DATA ANALYSIS AUSTRALIA

STATISTICS MATHEMATICS INFORMATION

Analysis of Turbidity Events

Final Report

April 2023

Project: ALCOA/31

STRATEGIC INFORMATION CONSULTANTS

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Client: ALCOA

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Executive Summary

Alcoa has commissioned Data Analysis Australia (DAA) to undertake a study to identify and quantify relationships between turbidity, mining activity and catchment characteristics including slope and area cleared. This will assist in understanding causes of **high turbidity events**, particularly those associated with drainage events, and how to mitigate them in the future. Additionally, this study may also guide quality control processes for Alcoa's turbidity data collection and processing in current and future mining regions, providing the framework for routine monitoring and statistical assessment.

Data from turbidity monitors are subject to numerous errors, including sensor saturation, obstruction by leaves or debris and streams flushing or drying out. Alcoa provided data for 27 monitors in the Huntly region from four data sources with varying degrees of coverage and error.

Interim results, not reported here, were obtained using a smaller dataset of six monitors for the period 2021-2022 that has been cleaned of gross errors caused by sensor malfunction or telemetric issues. They suggested that **the relationships between high turbidity events and the cleared percentage area and slope of catchments are more complex than can be expressed by simple univariate thresholds**. Using the smaller dataset, slope appeared to have a stronger relationship with the number of high turbidity events than clearing, with no apparent relationship between the number of high turbidity events and clearing. While not statistically significant, the area rehabilitated was suggested as an important factor with the number of high turbidity events decreasing with levels of rehabilitation.

This report describes the results of using a larger dataset for top level analysis and statistical modelling.

Top Level Analysis

A subset of 10 monitors with 80% turbidity data availability for the winter period May to September 2021 was identified and the total number of high turbidity events during that period was correlated with catchment characteristics. These included mean and maximum slope, the percentage of the catchment with slope greater than 16 degrees, mean and maximum slope of the cleared area, area cleared, area rehabilitated and several indices derived from leaf area index (LAI) data. Five of the ten catchments recorded no high turbidity events during this period.

We found a correlation of close to zero between the percentage area of catchment that has been cleared (total area cleared including areas subsequently rehabilitated) with the number of high turbidity events meaning. While there was a positive correlation between the percentage area of a catchment that has been cleared but not yet rehabilitated (ie. open area) and the number of high turbidity events, it was not significant. Mean catchment slope and the percentage area of the catchment that has been rehabilitated were the only factors found to have a significant correlation with the number of high turbidity events. This suggests that rehabilitation should be considered when managing turbidity risk.

Statistical Modelling

While the top level analysis can highlight individual relationships, multivariate analysis is critically important because the effects of multiple factors and their possible interactions can be considered simultaneously. A subset of turbidity data for 14 monitors between January 2021 and September 2022 was used to estimate a sequence of multivariate statistical models designed to consider: (1) effects of total clearing (including areas subsequently rehabilitated); (2) effects of clearing prior to rehabilitation; and (3) effects of clearing and rehabilitation combined.

The results showed that:

- Catchment slope has a significant positive effect on either the occurrence or number of high turbidity events and their number using any model, with more events in catchments with higher mean slope.
- Rainfall has a significant positive effect on both the occurrence and number of high turbidity events and their number using any model, with more events in wetter months.
- When only total percentage cleared area (including subsequently rehabilitated areas) is considered, it has no effect on the chance of high turbidity events occurring or on the number of high turbidity events if they occur.
- When the percentage area cleared but not rehabilitated is considered, it is found to have a significant positive effect on the occurrence of events but not on their number.
- When both clearing and rehabilitation are considered, percentage area rehabilitated has a significant negative effect on the chance of high turbidity events occurring.

Putting these results together, we find that as a whole, the total percentage cleared area has no significant effect (negative or positive) on high turbidity events, but the two components of it do: percentage cleared but not rehabilitated has a positive effect and percentage cleared and rehabilitated has a negative effect.

The best-fitting model can be used to predict the expected number of events in different scenarios and we can consider changes in a single factor, keeping all else constant. This shows that:

a) Risk of high turbidity events increases with increasing areas of clearing in the absence of rehabilitation.

b) Risk of high turbidity events decreases with increasing levels of rehabilitation.

c) Risk of high turbidity events increases with increasing catchment mean slope.

d) High turbidity events can be expected within uncleared catchments.

Because the factors act together to affect turbidity risk the predictions can tell a more complex story.

The modelling results strongly suggest that selection of a threshold on catchment clearing to minimise risk of high turbidity events should consider rehabilitation. Cleared areas that have not been rehabilitated pose a risk, but cleared areas that have been subsequently rehabilitated do not.

While we found that risk of high turbidity events increases with increasing catchment mean slope, it is unclear that this can be used to select a specific slope threshold for turbidity risk management. Model predictions to understand the joint effects of clearing and catchment slope on the number of high turbidity events showed a marked curvilinear response to the percentage area of the catchment that has been cleared and not rehabilitated, with the predicted number of high turbidity events increasing more rapidly when the **currently** cleared area is over 30% of the catchment. In contrast, the response to mean catchment slope is more linear.

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1. Introduction

Alcoa conducts mining activities in the Darling Range which involves clearing the forest, mining the shallow depth bauxite, then completing rehabilitation. The Alcoa Huntly Bauxite Mine located east of North Dandalup in Western Australia (WA) was established in 1976 in the North Dandalup catchment area and extended into the Serpentine catchment in 2000s.

While natural processes of stream bank erosion and sediment mobilisation exist in forested catchments, trees and other vegetation help absorb and filter water, reducing stream flow and risk of erosion and turbidity. Infrastructure (such as tracks, roads and firebreaks around powerlines) in forests is associated with increased erosion. Bauxite mining increases the risk until subsequent rehabilitation restores the forest system.

Exposed surfaces within the mining envelope present a direct risk for erosion and delivery of sediment into streams (eg. sump and drainage failures). This is managed through operational drainage design and management controls which includes application of the Alcoa WA Mining and Haul Road Drainage Design Manual.

Mining may also cause indirect risks due to forest clearing. Borg et al.[1] undertook one of the most comprehensive studies of the impact of logging on stream flow and water quality in south-west WA. They found that logging caused increased annual streamflow for 2-3 years. Stream turbidity increased in some logged catchments for 2-3 years after, then reverted to pre-logging levels. However, no increase in stream turbidity occurred in logged catchments where 30-100 metre strips of forest were retained along the streamlines.

Alcoa monitors turbidity in catchment streams along with other surface water quality parameters to measure and evaluate water resource quality relative to mining activity. Turbidity risk is managed using a range of operational practices including turbidity monitoring and maintenance of an uncleared riparian stream buffer that has historically been 20 – 50 metres wide in Huntly catchments, dependent on proximity risk, but has been increased to 100 metres for proposed mining areas as outlined in the Alcoa 2023-2027 Mining Management Plan (MMP).

High turbidity events are defined as incidents when measured Nephelometric Turbidity Units (NTU) is continuously greater than 25 for a period of one hour or longer. When these events are recorded via sensors, Alcoa investigates the cause of the turbidity event to determine whether it is due to a drainage failure event at one of their mining areas so that remedial action can be taken.

Alcoa has commissioned Data Analysis Australia (DAA) to undertake a study to identify and quantify relationships between high turbidity events, mining activity and catchment characteristics. This will assist in understanding risk factors for high turbidity events

[1] Borg, H., King, P.D. and Loh, I.C., 1987a. Stream and ground water response to logging and subsequent regeneration in the southern forest of Western Australia: Interim results from paired catchment studies. WH 34, Water Authority of Western Australia, Water Resources Directorate, Surface Water Branch, Perth, W.A.

and enable targeted management to mitigate them in the future. The study may also guide quality control processes for Alcoa's turbidity data collection and processing in current and future mining regions.

This study was performed in three stages.

Data Review and Pre-processing

The first stage involved data review and pre-processing. This included obtaining turbidity data recorded by Huntly monitors, combining the data into a single dataset and identifying a subset of monitors with sufficient data for use in this study. Because measured data from turbidity monitors are subject to numerous errors, high turbidity events detected from the turbidity data were verified prior to analysis by cross-checking them against Alcoa's investigation reports. The catchment area upstream of each monitor was used to calculate catchment characteristics that may explain high turbidity events, including slope and degrees of clearing and rehabilitation.

Top Level Analysis

The second stage considered relationships between single catchment characteristics and the number of high turbidity events occurring in catchments using correlation analysis. Statistical tests were conducted for each catchment characteristic to determine which have significant correlations with the number of high turbidity events. Comparisons of the number of events for different catchments requires a set of monitors that have good data coverage for the same time period, preferably in winter when high turbidity events are more likely to occur. We identified 10 monitors with > 80% turbidity data availability for the winter period May to September 2021 for top level analysis.

Statistical Modelling

While the top level analysis can highlight individual relationships, the many factors affecting turbidity can interact. Multivariate analysis is critically important to consider the effects of multiple factors simultaneously. Moreover, statistical modelling allows the data can be restructured so that data gaps have less impact by considering monthly counts of events and including terms to account for seasonal effects where more events occur in winter than in summer. This allows use of a longer time period of data.

The third stage of this study therefore considered relationships between multiple catchment characteristics using statistical modelling. We identified 14 monitors with greater than 70% turbidity data availability for the period January 2021 and September 2022, which covers two winters. The data were restructured to consider the number of events occurring in a month. A subset of catchment characteristics for modelling was selected to avoid collinearity. Because the counts of high turbidity events are mostly zero, a hurdle model was estimated and used to predict the number of high turbidity events for different catchment scenarios.

2. Stage 1: Data Review and Pre-Processing

The first stage of the project involved data review and pre-processing.

2.1 Turbidity Data

Turbidity monitors emit light and measure the amount scattered by particles in the sample. Measured data from turbidity monitors are subject to numerous errors, including sensor saturation, obstruction by leaves or debris, streams flushing or drying out and intermittent turbidity from animal or vehicle crossings.

Alcoa currently uses Greenspan TS1000 turbidity monitors (Figure 1) interfaced with DataTaker DT82e data loggers (Figure 2). The sensors' factory set measurement range is 1 to 100 NTU using an analogue 5-20mA signal.

Compliance monitors are located immediately upstream of neighbours or public water supply storage reservoirs in accordance with the operational requirements agreed in the Water Working Arrangements. Where telemetry is available, live data is transmitted to site to allow for a quick response to investigate elevated readings. Where transmission via telemetry is restricted, data is downloaded monthly or after every 20 mm or greater rain event. Agreed reporting limits are set by the DWER and WC, and all monitored turbidity events greater than 25 nephelometric turbidity unit (NTU) for an hour or more are reported.

Local monitors are positioned upstream from the compliance monitoring points. Local monitors provide information on the performance of the drainage infrastructure of the mine. They are generally located in streams below haul road crossings or in a series of large mine pits.

Figure 1. Turbidity monitor located within stream channel.

Figure 2. Turbidity data logger interfaced with stream channel monitor.

2.1.1 Holyoake Data

Turbidity data were sourced for 2 locations in the undisturbed Holyoake region (GHD 2022[2]), one for the 3.5 months from 15 July 2021 to 31 October 2021 (Figure 3) and the other for four months from 15 July 2021 to 16 November 2021.

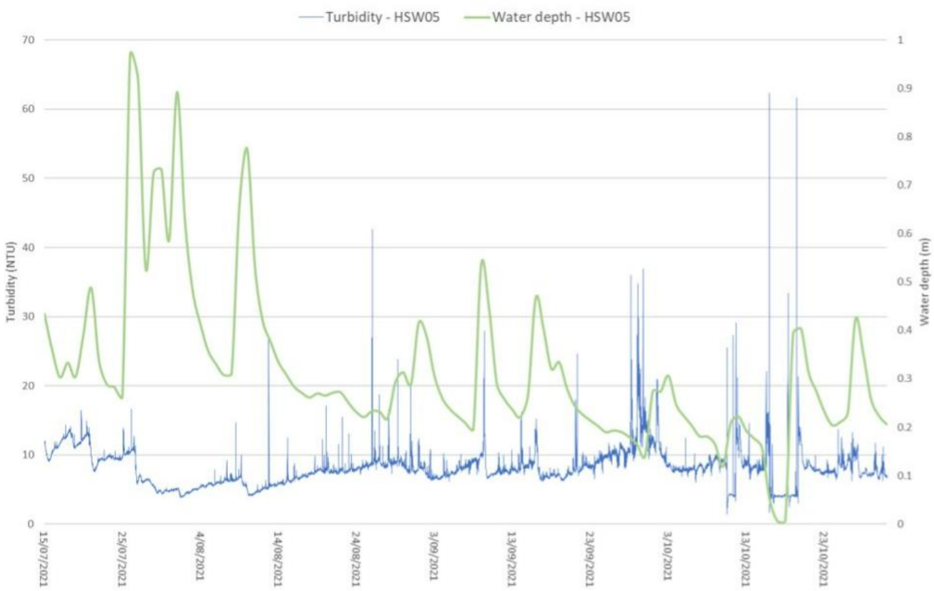

Figure 3. Holyoake turbidity and flow data (Site HSW05).

[2] GHD 2022. Surface and Groundwater Monitoring Report Myara North and Holyoake 2021 – 2022; 17 June 2022.

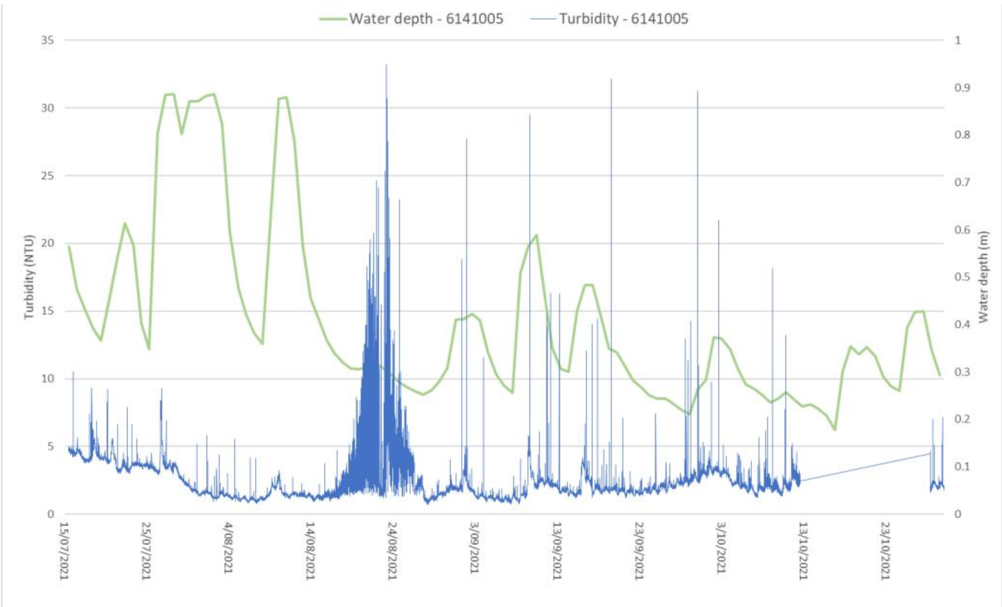

Figure 4. Holyoake turbidity and flow data (Site 6141005).

2.1.2 Huntly Data

Alcoa provided four overlapping sets of turbidity monitor data recorded in cleared catchments in the Huntly region dating back to 2016. Since then, the type of monitors and data loggers have changed, there have been multiple technologies used from transmitting data to databases and multiple databases have been used. Therefore, the data were sourced from several databases:

1. <u>2021-2022 Cleaned dataset</u>: Manually cleaned data interpolated to 6-minute intervals for six Huntly monitors (PD01, PD02, SE10, SE51, SE59 and SE61) for the period from January 2021 to September 2022. This data has been cleansed of gross errors resulting from monitor malfunction or data telemetry issues but may still include other errors where high NTU readings are not due to water turbidity.

2. <u>2016-2022 Raw dataset</u>: Data for 27 monitors (including the six listed above) for the period December 2016 to September 2022. The data are a mix of interpolated 6-minute interval data and irregularly spaced raw data that have been sourced from multiple databases.

3. <u>2001-2020 MIDAS dataset</u>: Data for 2 monitors for the period September 2001 to June 2020 recorded interpolated to 6-minute intervals and sourced from the MIDAS database.

4. <u>2020-2022 Osisoft dataset</u>: Data for 11 monitors for the period January 2020 to September 2022. The data are a mix of interpolated 6-minute interval data and irregularly spaced raw data that have been sourced from the Osisoft database.

Each of the four datasets were cleaned to remove data with missing timestamps, duplicates and zeroes before being combined into a single dataset. The 2021-2022 Cleaned data were used whenever these were available. Where the Cleaned data were unavailable, the Osisoft data were patched into fill gaps. If neither the Cleaned or Osisoft data were available, the Raw data were used. If there were no other data, the MIDAS data were used.

There were 30 monitors with unique IDs but only 25 of the IDs could be matched with metadata providing geolocation. Table 1 summarises the data for these 25 monitors. Appendix A contains time-series plots showing the patched data for each of the 25 monitors coloured according to the data source. Many have recorded data for a few months meaning they cannot be used in this study. Others exhibit substantial gaps where data are missing. Of the 25 monitors, we found:

1. 10 monitors with greater than 80% data coverage for the winter period from May to September 2021 to use for Top Level Analysis: DB01, DB02, PD01, SE10, SE48, SE51, SE52, SE53, SE59 and SE61.

2. 14 monitors with long-term coverage and greater than 70% data coverage for the period January 2021 and September 2022, which covers two winters to use for Statistical Modelling: DB01, DB02, ND06, ND07, PD01, PD02, SE10, SE48, SE51, SE52, SE53, SE59, SE61, SE62.

