Physical risks

London, January 19, 2018

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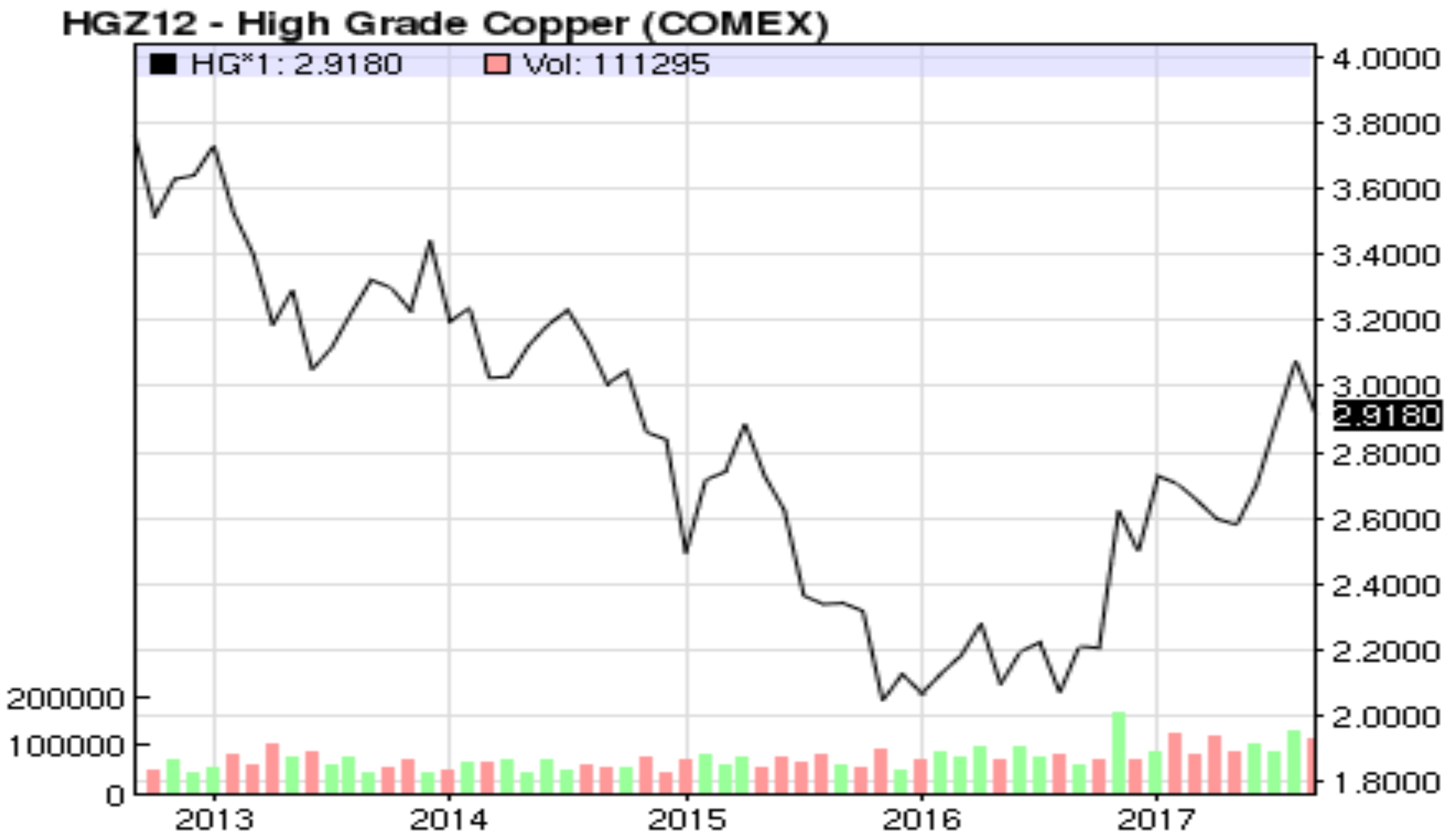
Water Use and Costs

Concern: Increasing scarcity, competition and conflict
→ increasing long run CAPEX and OPEX for water management
→ reduced IRR → asset stranding, especially as metal prices drop

Findings:

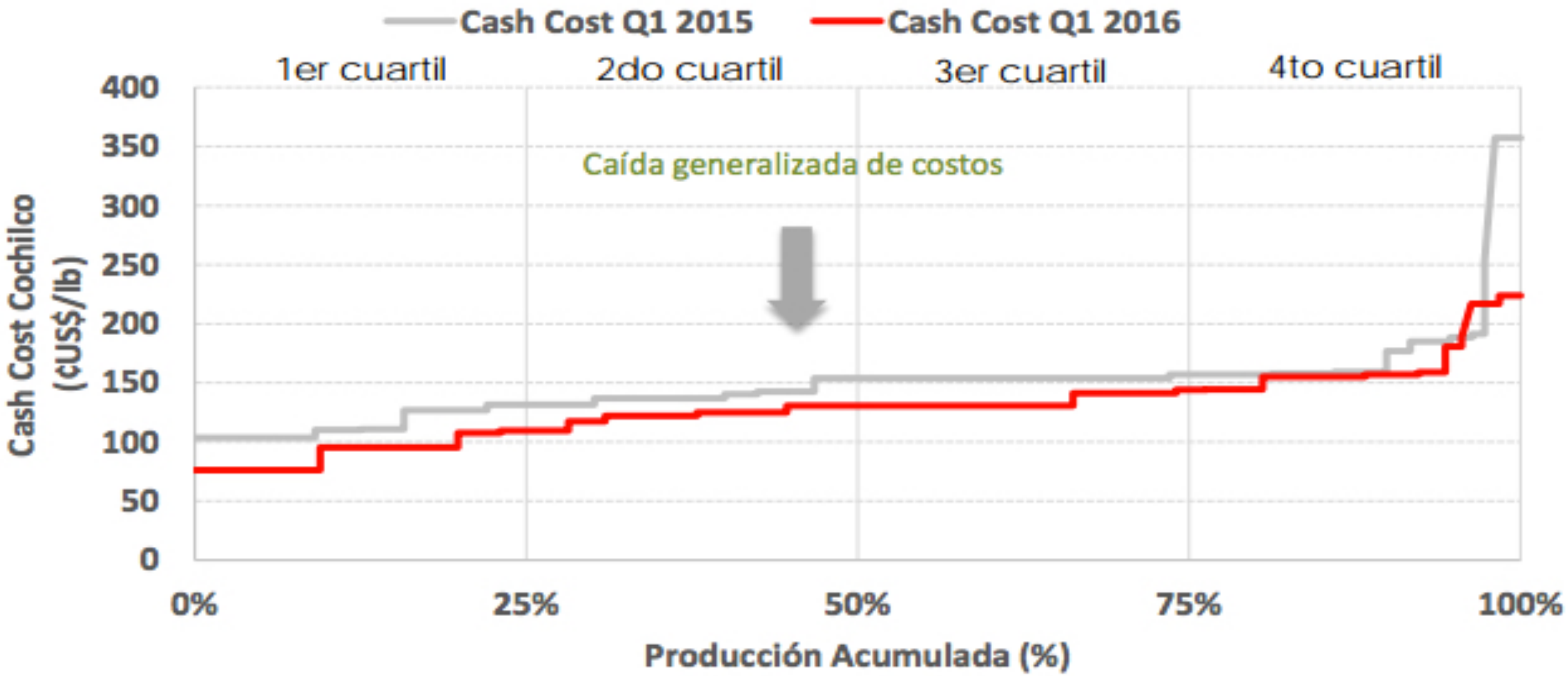
- Significant variations in water use and wastewater/ton produced
  - Declining ore grades = more process water use
- Trends towards re-use and desalination in arid regions, and produced water use in humid regions
- CAPEX and OPEX typically vary from 5 to 10% of total production costs, and efficiency/technology improvements suggest long run cost curves will hold
- Long run Cu/Au gold demand curves trend up faster than projected increase in water costs as a fraction of production costs
- Long run → industry cost curve rises → new demand-supply equilibrium
- WRI Aqueduct Scarcity Risk Index does not predict NAV or Credit Rating

Copper Price (NASDAQ)



Note the over 100% variation in copper prices over 5 years and year over year variations of +/- 50%

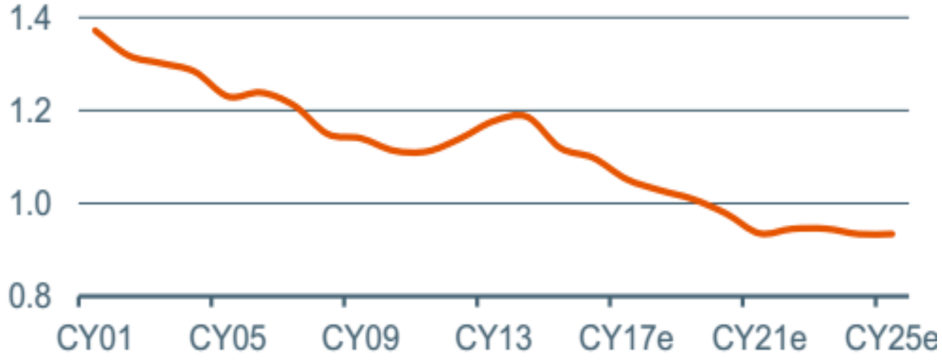
Water Use and Costs



- According to the study by the Chilean Copper Commission, mine level **cash costs at Chile's 19 largest mines fell to an average of $1.285 per pound** during the first three months of the year, **down 13.3%** or nearly 20c a pound from the same quarter of last year.
- …improved mine management, lower costs for electricity, services and shipping and lower treatment and refining charged by smelters. The trend of falling grades, coupled with increasing water costs in Chile makes the cost cutting even more remarkable.

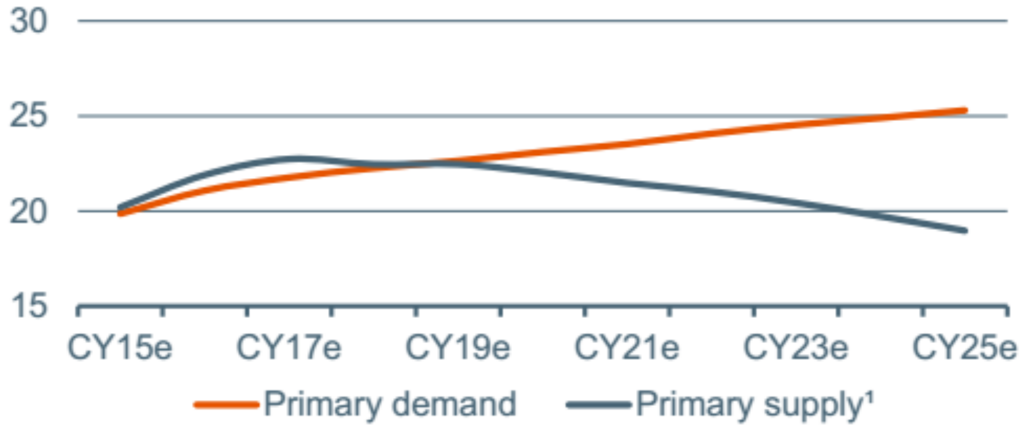
Industry grades continue to decline

Weighted average copper grade[1], %



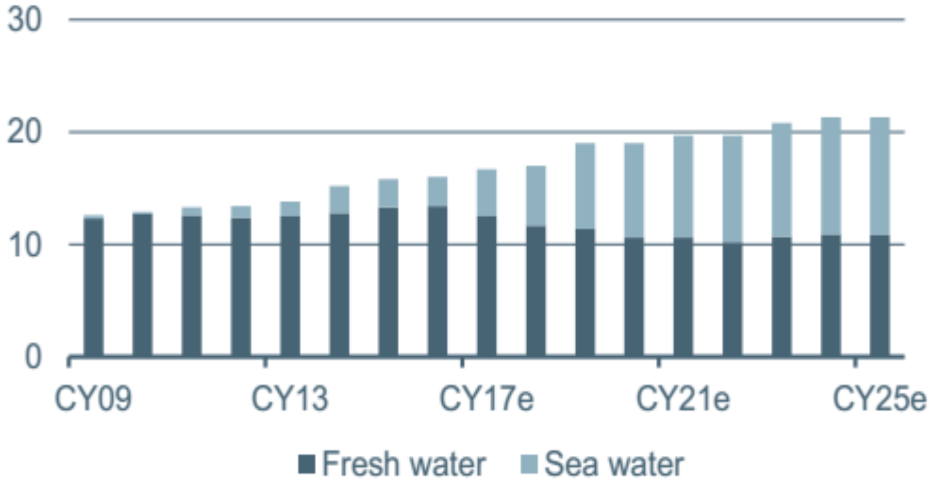
Deficit expected to emerge at the end of the decade

