



From Galamsey Hotspots to Supply-Chain Plausibility

EO, OSINT and local knowledge for environmental crime monitoring in Ghana's gold sector.

Thomas Blaschke¹, Bismark Ade¹, Samuel Ato Andam-Akorful², Omid Ghorbanzadeh¹

¹ University of Salzburg, Department of Geoinformatics – Z_GIS

² Kwame Nkrumah University of Science and Technology (KNUST), Ghana

Ongoing research within the SUSTAIN/KoEF PLUS–KNUST cooperation, connecting EO and GeoAI with UAV observations, field investigation, environmental measurements and local knowledge.



**UNIVERSITÄT
SALZBURG**

DEPARTMENT OF GEOINFORMATICS – Z_GIS

Z_GIS

Why this matters

Galamsey is an environmental crime, degradation and compliance challenge.

89%

of new mining extent in the study area was attributed to artisanal mining
2005–2019

>700 ha

of artisanal mining detected within protected areas

Monitoring challenge

- Where is mining occurring?
- How is it changing?
- What environmental resources are exposed?
- Where should investigation be prioritised?

Environmental impacts visible on the ground

Mining leaves physical and environmental impacts that can be investigated across multiple scales.

Land disturbance

Open pits, exposed soil, vegetation removal and altered landscapes

Water impacts

Sedimentation, siltation, altered waterways and water-quality concerns

Field evidence

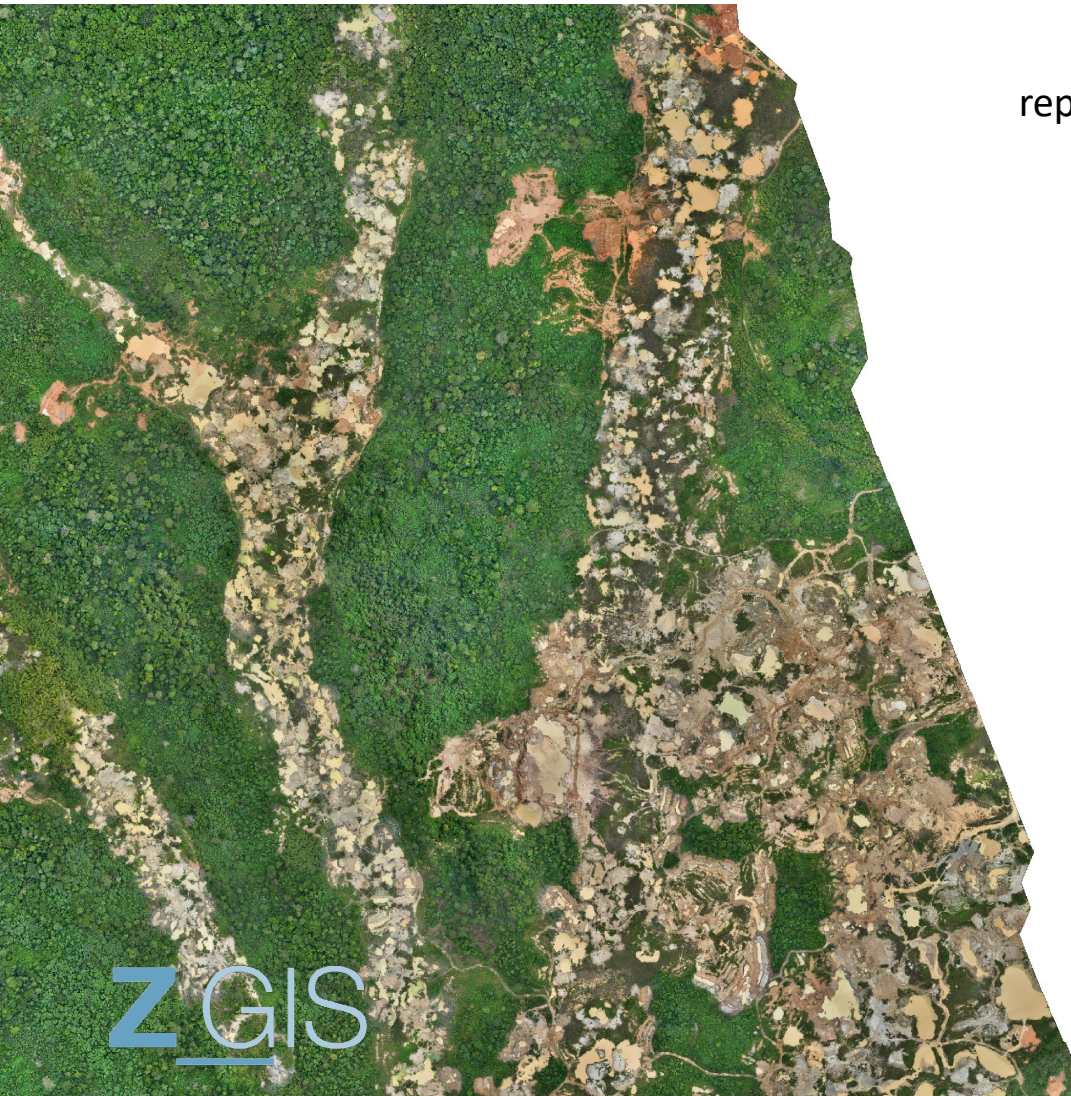
Local observations provide information that satellite imagery alone cannot establish

