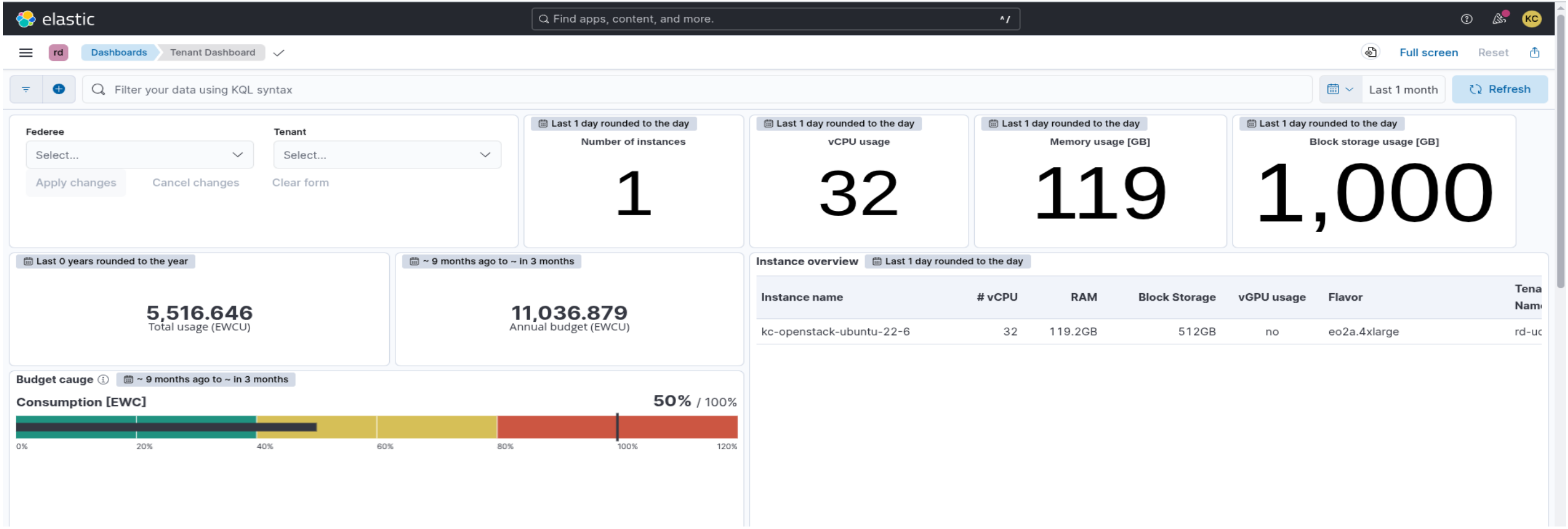
KAL - Eumetsat EWC framework - 1-Year Fast Track (2025 – 2026)

PART 3

A single Virtual Machine – Plan: eo2a.4xlarge 32 vCPU – 128 GB Ram – 2 TB storage