The first set is a subset of the second, therefore a total of 14 monitors were identified for use in this study and the time under consideration was limited to the period from January 2021 to September 2022. The 14 monitors include 11 compliance and 3 local monitors.

Table 1. Turbidity Data Temporal Coverage and Availability (25 Monitors).

ID	Start Date	End Date	Duration	NTU Availability	Jan 2021 – Sep 2022 Availability	May – Sep 2021 Availability
DB01	31/12/2016	07/09/2022	2,076 days	85%	81%	80%
DB02	31/12/2016	18/09/2022	2,087 days	73%	89%	92%
ND04	14/09/2001	29/09/2022	7,685 days	62%	0%	0%
ND06	31/12/2016	17/08/2022	2,055 days	61%	81%	55%
ND07	26/02/2021	03/07/2022	492 days	70%	70%	52%
ND14	04/06/2018	30/08/2022	1,548 days	12%	25%	10%
PD01	27/02/2019	30/09/2022	1,311 days	76%	80%	93%
PD02	18/05/2017	30/09/2022	1,961 days	56%	89%	73%
PD03	08/11/2021	29/09/2022	325 days	30%	30%	0%
SE01	17/03/2022	18/08/2022	154 days	34%	34%	0%
SE02	30/06/2022	18/08/2022	49 days	56%	56%	0%
SE05	01/07/2022	29/09/2022	90 days	71%	71%	0%
SE06	24/03/2022	04/10/2022	194 days	59%	58%	0%
SE07	14/06/2022	24/08/2022	71 days	91%	91%	0%
SE10	31/12/2016	30/09/2022	2,099 days	49%	80%	88%
SE12	14/06/2022	12/07/2022	28 days	100%	100%	0%
SE34T	13/02/2009	20/09/2022	4,967 days	43%	1%	0%
SE48	31/12/2016	04/10/2022	2,103 days	60%	75%	88%
SE51	14/07/2017	24/09/2022	1,898 days	75%	94%	95%
SE52	31/12/2016	18/09/2022	2,087 days	52%	76%	89%
SE53	31/12/2016	24/08/2022	2,062 days	65%	59%	100%
SE59	27/06/2019	30/09/2022	1,191 days	89%	85%	84%
SE60	14/06/2022	29/09/2022	107 days	98%	98%	0%
SE61	04/02/2021	30/09/2022	603 days	85%	85%	93%
SE62	26/02/2021	07/09/2022	558 days	40%	40%	38%

2.2 High Turbidity Events

For the purposes of this study, we define a high turbidity event based on the data alone, without categorisation of the cause, as **any occasion** when turbidity measurements exceed 25 NTU for one hour or longer. This includes both direct and indirect effects of mining. We further characterise true and false events, where readings for true events arise from an actual increase in water turbidity.

High NTU readings can occur in the absence of water turbidity, leading to detection of **false high turbidity events**. Such events may be caused by intermittent sensor saturation, obstruction by leaves or debris or when streams are dry. False events typically exhibit abrupt peaks/spikes or ‘city skyline’ patterns that flatline at maximum NTU (Figure 5).

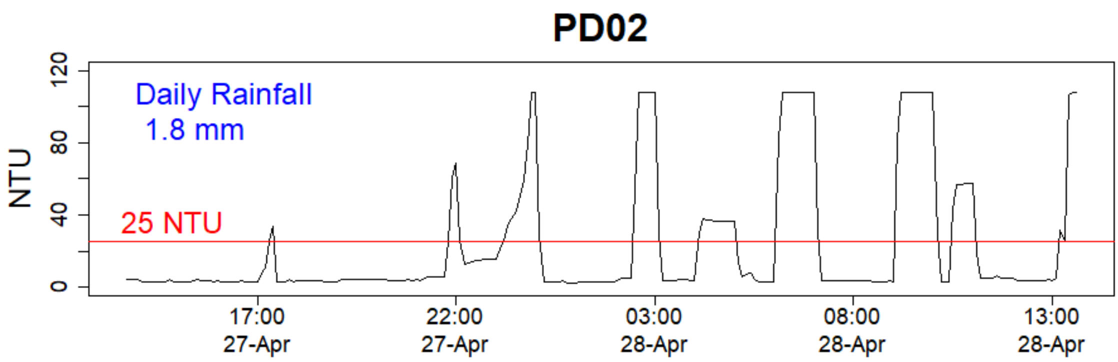

Figure 5. False high turbidity event showing a regular 'city skyline' pattern with tabletop flatlines for max stream turbidity measurements that are accompanied with sharp turbidity inclines and declines for each specific event.

In contrast, **true high turbidity events** are caused by an actual increase in stream water turbidity (e.g. from stream bank erosion, animal or vehicle crossings or sediment laden water entering a stream from operational mining areas). When graphed over time, true turbidity events typically show either a gradual (Figure 6) or sharp (Figure 7) increase in NTU following by a gradual decrease as the turbidity resolves. This is consistent with the findings of Landers and Sturm[3] and arises from the gradual process of dispersion of suspended solids over time.

True events are usually associated with rainfall events that cause runoff and erosion, which is also the case for true events that are caused by mining operations. They are therefore more common in winter than in summer.

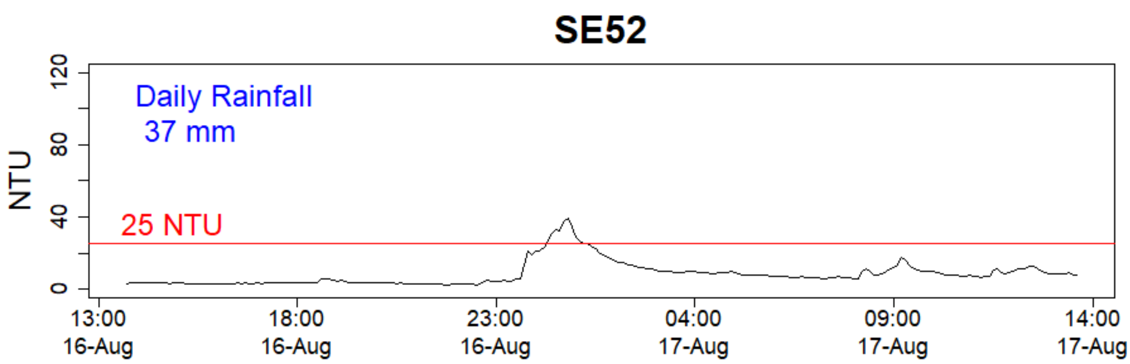

Figure 6. True turbidity event with a distinctive 'bell curve' shape before and after maximum NTU for the event.

[3] Landers, M. N. and Sturm T. W. (2013). Hysteresis in suspended sediment to turbidity relations due to particle size distributions, Water Resources Research 49, 5487-5500. DOI :10.1002/wrcr.20394

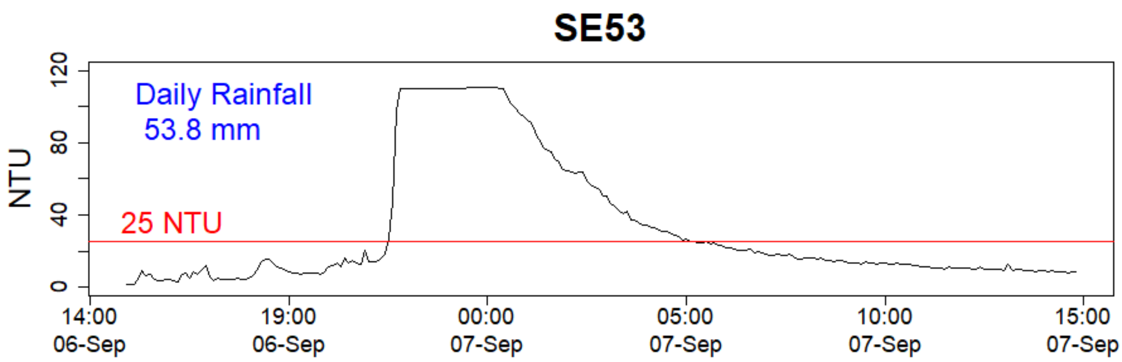

Figure 7. True high turbidity event where NTU increases sharply prior to reaching its maximum and then follows a gradual decline.

In some cases, false events exhibit a similar NTU pattern to true events (Figure 8). They can sometimes be distinguished from true events by considering rainfall and water flow data; if there is no flow, there cannot be turbidity. In other cases, they are assumed to be true until Alcoa can conduct a physical site inspection to determine the whether the high NTU reading is due to water turbidity.

While it is generally the case that events are more likely to occur after rainfall, events caused by mining-related drainage failures can release turbid waters into streams in the absence of rainfall.

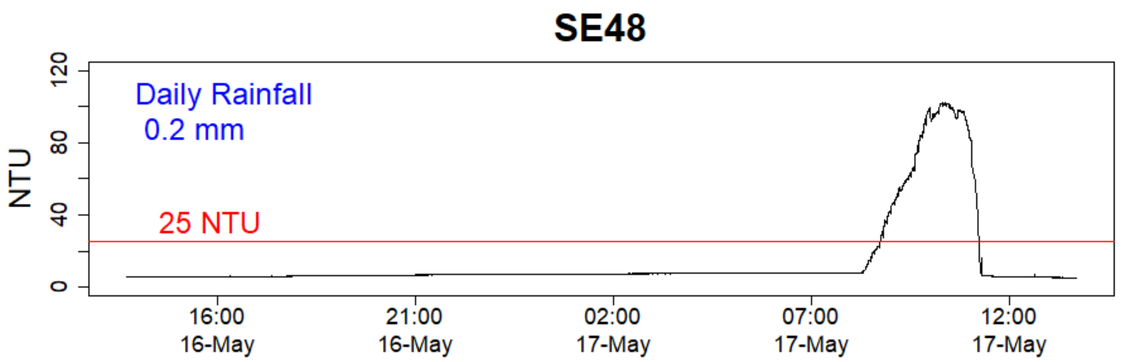

Figure 8. False high turbidity event with a sharp decline in NTU after its maximum caused by removal of a sensor obstruction.

2.2.1 Holyoake Data

No high turbidity events were detected by the two monitors in the undisturbed Holyoake catchment. However, both recorded occurrences of NTU above 25. One (HSW05) recorded 10 NTU peaks of NTU above 25, most were very short but one lasted for 10 minutes. The other (614005) recorded 21 peaks of NTU above 25, three for twenty minutes.

2.2.2 Huntly Data

Detection of high turbidity events for the 2021-2022 14-monitor patched Huntly dataset followed a well-established statistical methodology, which included cross-validation and verification as follows:

1. Detection and verification of events from the 6-monitor 2021-2022 Cleaned dataset. This involved cross-tabulating the event dates and locations of all high turbidity events with Alcoa's investigation records to determine whether they had been investigated. Investigated events were verified as true or false based on the results of the investigation. Any events that could not be verified were labelled true and retained in the dataset.
2. Development and cross-validation of an algorithm for removing detected false events using the verified events from Step 1. The algorithm was designed to remove as many false events as possible while retaining close to 100% of true events.
3. Detection, cleaning and verification of events from the 2021-2022 14-monitor Huntly dataset.

The detailed statistical methodology for each steps is described in Appendix C.

While it is generally the case that turbidity events tend to occur after rainfall, classification of high turbidity events as false based on rainfall data was not possible because of events caused when mining-related drainage failures release turbid waters into streams.

2.3 Spatial Data

Spatial data obtained from Alcoa included:

- A digital elevation model (DEM) at 5m resolution interpolated from contour data obtained from the WA Department of Land Administration (DOLA), now known as Landgate.
- Slope derived from the DEM.
- Monthly clearing maps from 1990 to August 2022.
- Annual rehabilitation maps from 1973 to 2021.
- Annual leaf area (LAI) index maps (scaled to between 0 and 6).
- Stream network map.

The location of turbidity monitors has been determined by mining locations and they are not necessarily located at catchment outlets. Because high turbidity events arise from surface and groundwater runoff, events measured by a monitor are only influenced by conditions upstream of the monitor's location. The location of turbidity monitors has been determined by mining locations and they are not necessarily located at conventionally defined catchment outlets. Consequently, this study has used the DEM to derived upstream catchment areas for each monitor used int this study. This process was performed using a sequence of Whitebox Tools[4] to breach and fill depressions in the DEM, create flow accumulation and pointer grids, snap monitor locations to streamlines and delineate watersheds.

The monitors and their upstream catchments are shown in Figure 9.

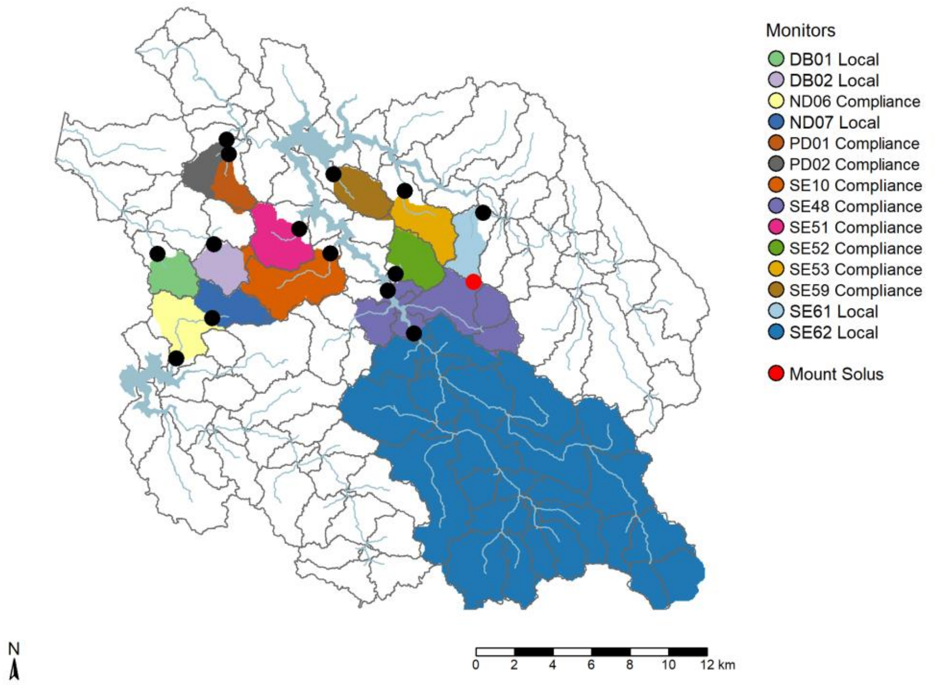

Figure 9. Upstream catchments calculated for the 14 turbidity monitors used in this study.

Appendix B includes time-series plots showing the area of upstream catchment cleared and revegetated for each monitor, and the distribution of the slopes in each catchment. The entire period since clearing is included in the clearing/revegetation time-series to allow interpretation of possible delayed effects on turbidity; note that the axis scales vary.

2.4 Rainfall Data

Rainfall recorded at Mount Solus (location shown in Figure 9) was sourced from the Bureau of Meteorology. Rainfall for January 2021 to September 2022 is shown in Figure 8. The year 2021 experienced the wettest July within the Mt Solus weather station record 2004 to 2022 (current) and 2022 May to August had above median rainfall as shown in Figure 11.

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[4] Lindsay, J. B. (2016). Whitebox GAT: A case study in geomorphometric analysis. Computers & Geosciences, 95: 75-84. DOI: 10.1016/j.cageo.2016.07.003.

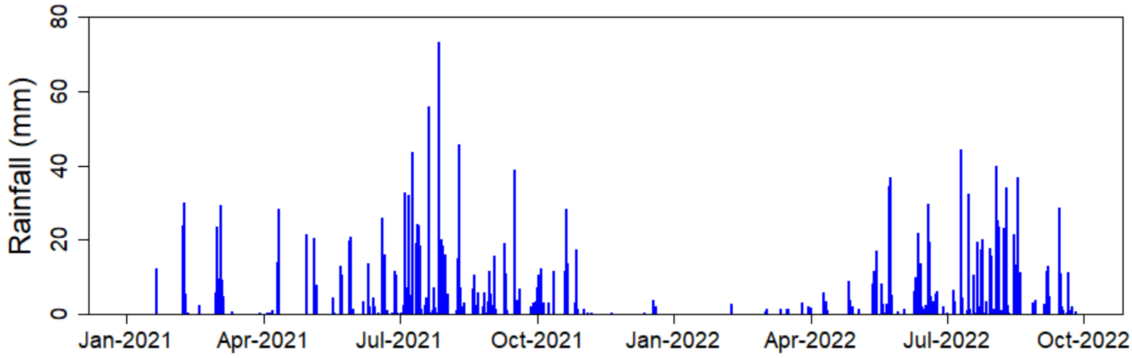

Figure 10. 2021 and 2022 daily rainfall recorded at Mount Solus.

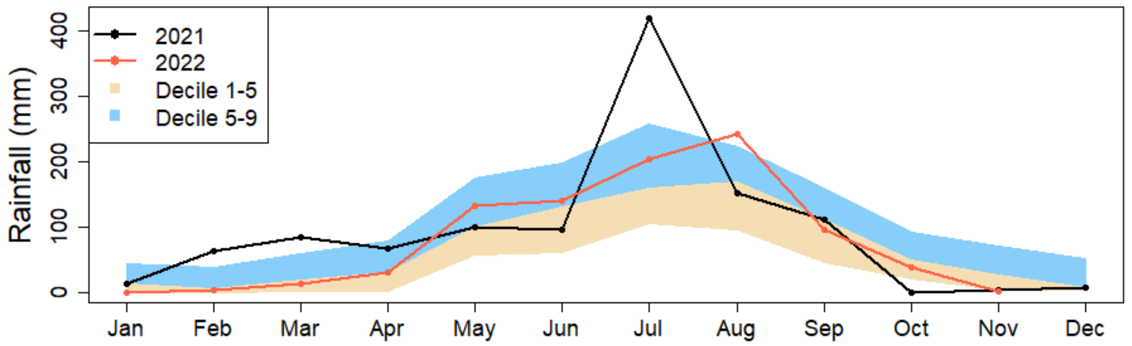

Figure 11. 2021 and 2022 monthly rainfall recorded at Mount Solus compared with historical rainfall (2004 to 2022) deciles.