KNUST field investigations

UAV surveys • GPS/field observations • land-use observations • water sampling • Local evidence for interpreting and validating remotely sensed mining activity.

What EO can see from above

Mining creates observable spatial patterns: exposed soil, forest clearing, excavation areas, pits, access tracks and affected waterways.



Satellite EO
repeated, scalable observation
across large areas



UAV imagery
very-high-resolution
characterisation of
local disturbance

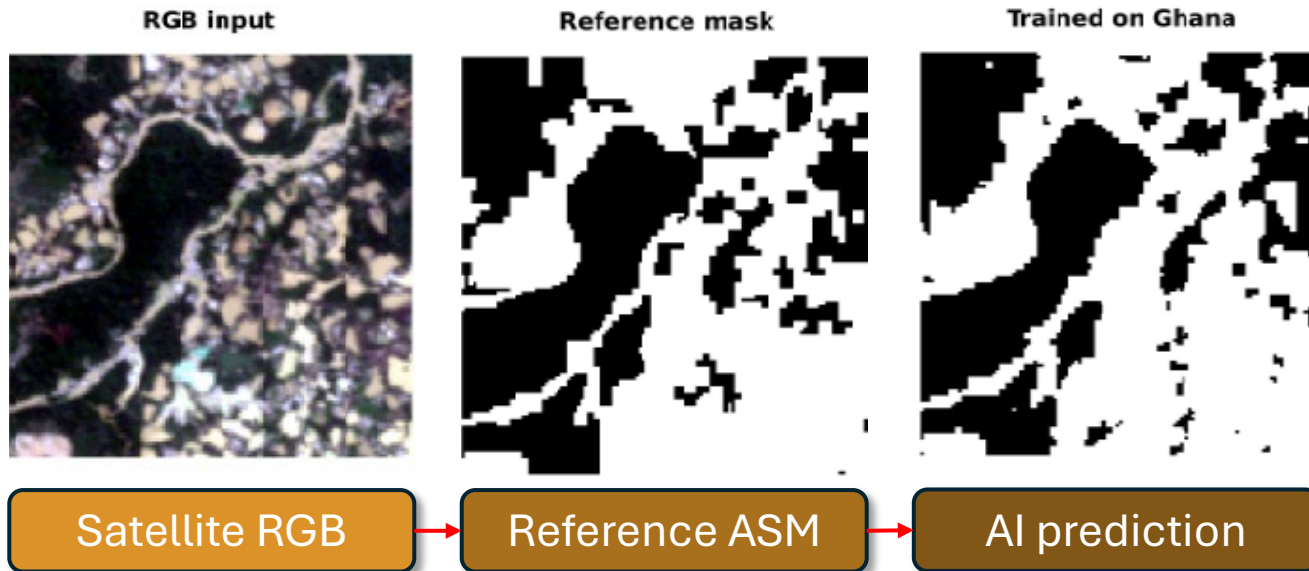


Field observations
local interpretation and
environmental evidence

EO detects mining-related
disturbance, not whether
it is legal or illegal.



