Detection of the evolution of mine sites and tailings dams in South Africa using Artificial Intelligence and Remote Sensing

UNEP/GRID-Geneva

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Automatic detection of mine sites

Mining:

- Great economic importance
- Major risks especially related to environmental damages

Objectives

- Create a catalogue of data for localization and characteristics of mines and dams, in South Africa, used for AI training
- Train an AI model able to detect mine sites and tailing dams using remote sensing data (Sentinel 2 images)
- Evaluate the AI ability to detect mine sites over the territory of South Africa
- Analyse and refine the results through space & time
- Analyse the characteristics of abandoned mines

Great advances in automatic monitoring environmental impact of mining:

- Artificial Intelligence (AI)
- Availability of a wide range of satellite images
- Access to powerful computing and storage resources

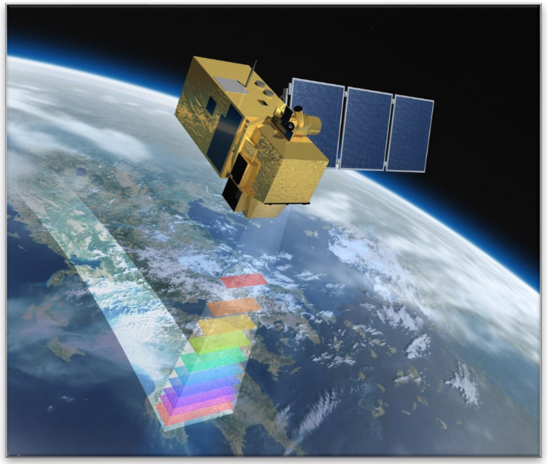
Methodology

Mine sites can be recognised by:

- Buildings/processing plants (a few to 100s meters)
- Cuts (100 to 1000s meters)
- Lake/pools with straight shores (10s to 100s meters)
- Tailings (10s to 100s meters)

Automatic detection of mine sites requires high resolution satellite images

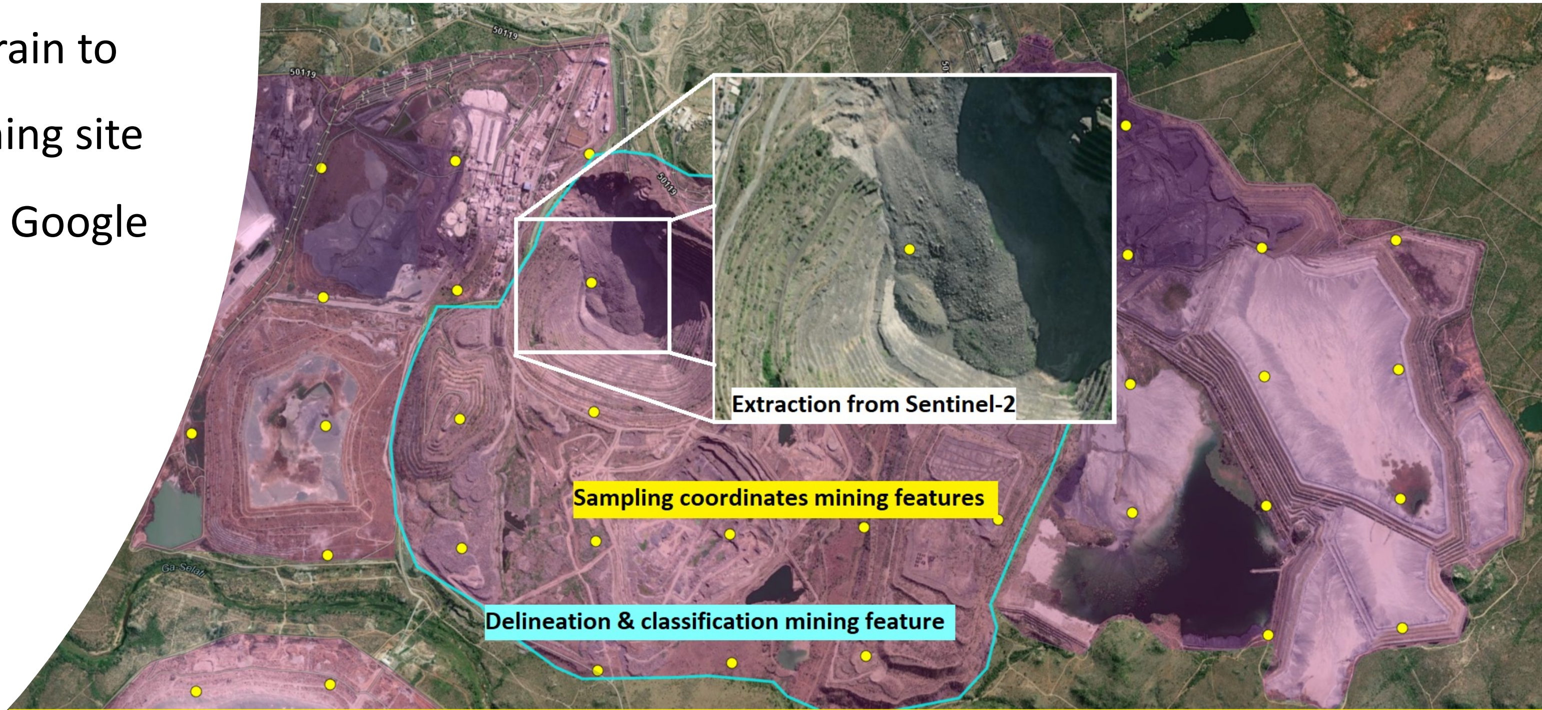
-> Sentinel 2 (10 m spatial resolution)



Methodology

AI Deep Learning

- Training data -> a balanced set of samples (Sentinel 2 patches) from the targeted classes (mine and background) -> minimise model bias
- Convolutional neural network classifier train to identify if an image contains or not a mining site
- Open-source software: TensorFlow, GGE, Google Collaboratory (Colab), Python, R, QGIS



Methodology

Code for satellite images extraction

Methodology

Code for satellite images extraction → Training the AI

Methodology

Code for satellite images extraction → Training the AI → Validation of the trained AI model

Methodology

1. Code for satellite images extraction
2. Training the AI
3. Validation of the trained AI model
4. Small scale prediction through time

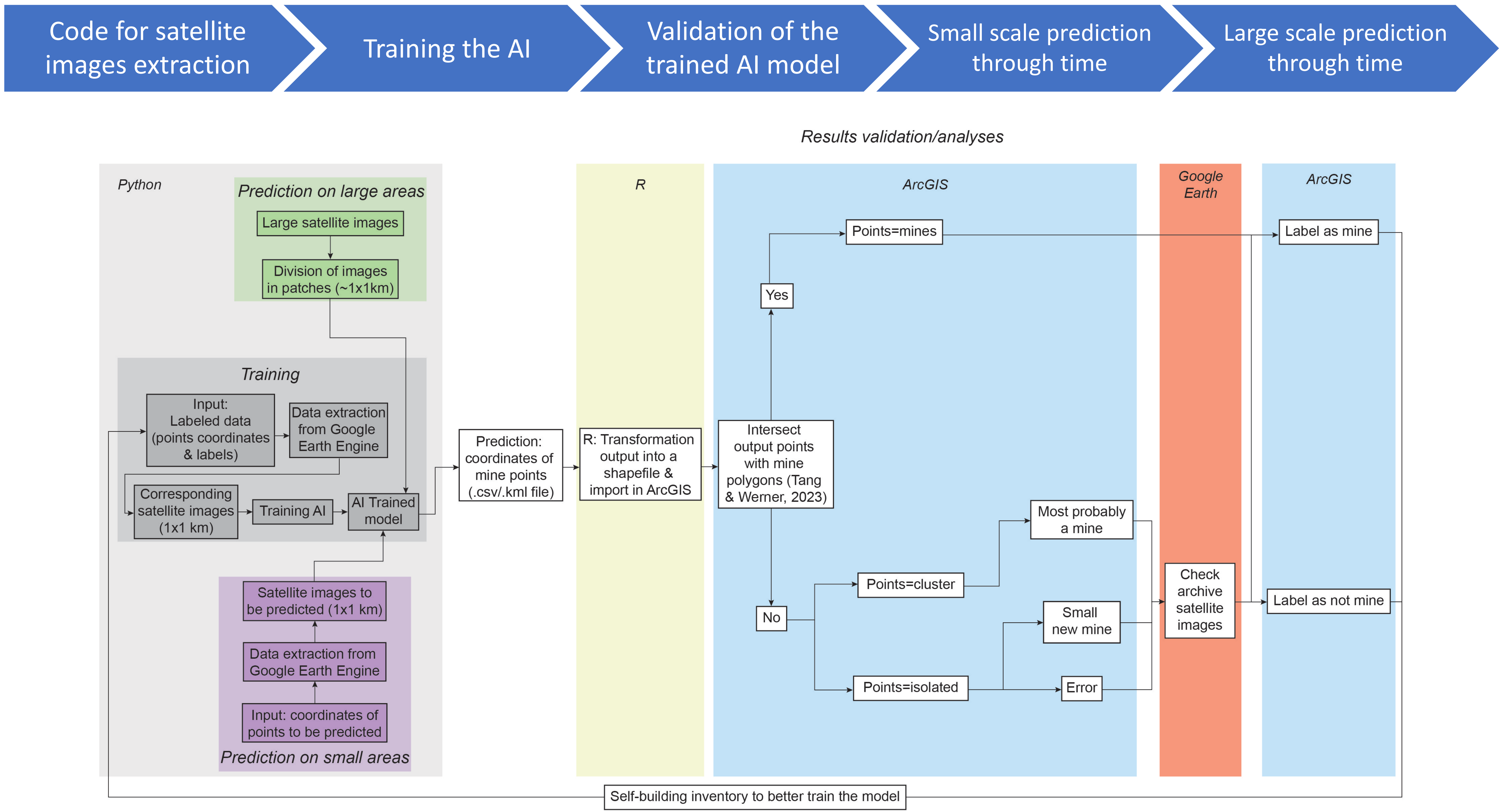
Methodology

Code for satellite images extraction → Training the AI → Validation of the trained AI model → Small scale prediction through time → Large scale prediction through time

Methodology

Code for satellite images extraction → Training the AI → Validation of the trained AI model → Small scale prediction through time → Large scale prediction through time

Focus: South Africa


Code for satellite images extraction
Training the AI
Validation of the trained AI model
Small scale prediction through time
Large scale prediction through time
Results validation/analyses
Python
Prediction on large areas
Large satellite images
Division of images in patches (~1x1km)
Training
Input: Labeled data (points coordinates & labels)
Data extraction from Google Earth Engine
Corresponding satellite images (1x1 km)
Training AI
AI Trained model
Satellite images to be predicted (1x1 km)
Data extraction from Google Earth Engine
Input: coordinates of points to be predicted
Prediction on small areas
Prediction: coordinates of mine points (.csv/.kml file)
R
R: Transformation output into a shapefile & import in ArcGIS
ArcGIS
Intersect output points with mine polygons (Tang & Werner, 2023)
Yes
Points=mines
No
Points=cluster
Points=isolated
Most probably a mine
Small new mine
Error
Google Earth
Check archive satellite images
ArcGIS
Label as mine
Label as not mine
Self-building inventory to better train the model

Methodology

Data acquisition, cleaning and ground truthing

Data acquisition	Published peer-reviewed mining databases
Location and delineation	Location and delineation of mining features based online and academic sources and based on satellite imagery
Classifying/tagging	Classifying/tagging the delineated mine features using the classes agreed with the client
Sampling	Sampling point coordinates within classified mining features and outside mining features to train the AI on what to recognize as a specific mining feature and what not
Extracting	Generating/extracting of Sentinel-2 images of the mining and non-features using the point coordinates of labelled features. The result are labelled satellite images which can be used for AI training

Automatic detection of mine sites

Challenges:

- The appearance of an abandoned mine is diverse and depends on:
  - The type of mining
  - The geographic conditions/landscape
  - The climate zone

E.g. South Africa has a wide variety of mining methods and past and present mining features which are in a variety of landscapes and climate zones.