2.5 Catchment Characteristics

For each monitor, we calculated catchment characteristics that could potentially impact risk of high turbidity events. These included:

- Catchment area (hectares).
- Area of the catchment with slopes higher than 16%.
- Mean and maximum catchment slope (%).
- Mean and maximum slope of the cleared part of the catchment (%).
- Area of the catchment that has been cleared, including includes areas that have subsequently been rehabilitated (hectares and percent of catchment).
- Area of the catchment that has been cleared and subsequently rehabilitated (hectares and percent of catchment).
- Area of the catchment that has been cleared and has not yet been rehabilitated (hectares and percent of catchment).
- LAI anomaly, being the difference between LAI at the time of the event and the long-term (1972 – 2022) mean LAI.
- LAI recovery, being the difference between LAI in rehabilitated parts of the catchment and LAI in the uncleared parts of the catchment.

Clearing, rehabilitation and leaf area index characteristics were calculated for each month from January 2021 to September 2022.

3. Stage 2: Top Level Analysis

The second stage of the project conducts correlation analyses to provide insight into the relationships between turbidity events and characteristics of their upstream catchment, including slope, clearing and rehabilitation.

3.1 Data for Top Level Analysis

To allow the number of events at each monitor to be directly compared, top level analysis requires a set of monitors that have good data coverage for a particular period of data, preferably in winter when high turbidity events are more likely to occur. We identified 10 monitors for use in top level analysis with > 80% turbidity data availability for the winter period May to September 2021: DB01, DB02, PD01, SE10, SE48, SE51, SE52, SE53, SE59 and SE61. Five of the 10 monitors experienced no high turbidity events. The other five experienced between 4 and 15 events.

Interim Report 2: Top Level Analysis of 2021-2022 Dataset reported the results of top-level analysis of the 6-monitor 2021-2022 Cleaned dataset. Upstream catchment characteristics were calculated at the time of event occurrences and averaged for each catchment. This approach cannot be used for catchment with no events, so we have adopted a different approach. We determined that minimal clearing and rehabilitation occurred during the 5-month period being considering, and therefore calculated clearing and rehabilitation areas and percentages at the end of the period, 30 September 2021.

Table 2 summarises the upstream catchment characteristics and numbers of high turbidity events for each monitor. The mean and maximum slope were calculated from the 5m resolution slope map.

Table 2. Summary of May to September 2021 data used for the top level analysis. Note that the areas cleared are the total areas cleared including areas that have been subsequently rehabilitated.

ID	Area (ha)	Area > 16% Slope (ha)	Mean Slope (%)	Max Slope (%)	Mean Slope of Cleared Area (%)	Max Slope of Cleared Area (%)	Area Cleared (ha)	Area Cleared > 16% Slope (ha)	Area Rehabilitated (ha)	Area Rehabilitated > 16% Slope (ha)	Number of Events
DB01	492	21	8.9	26.8	10.3	24.7	160	8	155	8	0
DB02	519	2	6.5	21.2	6.7	17.9	203	0	79	0	0
PD01	376	57	10.4	49.6	11.4	25.2	95	17	11	6	7
SE10	1,198	147	9.0	48.8	8.9	27.8	448	49	112	2	0
SE48	18,301	1,505	7.7	97.0	8.5	27.2	3,241	186	2,505	105	0
SE51	749	111	10.8	32.1	10.9	25.1	369	48	42	2	10
SE52	609	274	15.7	64.0	14.2	34.8	186	77	13	4	4
SE53	675	211	12.9	40.3	11.6	34.0	273	68	19	10	0
SE59	573	37	9.7	28.7	9.7	22.8	192	9	0	0	8
SE61	515	215	15.8	66.0	13.0	29.6	141	45	6	0	15

3.2 Methodology

The relationships between number of high turbidity events and individual catchment characteristics are explored using correlation plots. Each point in the plots represents a particular turbidity monitor and its associated upstream catchment area. For each plot, the line of best fit between the catchment characteristic shown on the x-axis and the number of turbidity events shown on the y-axes is drawn in black.

The R value shown in the plots is the Pearson's correlation coefficient which ranges in value from -1 to 1. Negative R values indicate a negative relationship where higher values on the x-axis correspond to lower numbers of events. Positive R values indicate a positive relationship where higher values on the x-axis correspond to higher numbers of events. The strength of the relationship is indicated by the magnitude of R where R values of zero mean there is no relationship, R values of -1 indicate a strong negative relationship and R values of 1 indicate a strong positive relationship.

The p-value is an indicator of statistical significance of the linear relationship, or how confident we are that a real relationship exists, with lower values indicating that the relationship is more likely to be real and not due to chance. A p-value of 0.1 means that there is a 10% chance the identified relationship may be due to chance and a p-value of 0.05 means there is only a 5% chance that the relationship may be due to chance. We say that a relationship is statistically significant at the 0.1 level if $p \leq 0.1$ or at the 0.05 level if $p \leq 0.05$.

Statistical significance is affected by the size of the dataset used, making it difficult to find statistically significant relationships using smaller datasets. This makes sense because larger datasets provide more information, and we can therefore be more confident about the conclusions we can reach from the data. The results presented in this section should therefore be interpreted cautiously as they are limited by the small number of monitors and short time period.

3.3 Slope and Catchment Area

Figure 12 shows correlation plots for the number of events in a catchment compared with catchment area, the area of the catchment slopes greater than 16%, mean and maximum slope and the mean and maximum slope of the cleared area. The only significant relationship found is that between mean slope and number of events, such that the number of events increases with mean slope, which is significant at the 0.1 level, meaning there is only 10% probability the relationship may be due to chance. The mean slope of the cleared area is highly correlated with the mean slope of the entire catchment ($R = 0.95$, $p = < 0.001$).

The correlation plots appear to be influenced by the large catchment associated with the SE48 monitor, which is 18 times as large any other catchment. However, if SE48 is excluded, the correlations are largely unchanged, except for the area of the catchment slopes greater than 16%, which changes from R = -0.24 to R = 0.2 with neither value significant meaning that no real relationship exists.

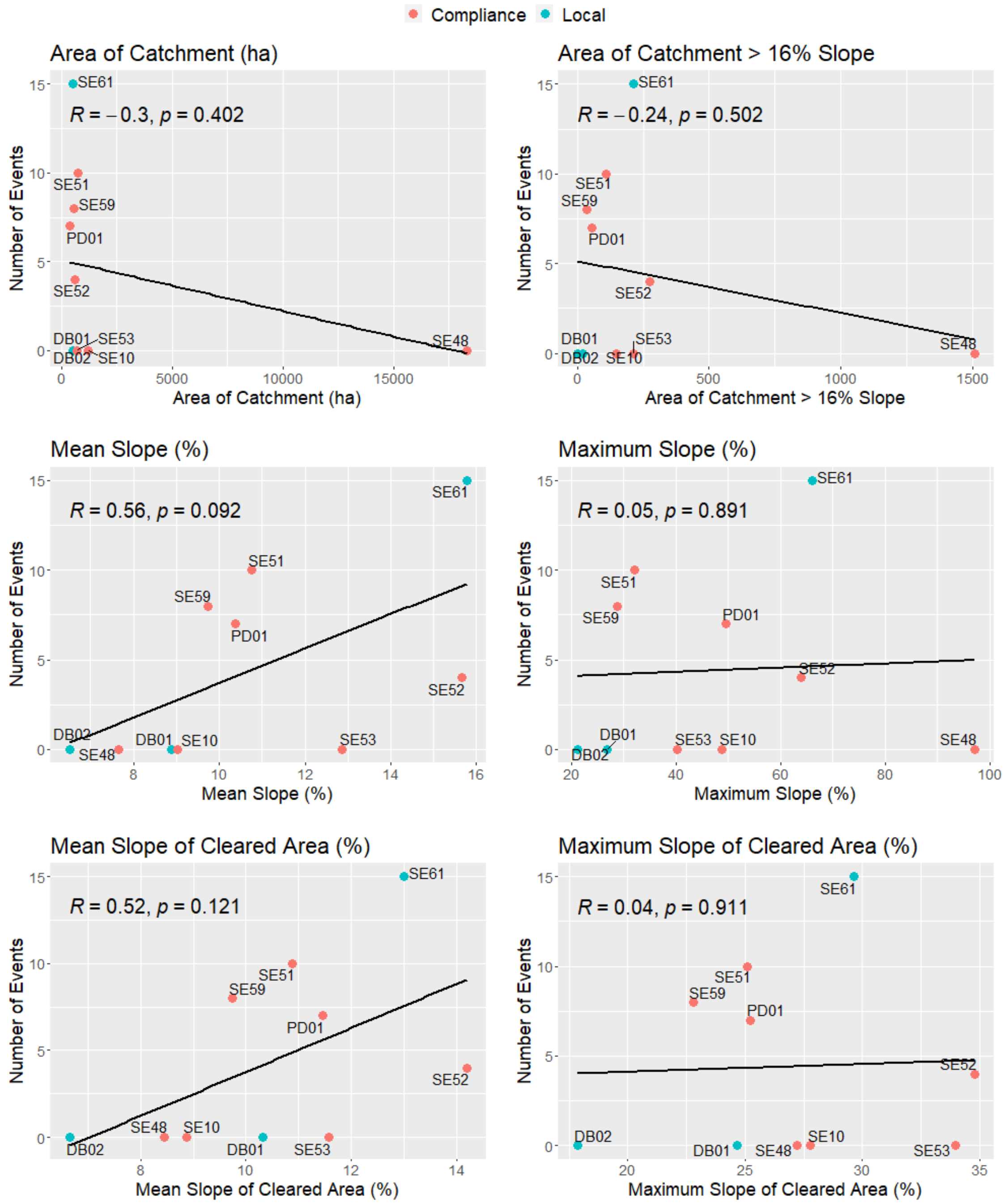

Figure 12. Correlation of the number of high turbidity events with static catchment characteristics of upstream catchments.

3.4 Clearing and Rehabilitation

Figure 13 shows the correlation between the number of events in a catchment with the area cleared (including areas subsequently rehabilitated), area rehabilitated and area cleared and not yet rehabilitated. It shows that the number of events is not significantly affected by the area of the catchment that has been cleared or rehabilitated. Again, monitor SE48 appears to be an outlier. If SE48 is removed, the relationships between the cleared area with slopes greater than 16% and current cleared area become positive but not significant.

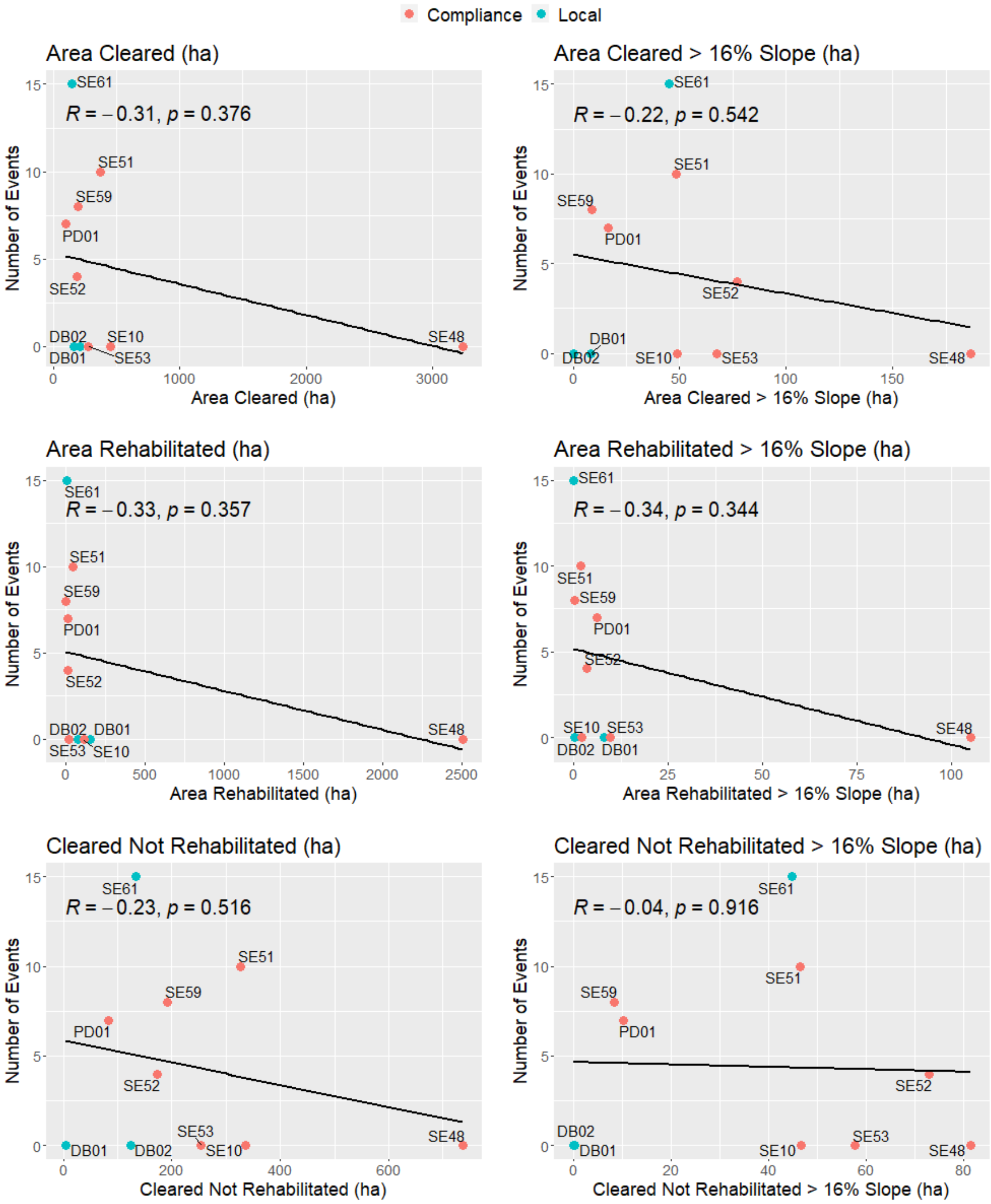

Figure 13. Correlation of the number of high turbidity events with area cleared (including areas subsequently rehabilitated), area rehabilitated, and area cleared but not yet rehabilitated (left column) and the same for parts of the catchment with slopes greater than 16% (right column).

Figure 14 shows the correlation between the number of events in a catchment with the percentage of the catchment that has been cleared (including areas subsequently rehabilitated), the percentage that has been rehabilitated and percentage cleared and not yet rehabilitated. There is a significant negative relationship (at the 0.1 level) between the percentage of the catchment that has been rehabilitated, with fewer high turbidity events occurring in catchments with more rehabilitation. The relationship between the percentage area of the catchment that has been cleared but not yet rehabilitated is positive but not significant.

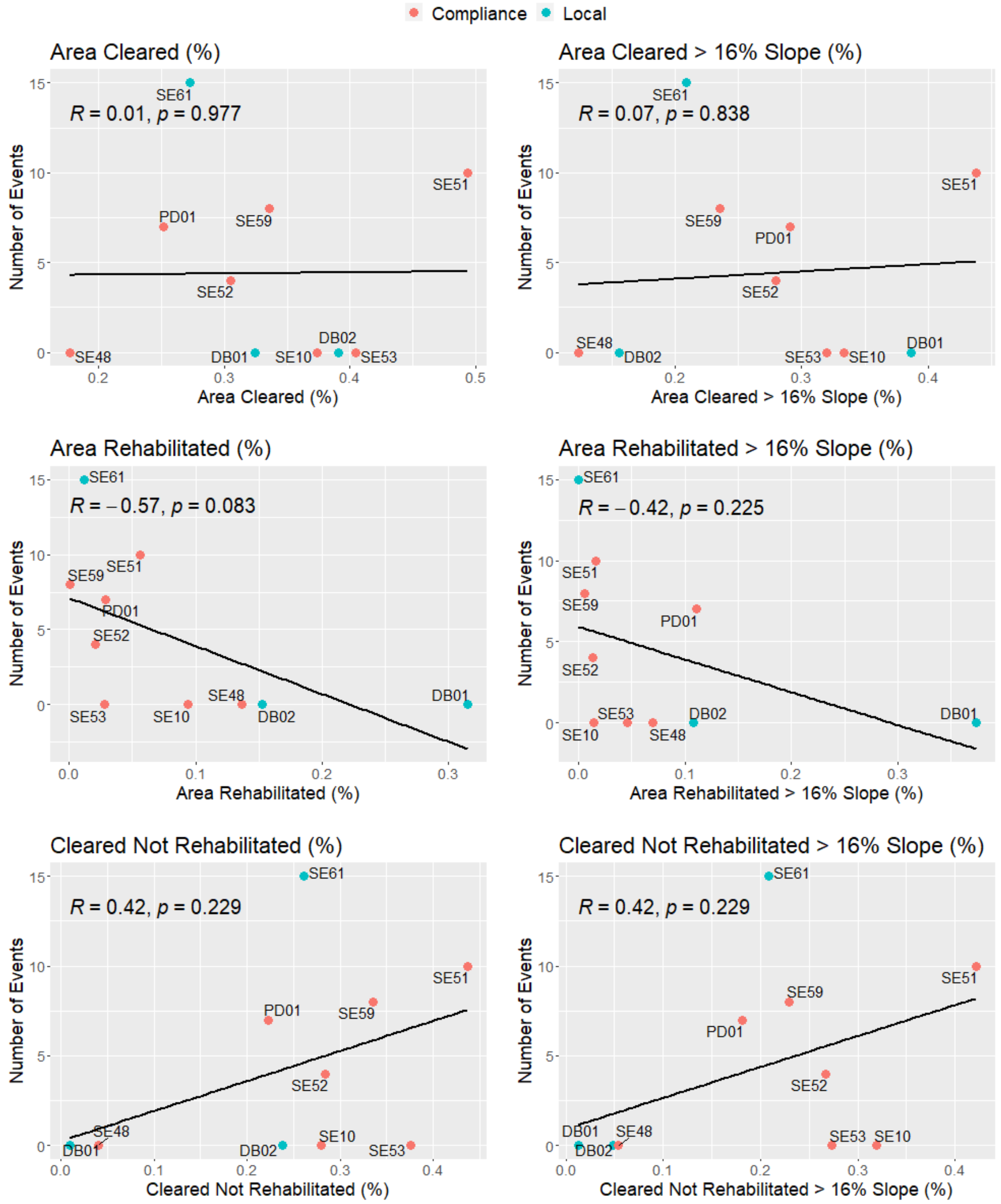

Figure 14. Correlation of the number of high turbidity events with percentage area cleared (including areas subsequently rehabilitated), percentage area rehabilitated, and percentage area cleared but not yet rehabilitated (left column) and the same for parts of the catchment with slopes greater than 16% (right column).