From Satellite Imagery to Galamsey Hotspots

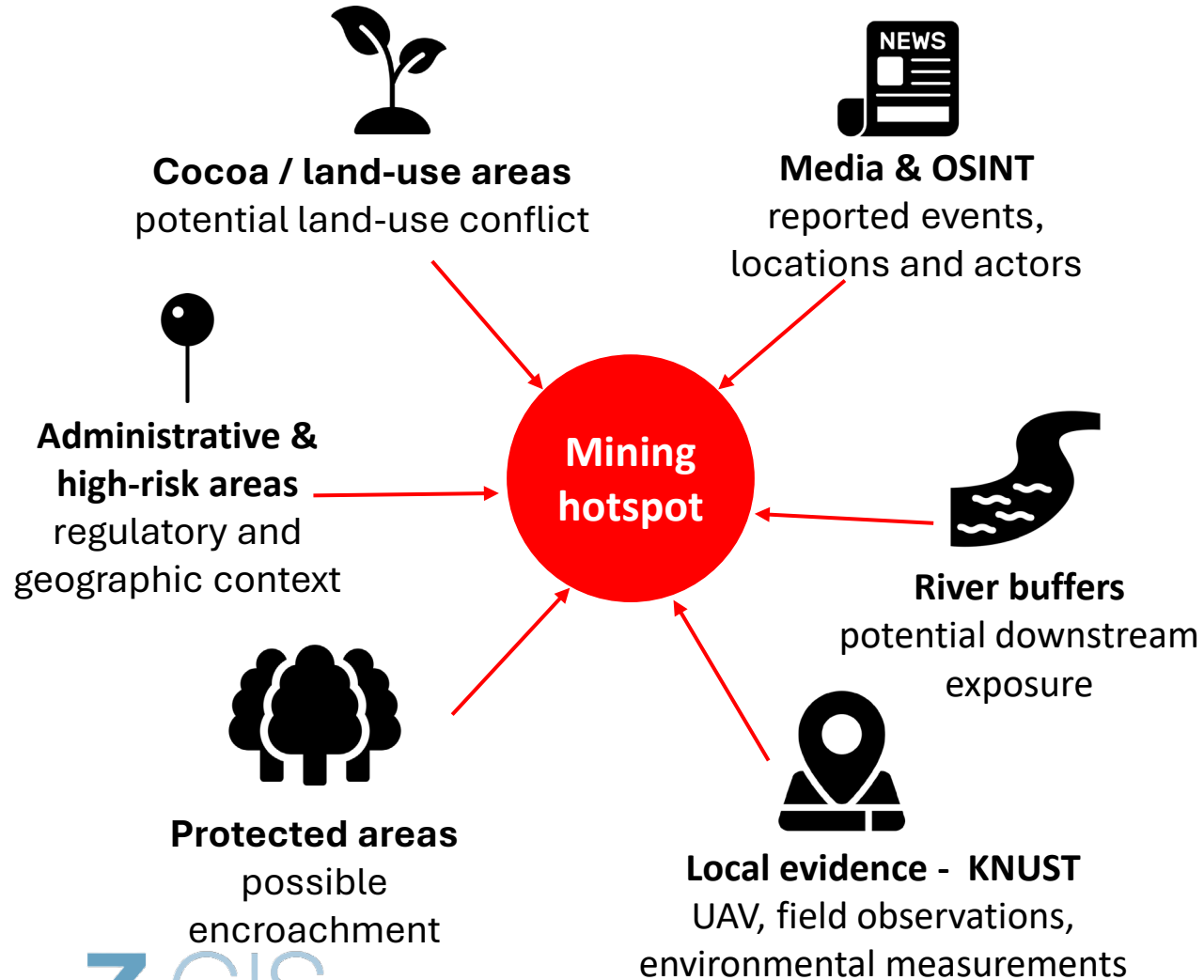


**Hotspot detection provides a screening signal
not proof of illegal activity.**

- **AI-assisted mining detection**
- Deep-learning segmentation converts Sentinel imagery into spatially explicit ASM activity cues.
- **Detect**
Mining-related land disturbance
- **Map**
Probable ASM hotspots
- **Monitor**
Changes across large areas
- **Ghana benchmark**
IoU 0.748 · F1 0.856
- **Transferability matters**
Performance depends on geographic context.
- **Cloud-resilient monitoring**
Sentinel-1 supports monitoring under persistent cloud cover.