Copper, Mt



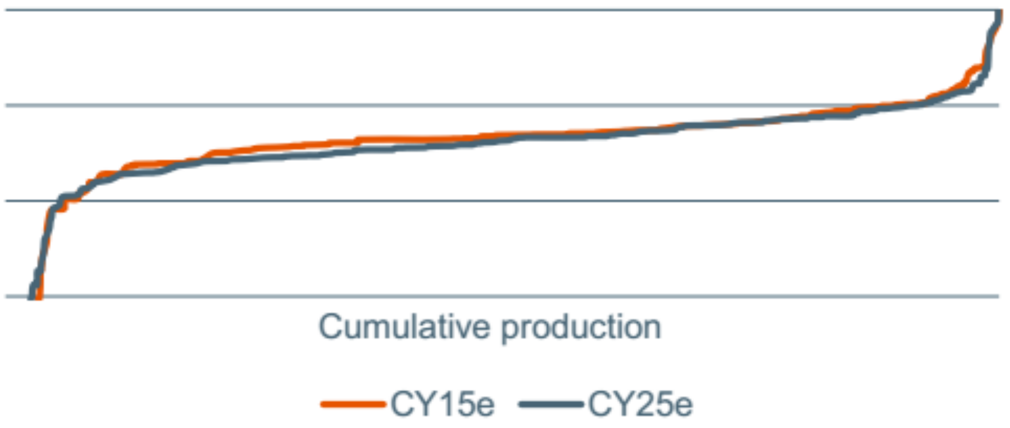
Water use in copper mining in Chile

m³/second



Industry-wide challenges expected to maintain shape of the cost curve in the long run

C1 cash cost, copper US$/lb



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Bias in Reporting – Reclamation Cost Disclosure Analysis

Concerns: If mining companies systematically under-report reclamation costs, then long term investors may face significant residual financial and reputational liabilities.

- Companies may engage in strategic behavior to avoid covering actual reclamation needs since they were not budgeted or disclosed.
- Do biases in this aspect reflect systematic biases in other disclosure?

Findings:

- A longitudinal data on reclamation cost, reserves, production and other economic factors was derived from quarterly reports.
- Regression model shows that controlling for changes in production, reserves, inflation and other factors, the % of remaining life of mine emerges as a significant predictor of reported reclamation costs → early estimates are significantly biased lower.
- Comparisons were also made with the EPA's recently released model which only uses a single disclosure of costs by a company, and focuses on a mean value.
- Difficult to compile data on actual reclamation costs vs earlier estimates, but we recommend reclamation bonds reflect 90% probability coverage based on uncertainty estimates

Database and Regression Model Developed available.
Applied to estimate/predict degree of systematic under-reporting of Reclamation costs

Bias in Reporting – Background

- Mining companies are required to estimate reclamation costs prior to the commencement of construction in order to:
  - Allow management and investors to assess the overall economics of a given project and provide regulators
  - Allow local stakeholders the opportunity to ensure assets can be rehabilitated responsibly prior to any major impact taking place
- These company-formulated estimates (compiled with the assistance of company-engaged third parties) are incorporated into:
  - feasibility study work (which are often the basis for project sanctioning by management and investors)
  - environmental impact assessments (which often are the basis for mine permitting applications)
- Depending on the jurisdiction, reclamation bonds are often required to ensure mandated post-mining closure activities are complied with
- In recent years, regulators have attempted to standardize mine reclamation plans included in feasibility studies (under NI 43-101, JORC and SAMREC) to allow for more transparency and consistency across company-level reporting
- Reclamation cost estimates are among the easiest assumptions to mis-specify given that they are the furthest away from becoming a reality

Bias in Reporting – Data

Example Variables:

Company level:
- Company Owner
- Owner Location

Project level:
- Primary Commodity
- Location of the mine
- Mine type

Report level:
- Expected remaining closure cost
- Expected remaining mine life
- Expected remaining production
- Total Expected Production
- Total Expected Closure Cost
- % Life of Mine
- % Production
- Reserves
- Cost production ratio

Key Data Sources	
Variable	Source
Closure Cost Estimates	Company Technical Reports (SEDAR, EDGAR, ASX websites)
Mine / Company Specific Factors	SNL
Macroeconomic Indicators	Bloomberg, Factset

Variable Summary Analysis	
Variable	Number
Number of Commodities	43
Number of Projects Considered	74
Number of Reports	157
Number of Companies	65

Example Company Closure Cost Estimates						
Company	Project	Original	1st update	2nd update	3rd update	4th update
Asanko Gold, Inc.	Esaase Gold Project	$20.00 201005	$20.00 201012	$20.00 201102	$29.00 201109	$29.60 201305

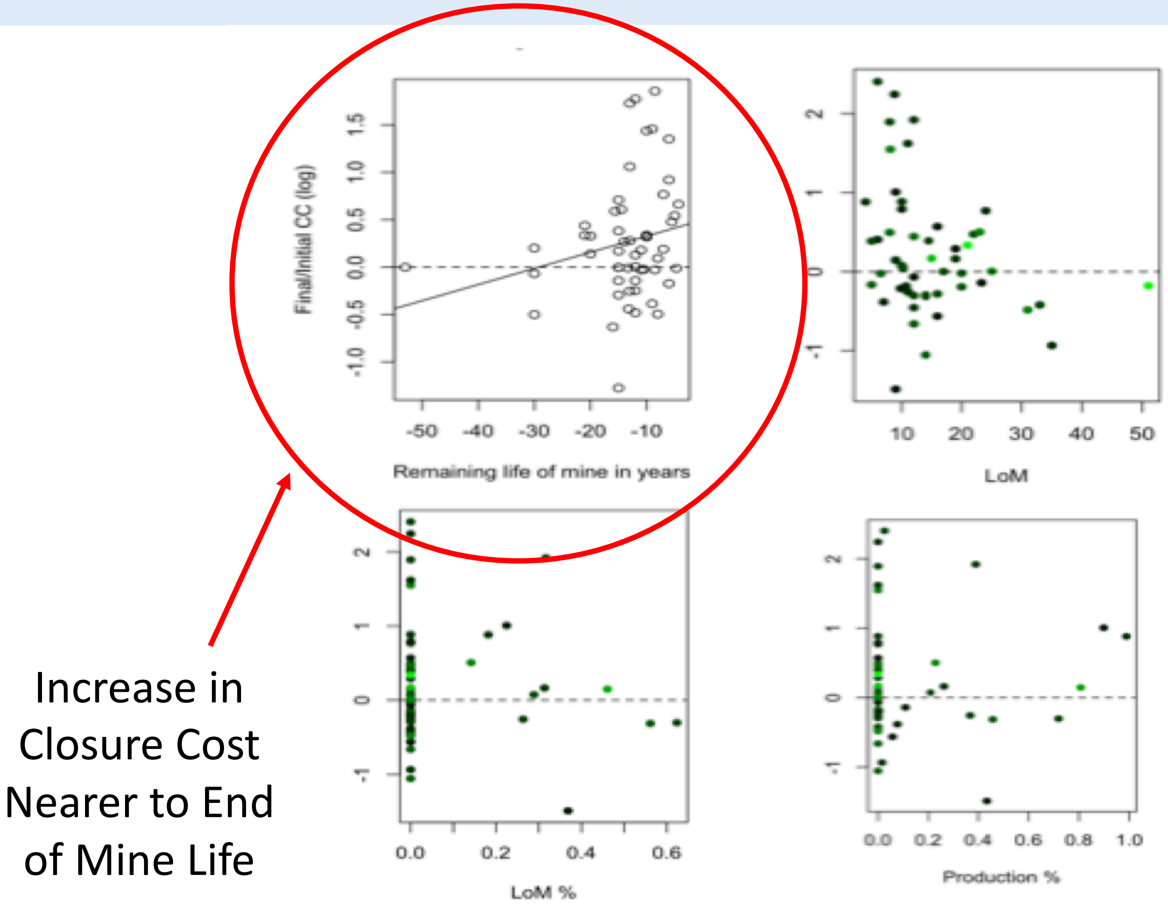
Bias in Reporting – Methodology/Results

- Compares the first closure estimate on a project to the last available closure cost estimate on a project

- Of those projects with more than one closure cost estimate:
  - 61% showed an increase in closure costs
  - 24% showed a decrease in closure costs
  - 15% remained the same

- Nearly 20% of projects from the first report to the last report increased by more than 2x

- Other analyses performed were:
  - Change in Closure Cost vs. Mine Life
  - Change in Closure Cost vs. LOM %
  - Change in Closure Cost vs. Production %



Bias in Reporting – Fitted Model

- Produces a model to estimate closure cost estimates based on company level and mine specific factors (as well as temporal factors) using regression

- Key conclusions are:
  - Remaining mine life (time.perc) is a significant variable, implying that estimates increase as the end of the mine life becomes nearer
  - Mine location, owner location and primary commodity are significant variables – this is likely due to more lax regulations and lower labor costs in certain jurisdictions
  - Production and reserves are statistically significant in predictors – moving more material requires greater amounts of remediation

```
##
## Call:
## lm(formula = cc ~ ., data = M.cc)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.1785 -0.5674  0.1584  0.5395  1.8099
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   3.15943    0.95387   3.312 0.001168 **
## prod                          0.28975    0.05297   5.470 1.92e-07 ***
## reserves                      0.37912    0.04485   8.454 2.75e-14 ***
## time.perc                     1.69377    0.38458   4.404 2.05e-05 ***
## f.commodityGold               0.99442    0.16184   6.145 7.34e-09 ***
## f.countryMexico              -1.23404    0.24223  -5.095 1.07e-06 ***
## f.countryOther               -0.69523    0.15418  -4.509 1.33e-05 ***
## f.countryUSA                 -0.71393    0.24820  -2.876 0.004629 **
## f.owner.countryAustralia      2.50152    0.57795   4.328 2.79e-05 ***
## f.owner.countryCanada         1.45373    0.48252   3.013 0.003056 **
## f.owner.countryUnited.Kingdom 1.80793    0.57148   3.164 0.001899 **
## f.owner.countryUSA            1.89118    0.51191   3.694 0.000312 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7952 on 145 degrees of freedom
## Multiple R-squared:  0.6392, Adjusted R-squared:  0.6118
## F-statistic: 23.35 on 11 and 145 DF,  p-value: < 2.2e-16
```