3.5 Leaf Area Index

Figure 15 shows the correlation between the number of events in variables derived from the LAI data. The LAI anomaly is the difference between LAI at the time of the event and the long-term (1972 – 2022) mean LAI. Higher values indicate the LAI in the catchment at the time of the event is greater than average LAI. LAI recovery compares the LAI in the rehabilitated parts of the catchment to LAI for the uncleared part of the catchment. Higher values indicate the LAI of the rehabilitated area is greater than the LAI of the uncleared area. There is no relationship between number of events and LAI anomaly, and a small non-significant positive relationship with number of events and LAI recovery. This positive relationship indicates some positive effect of hydrological recovery in the catchments.

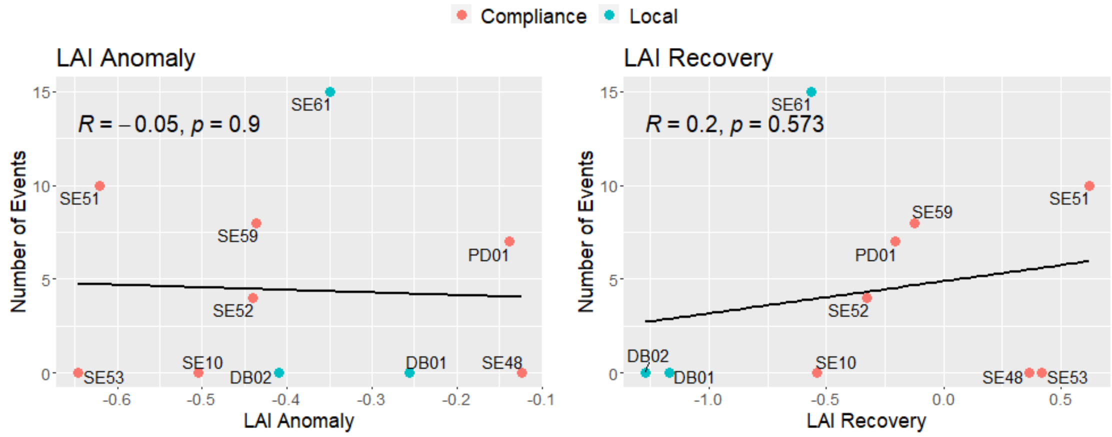

Figure 15. Correlation of the number of high turbidity events with LAI index anomaly (the difference between LAI in September 2021 and the long-term LAI) and LAI recovery (the difference between LAI in the rehabilitated part of the catchment and LAI in the uncleared part of the catchment).

3.6 Summary of Results

Table 3 summarises the correlations of catchment characteristics with the number of high turbidity events in each catchment. The only significant (at the 0.1 level, meaning only a 10% probability that the relationship is due to chance) correlations are with mean catchment slope and the percentage area of the catchment that has been rehabilitated (shown in grey). The second highest correlation is with area of the catchment in hectares followed by mean slope of the cleared part of the catchment and mean slope of the whole catchment.

Table 3. Summary table of correlations with numbers of events (significant correlations are shaded grey).

Variable	R^2	p-value
Area (ha)	-0.30	0.402
Area > 16% Slope (ha)	-0.24	0.502
Mean Slope	0.56	0.092
Max Slope	0.05	0.891
Cleared Mean Slope	0.52	0.121
Max Cleared Slope	0.04	0.911
Area Cleared	-0.31	0.376
Area Cleared > 16% Slope	-0.22	0.542
Area Rehabilitated	-0.33	0.357
Area Rehabilitated > 16% Slope	-0.34	0.344
Area Cleared not Rehabilitated	-0.23	0.516
Area Cleared not Rehabilitated > 16% Slope	-0.04	0.916
Percent Area Cleared	0.01	0.977
Percent Area Cleared > 16% Slope	0.07	0.838
Percent Area Rehabilitated	-0.57	0.083
Percent Area Rehabilitated > 16% Slope	-0.42	0.225
Percent Area Cleared and not Rehabilitated	0.42	0.229
Percent Area Cleared and not Rehabilitated > 16% Slope	0.42	0.229
LAI Anomaly	-0.05	0.900
LAI Recovery	0.20	0.573

4. Stage 3: Statistical Modelling

The top level analysis reported in the previous section is useful for highlighting individual relationships, but the many factors affecting turbidity can act interact and it is vital to consider relationship between multiple factors simultaneously. The third stage of this study considers relationships between multiple catchment characteristics using statistical modelling. This also allows the use of a larger dataset since a statistical model can be used when there are temporal gaps in the data.

4.1 Data for Statistical Modelling

We used January 2021 to September 2022 data from 14 monitors for statistical modelling: DB01, DB02, ND06, ND07, PD01, PD02, SE10, SE48, SE51, SE52, SE53, SE59, SE61, SE62.

Data for the 14 monitors were aggregated to monthly counts of high turbidity events, and timed rehabilitation, clearing, LAI and rainfall characteristics were extracted for the 28th of each month. The temporal availability of NTU data for each month was calculated and months with less than 80% NTU availability were excluded.

Table 4 shows the counts of months with different numbers of events per month for each monitor and the total number of events for each monitor. While most months have zero or one event only, there are months with up to seven events recorded.

Table 4. Counts of months with different numbers of events and total number of events for each monitor in the statistical modelling dataset.

ID	< 80% NTU Available	Number of events per month								Number of Events
		0	1	2	3	4	5	6	7	
DB01	1	14	0	0	0	0	0	0	0	0
DB02	0	15	0	0	0	0	0	0	0	0
ND06	3	13	1	0	1	0	0	0	0	4
ND07	6	11	0	0	0	0	0	0	0	0
PD01	4	12	1	0	2	0	1	0	0	12
PD02	1	11	4	1	1	0	0	0	0	9
SE10	2	13	3	0	0	0	0	0	0	3
SE48	2	14	0	0	0	0	0	0	0	0
SE51	0	8	8	1	0	1	1	0	0	19
SE52	4	13	1	0	1	0	0	0	0	4
SE53	8	10	0	0	1	0	0	0	0	3
SE59	0	10	3	3	0	0	0	0	0	9
SE61	2	7	1	3	1	1	0	1	1	27
SE62	7	6	0	0	0	0	0	0	0	0

Figure 16 shows the monthly event counts for each monitor. Most of the counts are zero. This is known as zero-inflation and it affects the type of statistical models that can be used.

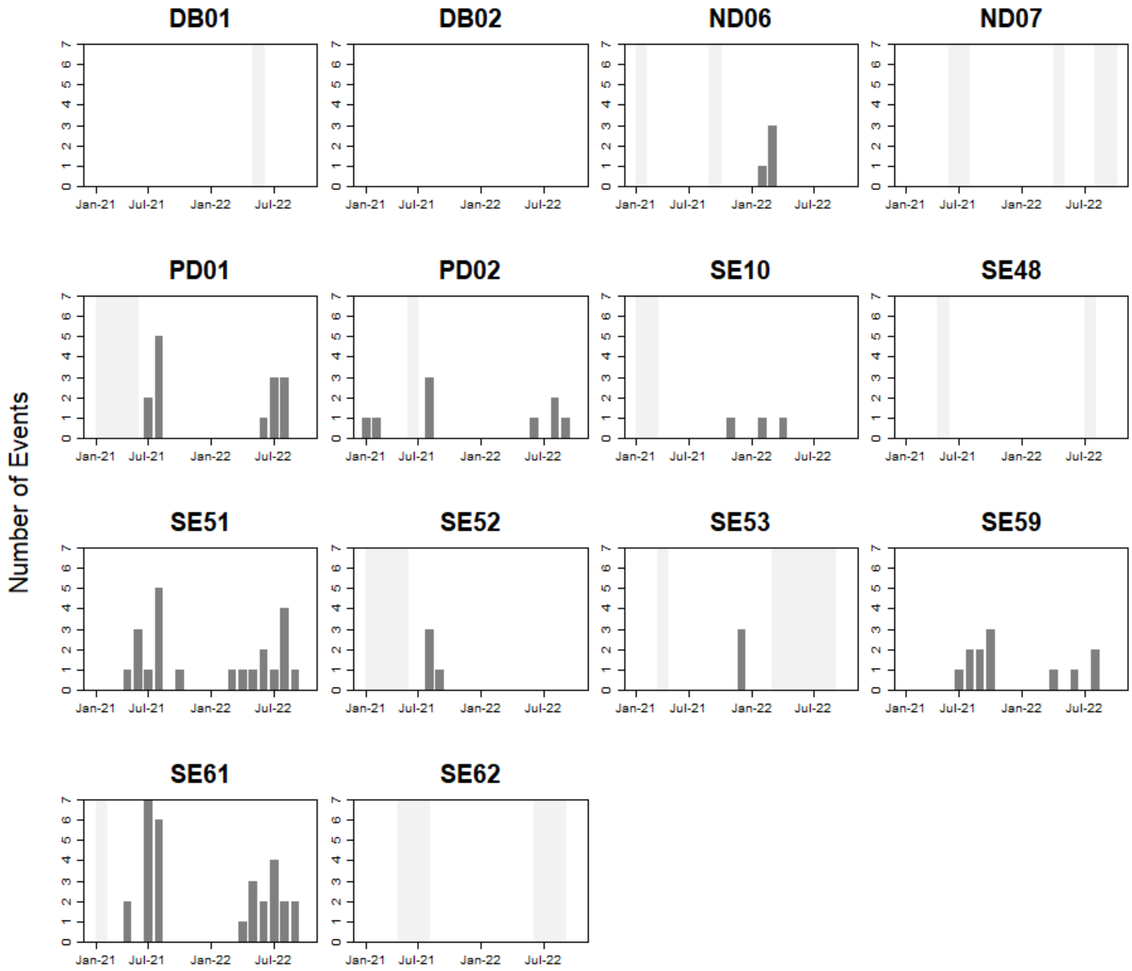

Figure 16. Monthly counts of events for each monitor in the statistical modelling dataset. Months with <80% NTU availability have been marked in grey and are excluded.

Table 5 summarises the mean monthly upstream catchment characteristics and numbers of high turbidity events for each monitor.

Table 5. Summary of mean January 2021 to September 2022 monthly data used for statistical modelling. Note that the areas cleared are the total areas cleared including areas that have been subsequently rehabilitated.

ID	Area (ha)	Area > 16% Slope (ha)	Mean Slope (%)	Max Slope (%)	Mean Slope of Cleared Area (%)	Max Slope of Cleared Area (%)	Area Cleared (ha)	Area Cleared > 16% Slope (ha)	Area Rehabilitated (ha)	Area Rehabilitated > 16% Slope (ha)
DB01	492	21	8.9	26.8	10.3	24.7	160	8	155	8
DB02	519	2	6.5	21.2	6.7	17.9	206	0	88	0
ND06	783	64	8.7	29.4	9.2	27.8	311	26	151	7
ND07	598	39	8.1	24.5	8.6	24.5	269	22	75	3
PD01	376	57	10.4	49.6	11.5	25.2	94	17	26	9
PD02	390	98	11.5	39.1	10.3	20.8	18	1	5	0
SE10	1,198	147	9.0	48.8	8.9	27.8	450	50	114	4
SE48	18,301	1,505	7.7	97.0	8.5	27.3	3,243	187	2,578	109
SE51	749	111	10.8	32.1	10.9	25.1	369	48	42	2
SE52	609	274	15.7	64.0	14.2	34.8	186	77	15	4
SE53	675	211	12.9	40.3	11.6	34.0	281	69	20	10
SE59	573	37	9.7	28.7	9.7	22.8	195	8	0	0
SE61	515	215	15.8	66.0	13.0	29.6	142	45	7	0
SE62	16,150	961	7.1	54.6	8.1	25.1	2,640	102	2,237	77

4.2 Methodology

Using a statistical model, we can consider how catchment characteristics combine to affect the number of high turbidity events in a catchment.

Trigonometric terms are useful when data are affected by seasonality; however, we found that they are correlated with rainfall and add no further explanation beyond what could be found using rainfall alone. They are therefore not included.

Poisson regression models provide a standard framework for analysis of count data. Poisson regression is a particular case of a generalised linear model (GLM). It is usually implemented with a logarithmic link function that gives the model a relative risk structure.

Because the high turbidity event counts are zero-inflated, we used a two-part hurdle model. The first part considers which catchment characteristics explain events occur or not. A binomial GLM with a logit link function is used to binary case of events versus no event. The second part of the model considers what influences the number of events when they occur. A truncated Poisson GLM with a log link function is used for the second part.

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Statistical models require that the predictor variables (the catchment characteristics) are independent. When predictor variables are correlated, they cannot independently explain changes in the dependent variable (number of events). This situation is referred to as collinearity.

Figure 17 shows that catchment area, area cleared, area rehabilitated and the equivalent areas with slopes greater that 16% are all highly correlated to each other. Similarly, the mean slope and means slope of cleared areas are highly correlated.

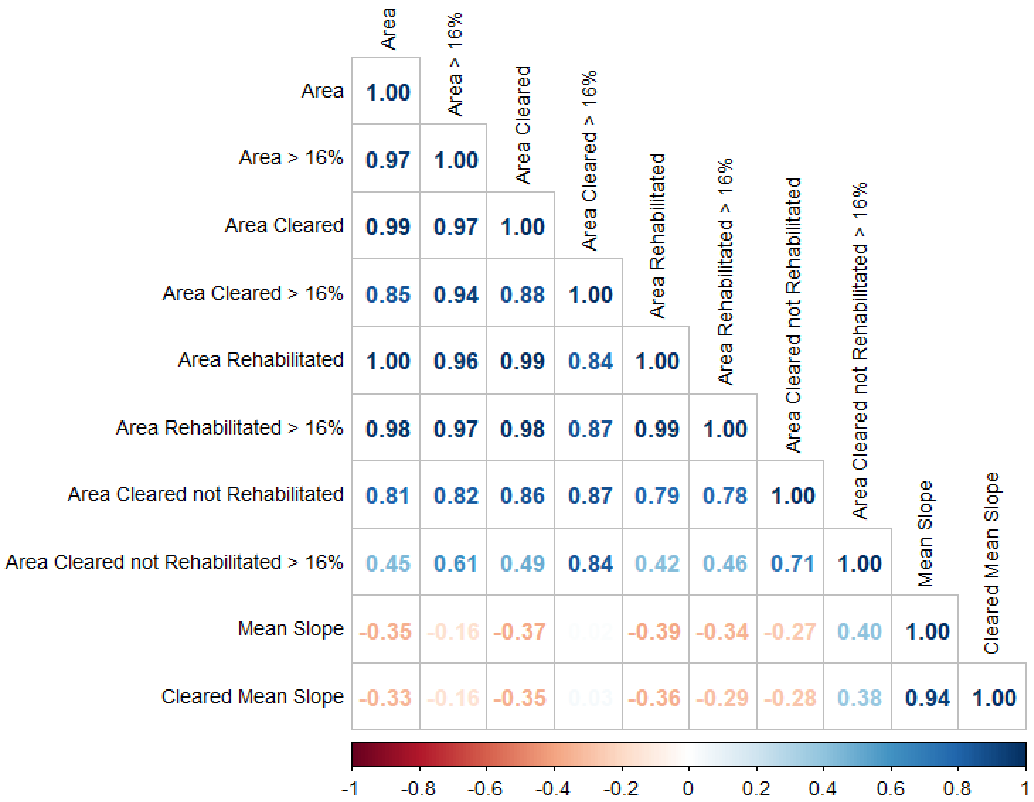


Figure 17. Cross-correlations between catchment characteristics.

We also considered whether it was more appropriate to consider areas cleared and rehabilitated in hectares or as percentages of the catchments. Figure 18 shows that if the SE48 and SE62 monitors with very large catchment area are removed, then the areas in hectares and percentages are correlated. Since catchment scale influences processes such as deposition and settlement of eroded materials and dilution by cleaner water from other parts of the catchment, we model using areas expressed as percentages of catchment area.