Detection Alone Is Not Enough

Adding geospatial and open-source context to EO-derived mining activity



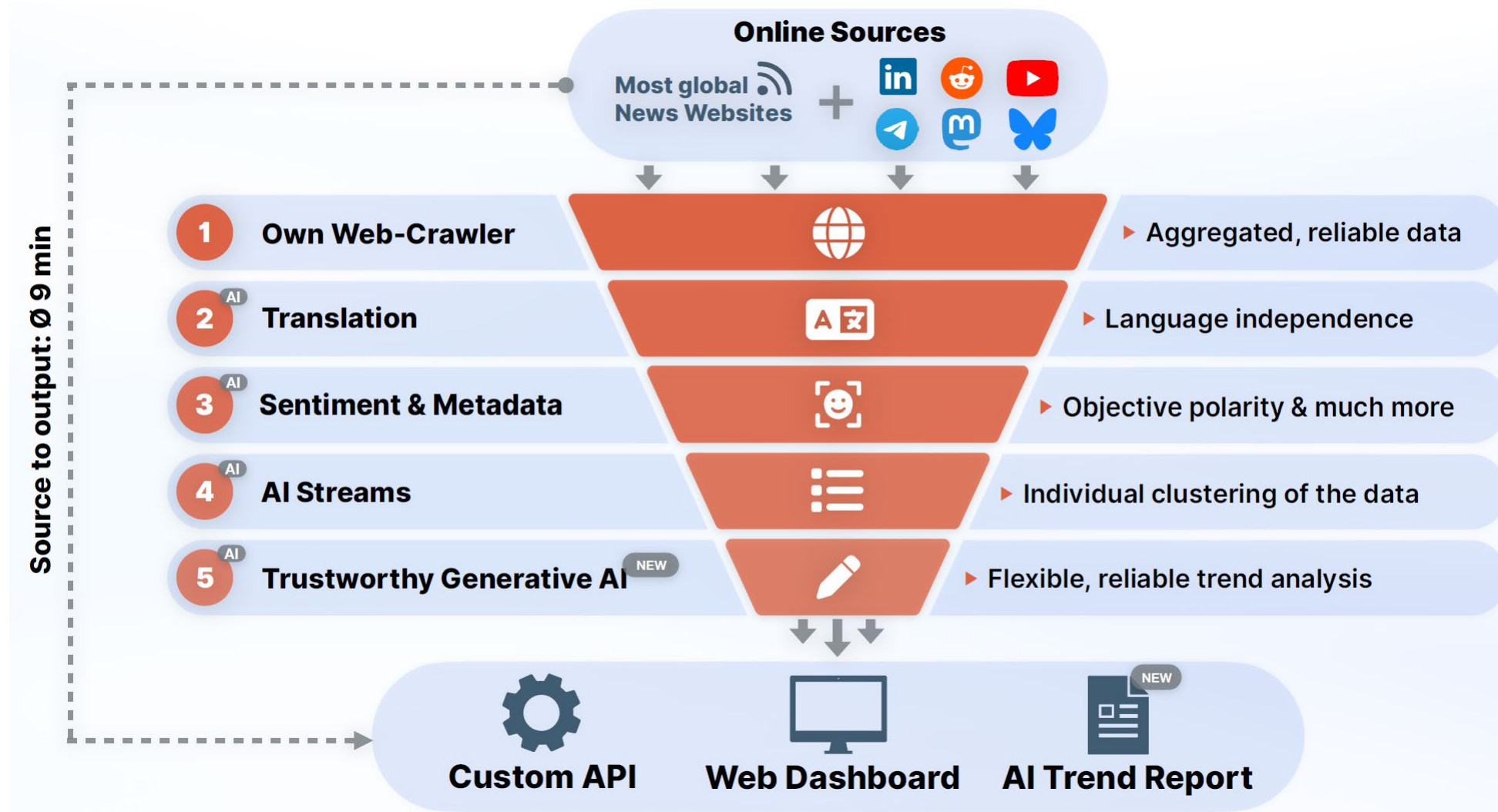
EO-derived activity cues are evaluated together with contextual information to identify where mining may create environmental, regulatory or supply-chain risks.