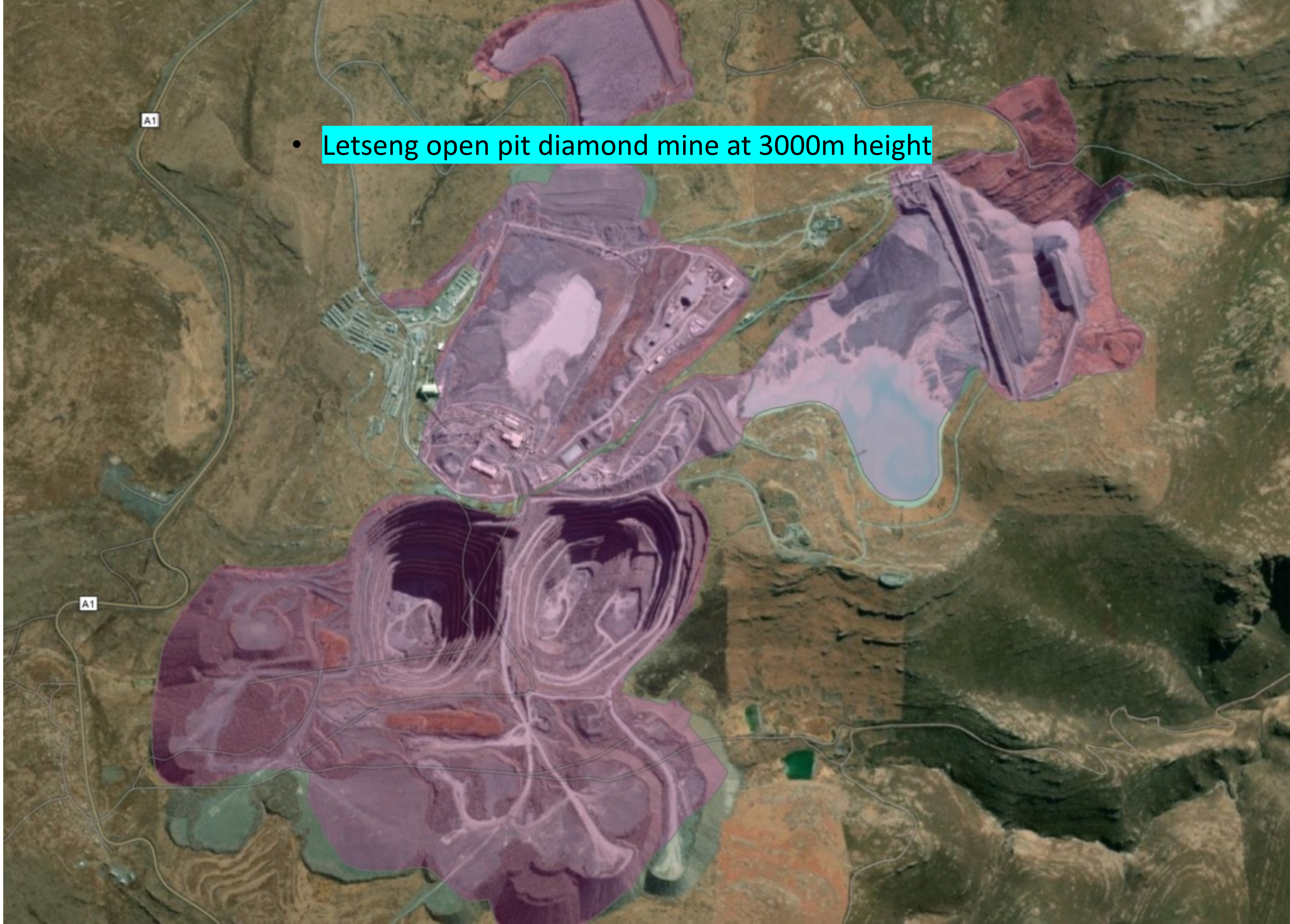
The diversity of mines and mining legacy features

Mogalakwena open pit platinum mine

Active open pit mine with acid leaching facilities and with tailings dams

- Letseng open pit diamond mine at 3000m height

Active open pit mine without acid leaching facilities but with tailings dams and stockpiles of overburden



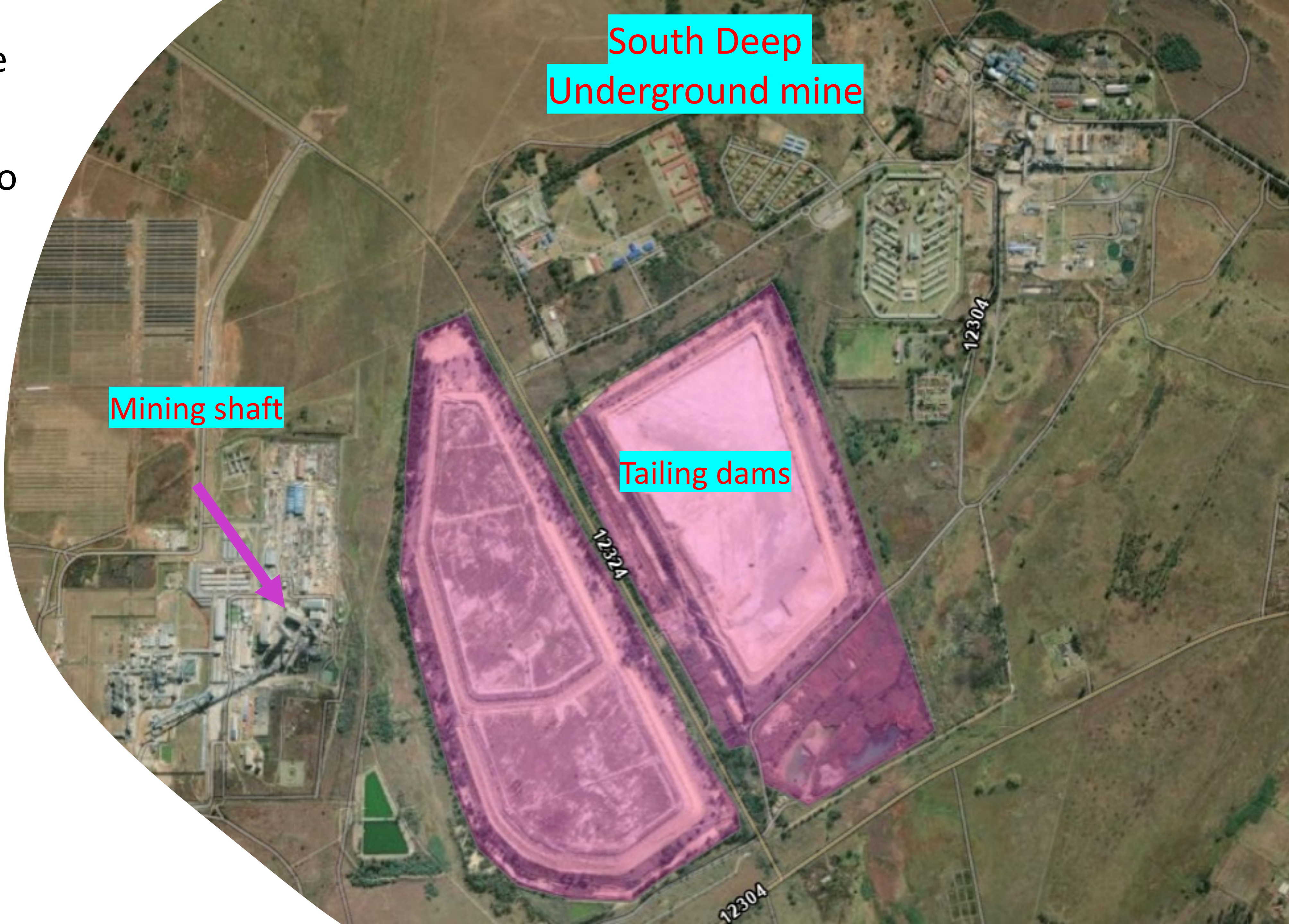
Rock quarry

- No tailings
- No acid treatment
- No rock overburden
- Crushing, screening and milling

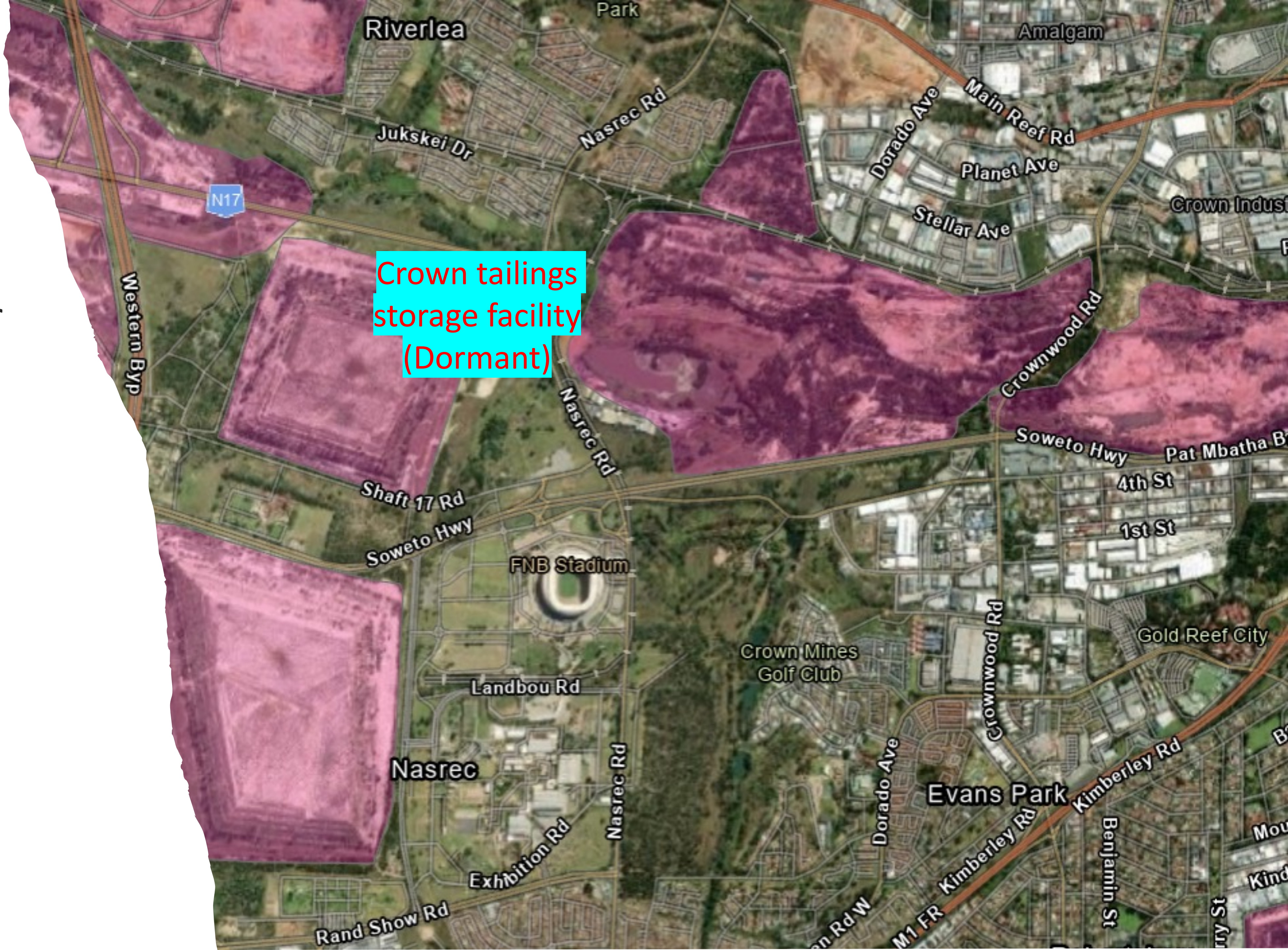
Beach Diamond mining of South African West Coast