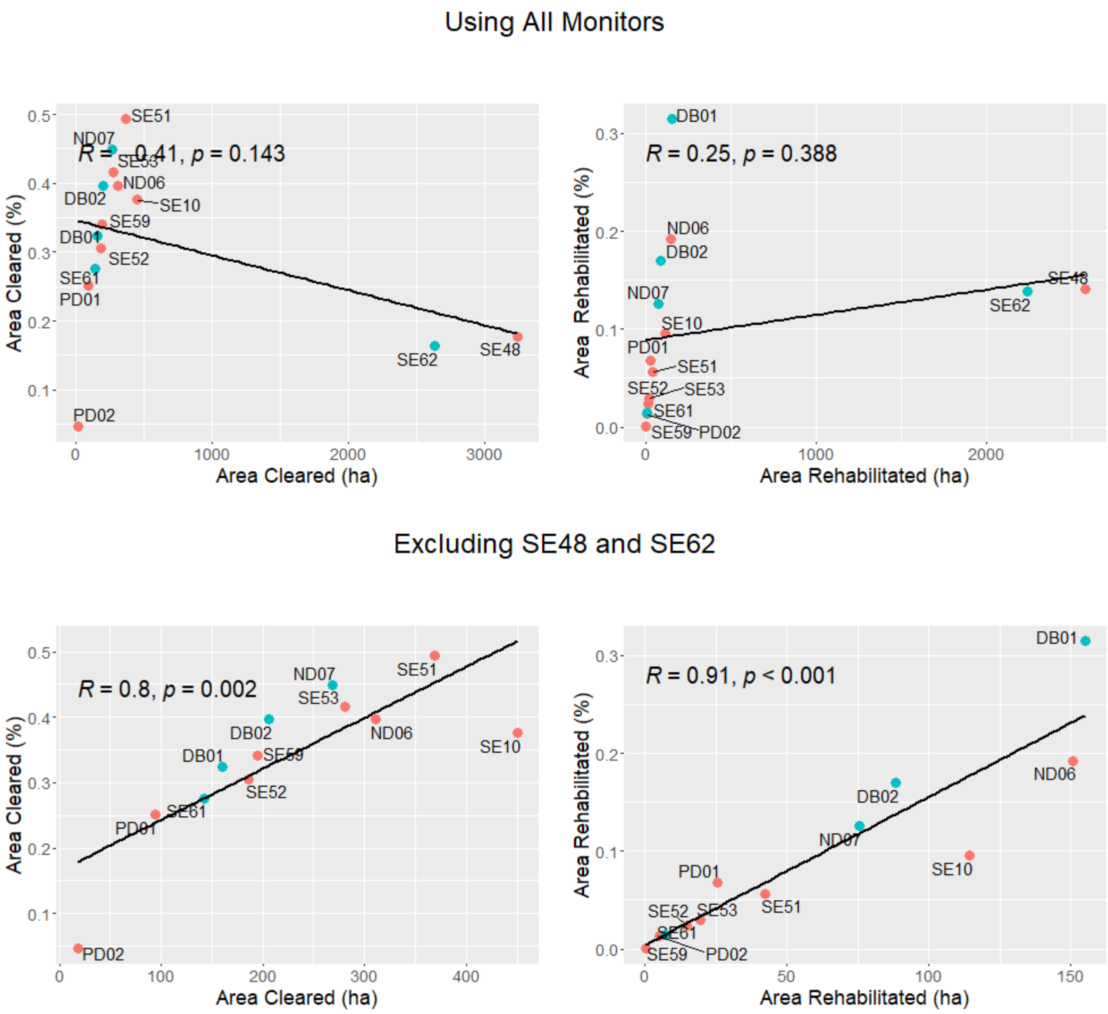


Figure 18. Correlations between areas cleared and rehabilitated in hectares and as percentages of the catchments, with and without including outliers SE48 and SE62.

To avoid issues of collinearity, we need to use a smaller subset of catchment characteristics for statistical modelling, selecting the most informative characteristic from those groups that are correlated. However, we can use different characteristics to answer different questions.

We estimate three statistical models with different sets of characteristics to answer two specific questions.

Model 1: Total Clearing

To determine how clearing influences the number of high turbidity events, we use the:

- Percentage of the catchment that has been cleared (including areas that have been subsequently rehabilitated).
- Mean catchment slope.
- Rainfall.

Model 2: Clearing Prior To Rehabilitation

To take rehabilitation into account, we consider how the currently cleared area (ie. cleared land that has not yet been rehabilitated) influences the number of high turbidity events, we use the:

- Percentage of the catchment that has been cleared but not yet rehabilitated.
- Mean catchment slope.
- Rainfall.

Model 3: Clearing and Rehabilitation

To determine the total effect of both clearing and rehabilitation, we use the:

- Percentage of the catchment that has been cleared but not yet rehabilitated.
- Percentage of the catchment that has been cleared and rehabilitated.
- Mean catchment slope.
- Rainfall.

4.3 Results

Model 1: Total Clearing

Model 1 considers how clearing influences the number of high turbidity events. Table 6 shows the estimated hurdle model coefficients, standard errors and associate *p*-values for Model 1. The stars indicate statistical significance where *p*-values where one star means a variable is statistically significant effect at the 0.05 level and more stars indicate higher significance.

Table 6. Model 1 summary.

High turbidity event occurrence model	Coefficient	SE	*p*-value
Intercept	-4.882	1.027	< 0.001 ***
Mean catchment slope (%)	0.227	0.065	< 0.001 ***
Area cleared (%)	1.663	1.6106	0.474
Rainfall (ha)	0.005	0.002	< 0.001 ***
High turbidity event count model	**Coefficient**	**SE**	***p*-value**
Intercept	-2.193	0.878	0.012 *
Mean slope (%)	0.125	0.053	0.011 *
Area cleared (%)	0.782	1.093	0.474
Rainfall (mm)	0.004	< 0.001	< 0.001 ***

The results show that:

- The total percentage area cleared (including subsequently rehabilitated areas) has no effect on the chance of high turbidity events occurring or on the number of high turbidity events if they occur.
- Catchment slope has a significant effect on both the occurrence of high turbidity events and their number, with more events in catchments with higher mean slope.
- Rainfall has a significant effect on both the occurrence of high turbidity events and their number, with more events in wetter months.

Model 2: Clearing Prior To Rehabilitation

Model 2 considers how the currently cleared area (ie. cleared land that has not yet been rehabilitated) influences the number of high turbidity events. Table 7 shows the estimated hurdle model coefficients, standard errors and associate *p*-values for Model 2. The stars indicate statistical significance where *p*-values where one star means a variable is statistically significant effect at the 0.05 level and more stars indicate higher significance.

Table 7. Model 2 summary.

High turbidity event occurrence model	Coefficient	SE	*p*-value
Intercept	-4.752	0.855	< 0.001 ***
Mean catchment slope (%)	0.183	0.065	0.005 **
Area cleared but not rehabilitated (%)	0.354	1.553	0.022 *
Rainfall (ha)	0.005	0.002	0.002 ***
Cou High turbidity event count model	**Coefficient**	**SE**	***p*-value**
Intercept	-2.295	0.795	0.015 *
Mean catchment slope (%)	0.156	0.052	0.013 *
Area cleared but not rehabilitated (%)	-0.001	1.113	0.776
Rainfall (mm)	0.005	< 0.001	< 0.001 ***

The results show that:

- Percentage area cleared but not rehabilitated has a significant effect on the chance of high turbidity events occurring.
- Percentage area cleared but not rehabilitated does not affect the number of high turbidity events if they occur.

Model 3: Clearing and Rehabilitation

Model 3 considers the total effect of both the total effect of clearing and rehabilitation. Table 8 shows the estimated hurdle model coefficients, standard errors and associate *p*-values for Model 3. The stars indicate statistical significance where *p*-values where one star means a variable is statistically significant effect at the 0.05 level and more stars indicate higher significance.

Table 8. Model 3 summary.

High turbidity event occurrence model	Coefficient	SE	*p*-value
Intercept	-2.336	1.279	0.068 **
Mean slope (%)	0.052	0.086	0.544
Area cleared but not rehabilitated (%)	2.370	1.568	0.131
Area cleared and rehabilitated (%)	-9.841	4.320	0.023 *
Rainfall (ha)	0.005	0.002	0.003 **
High turbidity event count model	**Coefficient**	**SE**	***p*-value**
Intercept	-3.028	1.045	0.004 **
Mean slope (%)	0.180	0.062	0.004 **
Area cleared but not rehabilitated (%)	0.316	1.142	0.782
Area cleared and rehabilitated (%)	7.694	3.985	0.053
Rainfall (mm)	0.005	0.001	< 0.001 ***

The results show that:

- When rehabilitation is considered, percentage area cleared but not rehabilitated has no significant effect on the chance of high turbidity events occurring or on the number of high turbidity events if they occur.
- Percentage area rehabilitated has a significant negative effect on the chance of high turbidity events occurring.

4.4 Model Predictions

Comparison of the goodness of fit of each of the three models using the Akaike Information Criterion suggests that while each of the model fits well, model 3 is the best model for making predictions given that it has the minimum AIC (Table 9). This model allows us to predict the expected number of high turbidity events given different rainfall, catchment slope, clearing and rehabilitation scenarios.

Table 9. Model Comparison.

Model	Degrees of Freedom	AIC
Model 1	8	306.37
Model 2	8	302.32
Model 3	10	296.99

This is done by combining the two parts of the model – the occurrence model and the count model – to give the most likely number of events as a continuous-valued number. In reality, the numbers of events are integers, but the continuous-valued prediction gives what would be expected on average for a given set of conditions.

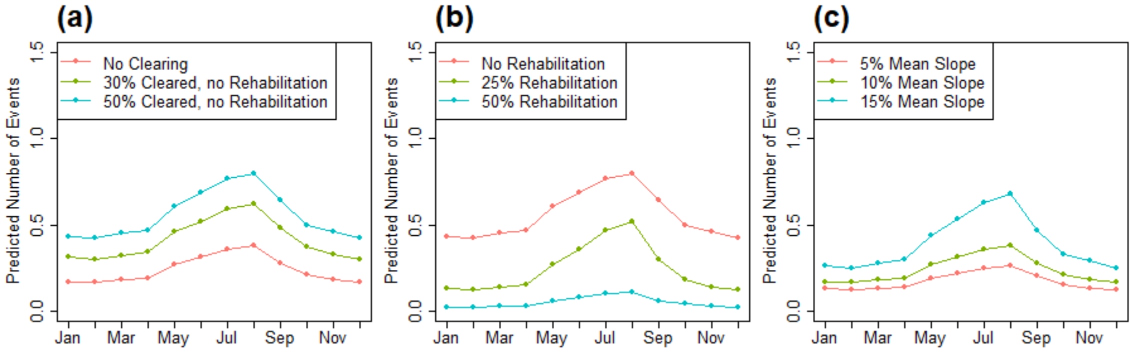


Figure 19. Model predictions for a median rainfall year: (a) Effect of changes in cleared area in a catchment with 10% mean slope; (b) Effect of changes in rehabilitation (expressed as the percentage of the catchment) where 50% of a catchment with 10% mean slope has been cleared; and (c) Model predictions showing the effect of mean slope in a catchment with no clearing.

Figure 19 shows examples of predictions that consider changes in a single factor, keeping all else constant. It shows that:

(a) Risk of high turbidity events increases with increasing areas of clearing in the absence of rehabilitation.

(b) Risk of high turbidity events decreases with increasing levels of rehabilitation.

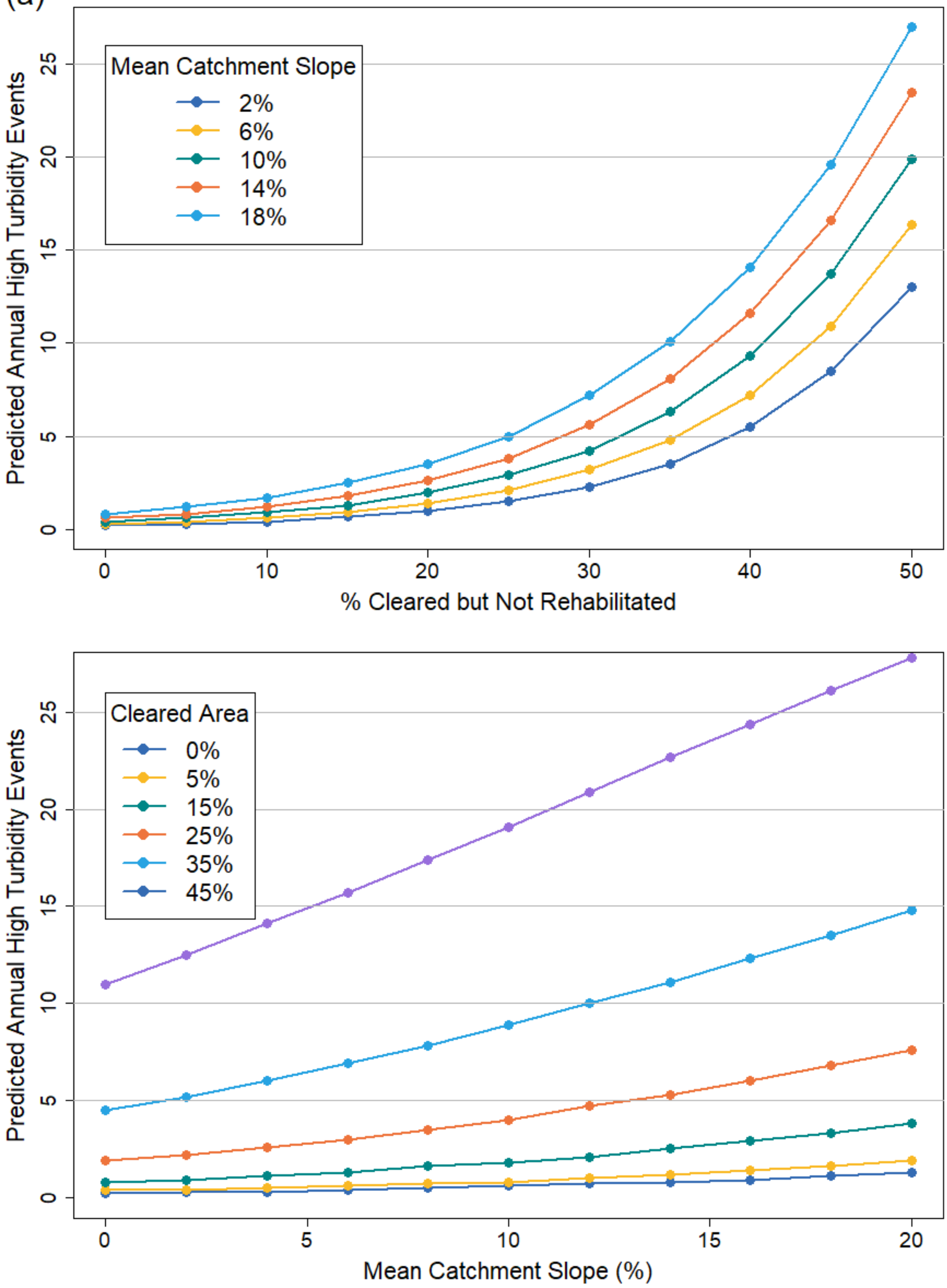
(c) Risk of high turbidity events increases with increasing catchment slopes.

Model predictions can be further explored for different scenarios using a web tool accessible from https://mnhw0z-daa.shinyapps.io/ALCOA_31_App/.

4.4.1 Predicted Effects of Catchment Slope and Clearing

Model predictions can be used to understand the joint effects of clearing and catchment slope on the number of high turbidity events.

(a)



show the predicted annual number of high turbidity events expected in a median rainfall year. Figure 20 (a) shows a marked curvilinear response to the percentage area of the catchment that has been cleared and not rehabilitated, with the predicted number of high turbidity events increasing more rapidly when the currently cleared areas is over

30%. In contrast, Figure 20 (b) shows that the response to mean catchment slope is more linear.

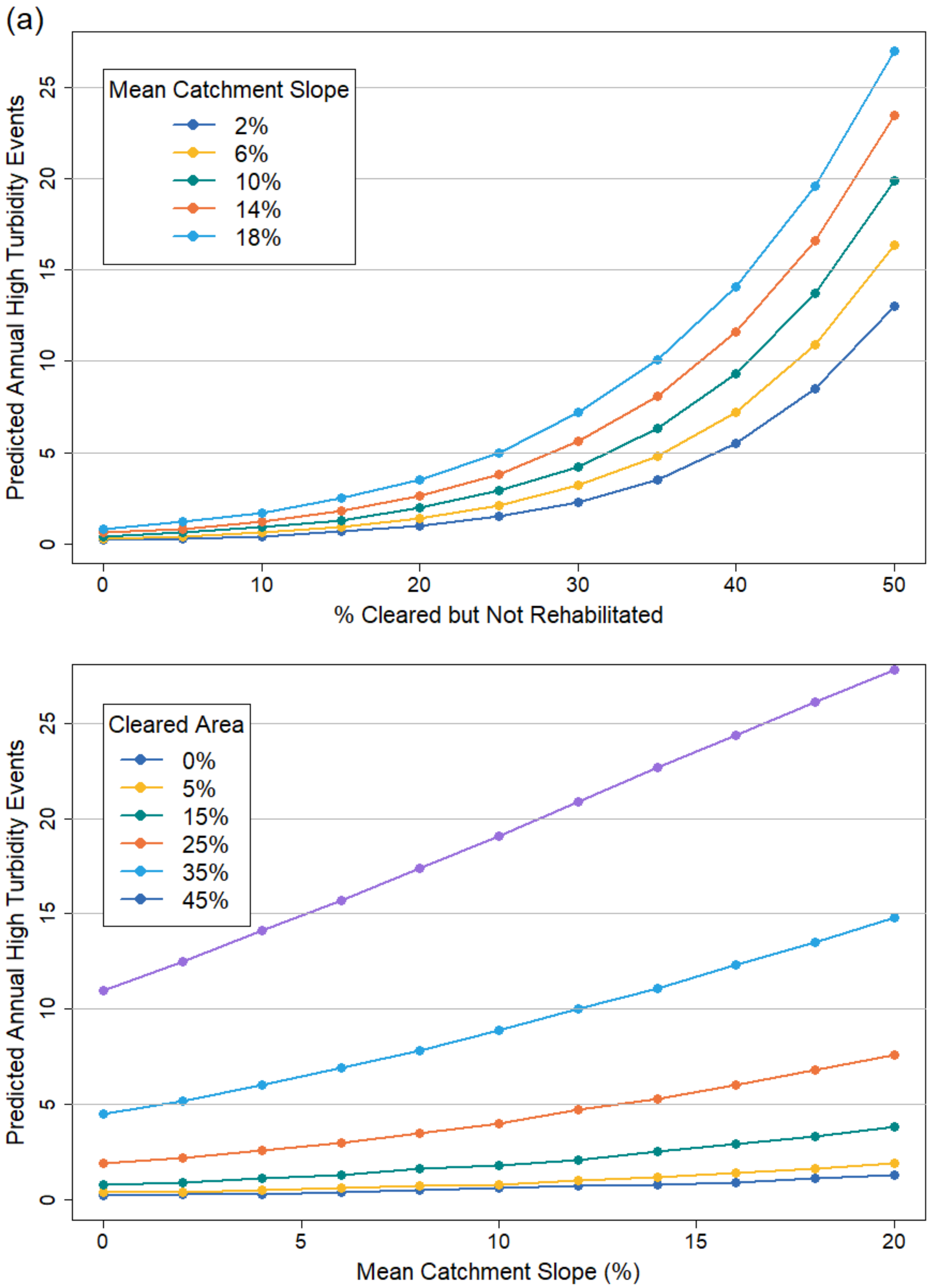


Figure 20. Predicted annual number of high turbidity events for different clearing and slope scenarios in a median rainfall year in a catchment.