A mining hotspot becomes more meaningful when its location, context and reported activity are considered together.

Detection shows where change may be occurring. Context helps explain why it matters.

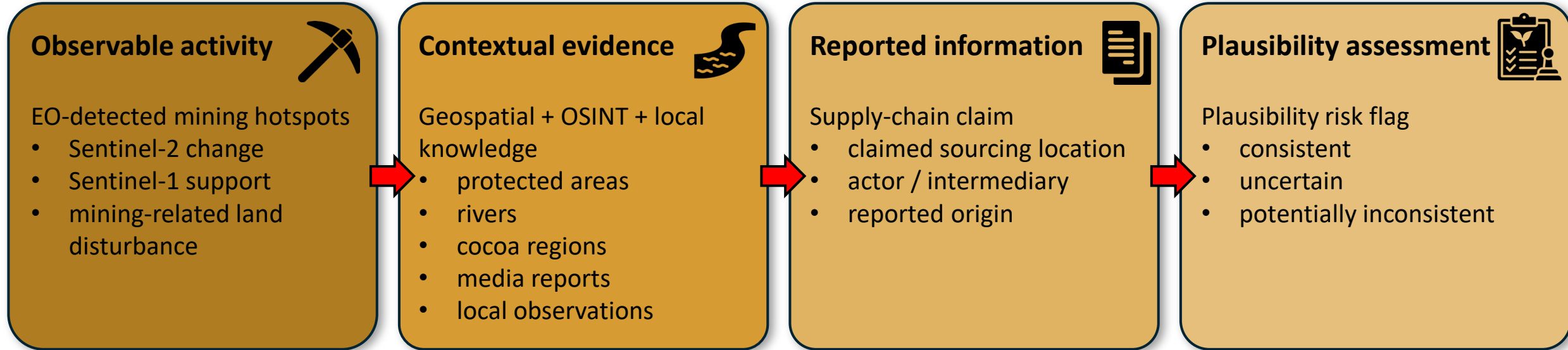
Nursamsi et al. (2024); Blaschke et al. (2026)

Media intelligence pipeline in detail



From Hotspots to Supply-Chain Plausibility

Can observable mining activity and independent contextual evidence be reconciled with reported sourcing information?