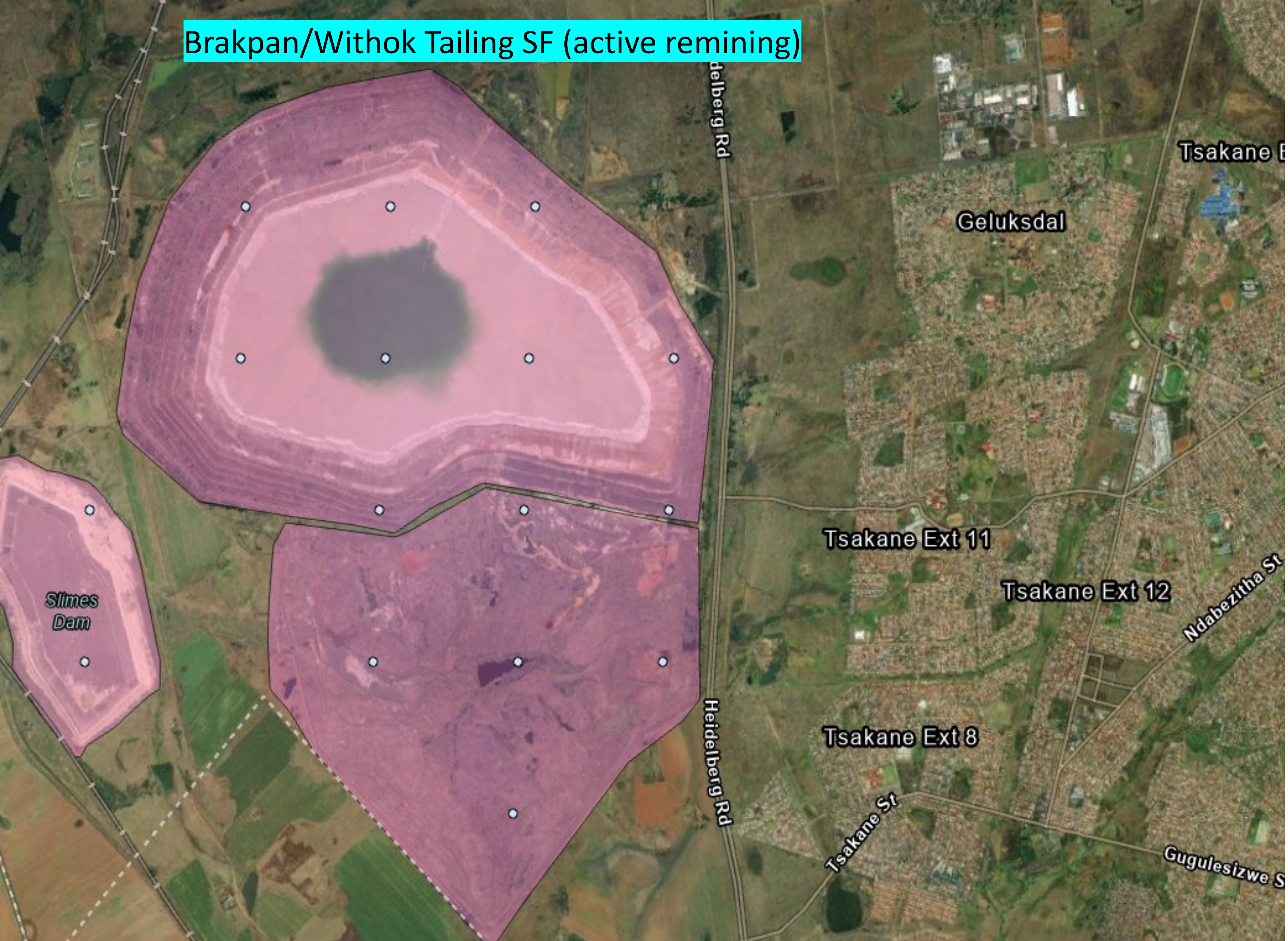
Beach mining with “tailing dams” and stockpiles

Underground mine with acid leaching facilities and with tailings dams but no overburden



Old tailings of former underground gold mines





Old tailings – new resources

Retreatment of surface dumps including acid leaching.

The retreatment process involves the extraction of minute particles of gold from past mining 'waste' and turns mining legacies into active mines.

What is active, dormant or historic is very hard to tell.

Legacy or active?

Coastal diamond mining in arid climate along the coast of West Africa

The legacy of mining in dynamic areas such as river and coastal areas express themselves very differently from open-pit mining in static environments

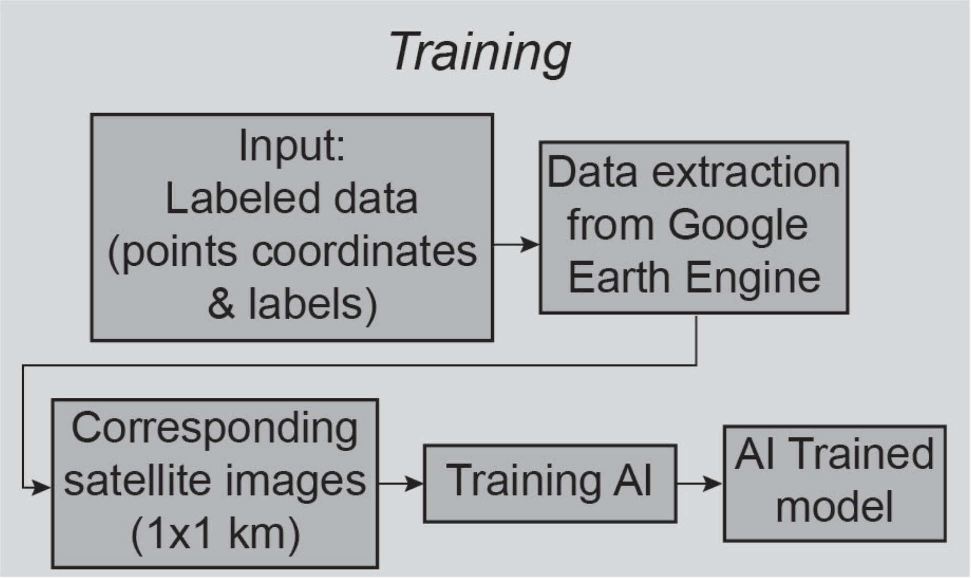
Abandoned mine?

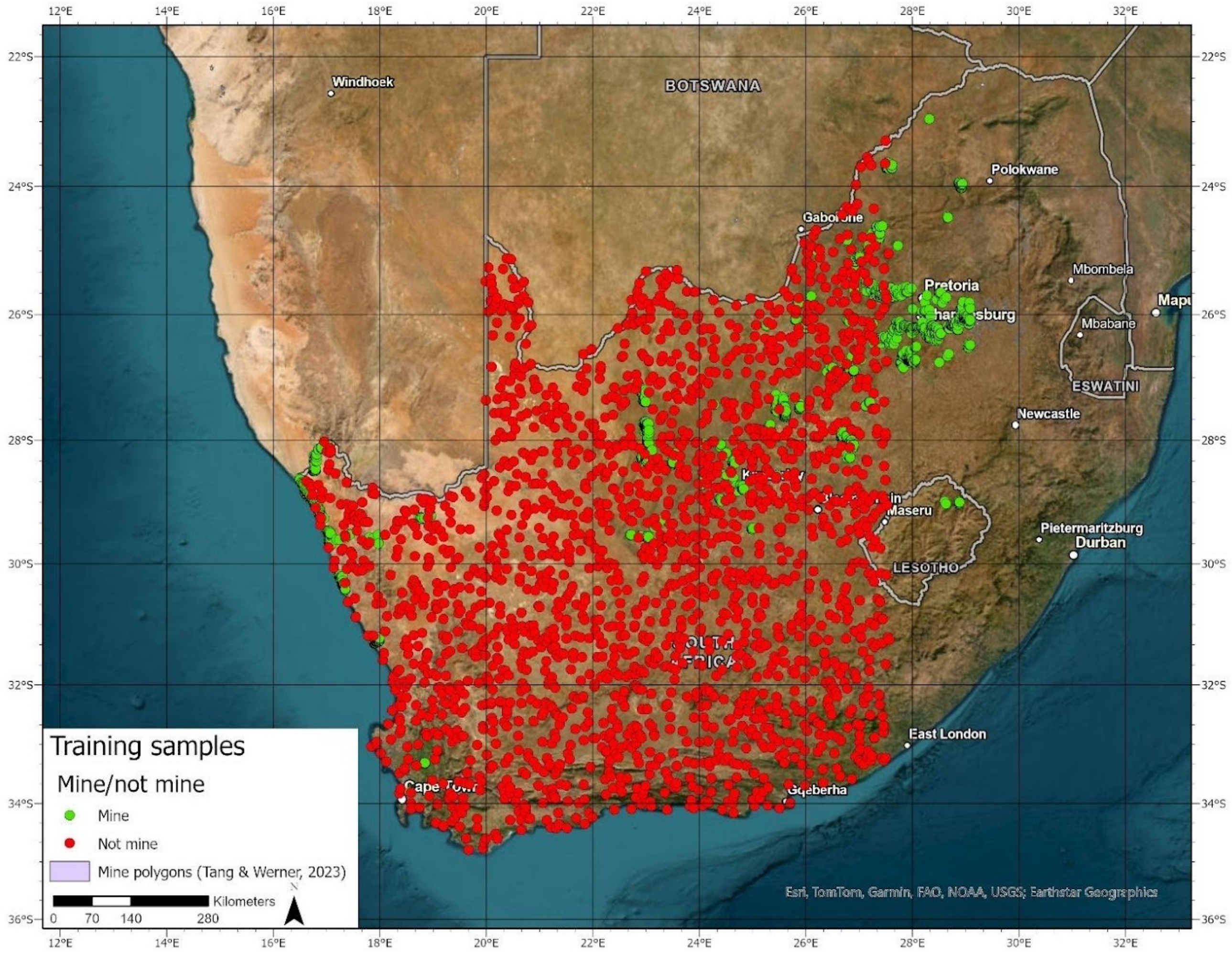
Museum?