5. Discussion and Conclusions

This study considered turbidity risk using NTU data collected by monitors in the Huntly mining region of Western Australia. Data from 30 monitors were sourced from multiple Alcoa databases and patched into a single dataset. Only 25 of the monitors could be geo-located, many monitors had short recording periods and most experienced data gaps where no data were available. Two set of monitors were identified for use in this study.

1. 10 monitors with greater than 80% data coverage for the winter period from May to September 2021 were used for Top Level Analysis: DB01, DB02, PD01, SE10, SE48, SE51, SE52, SE53, SE59 and SE61.
2. 14 monitors with greater than 70% data coverage for the period January 2021 and September 2022, which covers two winters were used for Statistical Modelling: DB01, DB02, ND06, ND07, PD01, PD02, SE10, SE48, SE51, SE52, SE53, SE59, SE61, SE62.

The first set is a subset of the second, therefore data from 14 monitors were used in total.

Detection of high turbidity events was made difficult by the high degree of noise in the data caused by factors other than turbid water. To avoid data cleaning that might obscure detection of high turbidity events, we adopted an approach that first detected all events, then classified them as true or false using an algorithm designed to err on the side of caution by only removing events that we could be confident were false. This left a large number of events that Alcoa cross-checked against their investigation records before removing those known to be false.

For each monitor we delineated the catchment area upstream of that monitor and calculated catchment characteristics including area, mean and maximum slope, percentage area of the catchment with slopes greater than 16%, area cleared and area rehabilitated.

Top level analysis considered relationships between individual factors affecting turbidity and the total number of high turbidity events. To ensure counts of high turbidity events could be compared across and between monitors, this needed a set of monitors with consistent data coverage for a common time period and therefore a 10-monitor May to September 2021 dataset was used. Five of the ten catchments recorded no high turbidity events during this period.

We found a correlation of close to zero between the percentage area of catchment that has been cleared (total area cleared including areas subsequently rehabilitated) with the number of high turbidity events meaning. While there was a positive correlation between the percentage area of a catchment that has been cleared but not yet rehabilitated (ie. open area) and the number of high turbidity events, it was not significant. Mean catchment slope and the percentage area of the catchment that has been rehabilitated were the only factors found to have a significant correlation with the number of high turbidity events. This suggests that rehabilitation should be considered when managing turbidity risk.

While top level analysis was useful for investigating individual relationships, multivariate analysis is critically important because the effects of multiple factors and their possible interactions can be considered simultaneously. Statistical modelling also allows the data to be restructured so that data gaps have less impact allowing use of a 14-monitor 2021-2022 dataset.

Because high turbidity events are not recorded in most months, the data were zero-inflated. We used a two-part hurdle model that first considers whether high turbidity events will occur in a month and then considers how many events will occur.

To avoid issues of collinearity due to catchment characteristics being correlated to each other, a smaller subset of catchment characteristics was used in three models designed to consider: (1) effects of total clearing (including areas subsequently rehabilitated); (2) effects of clearing prior to rehabilitation; and (3) effects of clearing and rehabilitation combined.

The results showed that:

- Catchment slope has a significant positive effect on either the occurrence or number of high turbidity events using any model, with more events in catchments with higher mean slope.
- Rainfall has a significant positive effect on both the occurrence and number of high turbidity events and their number using any model, with more events in wetter months.
- When only total percentage cleared area (including subsequently rehabilitated areas) is considered, it has no effect on the chance of high turbidity events occurring or on the number of high turbidity events if they occur.
- When the percentage area cleared but not rehabilitated is considered, it is found to have a significant positive effect on the occurrence of events but not on their number.
- When both clearing and rehabilitation are considered, percentage area rehabilitated has a significant negative effect on the chance of high turbidity events occurring.

Putting these results together, we found that as a whole, the total percentage cleared area has no significant effect (negative or positive) on high turbidity events, but the two components of it do: percentage cleared but not rehabilitated has a positive effect and percentage cleared and rehabilitated has a negative effect.

The best-fitting model can be used to predict the expected number of events in different scenarios and we can consider changes in a single factor, keeping all else constant. This shows that:

e) Risk of high turbidity events increases with increasing areas of clearing in the absence of rehabilitation.

f) Risk of high turbidity events decreases with increasing levels of rehabilitation.

g) Risk of high turbidity events increases with increasing catchment mean slope.

h) High turbidity events can be expected within uncleared catchments.

However, because the factors act together to affect turbidity risk the predictions can tell a more complex story.

The modelling results strongly suggest that selection of a threshold on catchment clearing to minimise risk of high turbidity events should consider rehabilitation. Cleared areas that have not been rehabilitated pose a risk, but cleared areas that have been subsequently rehabilitated do not.

The results also show that high turbidity events can be expected in catchments that have not been cleared, particularly in catchments with higher slopes and in higher rainfall years. Turbidity data for a few months were obtained for undisturbed Holyoake catchment. While no high turbidity events were detected, both Holyoake monitors recorded occurrences of NTU above 25 for up to ten or twenty minutes which may partially support the modelling results.

While we found that risk of high turbidity events increases with increasing catchment mean slope, it is unclear that this can be used to select a specific slope threshold for turbidity risk management. Model predictions to understand the joint effects of clearing and catchment slope on the number of high turbidity events showed a marked curvilinear response to the percentage area of the catchment that has been cleared and not rehabilitated, with the predicted number of high turbidity events increasing more rapidly when the currently cleared area is over 30% of the catchment. In contrast, the response to mean catchment slope is more linear.

6. Recommendations

6.1 Update Modelling Using Longer Data Record

The modelling results could be improved substantially by considering a longer record of turbidity data. This study compiled 2016 to 2020 turbidity data and undertook initial high turbidity event verification for 2021-2022. We recommend manual verification of detected events dating back to 2016 to expand the dataset available for modelling which would provide more confidence in modelling results and conclusions.

6.2 Baseline Monitoring Program

This study did not include data from uncleared catchments. The conclusions reached on uncleared catchments represent an extrapolation. They would be strengthened if data from uncleared catchments were available. The ideal data would be collected in catchments prior to and after clearing. We recommend that Alcoa establish a baseline monitoring program for several years prior to clearing to capture seasonal variability and directly measure the effects of mining on turbidity.

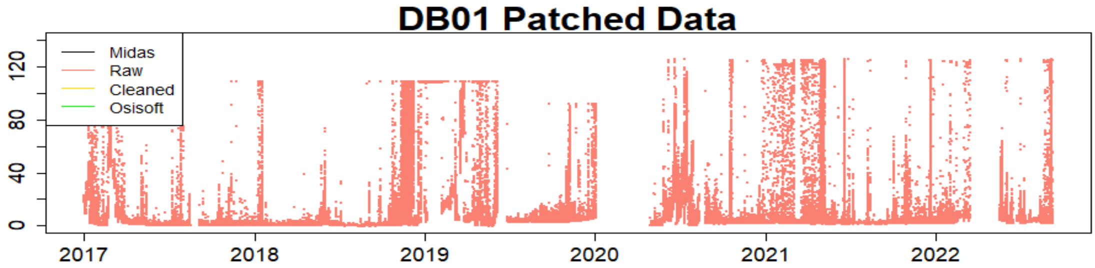
6.3 Improvements to monitoring program

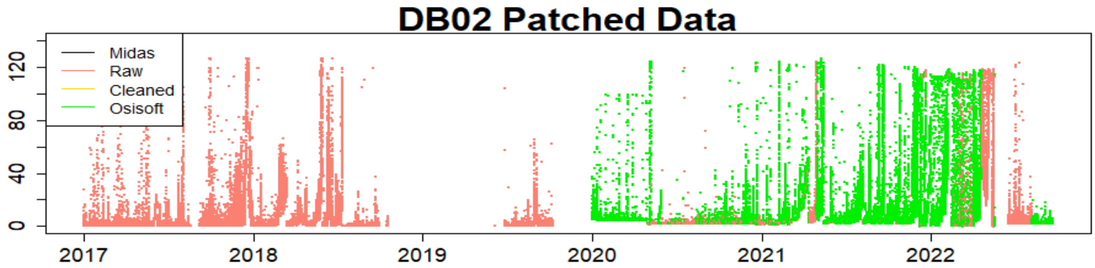
Future turbidity monitoring should endeavour to establish procedures to improve data capture and storage. We recommend recoding flow to assist with off-site detection, verification and modelling of high turbidity events, to facilitate detection and modelling of high turbidity events.

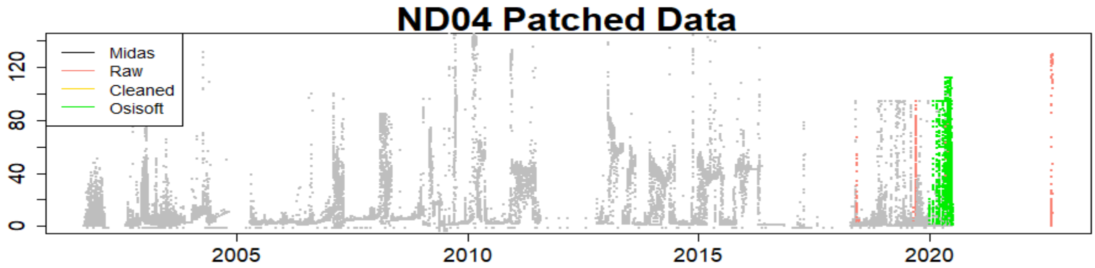
7. Study Limitations

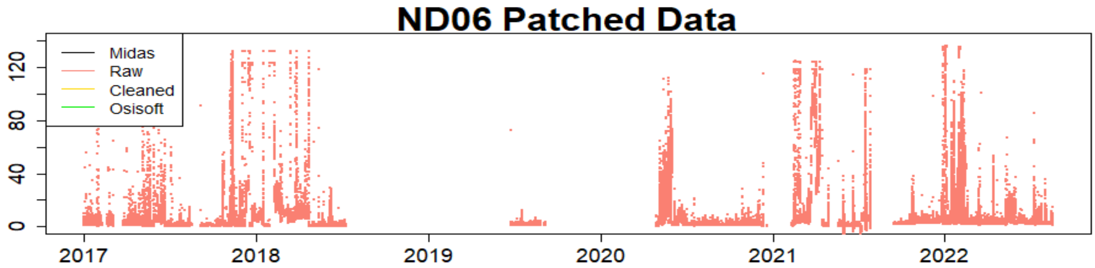
The study outcomes are limited to the dataset, the high turbidity event verification process, and statistical modelling approaches outlined herein.

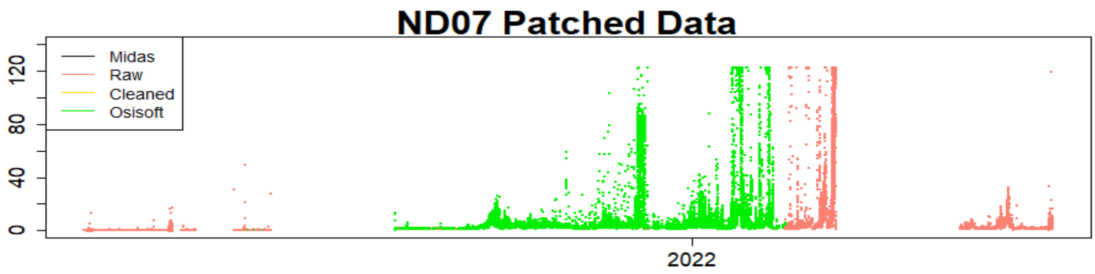
Appendix A. Time-Series Plots For 25 Huntly Monitors Showing Data Sources







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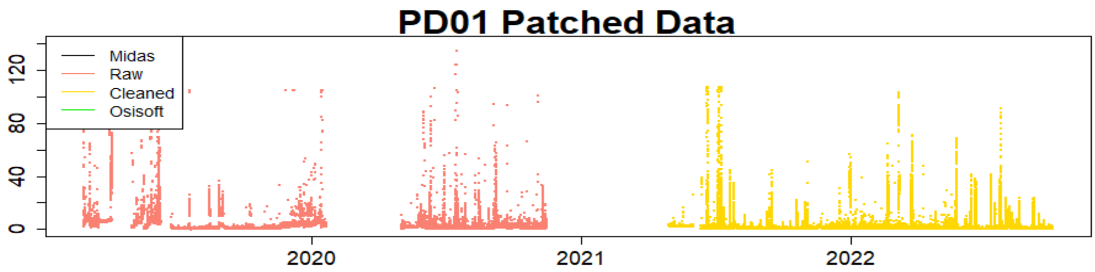
Midas
Raw
Cleaned
Osisoft
0
40
80
120
2022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Osisoft
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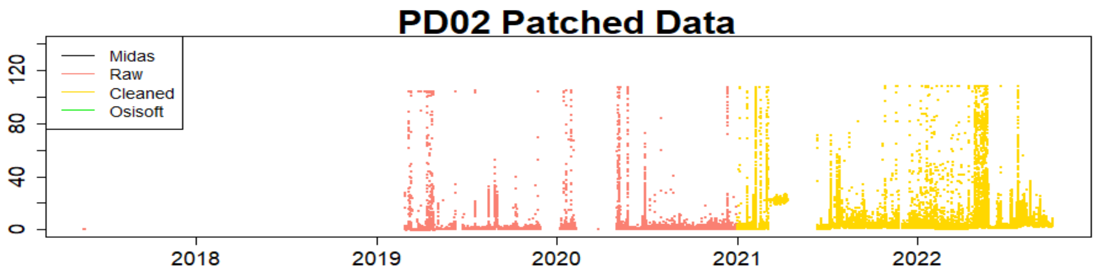
2021
2022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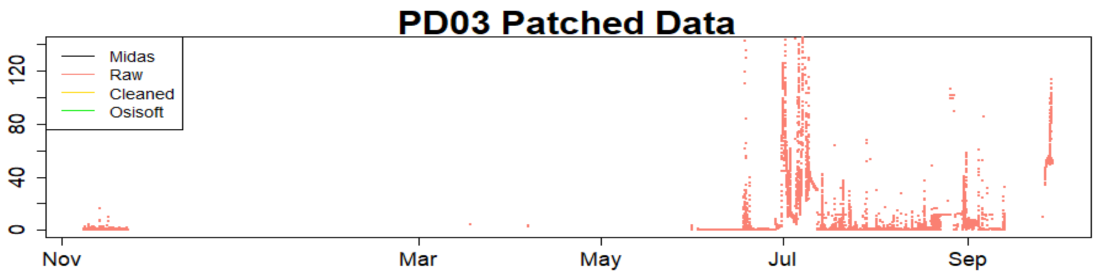
2019
2020
2021
2022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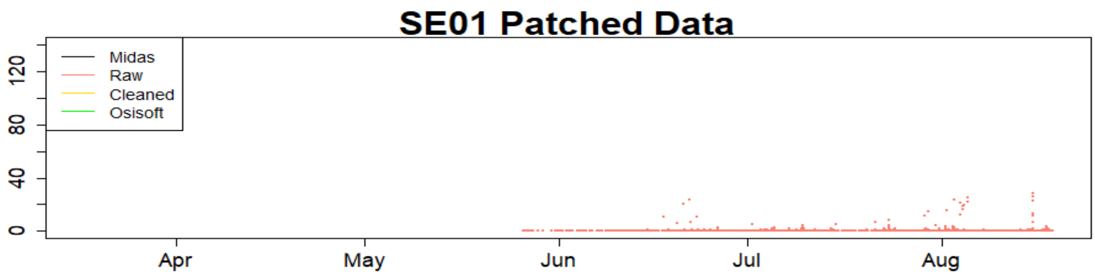
120
Nov
Mar
May
Jul
Sep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Apr
May
Jun
Jul
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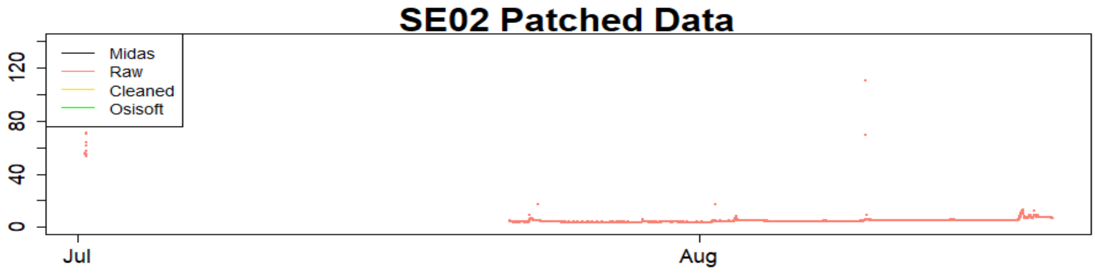
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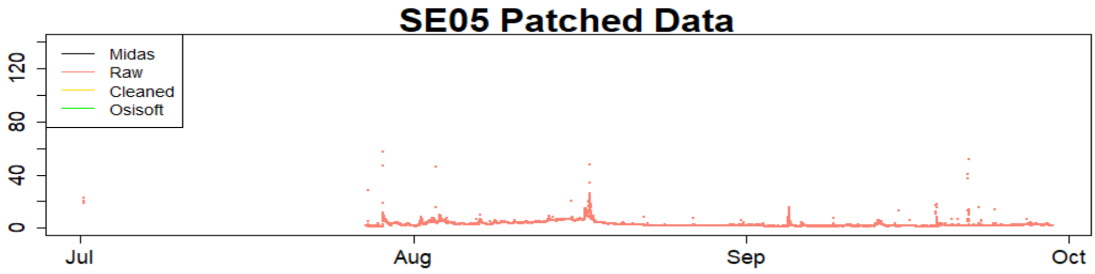
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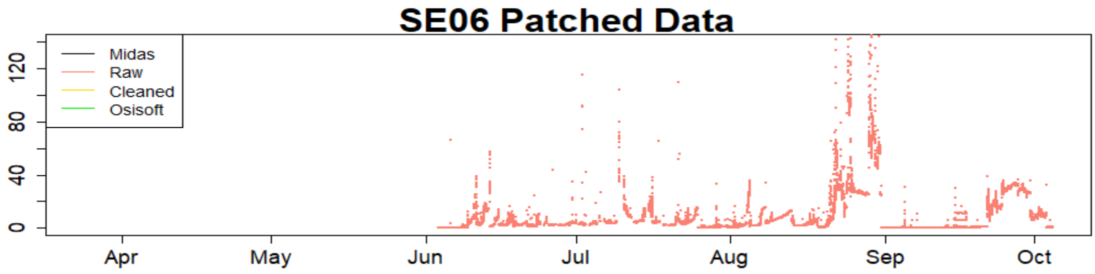
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Midas
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Cleaned
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120
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May
Jun
Jul
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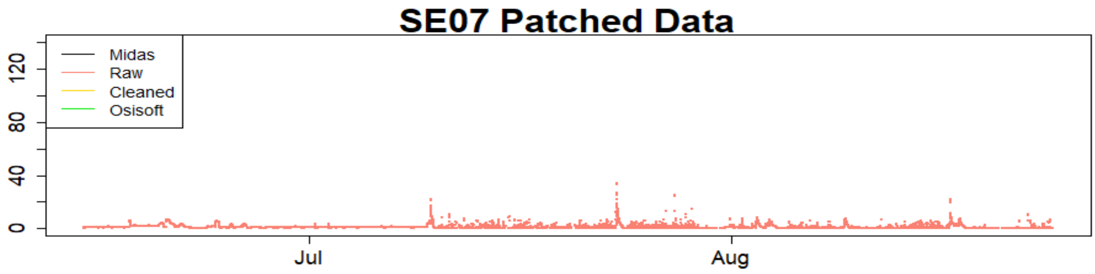
Sep
Oct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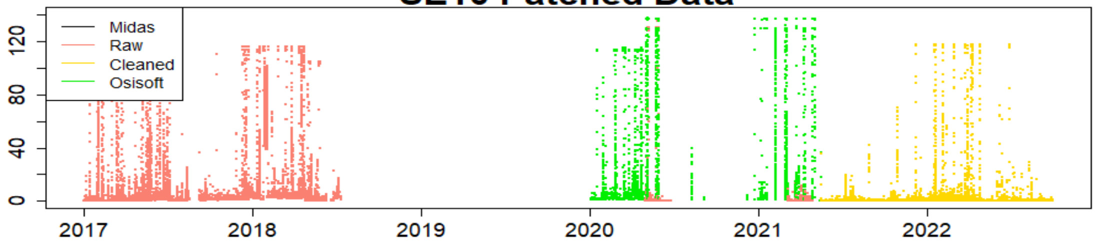
Midas
Raw
Cleaned
Osisoft
0
40
80
120
Jul
Aug