Benefits

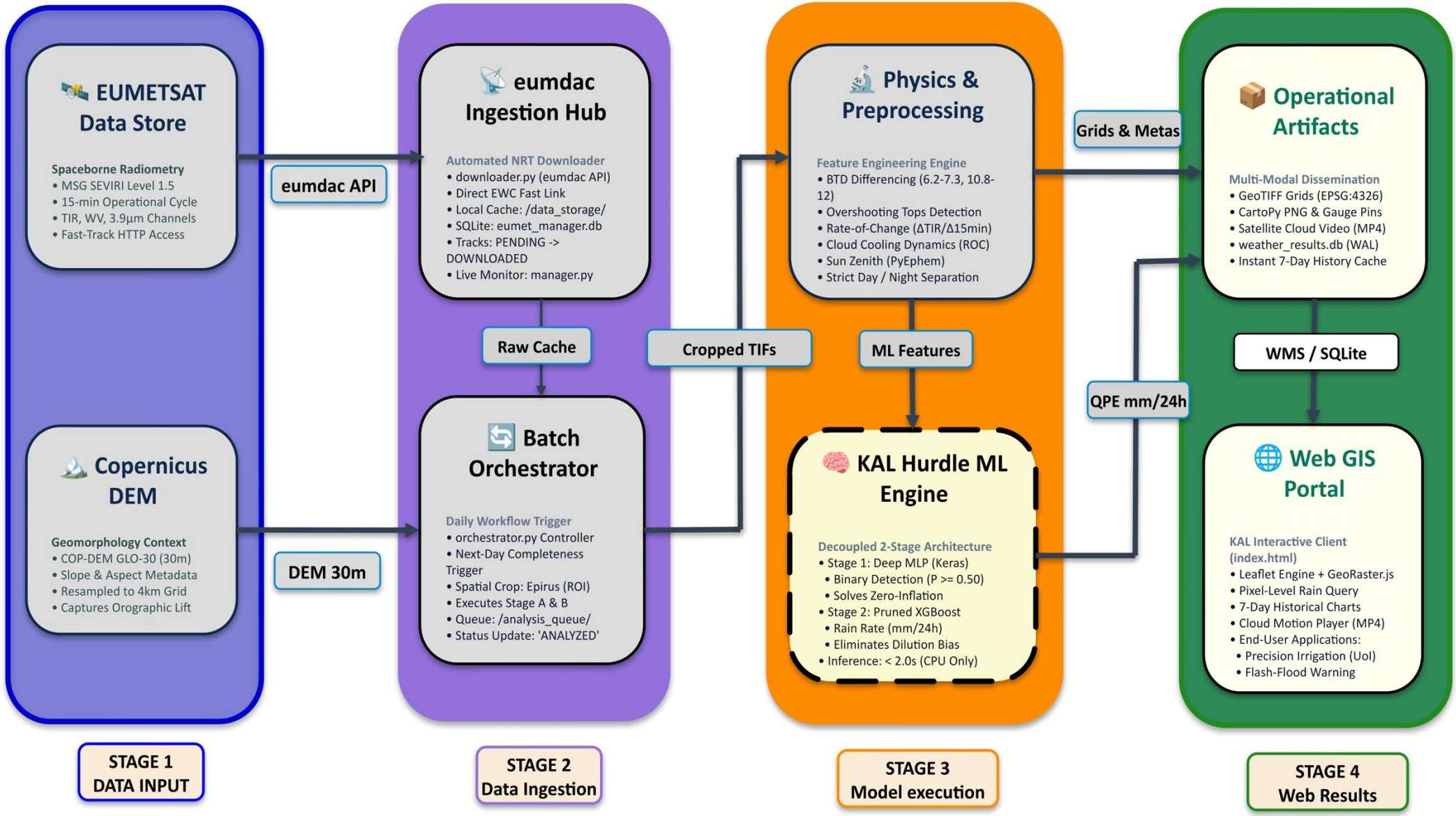
Overcoming data access & bandwidth bottlenecks
Stability of the system (uptime 99.988)
Compatibility with Linux tools and python code