(according to the Beers it is part of Kimberley's patrimony)

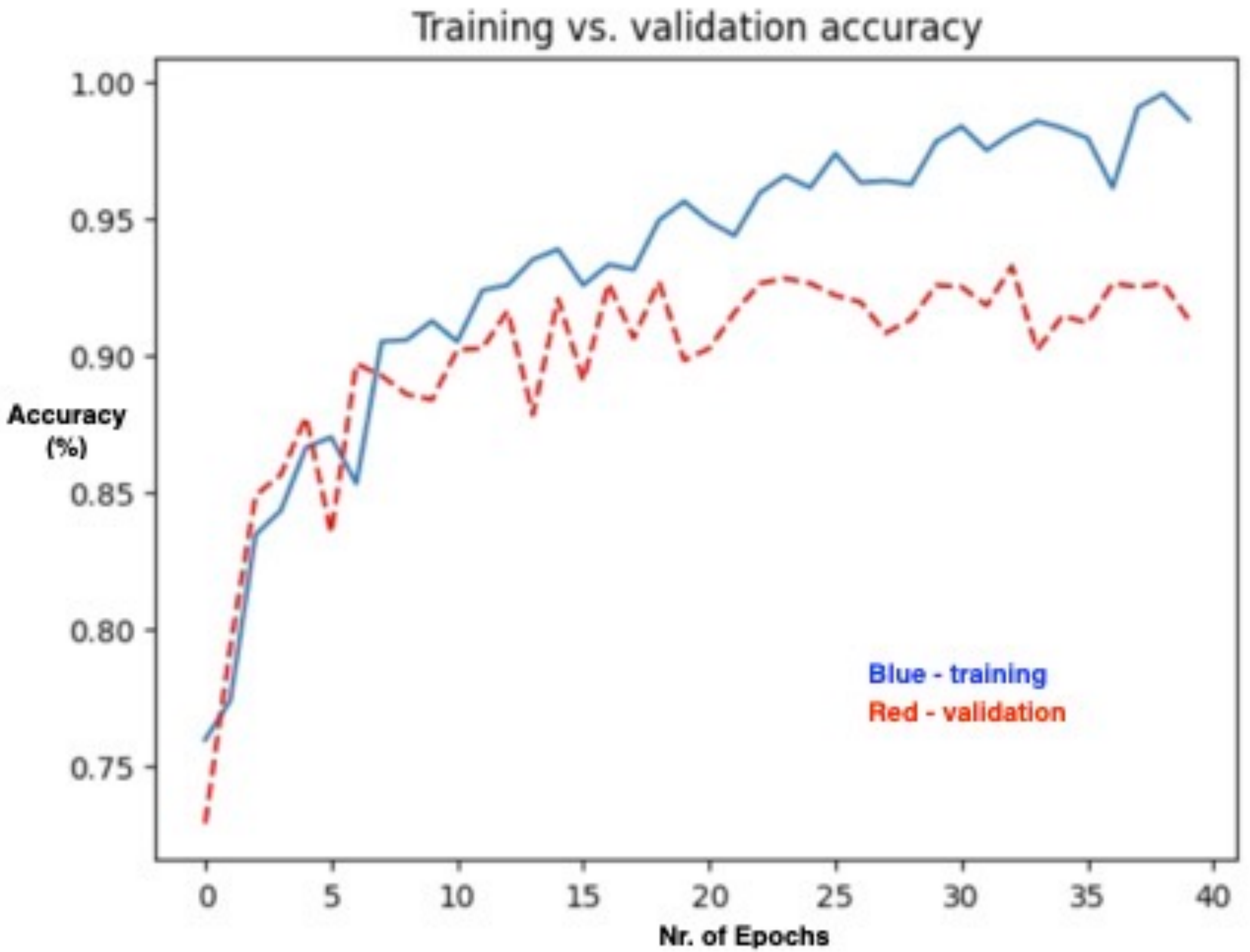
AI model training

- Training data: 4000 sample points
  - 2000 mine
  - 2000 not mine
- Interpretation of 1x1 km images
- 80% = training material
- 20% = testing & validating





AI model training

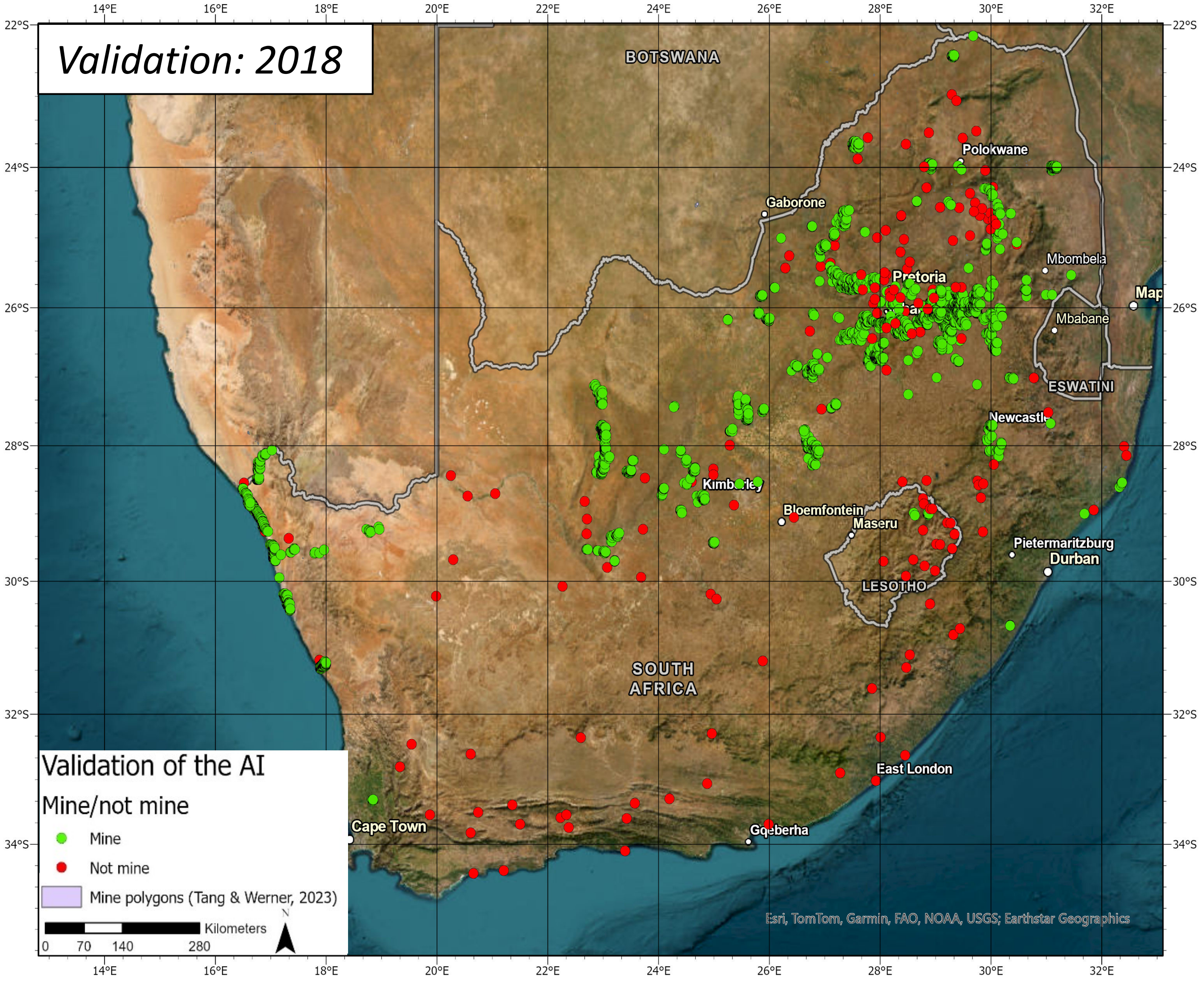


Validation of the AI model

Validation of the AI model on a subset of points based on 1x1 km Sentinel 2 images from 2018

- 6039 points in South Africa introduced for prediction:
  - 3027 mine
  - 3012 not mine
- AI returned results:
  2906 points interpreted as mine
- After manual correction:
  2626 mine points
  280 not mine points

- 9.2% of not mine areas - incorrectly labelled as mine
- 87% of introduced mine points correctly interpreted AND new mines were detected!



Validation of the AI model

Comparison with literature inventory

Mining area estimation:

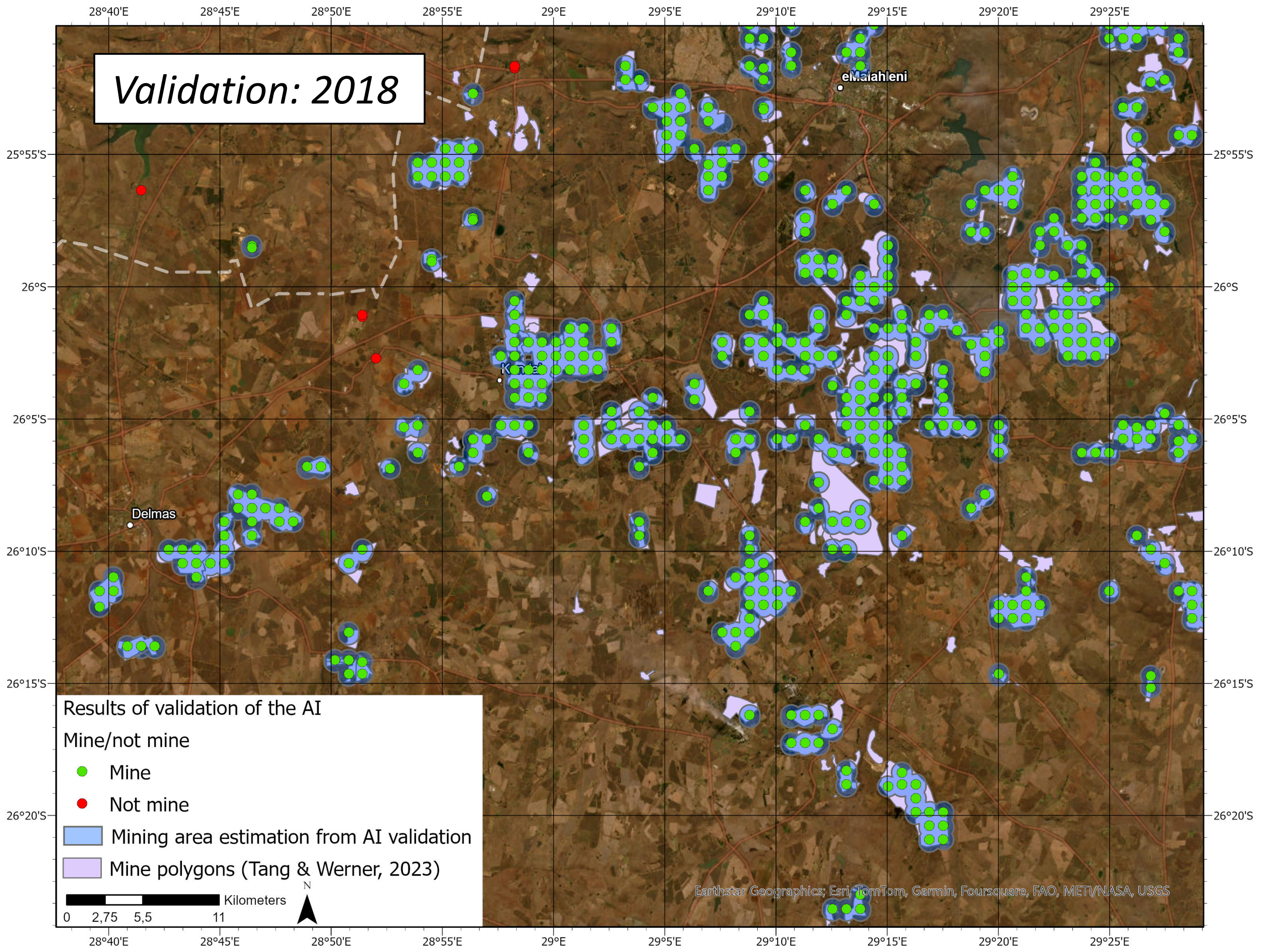
- After manual correction
- Using a buffer of 750m