EXAMPLE

Claim: Gold sourced from area A

EO evidence: Rapid mining expansion observed in area B

Context: Area B overlaps forest reserve/ river corridor

Result: **Potential inconsistency** → review

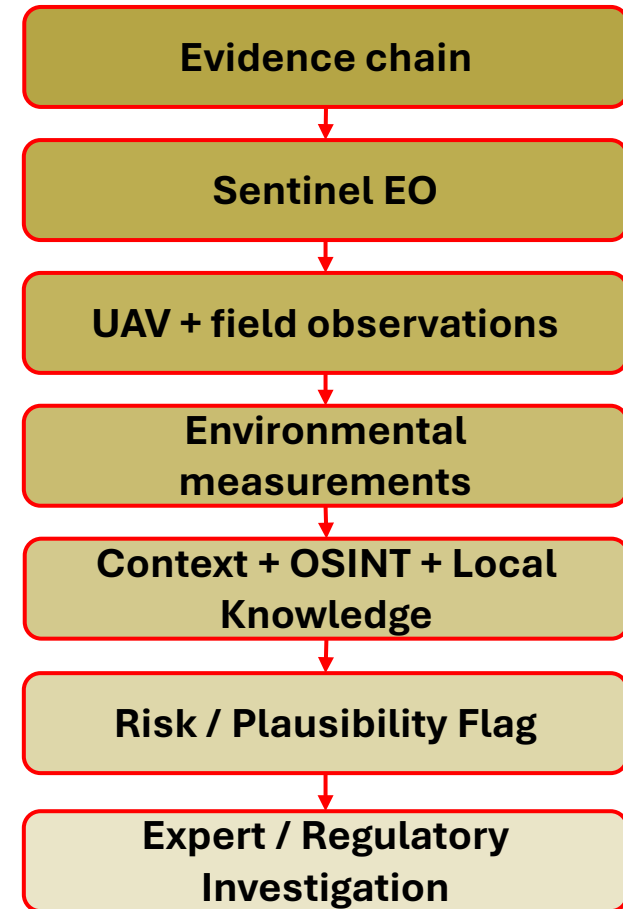
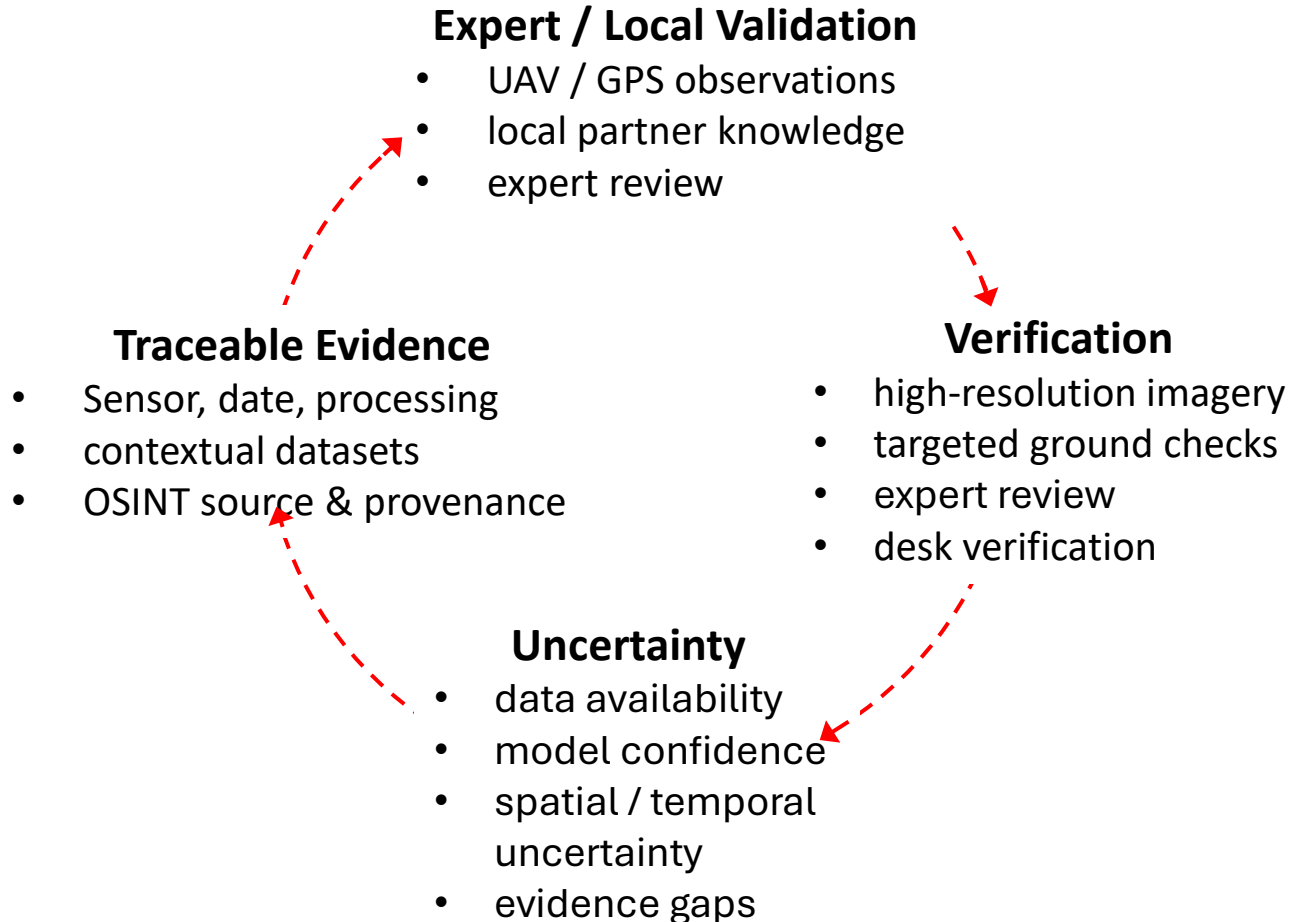
flag where the evidence does not align.