KAL Operational Pipeline: Quantitative Precipitation Estimation on EWC

EUROPEAN WEATHER CLOUD (EWC) - OPERATIONAL TENANCY

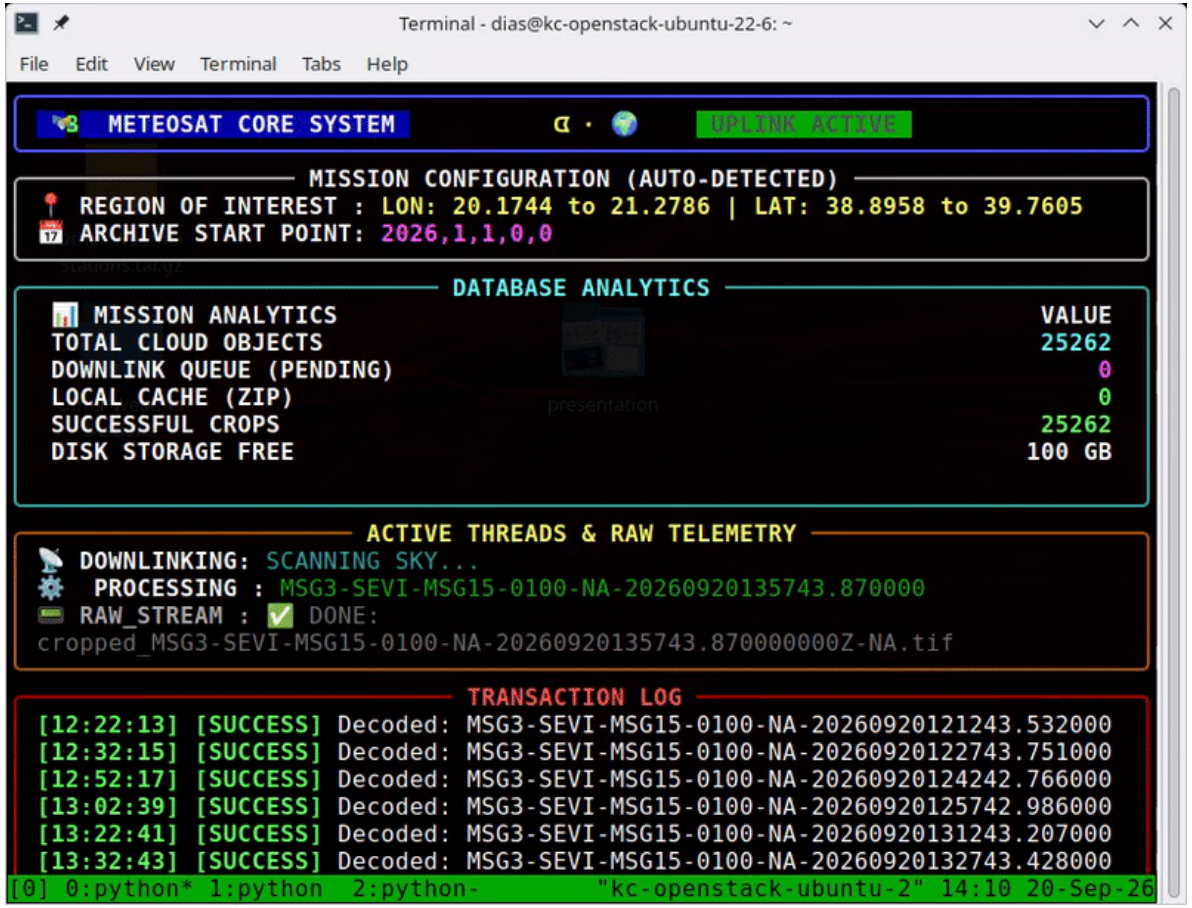
Dedicated Allocation: 32 vCPUs | 128 GB RAM | 2 TB Storage | High-Throughput Backbone