(~$^1/_2$ diagonal of 1x1 km square)

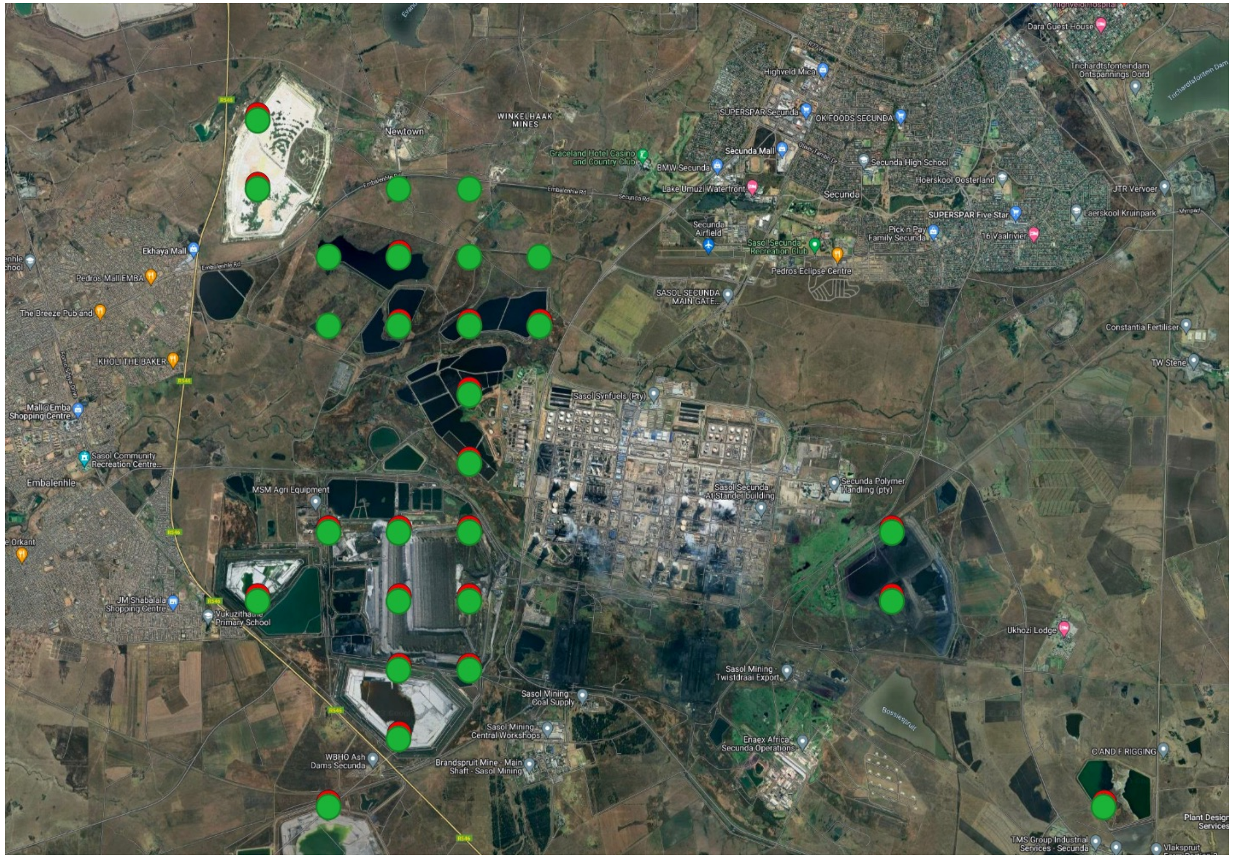
- ~3898 km^2

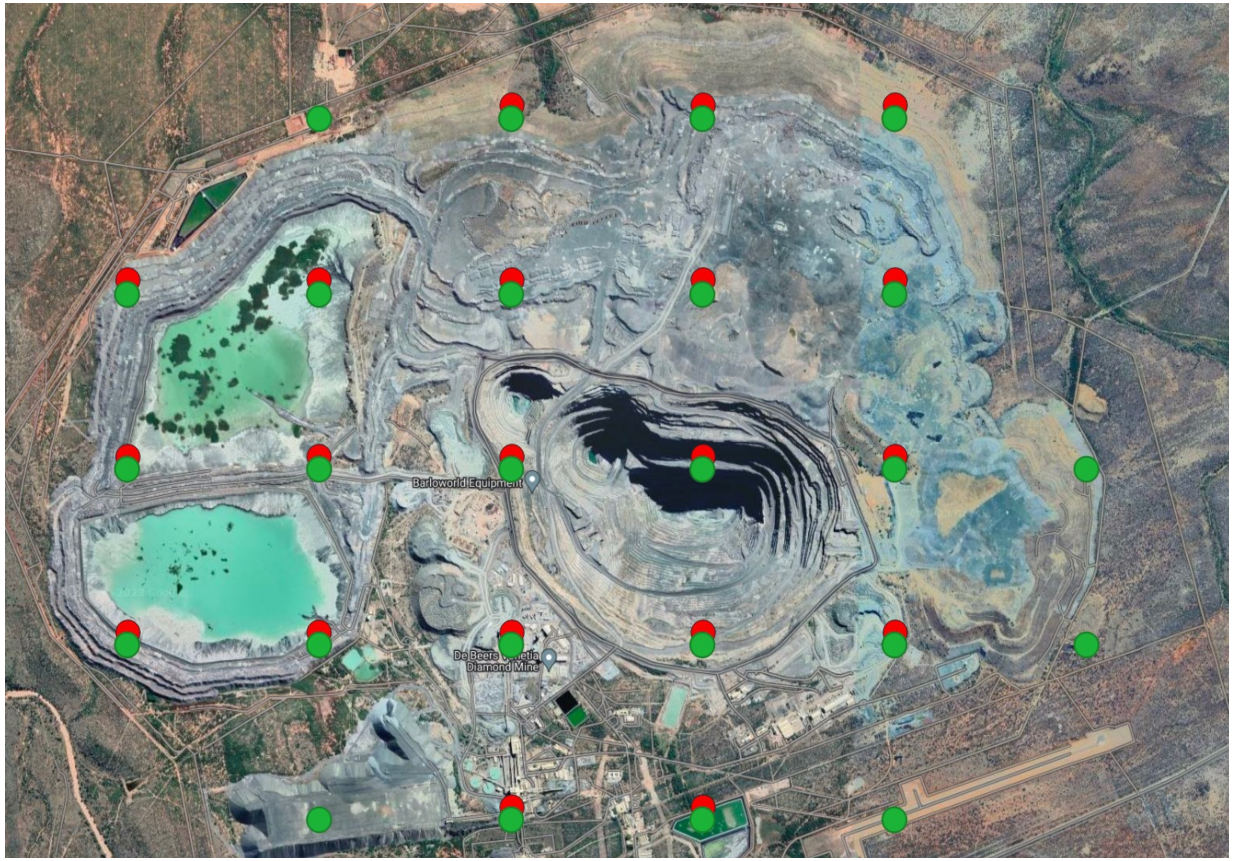
Currently estimated in literature: ~3020 km^2 *(Tang & Werner 2023)*

- Overestimation in our scenario
- *But* incomplete inventory of mine sites in literature (discovery of new sites in our study)



Validation of the AI model



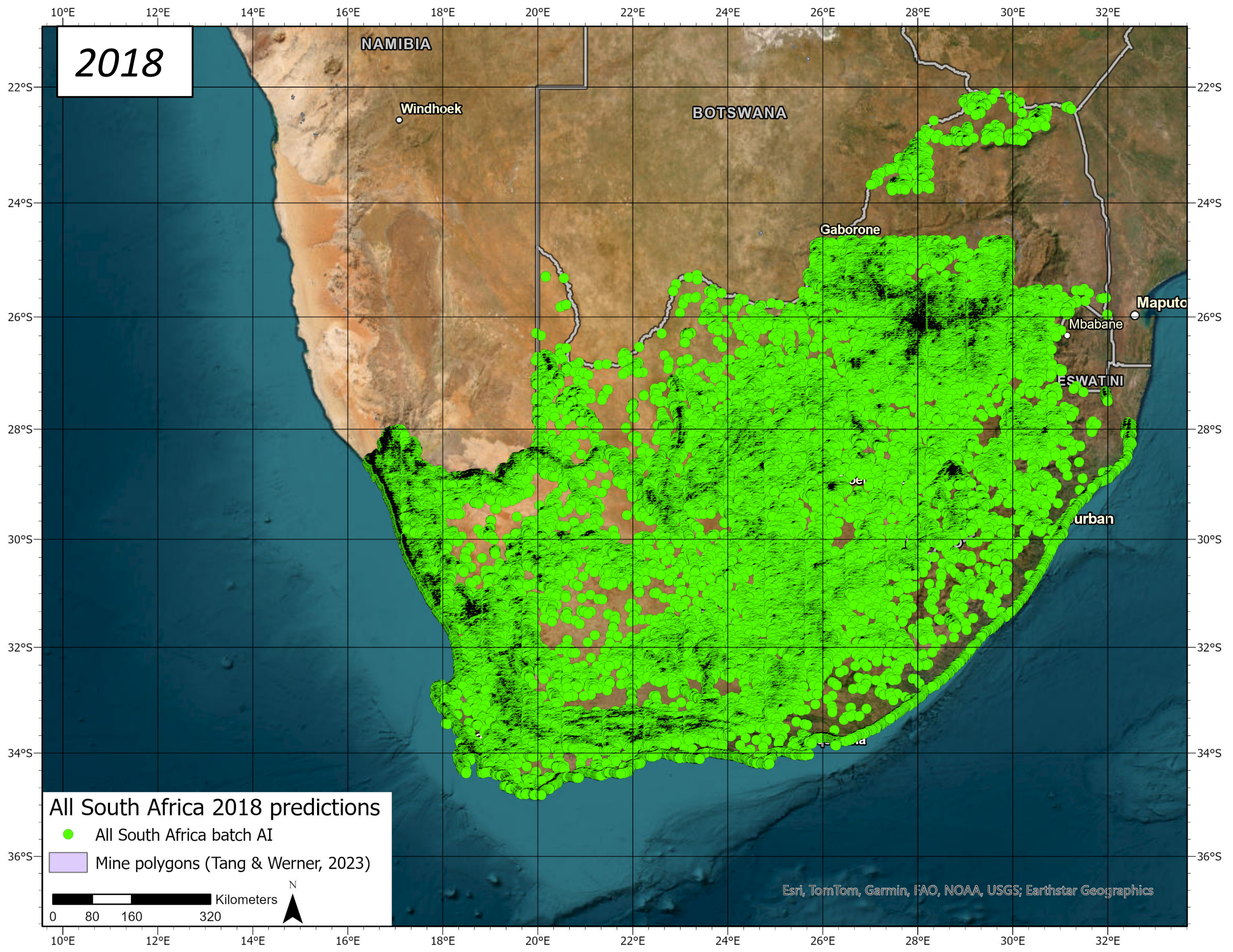


Mine detection – true positive examples
Red – ground truth
Green – AI prediction

Large scale prediction of mine sites full extent of South Africa (2018)