LOW PROBABILITY / HIGH IMPACT EVENTS

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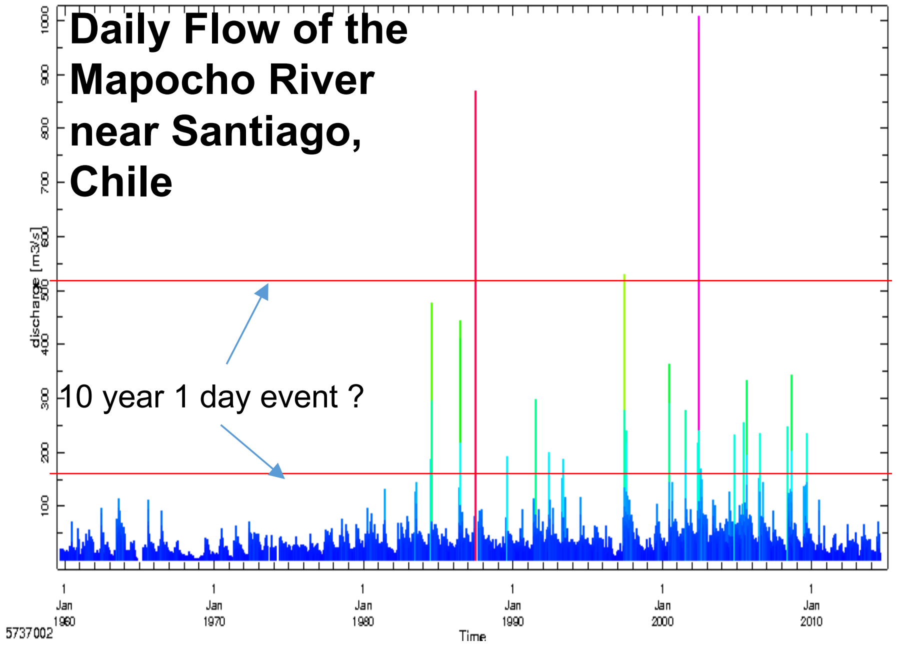
Climate Extremes – Mine site and Portfolio Risk, and its Change over Time



April 17, 2016: “Codelco, the world's top copper producer, said the rains forced the Chilean state-owned miner to suspend production at its century-old underground El Teniente mine, likely leading to the loss of 5,000 tonnes of copper production.”

Mine infrastructure is designed for a certain level of flood or drought risk. Insurance may cover the residual risk with a payout limit.
Assumption: data used to compute the probabilities is representative of the future.

Unfortunately, climate risk exhibits regime like behavior ➔
Design risk estimate may be out of phase with operation period risk

Climate risk exposure is also spatially correlated over a business cycle = Elevated Portfolio Risk

Database and exposure estimation/ranking App Developed and available.
Applied to rank companies in terms of VAR or cVAR exposure, and for Real options Model

Climate Extremes – Risk Clustering

- Regarding water and climate, this residual risk is a function of climate cycles in time, spatial structure of climate events, and data record length
- To address time clustering long data records are needed
- To address spatial clustering at the portfolio level global datasets are required
- One class of datasets can be leveraged: NOAA and ECMWF reanalysis

Climate Extremes – Framework to Think about Climate Risk

- Mines use standards to design facilities for a T-year floods and droughts. Often T=10, 100 or 1000 years suggesting a high degree of protection
- For a mine with a 30 (50) year life this could mean a failure probability over the life of the mine = 0.96(0.995), 0.26(0.39), 0.03 (0.05) respectively

  Failure probability can be high over mine life
- Given the short records used to estimate T, there is a high uncertainty in the estimate of T that is used for design.
  - Climate is non-stationary and regime like:
    - Any given n years of data may give a highly biased estimate of T for the next n years
      - High under/over design risk
    - Across a portfolio of assets, spatial correlation in failure occurrence is a concern that is not addressed in design, but is important for the investor

Climate Extremes – Analysis Set-up

Measure	Risk associated	Potential sources	Variables
x-day event with return level T	- Localized flooding	- Reanalysis	- Precipitation
	- Storms - Heatwaves	- IPCC - Station networks	- Wind speed - Temperature
Indices, e.g. PDSI & SPEI, Heat index	- Regional drought	- Academics - Paleoclimate Data	- Precipitation - Potential evapotranspiration
	- Regional wet event	- Reanalysis	
	- Heatwaves	- Drought Atlases	- Evapotranspiration
		- IPCC	- Temperature
		- Station networks	- Relative Humidity
Sea-level trend & cycles	- Localized flooding	- IPCC	Sea-level

Climate Extremes – Analysis set-up – Portfolio Level

Choose:

event of interest : e.g. 30-day precipitation event
return-level of interest: e.g. 10 years, 100 years

Compute the yearly extremum time series at every location
Identify the percentile threshold for the return period of interest

Identify events of interest: all exceedances of the percentile threshold for all days in the record at each location

Weight each event with a damage function
Compute the time series of weighted exceedances at the portfolio level

Compute VaR and CVaR-like measures to rank portfolios

Climate Extremes – Analysis Set-up – Portfolio Level

For a given event duration d, and return-level p, the process is the following:

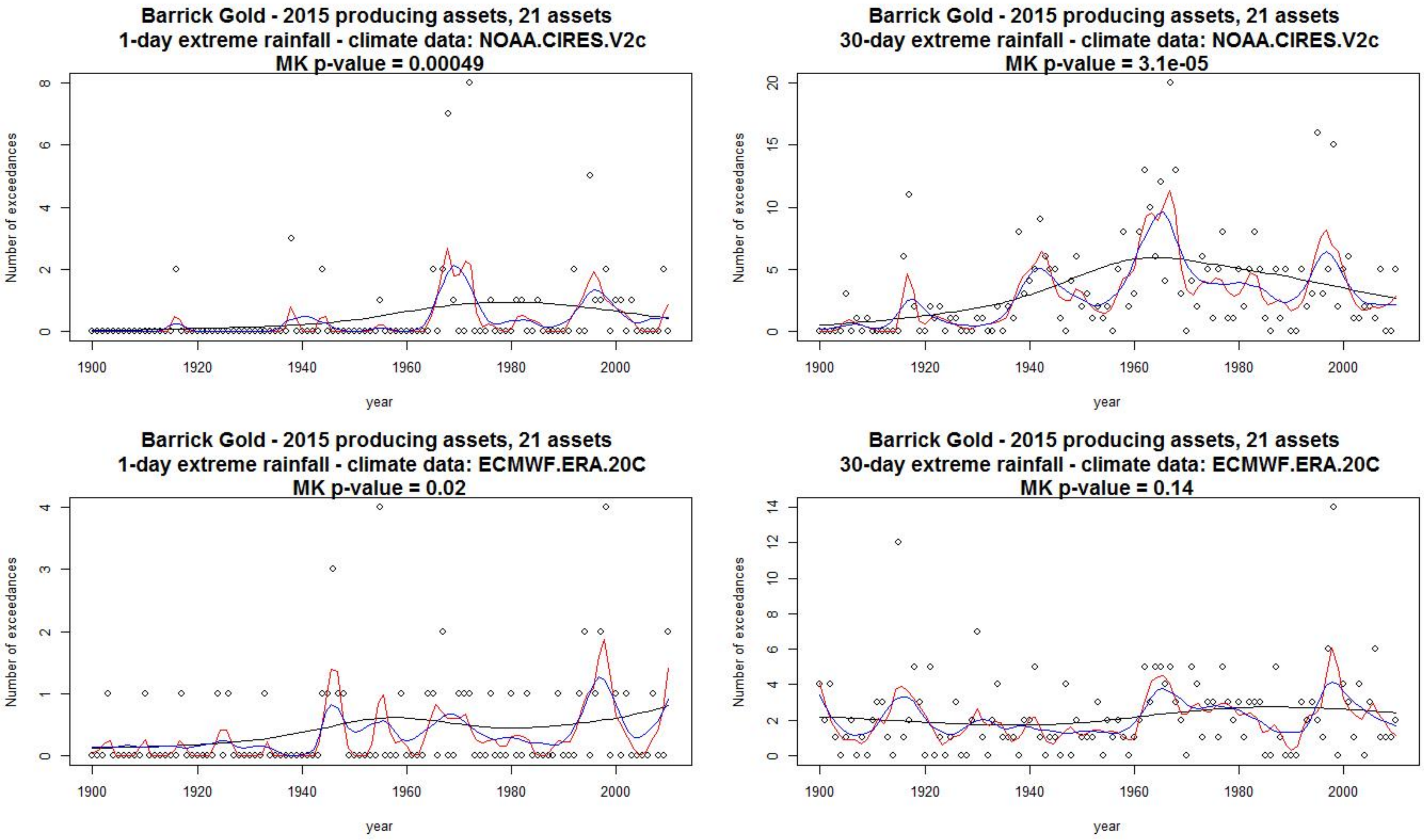
- compute local yearly maxima and find the local threshold based on p,
- for each site *i*, obtain

$$n_{i,t}(p,d) \text{ and } L_{\mathrm{i}}(p,d) = C(p,d)V_{\mathrm{i}} + D(p,d)F_{\mathrm{i}},$$

- define portfolio exposure as $S_{\mathrm{t}}(p,d) = \sum_{\mathrm{i}} L_{\mathrm{i}}(p,d)\, n_{\mathrm{i,t}}(p,d)$ or $R_t(p,d) = \frac{S_{\mathrm{t}}(p,d)}{\sum_{\mathrm{i}} V_{\mathrm{i}}}$
- compute VaRq-like measure using quantile$(R_t(p,d), q)$
- compute CVaRq-like measure using trapezoidal approximation:

$$CVR_{\mathrm{q}}(p,d) = \frac{1}{(1-q)(m+1)} \left\{ \frac{R_{\mathrm{q}}(p,d)+R_{\mathrm{m}}(p,d)}{2} + \sum_{\mathrm{k=q+1}}^{\mathrm{m-1}} R_{\mathrm{k}}(p,d) \right\}$$

