Volspruit South – Relogging, 6E Sampling, Quality Control, and Regression

Document No.: EARTH-PPD-PO_940-1-Report_1
Vendor No.: EAR001
Published: 20 September 2023

Relogging of Volsrpuit South Body including 6E sampling and regression modelling

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1 INTRODUCTION

1.1 Terms of Reference and Background

Pan Palladium South Africa (Pty) Ltd. ("PPD"), the mining right holder of the Volspruit Project ("Volspruit") commissioned Earthlab to investigate the unexpected metallurgical recoveries obtained by DRA during the flotation test work conducted for plant design. As part of the scoping of the investigation works to resolve and optimise the flotation response, Earthlab recommended that the resource model be remodelled at a higher minimum grade to determine the mineralisation continuity. A new mineral resource estimate (MRE) of the Volspruit North Body based on a higher minimum grade has been undertaken including a mining study, as well as a scoping level assessment of the planned processing plant and related infrastructure. Sylvania intended to follow the same process of recreating an MRE based on the reinterpreted geological understanding for the Volspruit South Body. As part of this process, the relogging programme for the Volspruit South Body was proposed to define in detail the stratigraphy of the deposit.

Several samples were selected for the assaying of Rhodium (Rh) from the Volspruit South Body historical drill core in an attempt to regress the data for inclusion of Rh into the MRE. The samples for Rh analyses were selected to provide a representative coverage of the entire mineralized ore domain as well as to cover a wide range grade distribution for the mineralized domain. Samples were analysed by SGS laboratory using a Nickel Sulphide collection for 6E analytes including Rh.

2 RELOGGING

2.1 Drill Hole Information

The fifty-four (54) drill holes listed in Table 1 were relogged and are represented spatially in Figure 1. The drill core is NQ sized core of which most of the drill holes have been sampled historically, in some cases only a quarter core was left behind.

Several drill holes (see Table 1) from the originally planned relogging list were completely left out as there were missing intervals in critical portions of the ore zone. One drill hole (GVS046) had core mixed up as a result of the core boxes falling off the stacking rails. In some cases where the first few boxes were missing which are not within the ore zones, the drill holes in this case were fully relogged. Two drill holes (GVS021B and GVS095) were located in the Sylvania coreshed, however they are not in the database provided to Earthlab, and they were also relogged.

Of the total fifty-four (54) drill holes planned for relogging, forty-six (46) drill holes were successfully relogged and handed over for use in the Mineral Resources Estimation.

Table 1. Volspruit South drill holes re-logged by Earthlab in 2022. Coordinate projection – Hartebeesthoek 94/ LO29

DHID	X	Y	Z	Depth (m)	Comments
GVS001	-4712.120	-2695163.65	1068.26	80.80	
GVS002	-4745.770	-2695068.65	1068.41	149.80	
GVS003	-4588.404	-2695173.028	1069.597	100.03	
GVS004	-4618.638	-2695078.439	1069.352	108.33	
GVS005	-4501.358	-2695159.461	1070.816	150.82	Drill hole abandoned, core missing in critical ore zones.
GVS006	-4523.507	-2695059.526	1070.385	202.20	Missing core (0 – 36.30 m).
GVS007	-4396.938	-2695115.439	1072.651	240.84	Missing core (0 – 41.86 m).
GVS008	-4430.452	-2695037.273	1071.898	411.56	Missing core (0 – 44.00 m).
GVS009	-4277.982	-2695040.333	1075.876	396.98	Missing core (0 – 44.08 m).
GVS010	-4208.728	-2695059.142	1078.965	400.18	Missing core (0 – 45.88 m).