AI predictions on the full extent of South Africa

- 300 full size Sentinel 2 images (9’472 x 9’472 pixels) divided into patches of ~1x1 km
- Returned results: 71’134 considered as mine by the AI model
- ***Looks like the entire South Africa is covered in mines … but actually is not that bad!***



Large scale prediction of mine sites full extent of South Africa (2018)

AI predictions on the full extent of South Africa

After manual correction:

7'053 actual mine points

64'081 errors

- ***Still looks like a big proportion of errors …***

But

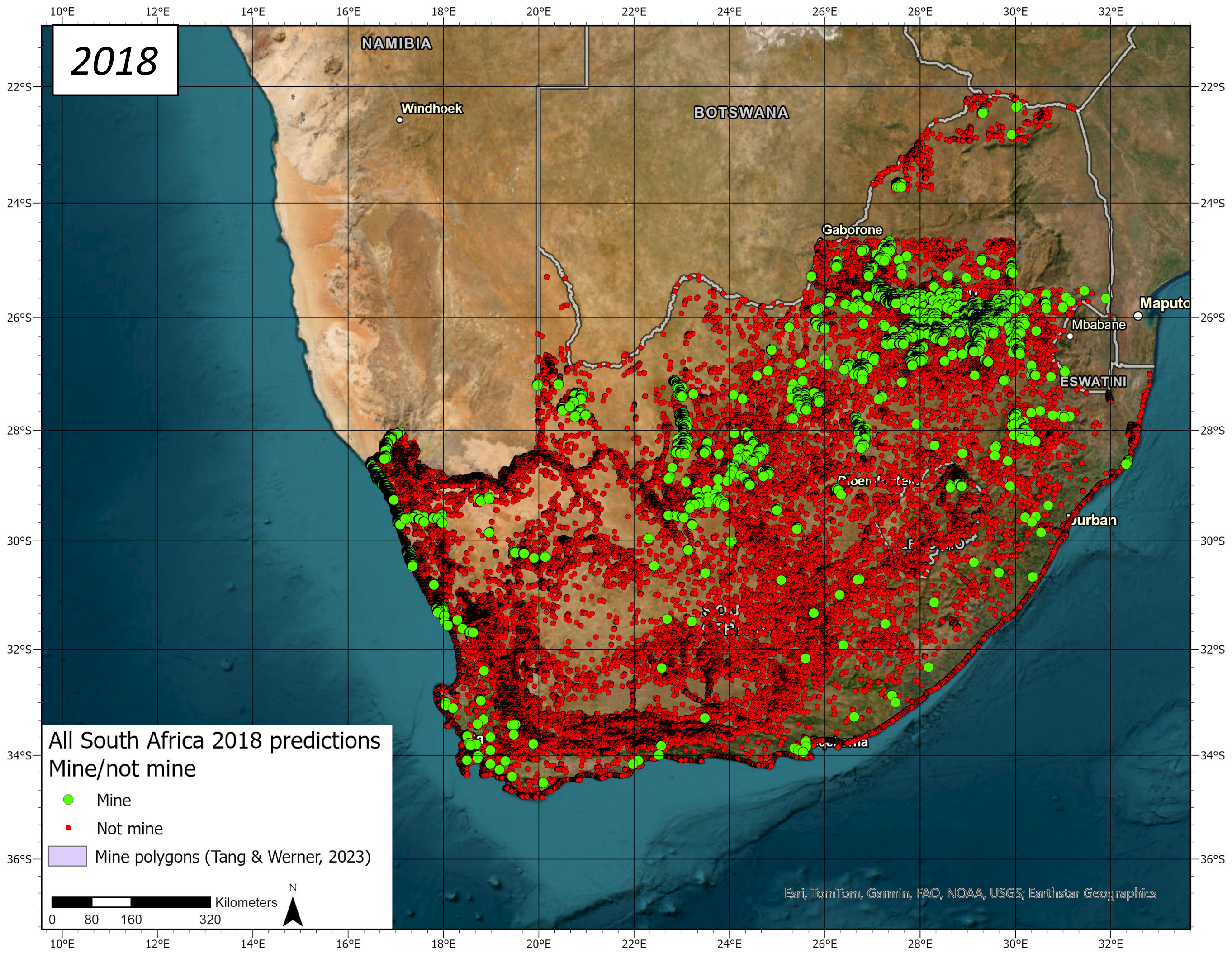
South Africa (+Lesotho)

~ 1 270 000 km²

~ 1 270 000 points *(1x1 km images)*

~ 5.05% not mines points wrongly attributed to mines

-> small percentage but still requires days of manual correction!



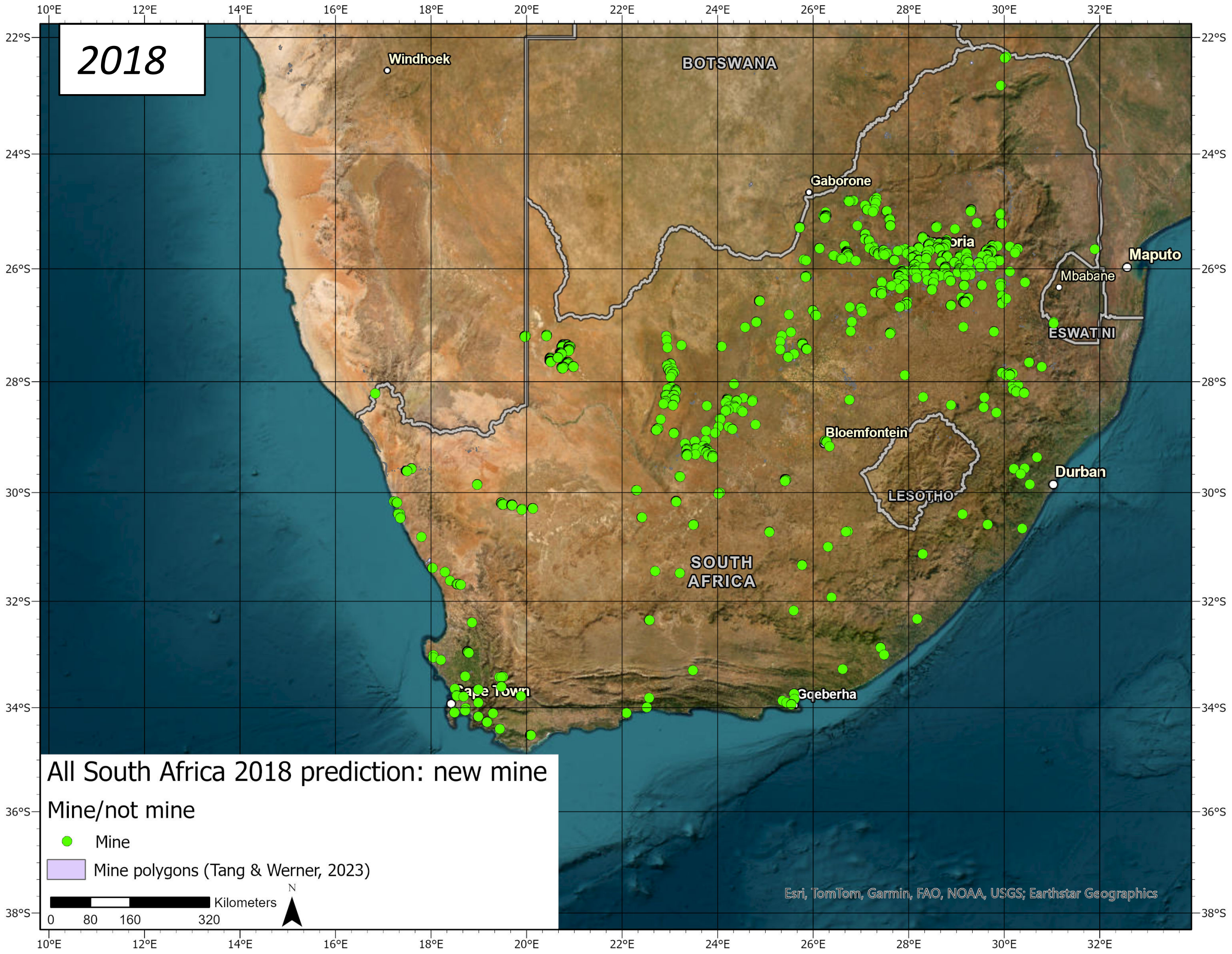
Large scale prediction of mine sites full extent of South Africa (2018)

AI predictions on the full extent of South Africa

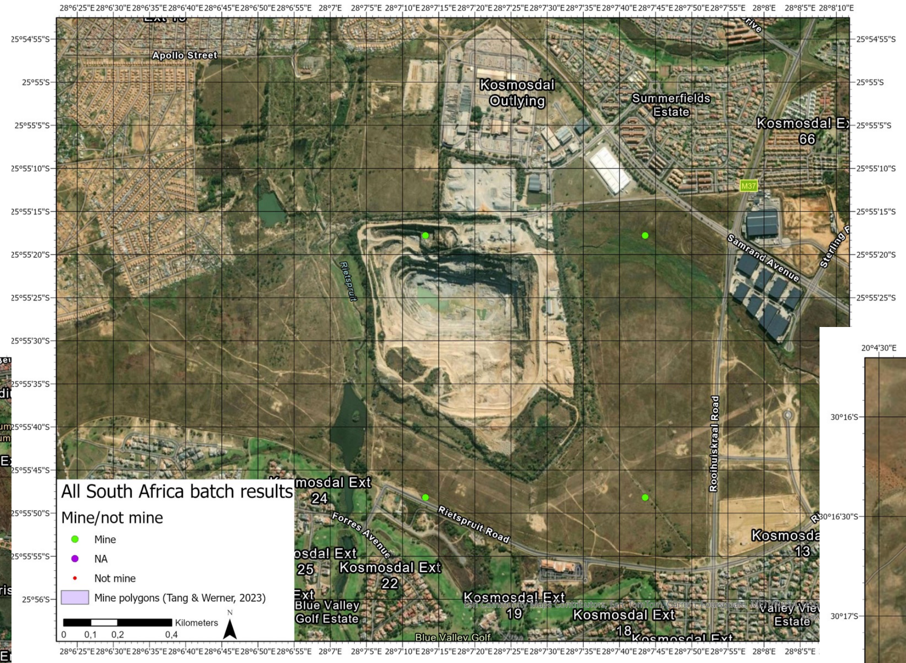
1006 new mine points (patches of 1km x 1km) =
tens of new mine sites

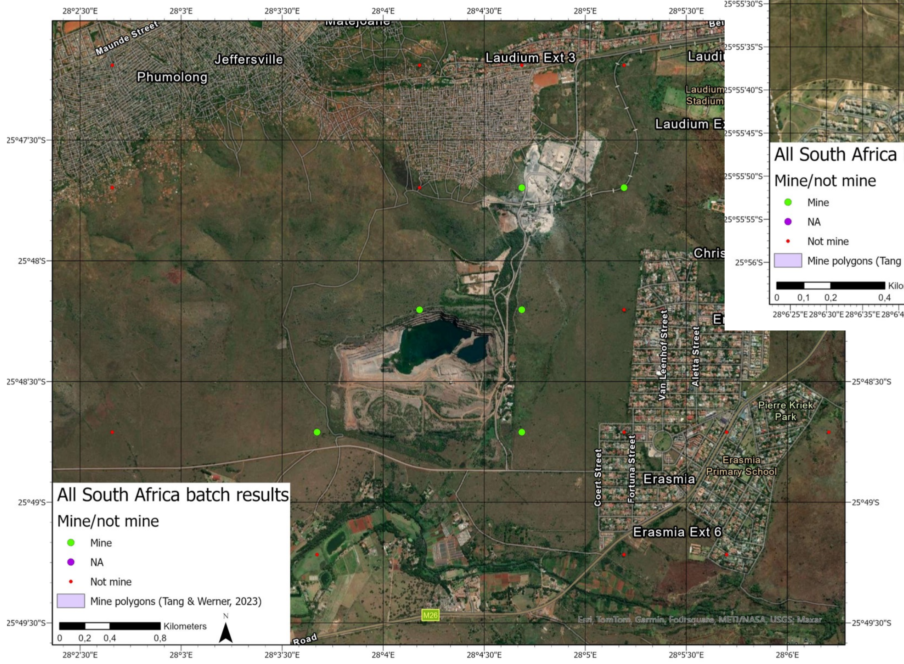
found compared to the literature inventory!