Climate Extremes – Result Example, Extreme Rainfall, T=10years

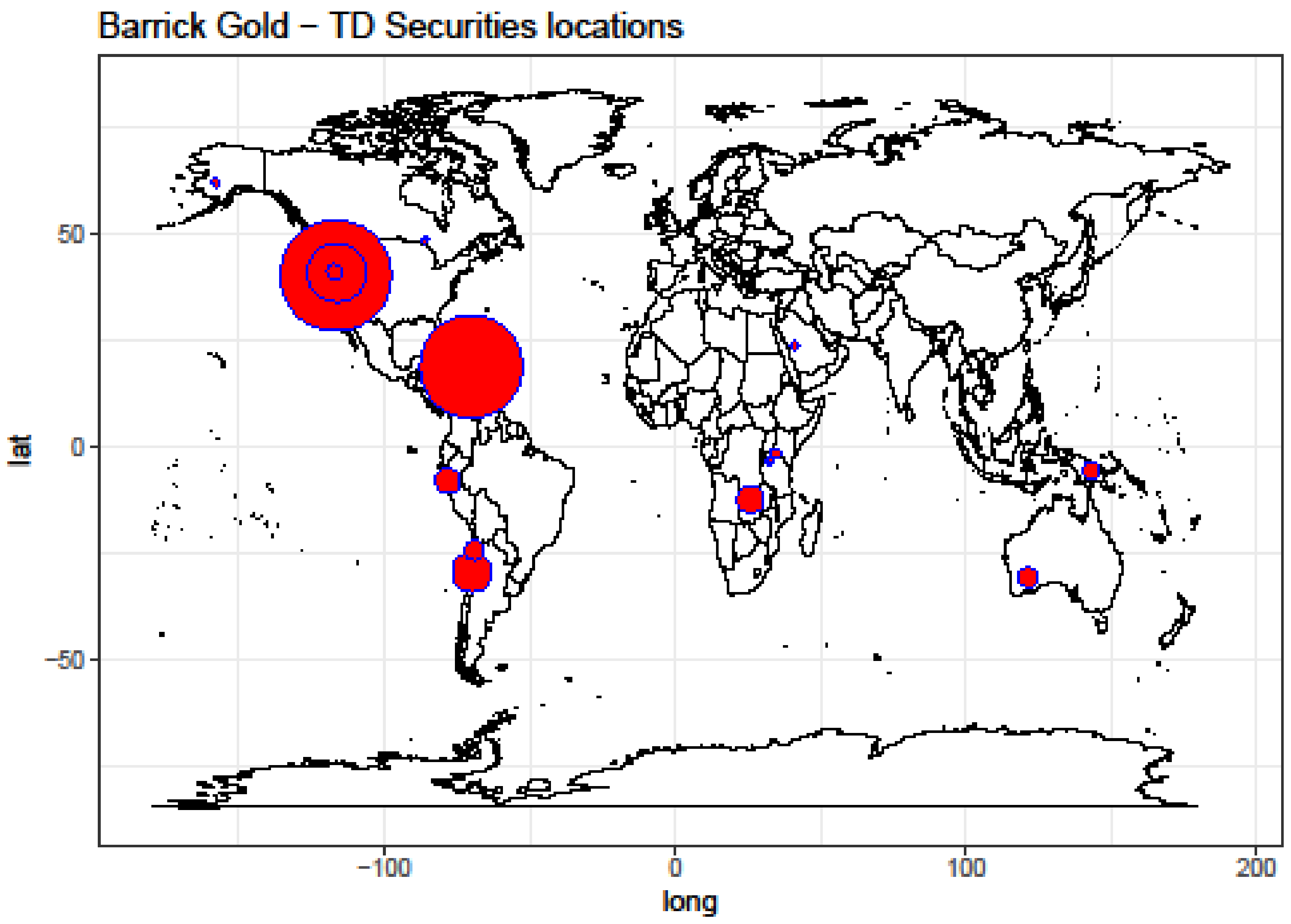


Barrick Gold

20 (14) out of 21 sites in the portfolio experienced a failure of a design for the 30 day extreme rainfall in the same year

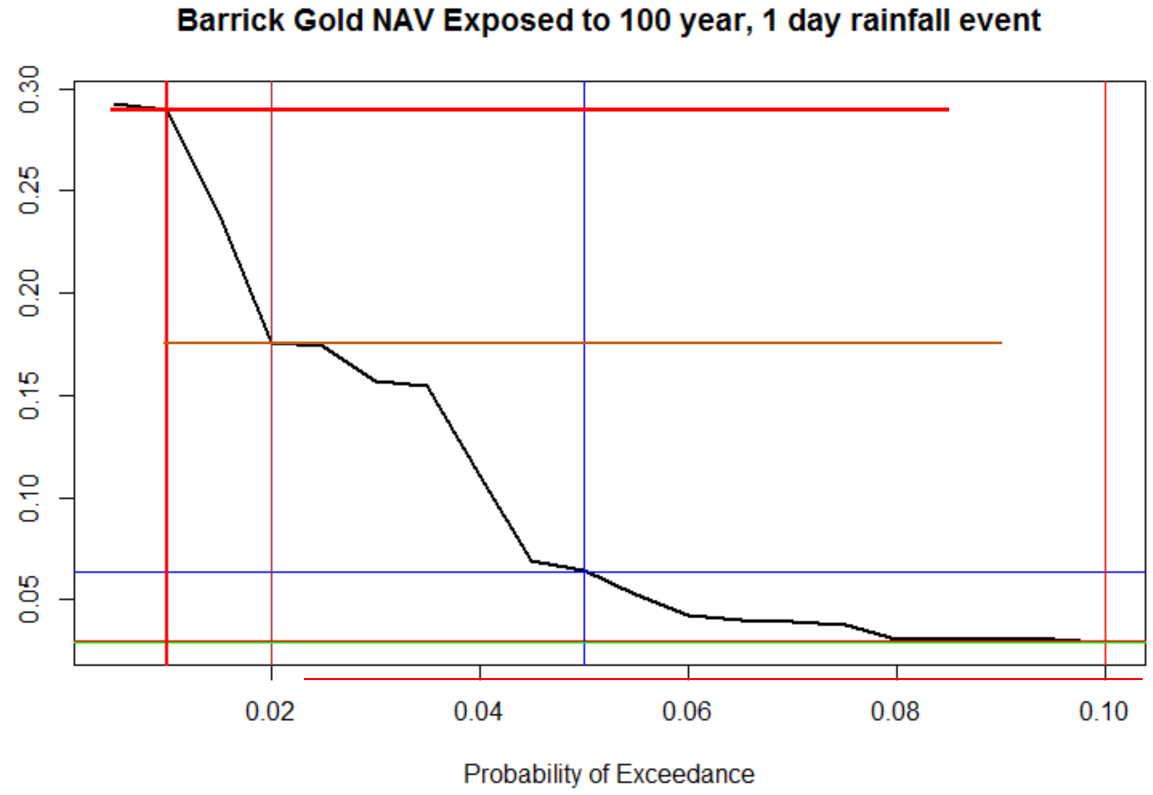
Based on the NOAA (ECMWF) data sets (numbers that never happen if the yearly exceedance is modeled with a Poisson process of $a = p \times N_{assets}$

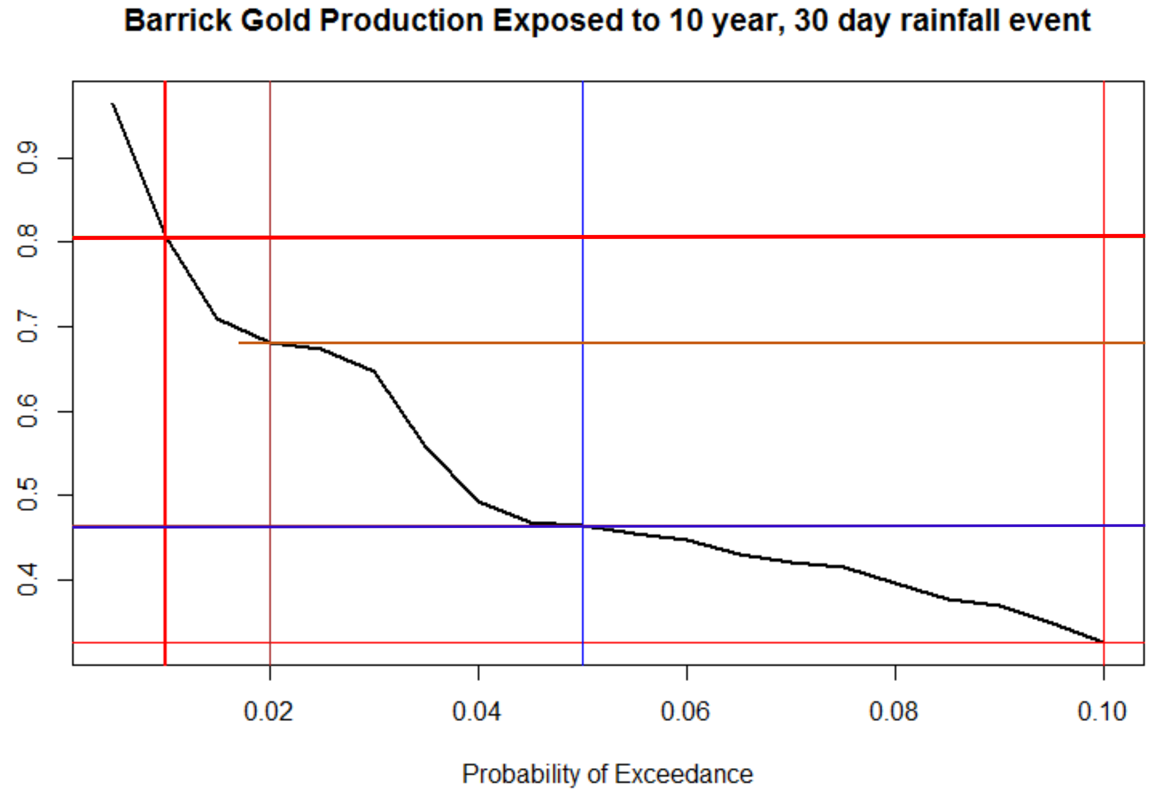
Climate Extremes – Result Example – Barrick Gold



Circle size = Asset NAV

Climate Extremes – Result example - Barrick Gold Portfolio Exposure

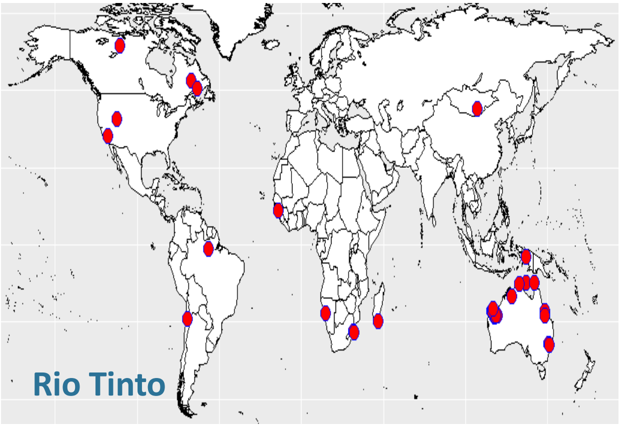


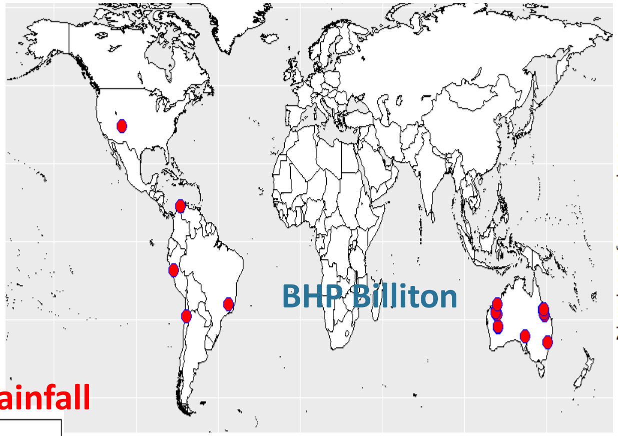


100 year 1 day rainfall event
30% NAV Exposed with a 1%/yr probability
7% with a 5%/yr probability