GVS011	-4131.358	-2695089.084	1083.508	400.62	Drill hole abandoned, core missing in critical ore zones.
GVS012	-4050.592	-2695080.881	1087.894	45.00	Drill hole abandoned, core missing in critical ore zones.
GVS013	-4017.234	-2695000.294	1086.602	45.00	Drill hole abandoned, core missing in critical ore zones.
GVS019	-4261.539	-2695148.984	1077.737	590.69	
GVS020	-3940.225	-2694978.316	1088.953	194.92	
GVS021	-3984.100	-2694925.068	1085.009	225.01	
GVS021B				21.98	Drill hole not in the database.
GVS022	-3994.299	-2695056.265	1089.519	132.04	
GVS023	-4017.773	-2694990.46	1086.142	168.01	
GVS024	-4054.304	-2694951.532	1082.63	231.01	
GVS025	-4055.255	-2695082.782	1087.31	120.01	
GVS026	-4133.561	-2694984.448	1080.115	249.07	
GVS027	-4192.489	-2695003.213	1078.024	206.92	
GVS028	-4470.965	-2695099.165	1071.076	219.01	
GVS029	-4552.068	-2695118.22	1069.991	114.01	
GVS030	-3866.574	-2694837.646	1084.688	254.99	
GVS031	-3725.391	-2694755.648	1084.062	247.80	
GVS032	-3820.831	-2694939.754	1091.364	195.06	
GVS033	-3630.84	-2694885.045	1092.124	215.81	
GVS034	-3729.794	-2694915.303	1091.902	179.81	
GVS035	-4624.592	-2695262.258	1069.073	89.00	
GVS036	-4425.119	-2695196.341	1072.126	165.10	
GVS037	-4457.179	-2695308.895	1071.905	120.01	
GVS038	-4272.276	-2695226.175	1077.796	63.01	
GVS039	-4079.663	-2695183.684	1088.485	65.04	
GVS040	-3940.951	-2695122.427	1096.175	72.01	
GVS041	-4525.506	-2695228.152	1070.569	88.01	
GVS042	-4354.525	-2695272.821	1074.553	63.01	
GVS043	-4643.707	-2695199.322	1069.163	103.44	
GVS045	-4657.339	-2695290.139	1068.687	95.10	
GVS046	-4636.477	-2695147.185	1069.385	100.80	Drill hole abandoned, core mixed up due to dropped core.
GVS047	-4598.354	-2695289.493	1069.641	100.62	
GVS048	-4578.854	-2695111.708	1069.889	82.15	
GVS048D	-4578.854	-2695111.708	1069.889	91.03	
GVS049	-4580.305	-2695210.551	1069.818	100.62	
GVS050	-4531.611	-2695190.800	1070.528	102.02	
GVS052	-4388.074	-2695132.488	1073.092	100.50	
GVS050A	-4533.036	-2695194.641	1070.501	62.74	
GVS056	-3972.000	-2694984.237	1088.275	120.24	Drill hole abandoned, missing core in critical portioins: (0 – 83.00 m; 115.62 – 120.00 m).
GVS060	-4300.288	-2695188.894	1076.324	251.30	
GVS061	-4123.426	-2695122.701	1084.832	250.57	
GVS062	-4010.677	-2695093.84	1090.773	250.84	
GVS063	-3985.577	-2695160.795	1095.016	150.08	
GVS095				81.05	Drill hole not in the database.
Total - 54 Drill holes				9,066.60 m	