Plausibility ≠ verification.

It identifies where evidence and reported information do not align and where further review may be warranted.

Explainable, Traceable and Verifiable Evidence

Every risk signal should show where it came from, what supports it, what remains uncertain and how it can be checked.



The objective is not simply a confidence score, but a traceable evidence chain.

How can EO, OSINT and local knowledge be combined to support practical environmental-crime monitoring?

Scientific challenges

- **Transferability**
How robust are EO/GeoAI models across different mining landscapes?
- **Evidence fusion**
How should satellite, UAV, field, environmental and open-source evidence be combined without overstating what each source can establish?
- **Uncertainty & provenance**
How can uncertainty and evidence provenance remain visible throughout the workflow?

Operational challenges

- **Validation**
How should local partners and field evidence be incorporated systematically?
- **Regulatory relevance**
Which risk indicators are actually useful to environmental and enforcement agencies?
- **Operationalisation**
How do we move from a research prototype to a transparent and reproducible screening workflow?

Next step

Co-develop and test the workflow with KNUST and relevant Ghanaian stakeholders using satellite, UAV, field and environmental observations.

References

Ade, B., Ghorbanzadeh, O., & Blaschke, T. (2026). Cross-country transferability of deep learning models for artisanal and small-scale mining mapping in Ghana and Côte d'Ivoire. *Geosciences*, 16(8), 310.

<https://doi.org/10.3390/geosciences16080310>

Barenblitt, A., Payton, A., Lagomasino, D., Fatoyinbo, L., Asare, K., Aidoo, K., & Pigott, H. (2021). The large footprint of small-scale artisanal gold mining in Ghana. *Science of the Total Environment*, 781, 146644.

<https://doi.org/10.1016/j.scitotenv.2021.146644>

Blaschke, T., Eitzinger, A., Dong, Y., Ebrahimi, H., & Naboureh, A. (2026). Geospatial data and workflows for environmental and sustainability compliance reporting: Including the private sector. *Big Earth Data*, 10(2), 701–727.

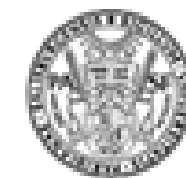
<https://doi.org/10.1080/20964471.2026.2618893>

Forkuor, G., Ullmann, T., & Griesbeck, M. (2020). Mapping and monitoring small-scale mining activities in Ghana using Sentinel-1 time series (2015–2019). *Remote Sensing*, 12(6), 911. <https://doi.org/10.3390/rs12060911>

Gallwey, J., Robiati, C., Coggan, J., Vogt, D., & Eyre, M. (2020). A Sentinel-2 based multispectral convolutional neural network for detecting artisanal small-scale mining in Ghana: Applying deep learning to shallow mining. *Remote Sensing of Environment*, 248, 111970. <https://doi.org/10.1016/j.rse.2020.111970>

Nursamsi, I., Phinn, S. R., Levin, N., Luskin, M. S., & Sonter, L. J. (2024). Remote sensing of artisanal and small-scale mining: A review of scalable mapping approaches. *Science of the Total Environment*, 951, 175761.

<https://doi.org/10.1016/j.scitotenv.2024.175761>



UNIVERSITÄT
SALZBURG



KNUST
KWAME NKRUMAH UNIVERSITY
OF SCIENCE AND TECHNOLOGY

University of Salzburg

Department of Geoinformatics – Z_GIS

thomas.blaschke [at] plus.ac.at

<https://scholar.google.com/citations?user=kMroJzUAAAJ>

In cooperation with
our spin-offs:



PeaceEye

Z_GIS



HOME PROGRAMME STUDY ADMISSION PARTICIPATION COSTS STUDENT LIFE FAQ CONTACT



**COPERNICUS MASTER
IN DIGITAL EARTH**



DEPARTMENT OF GEOINFORMATICS – Z_GIS