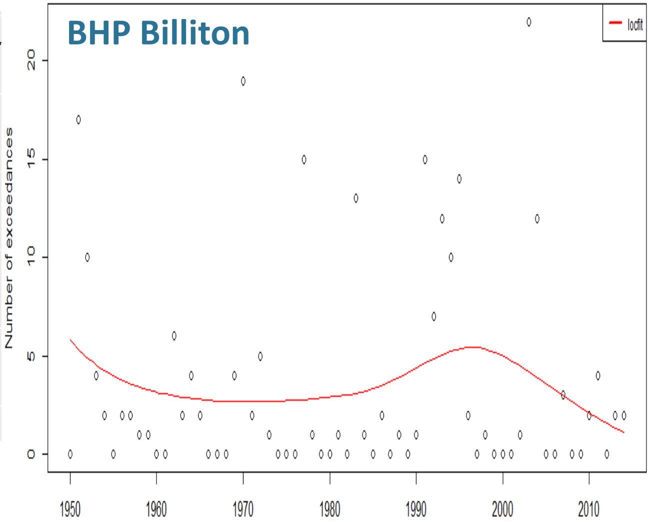
10 year 30 day rainfall event
80% Production Exposed with a 1%/yr probability
45% with a 5%/yr probability

Climate Extremes – Result example – Rio Tinto (40 assets), BHP Billiton (38 assets)

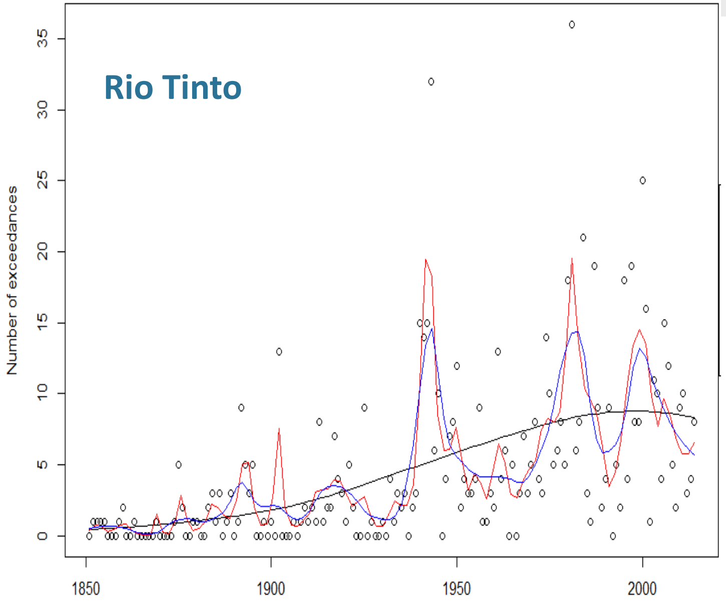




Annual exceedances of 10 year drought



Annual exceedances of 10 year 30 day rainfall



Drought: 38 mine BHP Billiton portfolio.

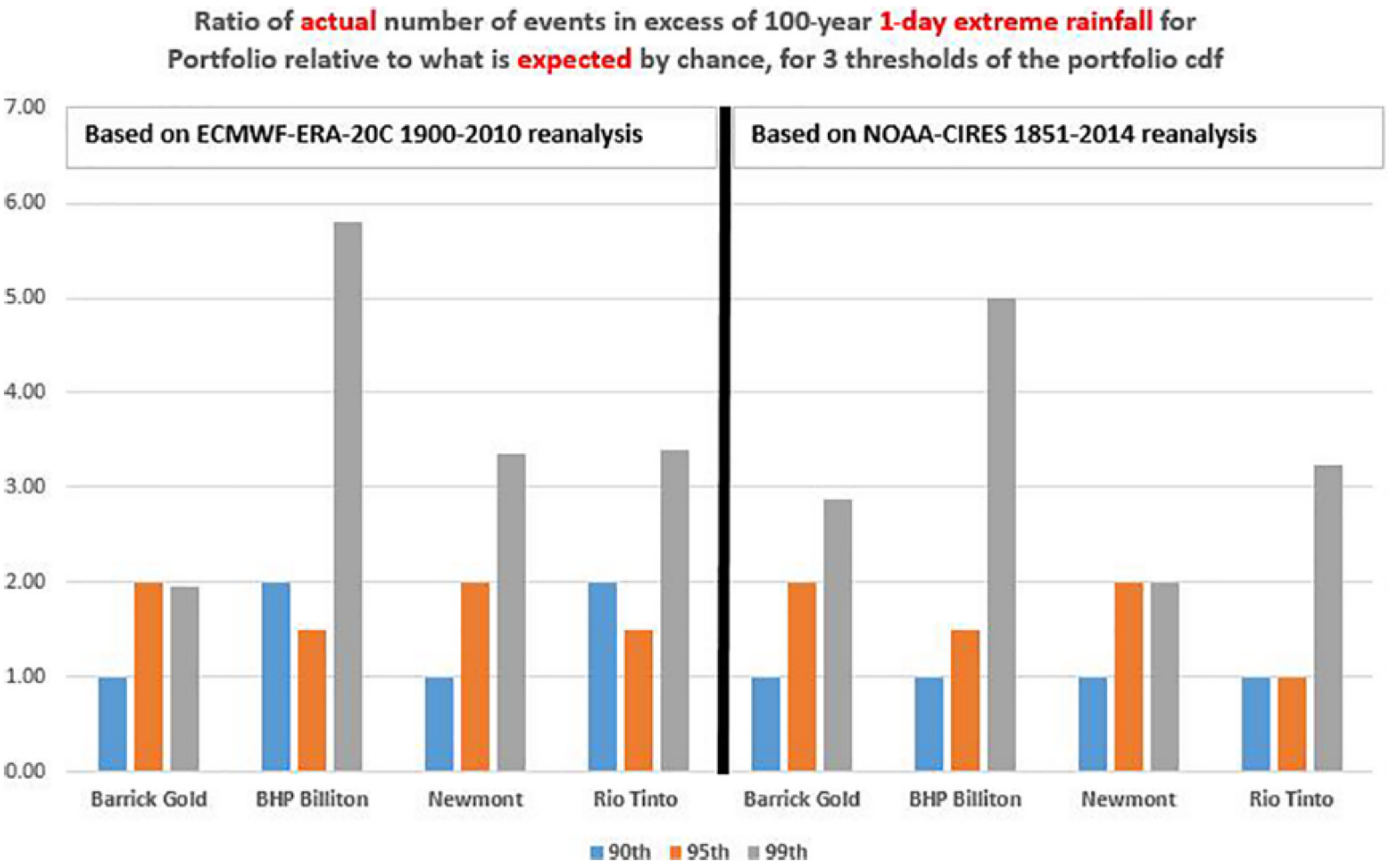
- High clustering : 24 exceedances in one year out of 60

Extreme Rainfall: 40 mine Rio Tinto portfolio.

- High clustering: 36 exceedances in one year out of 142
- There is a pronounced trend and decadal variability

Climate Extremes – Result Example – Four Companies – Two Climate Datasets

Fat tail risk due to spatial clustering:



For BHP Portfolio for T=100 years

The number of events experienced is 5 to 6x of expected

= Very high residual risk exposure across the Portfolio

The more rare the event (higher T), the higher is the effect of clustering on residual risk for all portfolios

Climate Extremes – Result example – Comparison across companies for drought exposure

Drought Risk Rankings by VAR and CVAR normalized to portfolio size

Table 2. Ranking of 15 Companies Based on $R_{0.95}(0.1)$ and $CVS'_{0.95}(0.1)$ Measures for a 12 Months Drought Event, Obtained Using the Dai PDSI Data Set and Mine Valuation Obtained From Broker Reports From TD Securities[a]

Company	$R_{0.95}(0.1)$	Rank $R_{0.95}(0.1)$	$CVR_{0.95}(0.1)$	Rank $CVR_{0.95}(0.1)$
Agnico Eagle	0.44	9	0.32	11
All 15	0.17	16	0.20	15
B2Gold	0.33	13	0.34	9
Barrick Gold	0.31	14	0.25	13
Capstone Mining	0.82	1	0.59	1
Eldorado	0.54	4	0.42	7
First Quantum Mineral	0.44	8	0.48	4
Franco Nevada	0.28	15	0.20	16
Goldcorp	0.47	6	0.37	8
Hudbay	0.51	5	0.33	10
Iamgold	0.45	7	0.50	3
Kinross	0.34	11	0.26	12
Lundin Mining	0.35	10	0.43	6
New Gold	0.56	3	0.45	5
Newmont	0.34	12	0.25	14
Teck Resources	0.64	2	0.53	2

[a]A lower rank means a higher exposure.

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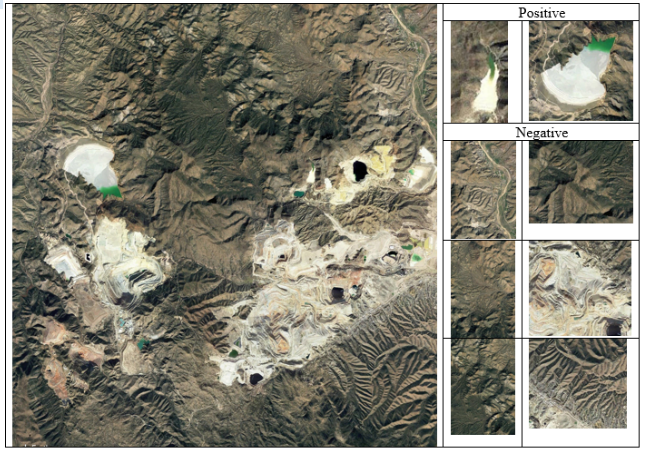
Tailings Dam State Identification & Failure Impact Analysis

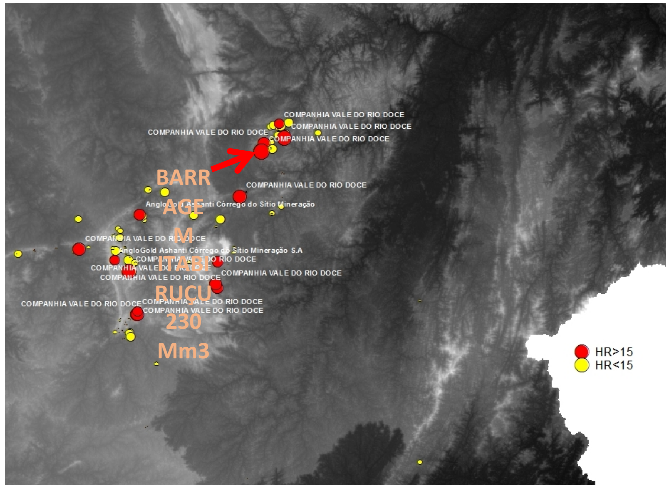
Concern: Tailings dams store highly toxic wastes. Their failure can lead to catastrophic, multi-billion $ liabilities and potential loss of license to operate, asset stranding.