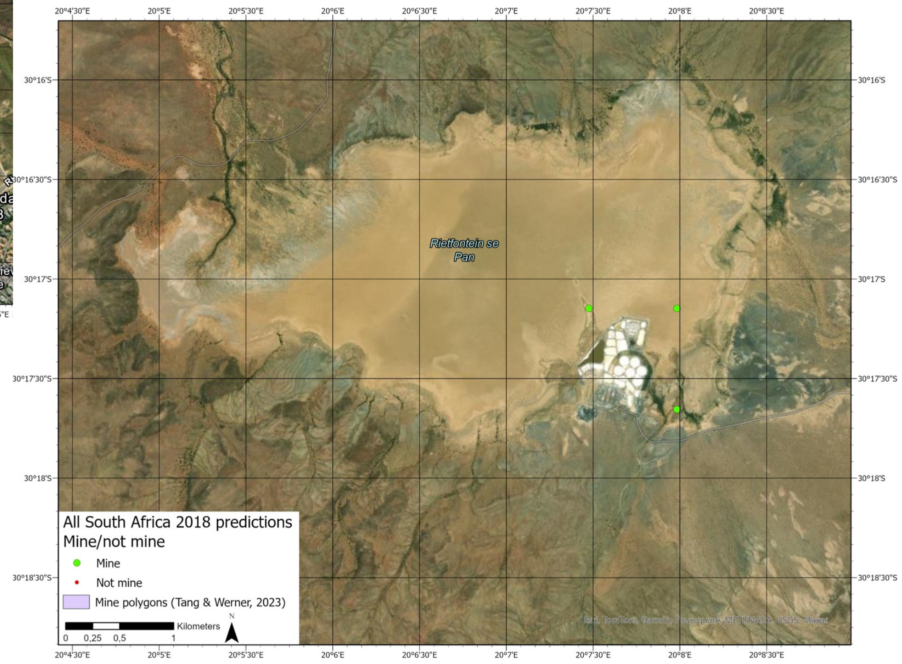
In particular sodium/salt mines



Large scale prediction of mine sites full extent of South Africa (2018) – new mines







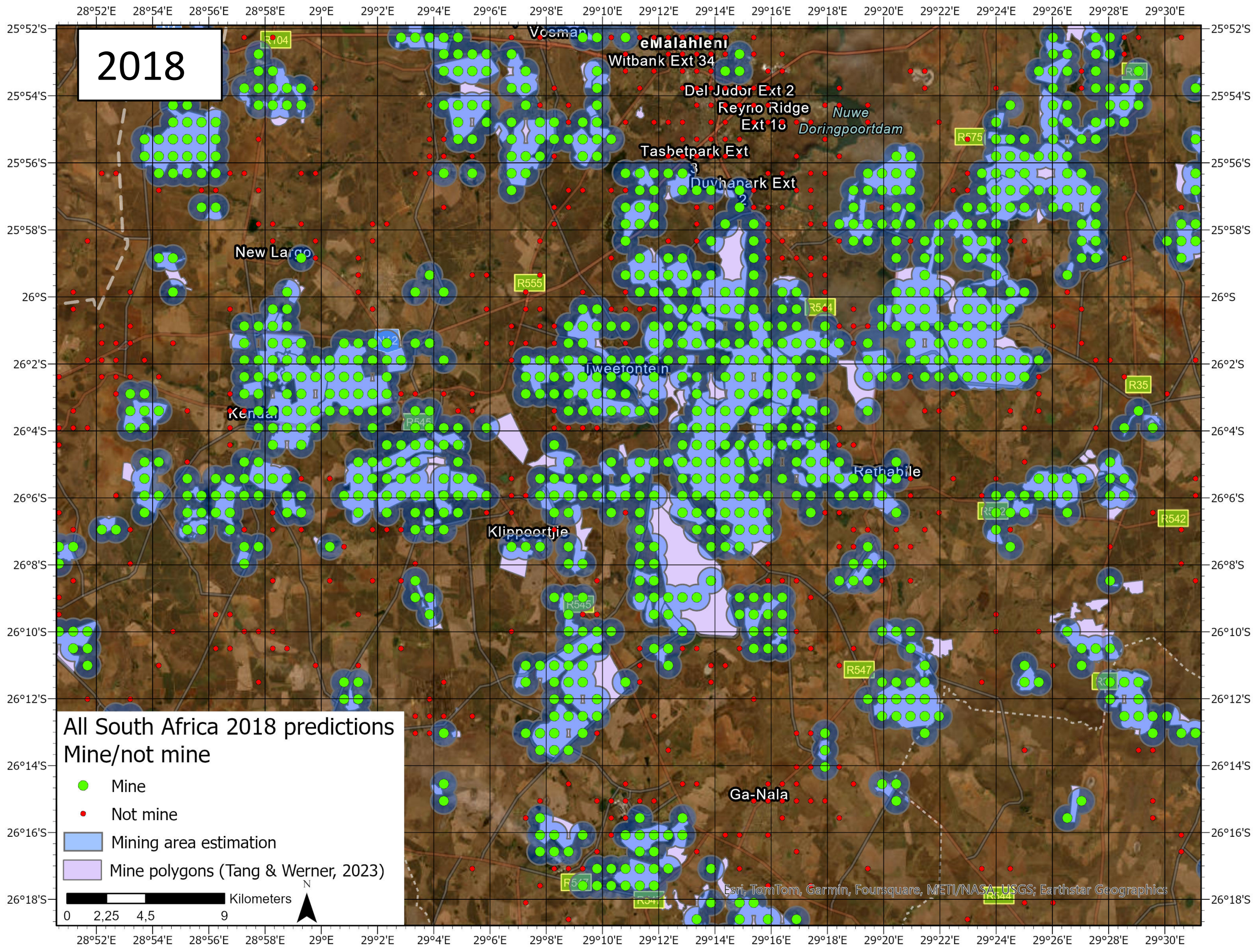
Large scale prediction of mine sites full extent of South Africa (2018)

Mining area estimation

- After manual correction
- Using a buffer of 750m
  (~1/2 diagonal of 1x1 km square)
- Total of ~8’178 km^2
  - ~29.3 km^2 Lesotho
  - ~8’148.7 km^2 South Africa

- Significant overestimation compared to the literature *~3’020 km^2 in Tang & Werner, 2023*

- <u>Mostly due to</u> incomplete inventory of mine sites in literature

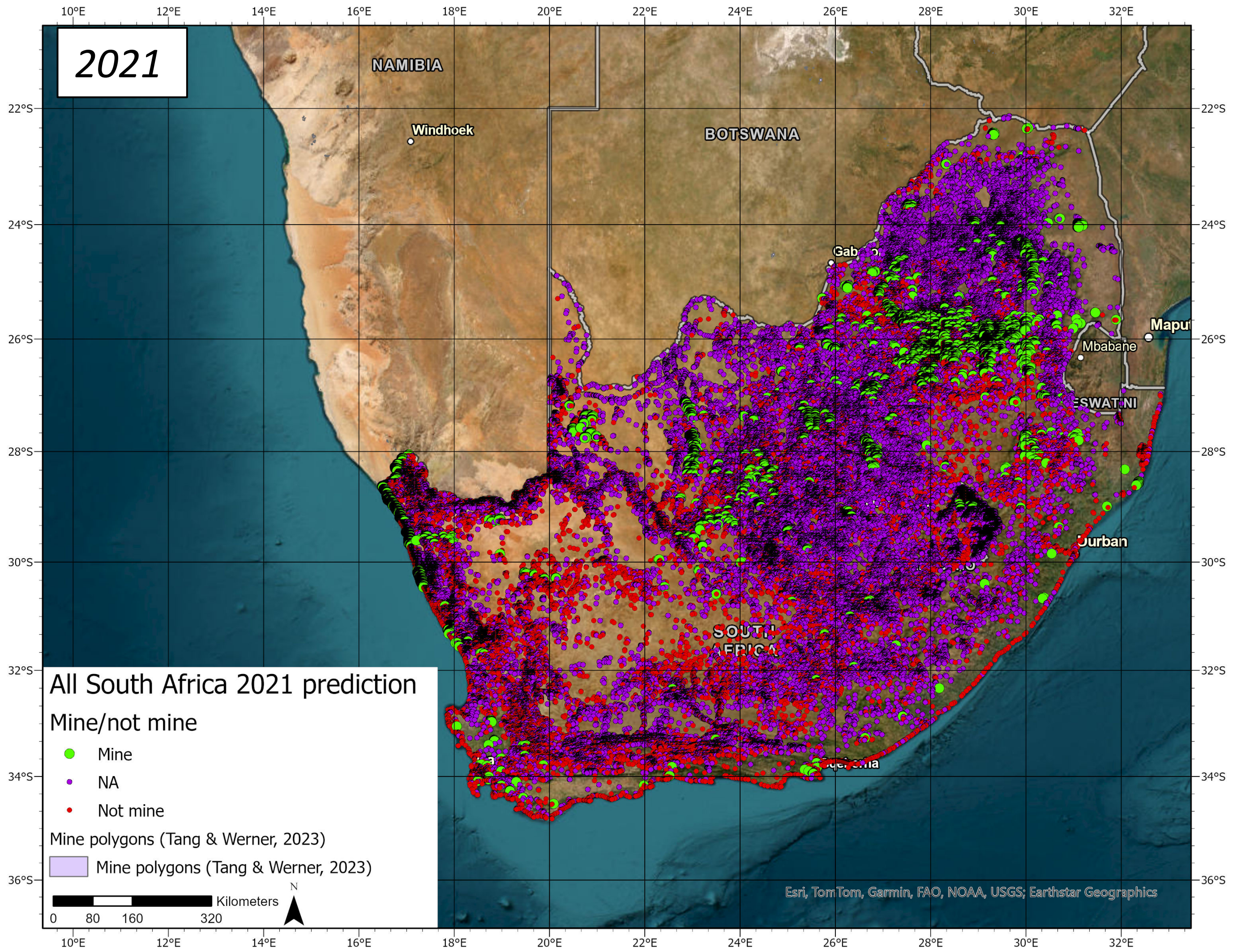


Large scale prediction of mine sites full extent of South Africa (2021)