SE10 Patched Data



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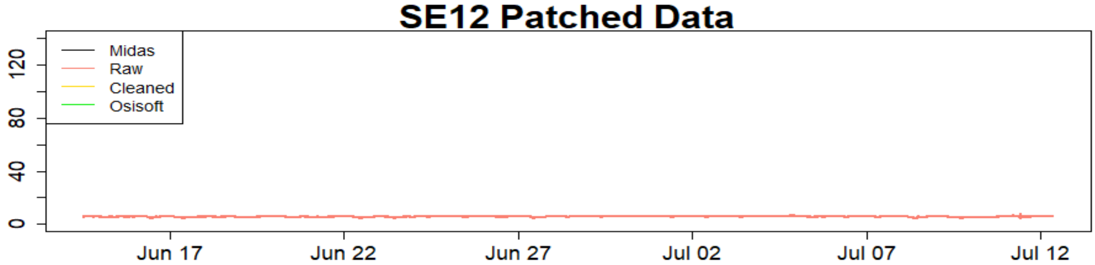

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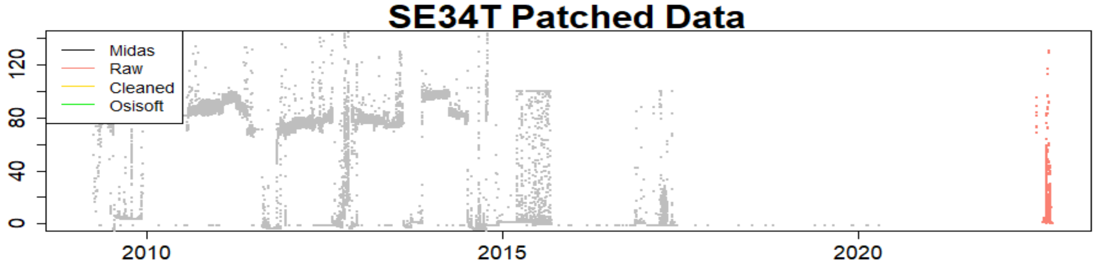

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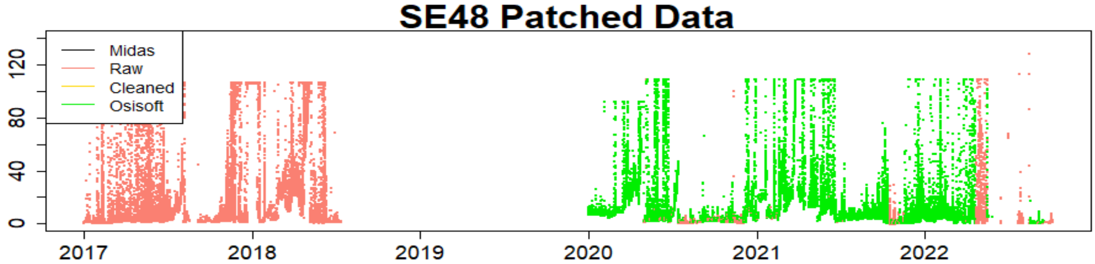

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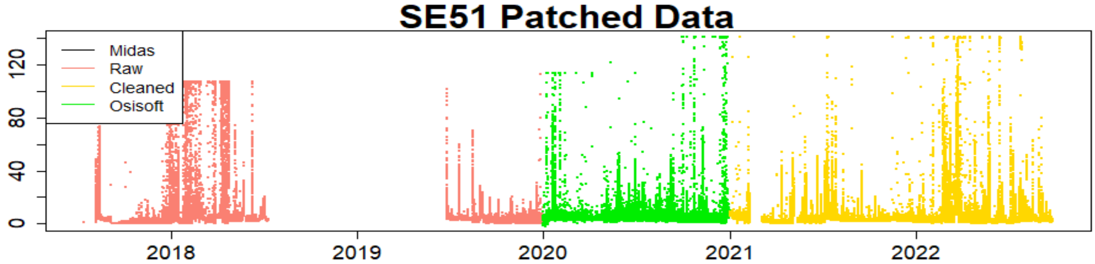

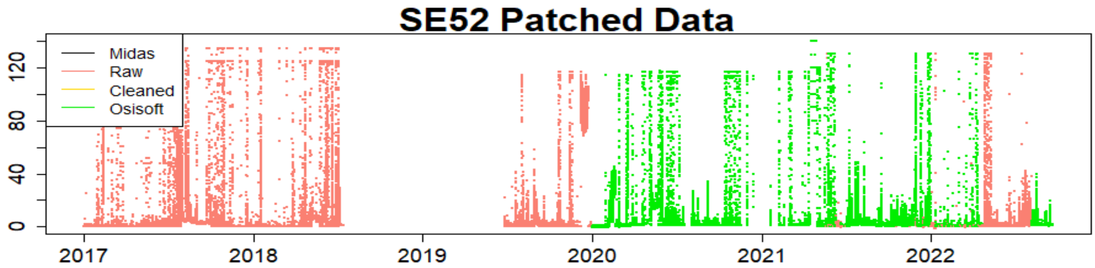
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Midas
Raw
Cleaned
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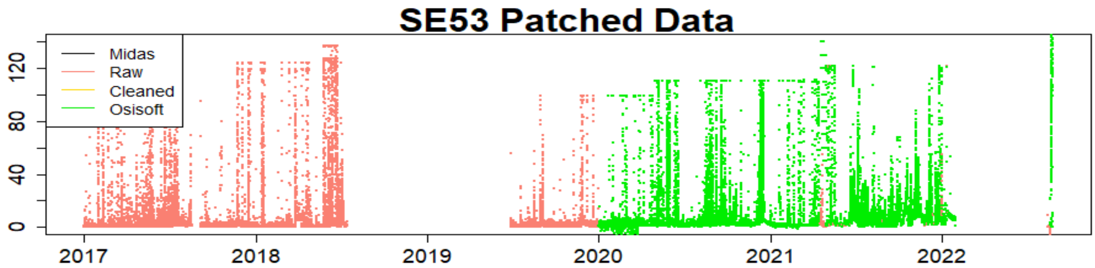
40
80
120
2017
2018
2019
2020
2021
2022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Midas
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Osisoft
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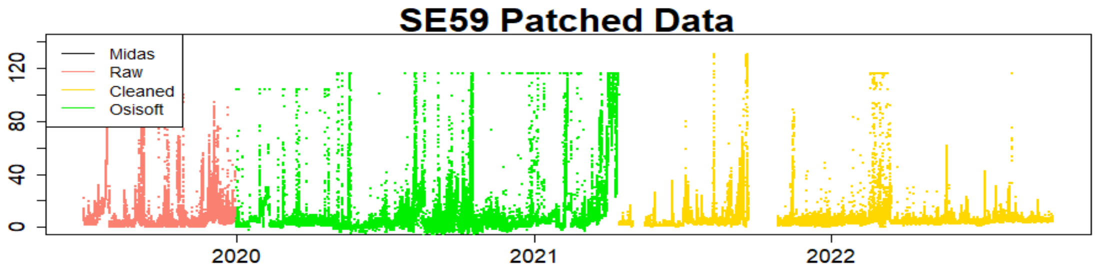
120
2017
2018
2019
2020
2021
2022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Midas
Raw
Cleaned
Osisoft
0
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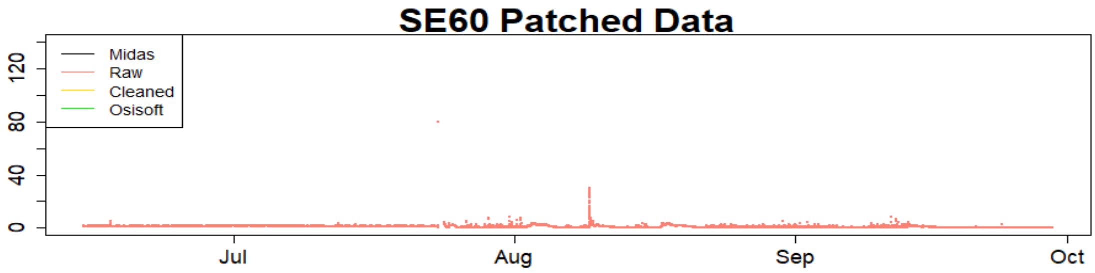
80
120
2020
2021
2022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Midas
Raw
Cleaned
Osisoft
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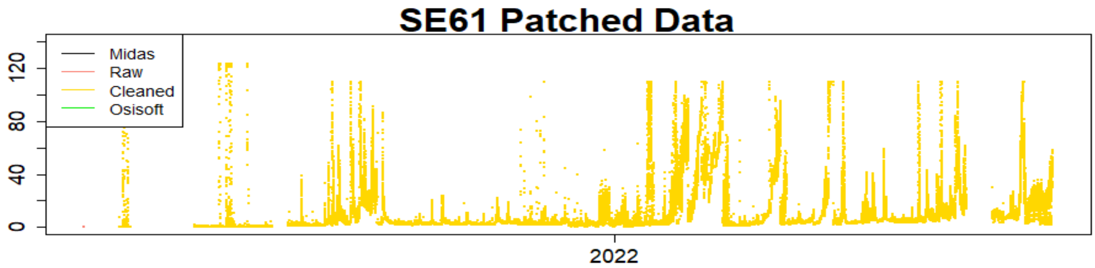
Jul
Aug
Sep
Oct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Cleaned
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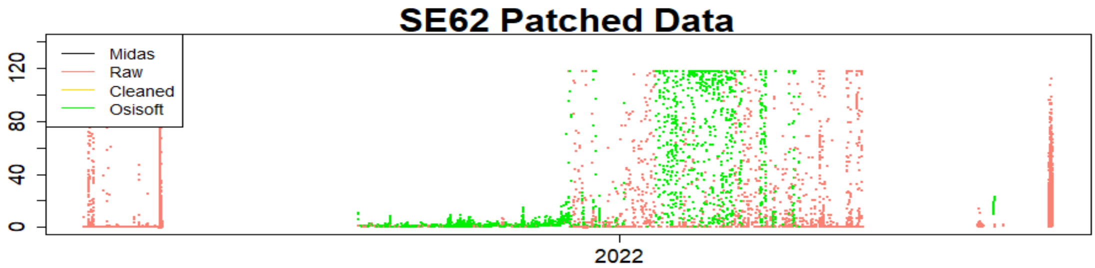
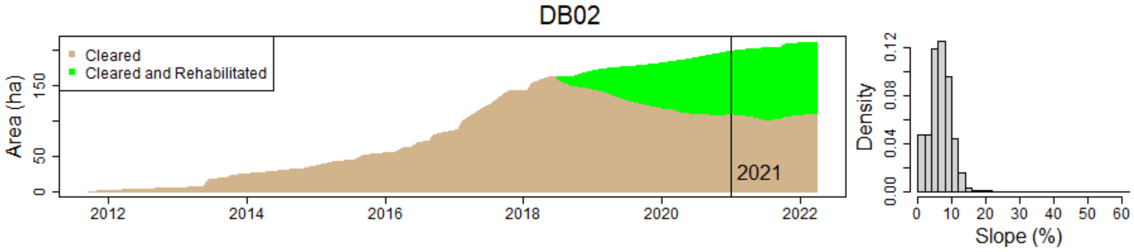
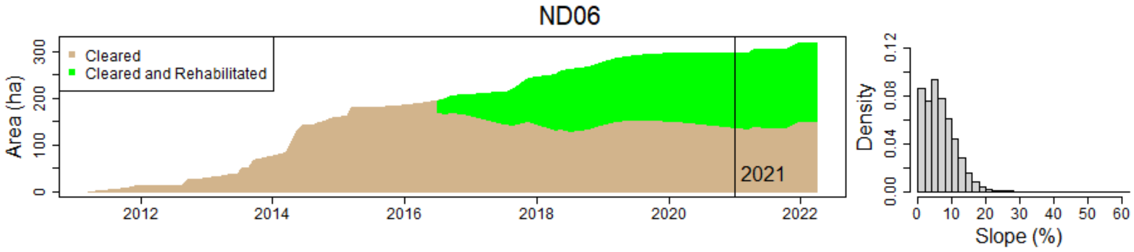
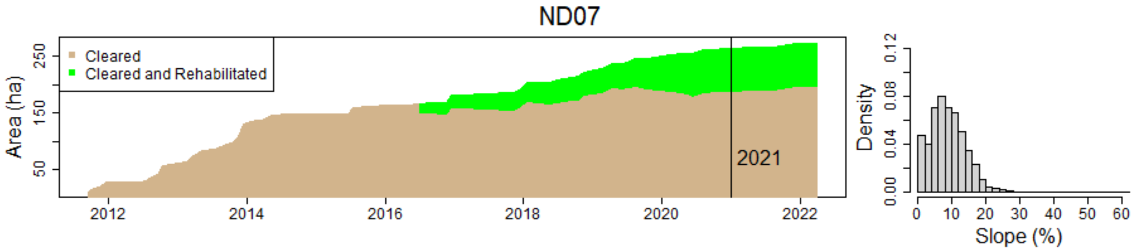
80
120
2022