- No global database of dams. Yet, failure rate 3-5x of river dams
- Sequentially constructed of earthen fill. More prone to failure
- Dominant failure modes: Overtopping due to high rain, Geotechnical Failure. Mismanagement



Approach & Findings:

- Machine Learning approach developed for automatic identification of tailing dams from satellite imagery
- Regression and indexing based approach for probabilistic impact analysis and ranking of dam failure impact (ecological, population) based on runout from failure.
- Prediction probabilities from the model cover actual Samarco impact
- However, hazard ratings for many other Brazilian tailing dams in the region are much higher than those estimated for Samarco

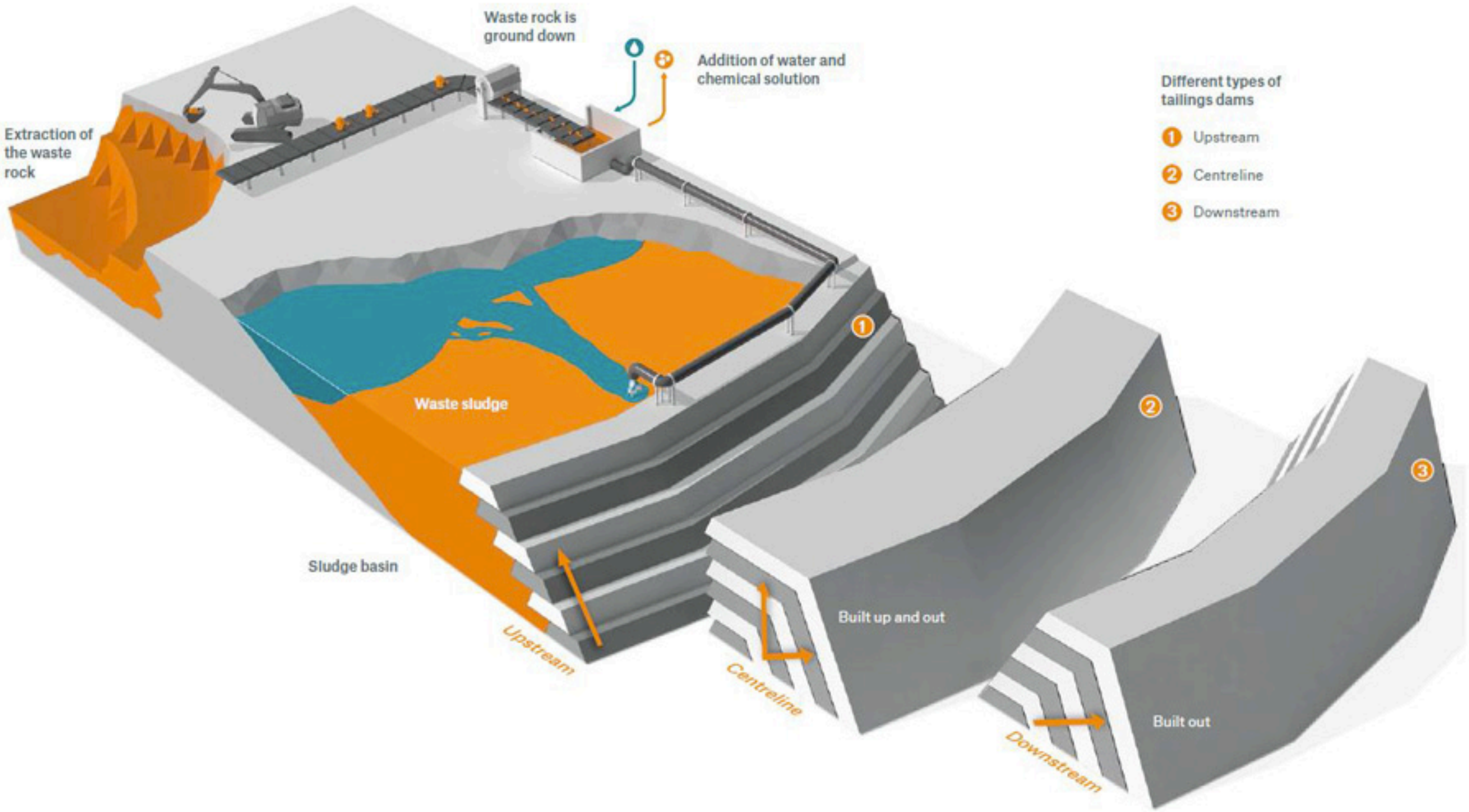


Dam Failure, Satellite Image Databases and Risk App Developed and available.
Applied to derive probabilistic hazard ratings and ranking for Minas Gerais dams

Tailings Dam Facility - Background

Made with local soil, rocks, tailings
Risk of seepage/stability

Elevated in multiple stages
Risk of seepage/stability/foundation

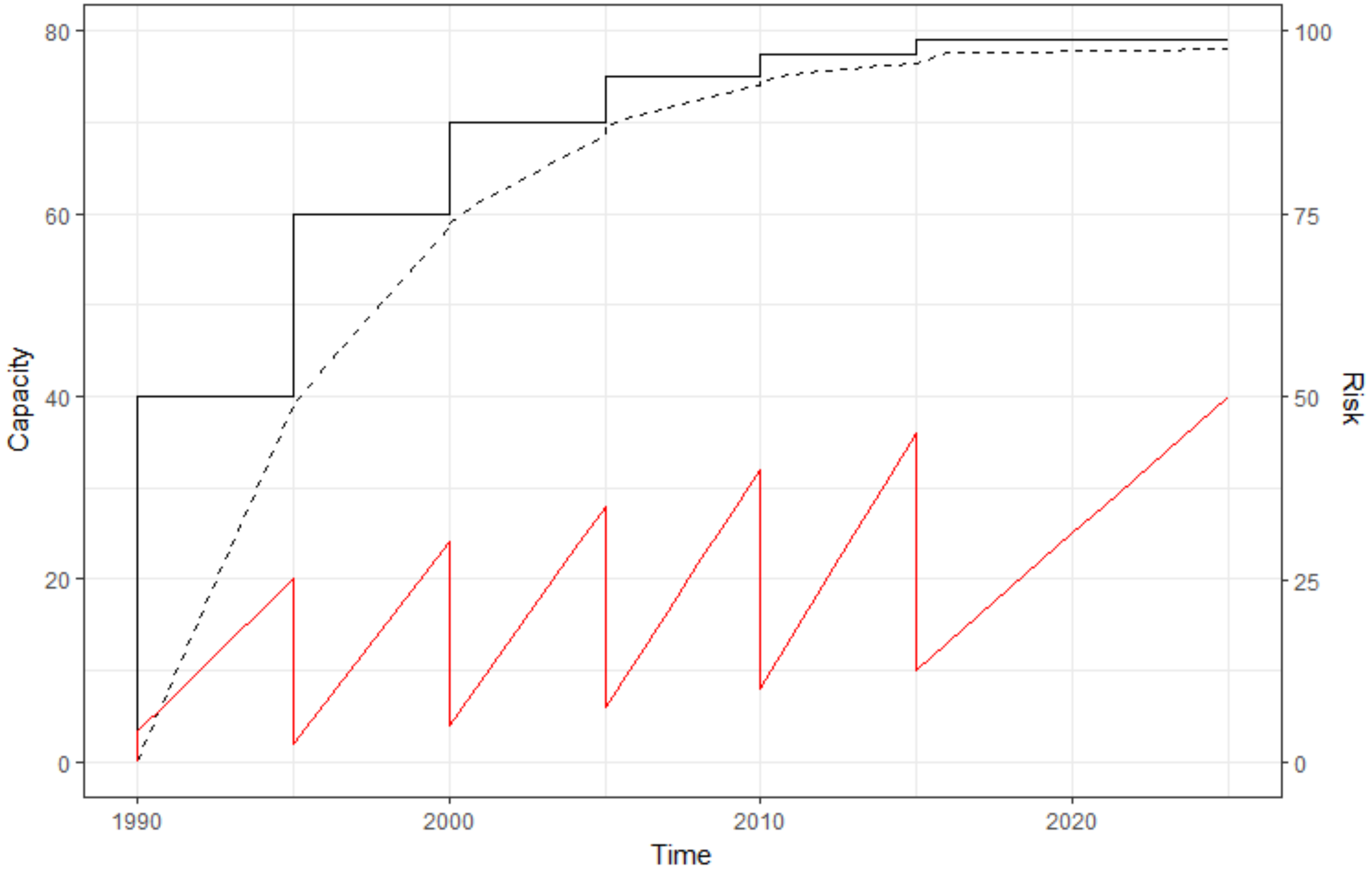


riskier, $ Upstream

Medium risk, $$ Centerline

Safer, $$$ Downstream

Tailings Dam Facility - Conceptual Risk Profile as TSF is Filled or Raised



Tailings Dam Facility – Samarco Dam Failure Example

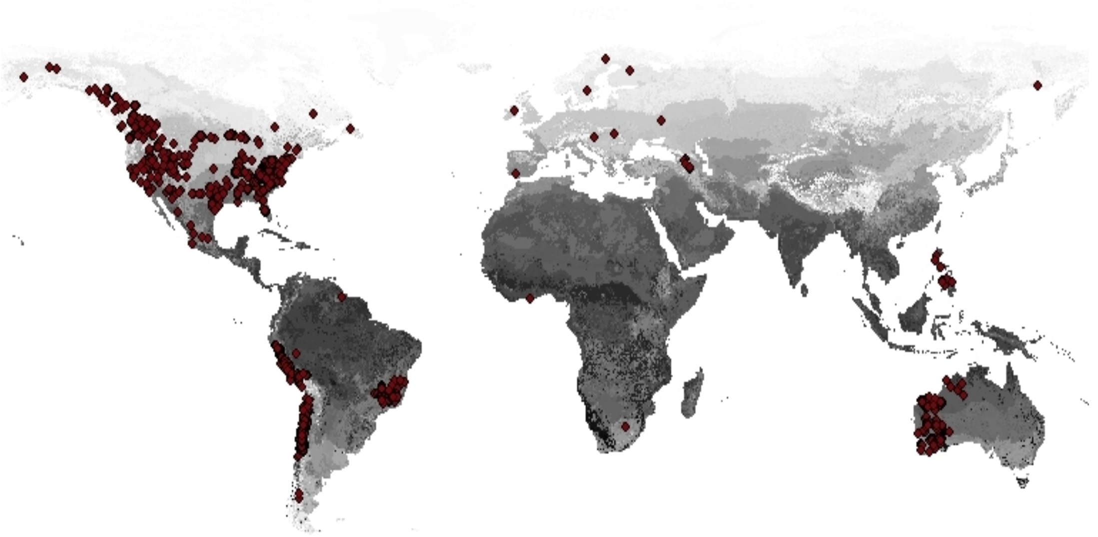
- Unanticipated/unpriced loss
- Vale and BHP are paying $1.2 billion each for Samarco
  - this does not include losses in production (debt restructuration) damages (only for compensation and restoration)
- Potential Impacts:
  - Loss of production and expense on rehabilitation
  - Environmental disaster downstream of mine + conflict
  - Stranded Asset