AI predictions on the full extent of South Africa

- 300 full size Sentinel 2 images (9'472 x 9'472 pixels) divided into patches of ~1x1 km
- Returned results: 120'326 points considered as mine by the AI
- After automatic labelling
  - 8'553 actual mine points
  - 44'583 errors
  - 67'190 not attributed -> days of manual processing

→ ***Need for a second phase of the study***

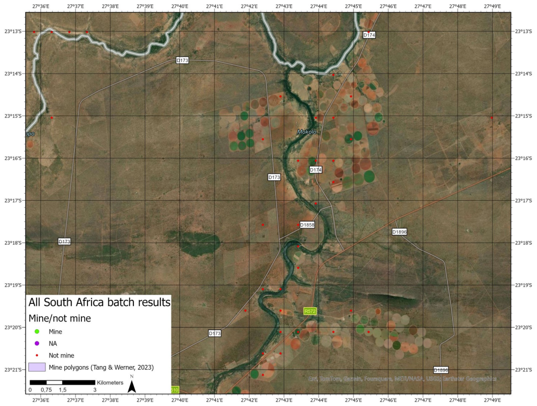


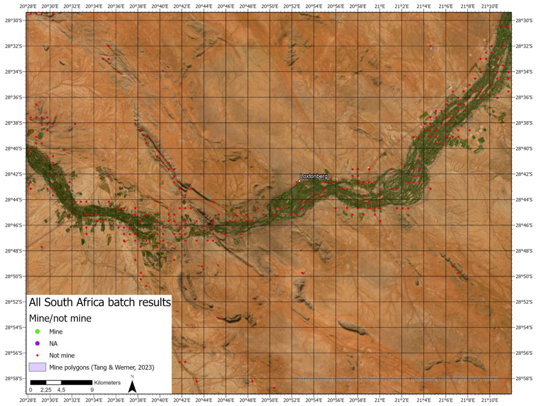
Recurrent AI misinterpretations

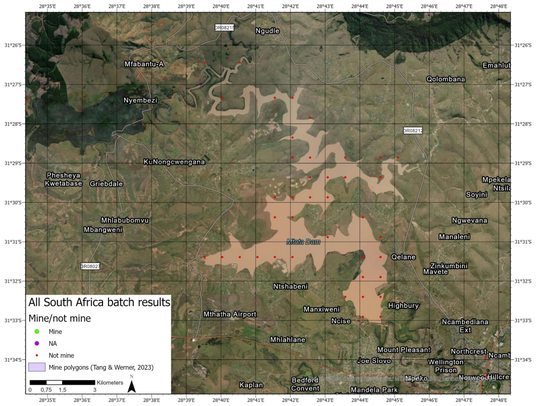
Errors:

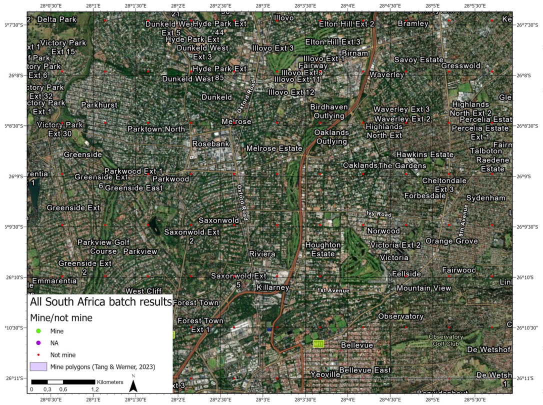
- Agriculture patterns (majority)
- Roads in the countryside
- Rivers
- Lakes with sharp shores
- Dams
- Residential areas
- Steep slopes in mountain ranges that look like open pit
- Beach

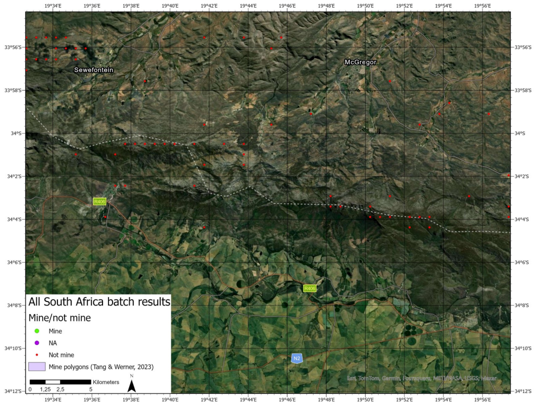
=> need for more diverse training dataset

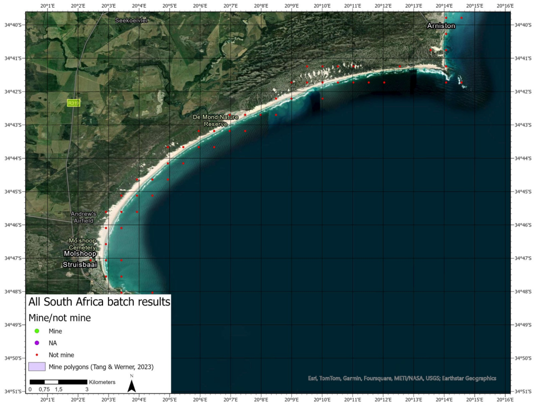












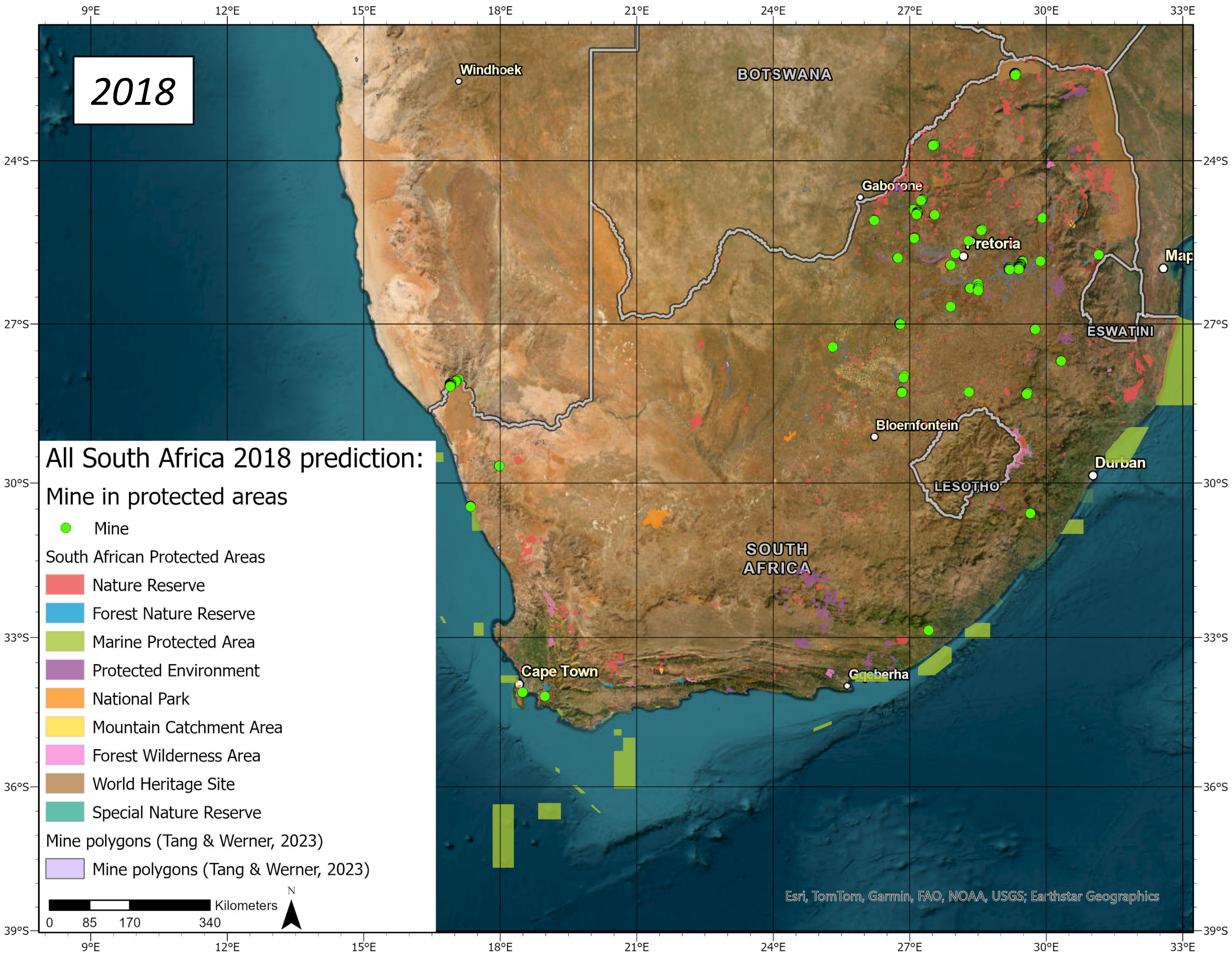
Mine sites & Protected Areas in South Africa

- Intersect mining sites identified in 2018 with protected areas

- 183 mine points within protected areas
  = 185 km² of mining area
  = 2.3% of the total mining area (2018)

- 35 protected areas involved – 4 types:
  - world heritage sites
  - nature reserve (private and public)
  - protected environment
  - national park

  -> declared as early as 1955 = before active mine opening



Conclusions

Model accuracy on prediction

- Good prediction rate on a validation set of points (6039 points in South Africa)
  - 87% of correctly interpreted mine points
  - 9.2% of non-mine areas incorrectly labelled as mine
- Successful identification of new mine sites
- Small scale predictions through time -> only 10% of random prediction
- At large scale (entire South Africa) -> more than 1000 newly identified mine points -> not known in literature

  => good AI model with more than 90% accuracy!
- 5% of mislabelling at the scale of South Africa & Lesotho -> still represents days of manual correction

  => a more diverse training dataset would bring large improvements for large scale predictions

Conclusions

Mining area estimations

- Entire South Africa + Lesotho, 2018 = *~8178 km^2*
  - *~29.3 km^2 Lesotho*
  - *~8’148.7 km^2 South Africa*
- Overestimation compared with literature
  - *~3020 km^2 South Africa, Tang and Werner, 2023*
- Best explained by >1000 newly identified mine points but also estimation procedure
- Implications on mining environmental impact

Conclusions

Protected areas affected by mine sites

- 183 mine points fall within protected areas = ~ 185 km^2 (2.3%)
- 35 protected areas involved: national/international, private/public
    - world heritage sites
    - nature reserve (private and public)
    - protected environment
    - national park

  -> declared as early as 1955 = before active mine opening

Conclusions

Detection of abandoned mines

- Identifying an abandoned mine on satellite images for a specific year can be very challenging
- Several factors influencing morphological changes of abandoned mine sites: climate, morphology, surrounding ecosystem, land use in addition to the nature and duration of the disturbance, etc.
- Prediction on a small area but through four successive years from 2018 to 2021:
    - ➢ reliability of the trained model in detecting new mine opening
    - ➢ 5% of points are no longer detected after being detected in previous years -> indicates closure of mine sites
    - ➢ The absence of mine site expansion is an indicator of the abandonment of the mine

Conclusions

Improvements

- Retrain the model using labeled points from previous predictions
- From image classification to object detection -> *Classify mines & tailing dams objects within an image instead of points*
- Differentiate mining & tailings dams in two different classes
- Improve selection and diversity of training points
- Enrich the training dataset with additional environmental data like topography, soil composition, vegetation indices, climatic factors, or land use/land cover classifications