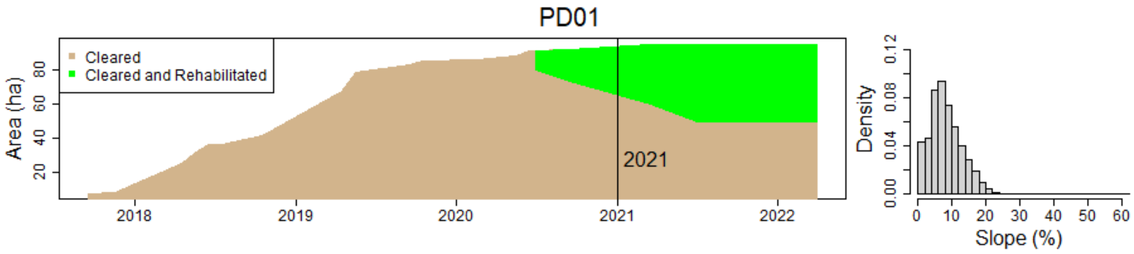

SE62 Patched Data
Midas
Raw
Cleaned
Osisoft
0
40
80
120
2022

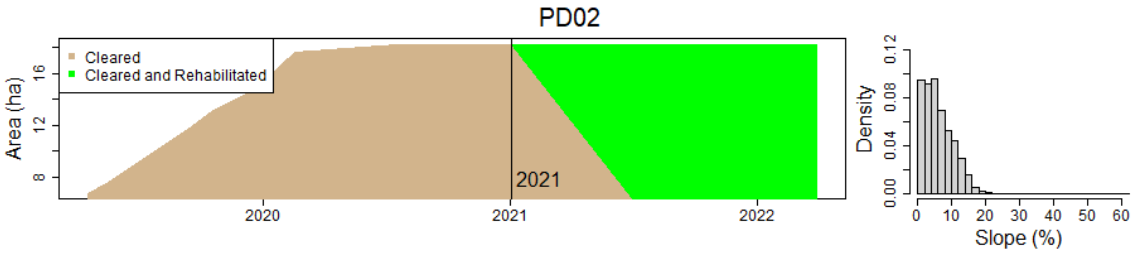
Appendix B. Clearing, Revegetation and Slope for each Catchment in the 14-monitor 2021-2022 Patched Huntly Dataset

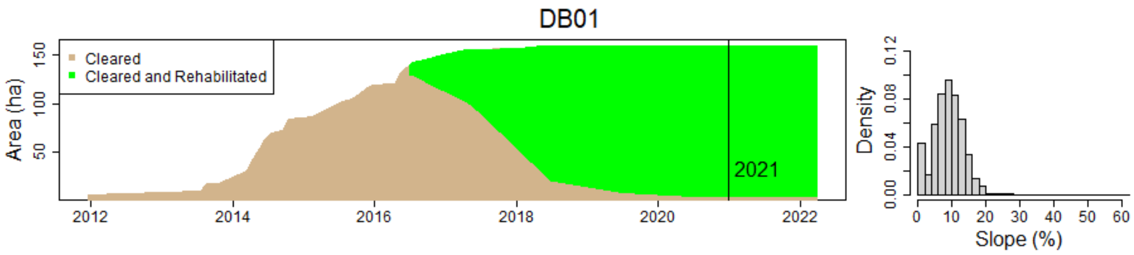


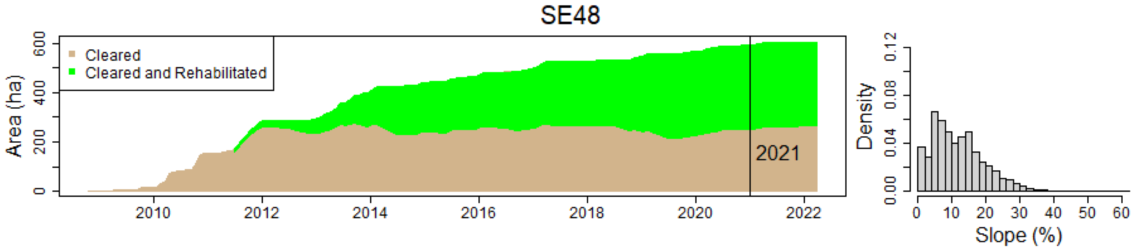


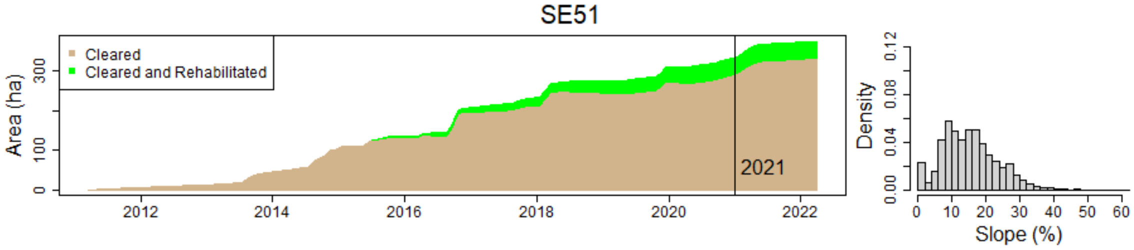


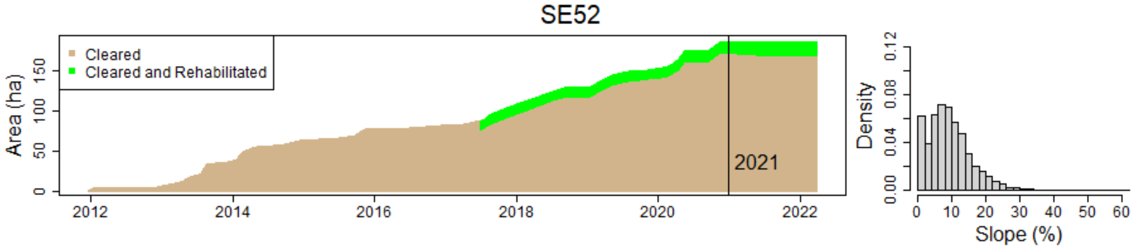


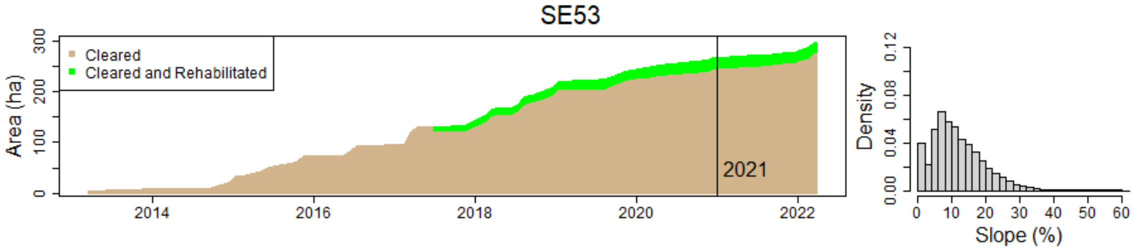


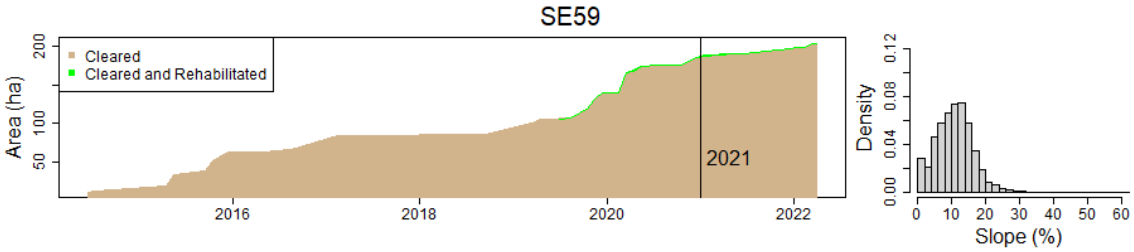


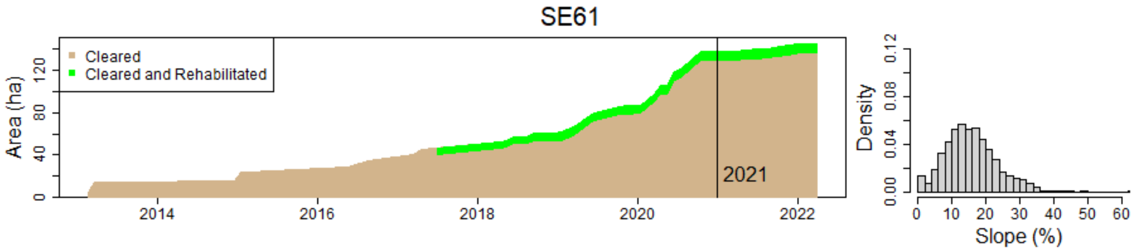

SE48
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)

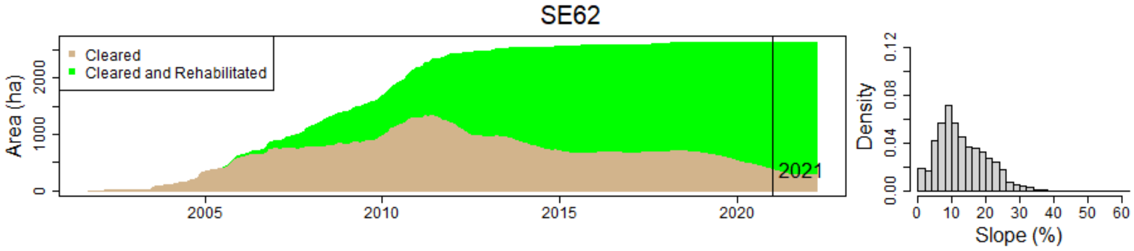

SE51
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)

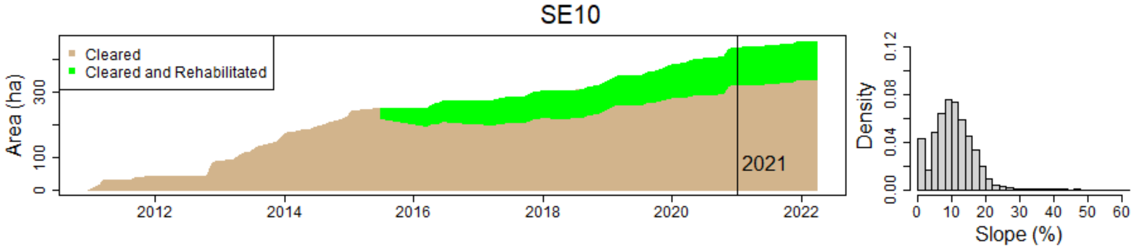

SE52
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)


SE53
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)


SE59
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)


SE61
Cleared
Cleared and Rehabilitated
Area (ha)
2021
Density
Slope (%)


SE62
Cleared
Cleared and Rehabilitated
Area (ha)
0
1000
2000
2005
2010
2015
2020
2021
Density
0.00
0.04
0.08
0.12
0
10
20
30
40
50
60
Slope (%)


SE10
Cleared
Cleared and Rehabilitated
Area (ha)
0
100
300
2012
2014
2016
2018
2020
2022
2021
Density
0.00
0.04
0.08
0.12
0
10
20
30
40
50
60
Slope (%)

Appendix C. Detection of High Turbidity Events

Event detection for the 6-monitor 2021-2022 Cleaned Dataset

All occurrences where turbidity measurements exceeded 25 NTU for one hour or longer were extracted from the 6-minute interval 2021-2022 Cleaned turbidity data available for six monitors.

Inspection of the turbidity data for these events showed that many were influenced by various types of error in the data, such as sensor drift, sensor saturation, streams flushing or drying out and obstruction by debris that was later removed. Verification of the events was performed by cross-tabulating the events with Alcoa's investigations to determine whether they had been investigated and identified as true or false.

Verification identified 98 true high turbidity events with known causes and 5 events with causes that could not be verified. The total of 98 true and 5 unverified high turbidity events were then aggregated into unique days experiencing high turbidity events (Table 10). Plots of each event are included in Appendix A.

Table 10. High turbidity events identified from the 2021-2022 Cleaned dataset.

Monitor ID	Number of events identified from NTU data	Number of verified false events	Number of verified true events	Number of days with true events
PD01	26	8	18	14
PD02	94	82	12	9
SE10	21	18	3	3
SE51	63	41	22	22
SE59	39	25	14	12
SE61	89	55	34	29
Total	**332**	**229**	**103**	**89**

Algorithms for Cleaning False Events

Considering all periods of time for which a monitor records NTU greater than 25 for an hour or longer leads to detection of many erroneous false events, we investigated methods for classifying detected events as true or false. We aimed to identify and removing as many false events as possible while retaining all true events for analysis.

Two methods were identified for classifying detected events as true or false based on their shape characteristics. The methods were tested using the 103 verified true and false events identified for the 2021-2022 Cleaned Dataset.

Dynamic time warping (DTW) measures the similarity of two time-sequences of data by warping the curves to minimise the distance between them.

Approach One: DTW Clustering

The first approach involved calculating pairwise DTW distances between normalised NTU for all pairs of events and then clustering the events into 12 similar share groups by partitioning around medoids (PAM) model. Figure 21 shows the curve clusters.

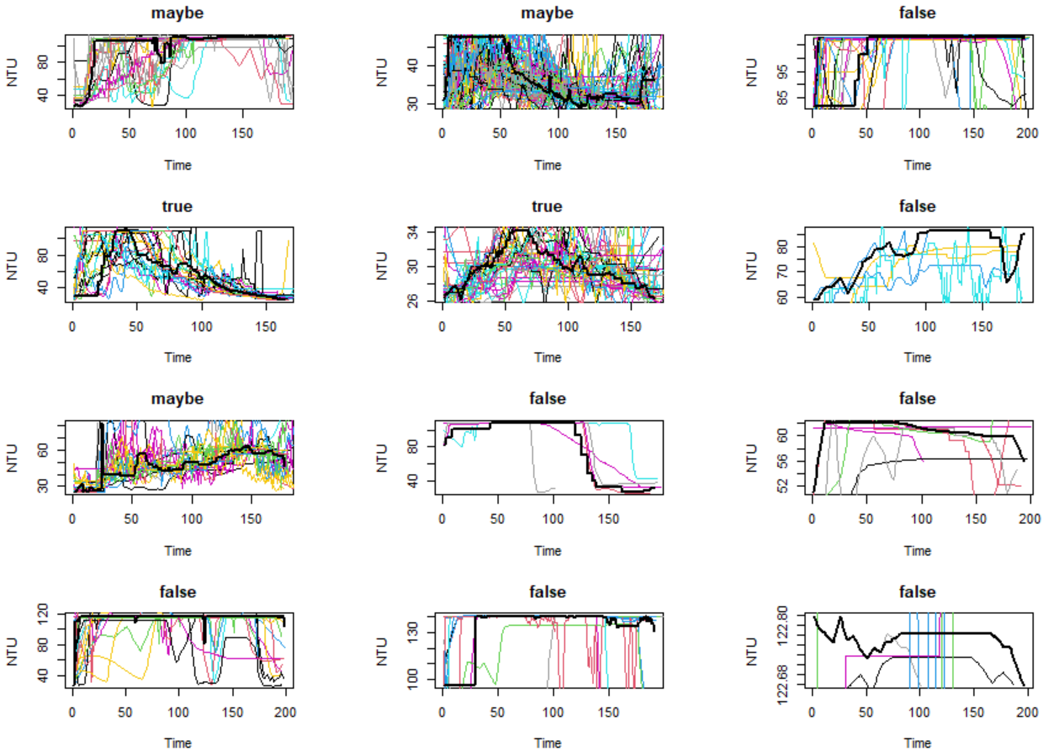


Figure 21. Clusters identified with medoids shown as black, bold line. Note that all clusters labelled 'maybe' are included in the 'true' class in Table 11 and Error! Reference source not found.**.**

The number of true/false events in each cluster is shown in Table 11. Assigning a true/false label based on these clusters shows that this approach can identify all but 5 true events while eliminating 131 false events giving a detection accuracy for true events of 95.1%.

Table 11. PAM of DTW distances clustering into 12 clusters.

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Verified labels	**False**	16	43	61	8	14	6	17	6	8	29	15	6
	True	4	40	2	16	29	0	9	1	0	2	0	0

However, the above results test the model on the same data that was used to train the model which can lead to over-estimation of accuracy. We therefore applied 5-fold cross-validation to get a better understanding of how well the model would work for unseen data. This involved splitting the high turbidity events into five independent set of data. Each split of 20% of the data is used to test the model trained using the other 80% of the data, and the results are averaged over the 5 splits or folds. The result was a cross-validated detection accuracy for true events of 87.4% (Table 12). That is, 13 true events were mis-labelled as false.

Table 12. Cross-validated accuracy for clustered DTW distances.

		False	True
Verified labels	**False**	145	84
	True	13	90

Approach Two: Pattern Match and Delete Typical Errors

The second approach to cleaning false events used DTW distance from the most typical false event that occurred: a step-type error where NTU suddenly jumped to it maximum value for some length of time before returning to a low value, as shown in Figure 22

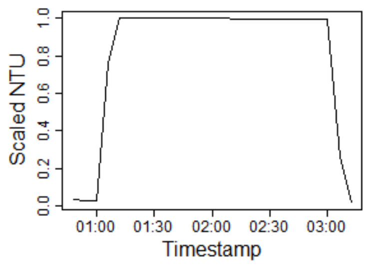


Figure 22. Normalised NTU for a typical step-type error used for pattern matching.

Mixture modelling was applied to find the optimal distance threshold for separating true and false events. When trained on the entire 103 events, this approach identified all but 5 true events while eliminating 111 false events giving a detection accuracy for true events of 95.1%. 5-fold cross-validation gave similar results (Table 13), however only around half of the false events could be successfully identified.

Table 13. Cross-validated accuracy for pattern-matched DTW distances.

		False	True
Verified labels	**False**	110	119
	True	5	98

Event detection for the 14-monitor 2021-2022 Patched Huntly Dataset

All occurrences where turbidity measurements exceeded 25 NTU for one hour or longer were extracted from the Patched Huntly turbidity data for 14 monitors with good long-term records. False turbidity events were eliminated using the second approach outlined above, events were aggregated to daily and verified manually by cross-tabulating against Alcoa's records.