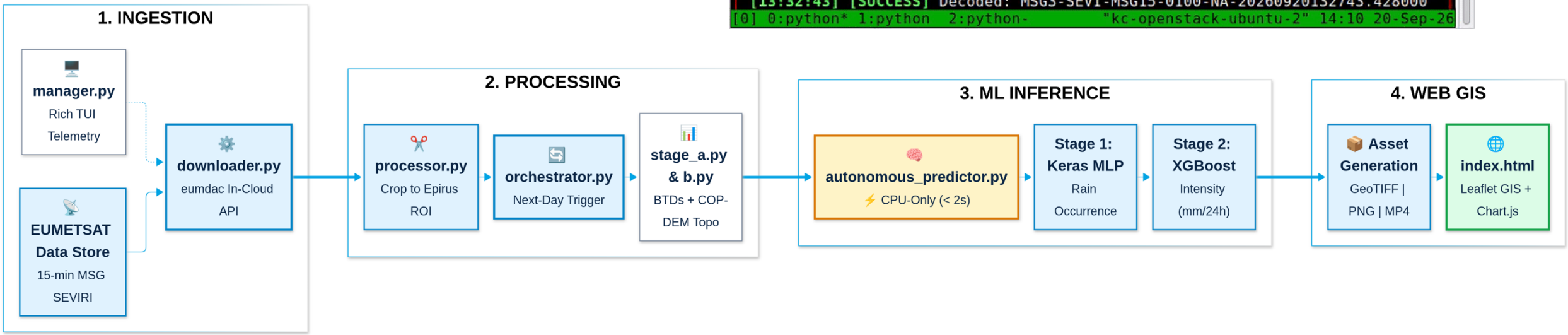


Backend & DevOps

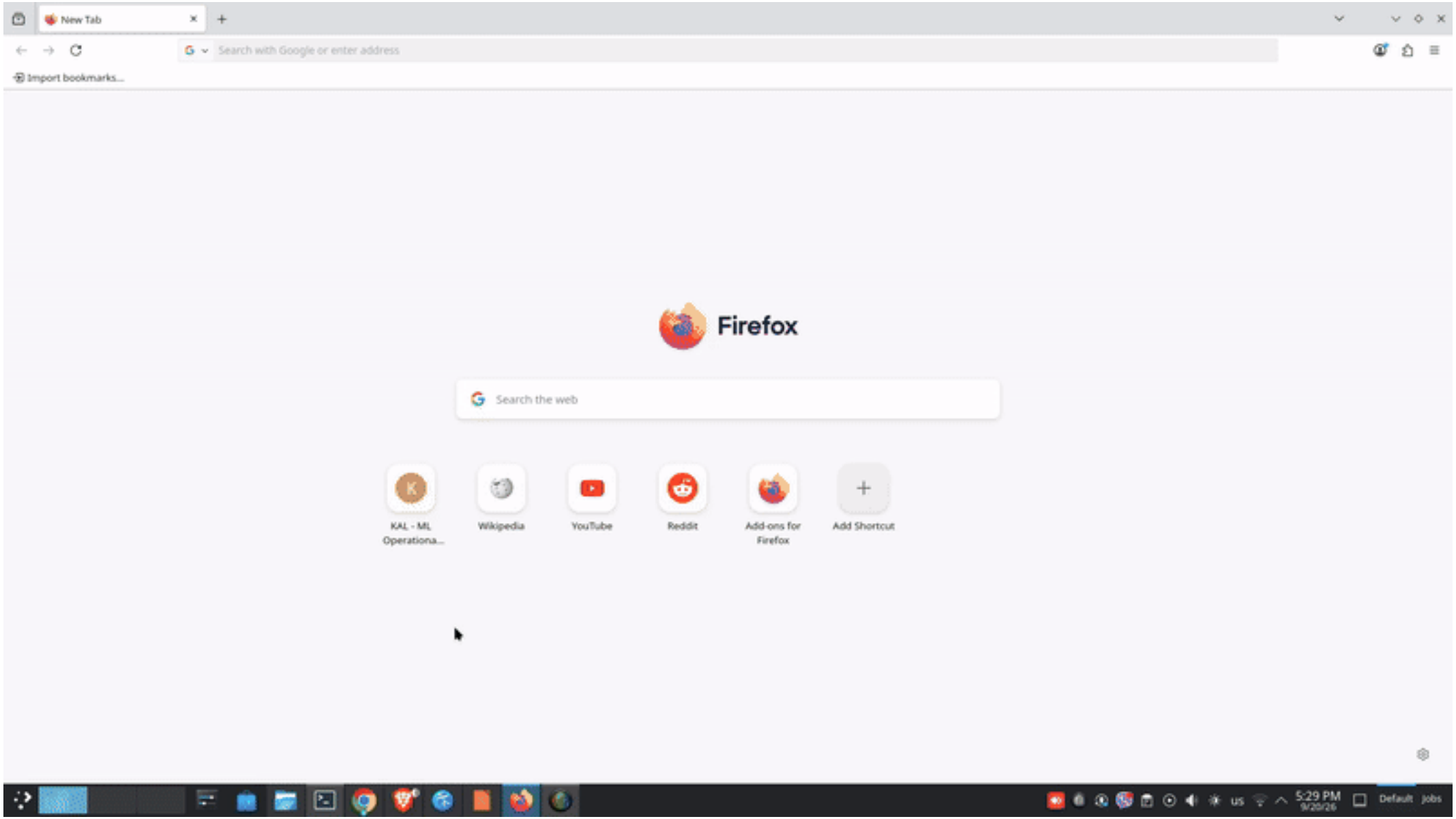
1. **downloader.py** and manager.py handle continuous in-cloud ingestion via the eumdac API.
2. **processor.py** crops the data to our domain, and orchestrator.py triggers feature engineering and Copernicus DEM fusion.
3. **autonomous_predictor.py** runs our two-stage Hurdle model (Keras MLP + XGBoost) on CPU in less than two seconds.

Finally, the engine automatically synthesizes GeoTIFFs, Cartopy maps, and cloud MP4 videos, served directly to our interactive Leaflet Web GIS."





KAL Operational Readiness - http://185.254.220.152/KAL/



Future Roadmap on EWC

PART 4

1. Transition to Meteosat Third Generation (MTG-FCI)
• Migrating from MSG SEVIRI to MTG.
• Unlocking sub-kilometer to 2 km spatial resolution and 10-min scan cycles.
• Resolving fine-scale convective initiation and complex orographic cloud dynamics.

2. Scaling KAL
• Expanding the operational domain from Epirus to other national region.
• Delivering seamless 24/7 precipitation mapping

3. Precipitation + Air Temperature (Tair)
• High-resolution near-surface Air Temperature (Tair) estimation from satellite thermal radiances.
• Coupling Precipitation (P) and Tair to compute Actual Evapotranspiration (ETa) and local daily water balance.
• Empowering precision irrigation scheduling, drought assessment.

4. EWC Cloud-Native Optimization & Community Rollout
• Migrating local storage pipelines to native EWC S3 Object Storage and use data TAILOR Apis.
• Packaging the complete end-to-end framework into a reusable Morpheus Blueprint for the EWC Marketplace.

5. Framework Maturity
• KAL Maturity: TRL 6-7 (Operational Prototype in Relevant Environment)
• Target Maturity: TRL 8 (Qualified Operational System)
•Maturing KAL into a technological core for a Regional Innovation Hub focused on Smart Agriculture, Precision Water Management & Flood Resilience.
•Funding Roadmap & Institutional Continuity. (open call for collaboration - 3 year application on EWC)

Thank you

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