Samarco, Brasil
Tailings Dam Failure

Tailings Dam Facilities – Global Picture

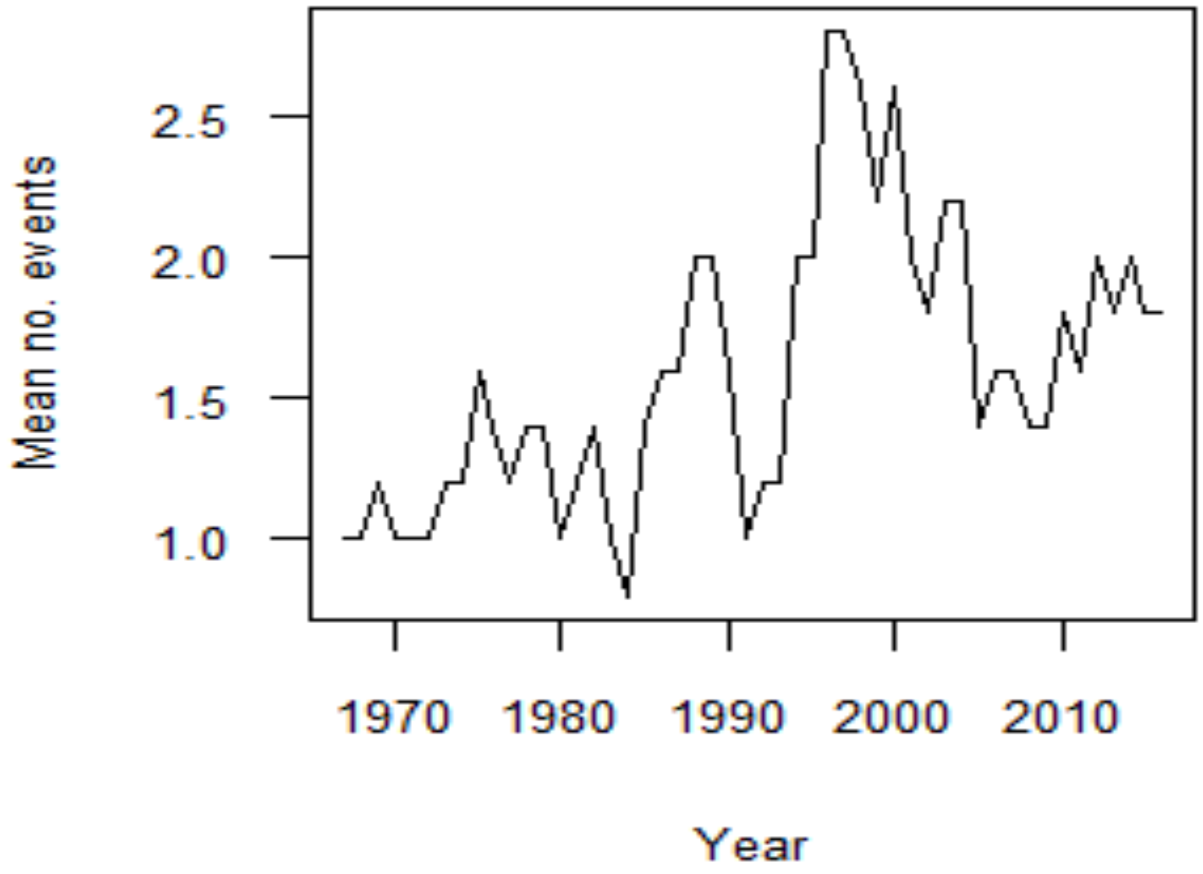
- No global inventory of tailings dams
  - At least one per site?
- Some regions present high risks, with a concentration of large infrastructures near population centers (e.g. Minas Gerais)
- Financial risk of a tailings dam failure is not reflected in any point of the design and approval process. It is also not reflected in the liabilities or in the insurance and potential impacts are almost never assessed since:
  - either "they never fail" (wrong risk assessment)
  - or "they won't have any impact" (actual consequences)

- Sample of TSFs around the world (data from multiple sources)
- Many mining-intensive countries are not pictured



Tailings Dam Facilities – Historical Failures

Serious and very serious incidents



Tailings Dam Facilities – Development of a Hazard Rating Index (HR)

- Objective: Assess and compare the potential damage that TSFs failures may cause downstream.
- Approach:
  - Statistical model for volume discharged and distance impacted
    - Based on tailings dam height and storage capacity
  - Convolution with Impact area information
    - Population, Land Use, High Value Conservation areas
  - Result: Hazard Rating HR (including uncertainty)
  - Application: prioritize where it may be more or less important to pursue inquiry into a more detailed TSF risk quantification process
  - Easy to update
- Overtopping is the failure mechanism in 30-40% of the cases. The climate data can be used to estimate the overtopping probability given additional topographic information

Tailings Dam Facilities – Evolution of Volume Released and Runout Distance

- Objective: Explore how additional data and a new predictor on TSF failures impact accepted relationships between TSF attributes, V_r and D_{max}
- Approach & Results:
  - Updated database of TSF failures
  - Model using the potential energy associated with the released volume H_f as opposed to the whole TSF impoundment as the main predictor improves the variance explained
  - Larger database is needed given the variety in at-site conditions, (rheology, failure type, etc.) to reduce uncertainty about the mean
  - Collaboration with ICOLD and Stanford envisioned to increase the data.

Tailings Dam Facilities – Hazard Rating Model

1
Calculate V_F

$$^*\log(V_F) = -0.477 + 0.954\log(V_T)$$

V_F= released volume of tailings in Mm^3
V_T= stored volume of tailings in Mm^3

2
Calculate D_{max}

$$^*\log(D_{max}) = 0.539 + 0.497\log(H_f)$$

$$H_f = HV_f(V_F/V_T)$$

D_{max}= distance traveled by the tailings in km
H= dam height in m

3
Estimate A

1. Buffer circular area = D_{max}
2. A= Areas within buffer where elevation < elevation at TSF

4
Calculate H_R

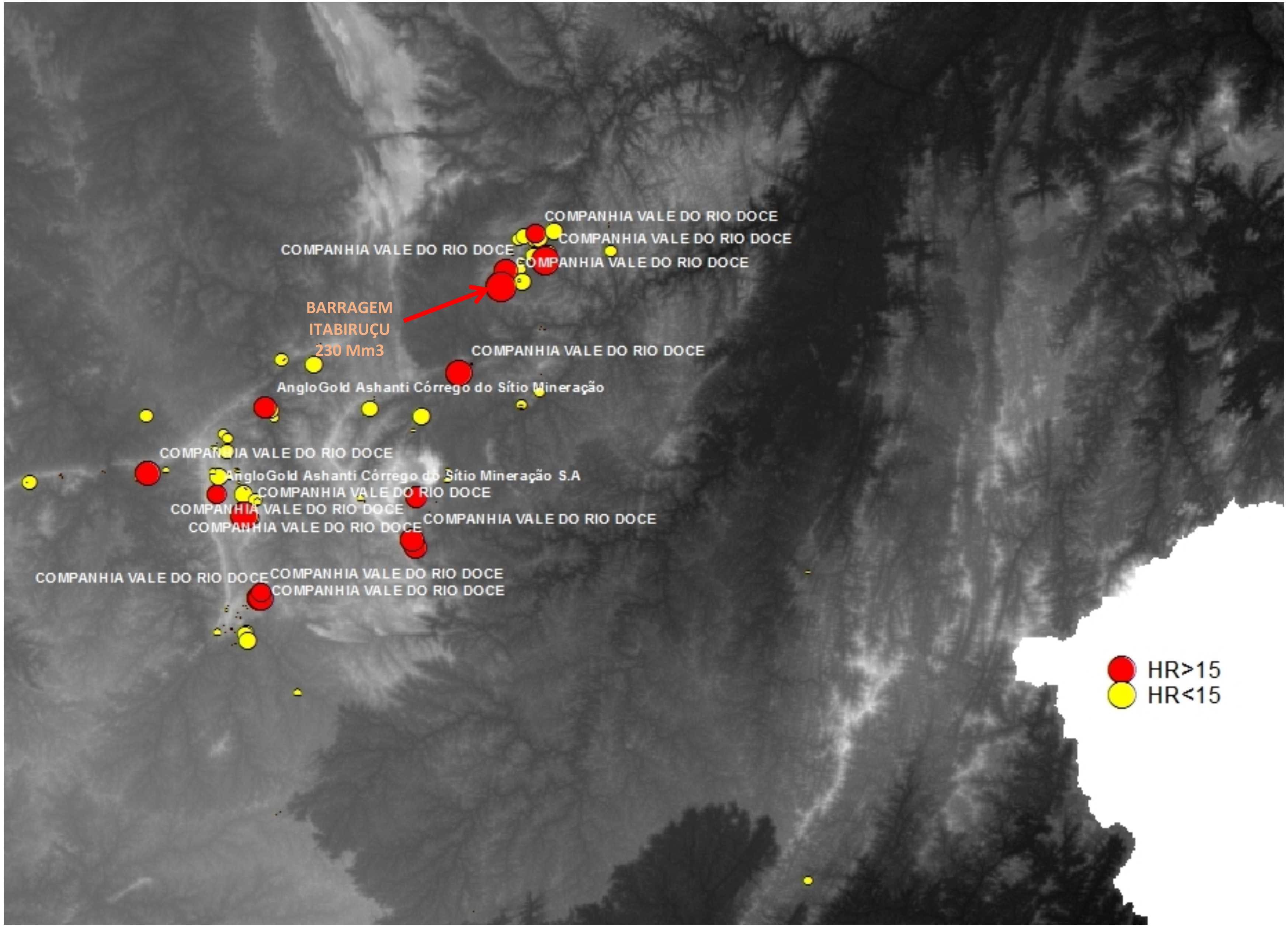
$$H_R = M_1 + M_2 + M_3 + M_4 + M_5 + M_6$$

M_1 =log(population in A), M_2=log(cropland in A), M_3=log(urban area in A),
M_4= log(water surface in A), M_5=log(forests in A), and M_6= log(Grassland in A)

Uncertainty bands estimated using Bayesian and classical regression

Tailings Dam Facilities – Hazard Rating for Minas Gerais, Brazil

Samarco Rating: 29.3
Several dams are much higher



Tailings Dam Facilities – TSF Automatic Detection and Monitoring

- Objective: Being able to globally map TSFs from satellite imagery in different types of climate zones (and perform basic change detection)

- Approach:
  - Gather high and medium resolution imagery from Google Earth and Landsat
  - Manually identify or segment tailings dams
  - Apply pre-trained neural networks on RGB images
  - Application: Build a global map of TSFs worldwide using mine coordinates
  - Easy to update

- Image sources:
  - Landsat
  - Sentinel
  - Google Earth Pro

Tailings Dam Facilities – TSF Automatic Detection and Monitoring

Challenges:

- Different types of TSFs,
- Different scales (resolution),
- Different environments (climate, nearby land-use)
- Waste may not be very spectrally different from surroundings
- Water bodies
- No pre-trained ANN on multispectral images
- Labor intensive to develop training set

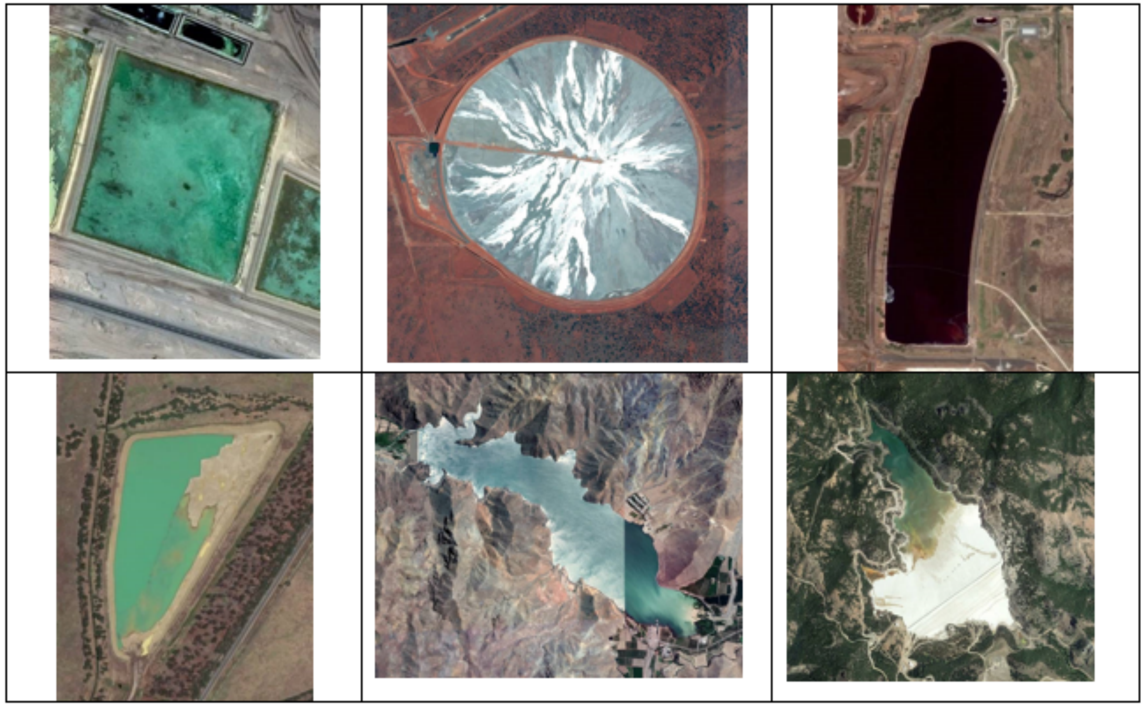


Figure 1 – Types of tailings dams can be represented by these six examples. The first row show TSFs with geometrical shapes with clearly define edges which are usually built in flat areas. The shape for the second row examples is not as well defined and are usually built in uneven areas. The last two examples show tailings dams that were built on top of mountains, to take advantage of its convexity and reduce costs, which are usually called valley impoundments. It is also convenient, as it can usually be expanded without effort. In these cases its expansion would be visible in a satellite image, as it would draw a new horizontal contour in the mountain that contains it. For the first cases, expansion usually means building more facilities, which are usually observed close to each other.

Tailings Dam Facilities – TSF Automatic Detection and Monitoring

Best Results so far: classification through ANN

- 282 images with 4400X4600 pixels were collected from Google Earth Pro - spatial resolution varies from 0.5 to 8m
- Tailings dams were manually identified
- Images were processed, rotated, translated and trimmed to give a total of 4,781negative images and 4,496 positive ones of size 128 x 128
- These images capture the complete mines and part of its surroundings – small mines were sometimes grouped into one image

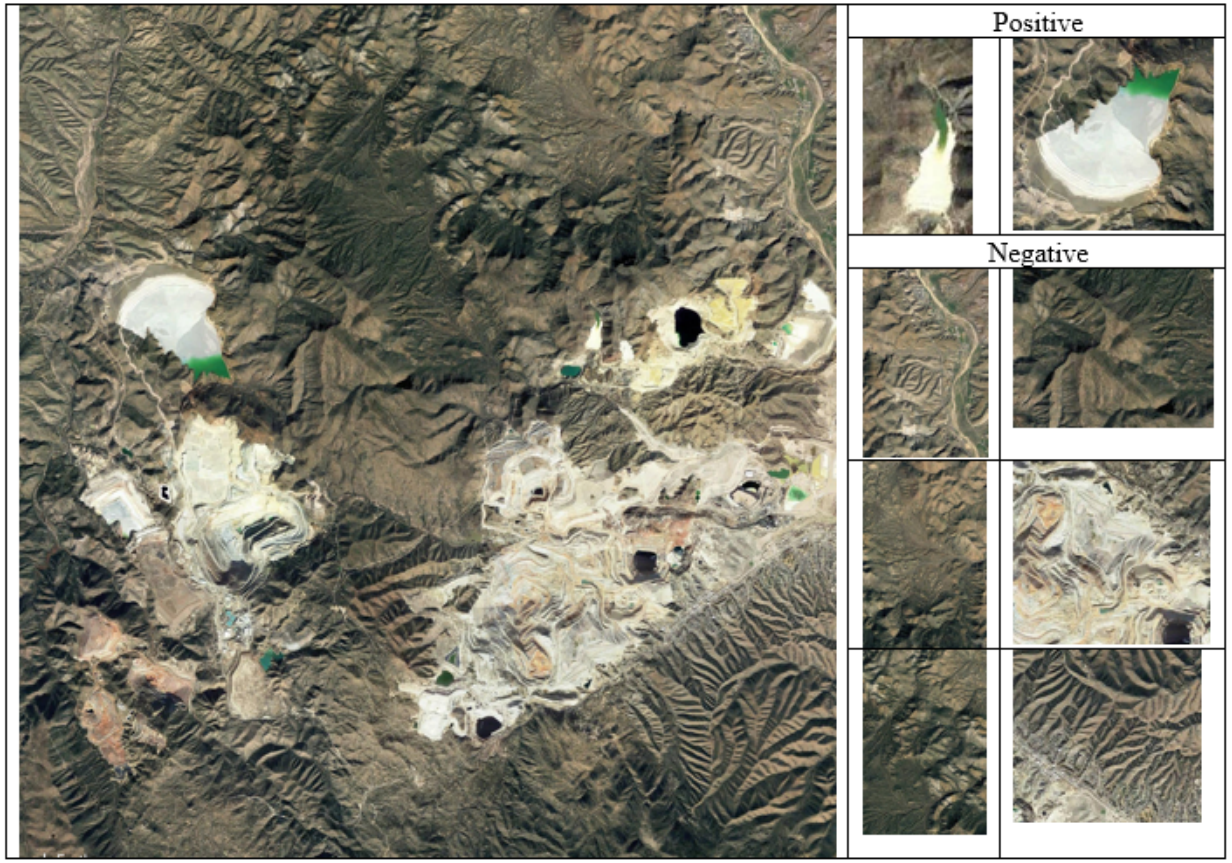


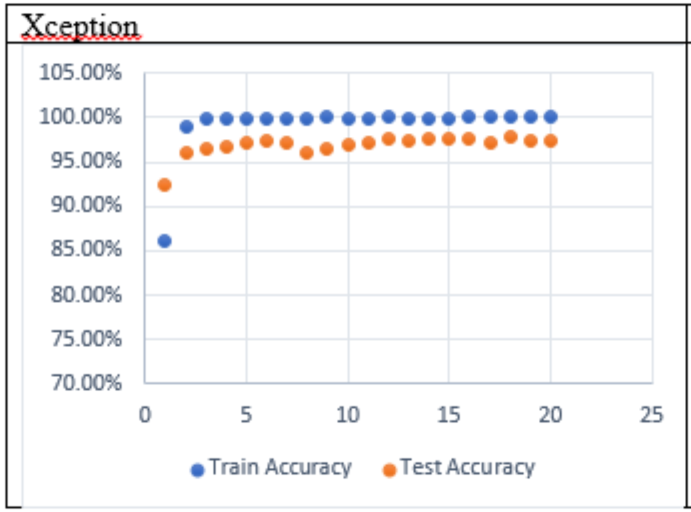
Figure 2 – Full mine with its environment, split into positive (containing TSFs) and negative images.

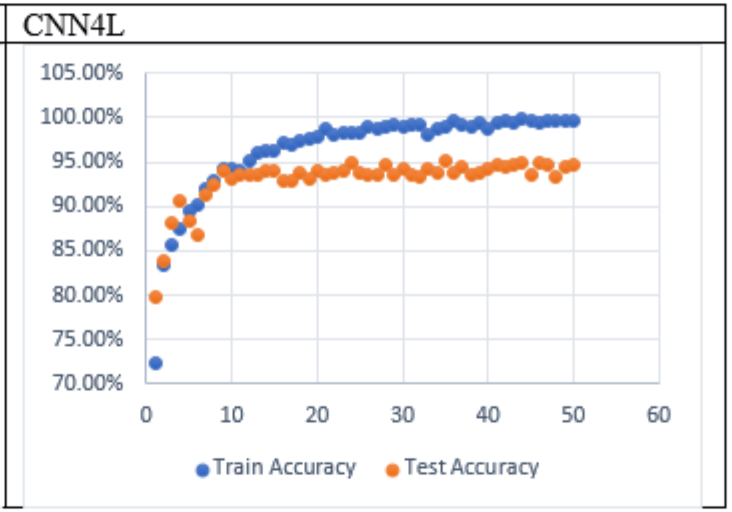
Tailings Dam Facilities – TSF Automatic Detection and Monitoring

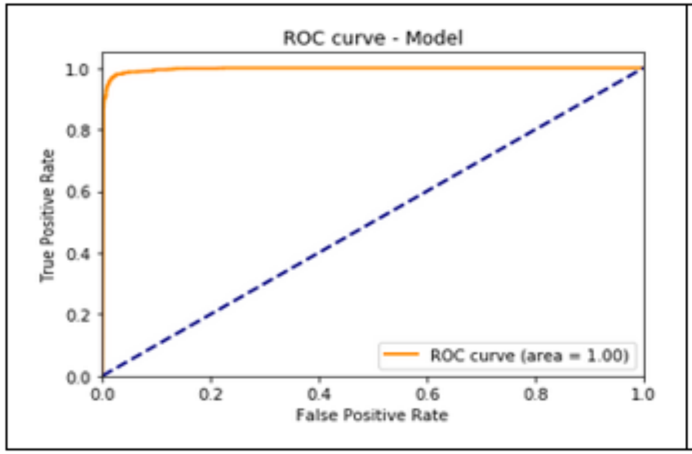
Best Results so far: classification through ANN

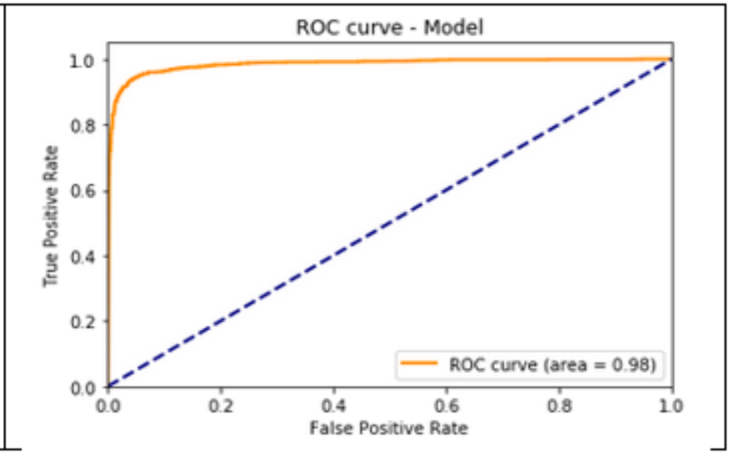
- CNN with 4 Layers
- Pre-trained model with new output layer

	Accuracy	Precision	Recall	FP Rate
CNN4L	94.7%	96.2%	93.2%	3.7%
Xception	97.5%	98.7%	96.3%	1.3%









1	WATER USE AND COSTS
2	BIAS IN REPORTING
3	CLIMATE EXTREMES
4	TAILINGS DAMS FAILURES
5	CUMULATIVE WATER POLLUTION EFFECTS

Cumulative Water Pollution Effects – Regulatory Effectiveness and Outcomes

Concerns: Even if site level regulation of mine effluents is effective, collective impacts from mining and other pollutant sources can compromise the water sources, leading to social conflict and loss of license to operate.

- Is there evidence to quantify these effects and attribute them to specific sources?
- Do current regulatory processes effectively address these risks?

Findings:

- Significant legacy water pollution effects of mining are identified in all countries
- Data sets to pursue space-time trend identification and attribution are sparse
- Mining companies face considerable risks as increasing water scarcity and competition exacerbate the impacts of polluted waters
- Environmental Impact Assessments and associated bonds are likely highly inadequate to address these challenges
- Risk quantification for the industry and for a mine is consequently difficult.
- An approach to regulation that builds in watershed outcomes and attribution is needed.

Database Water quality and predictive factors developed for basins in Peru & USA
Regression models illustrate trends and dependence on aggregate mining activity

Cumulative Pollution Effects – Proposed Vision to Reduce Stranding Potentials