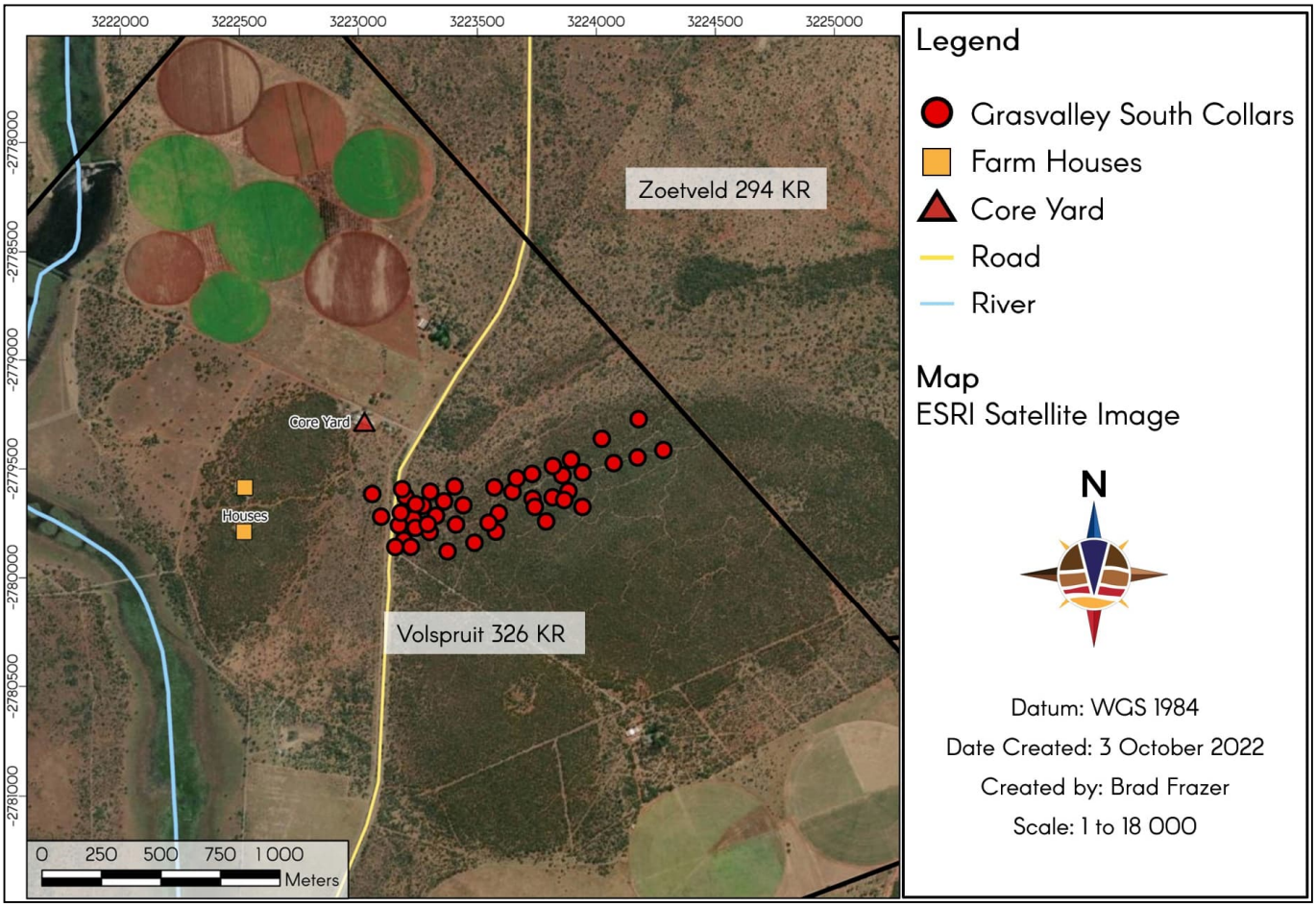

Figure 1 Collar positions for the Volspruit South Body drill holes that were relogged.

2.2 Methodology

The relogging entailed detailed lithological, mineralogical, and stratigraphic logging in line with the newly defined stratigraphic units (Figure 3). The relogging started in September 2022 and was completed in December 2022. A total of 8,324.36 m of core was relogged.

This was performed due to the historical stratigraphic logging that has been done using multiple naming conventions as well as being based on the larger-scaled cyclic units 10, 11, and 12 within the Volspruit pyroxenite stratigraphic unit. This method produces a much thicker unit which does not capture the resolution of the deposit within these cyclic units. Earthlab proposed a modified stratigraphic naming convention with new minor-sub and horizon-level stratigraphy fields in which the resolution of the deposit was captured. Figure 2 shows the proposed stratigraphic interpretation that was used to relog the Volspruit South deposit. The stratigraphic convention was supported by literature published by Hulbert (1983) and Tanner et al (2019). Additionally, with these newly defined stratigraphic units, it is possible to delineate specific hanging wall units, reef zones, and footwall units with confidence.

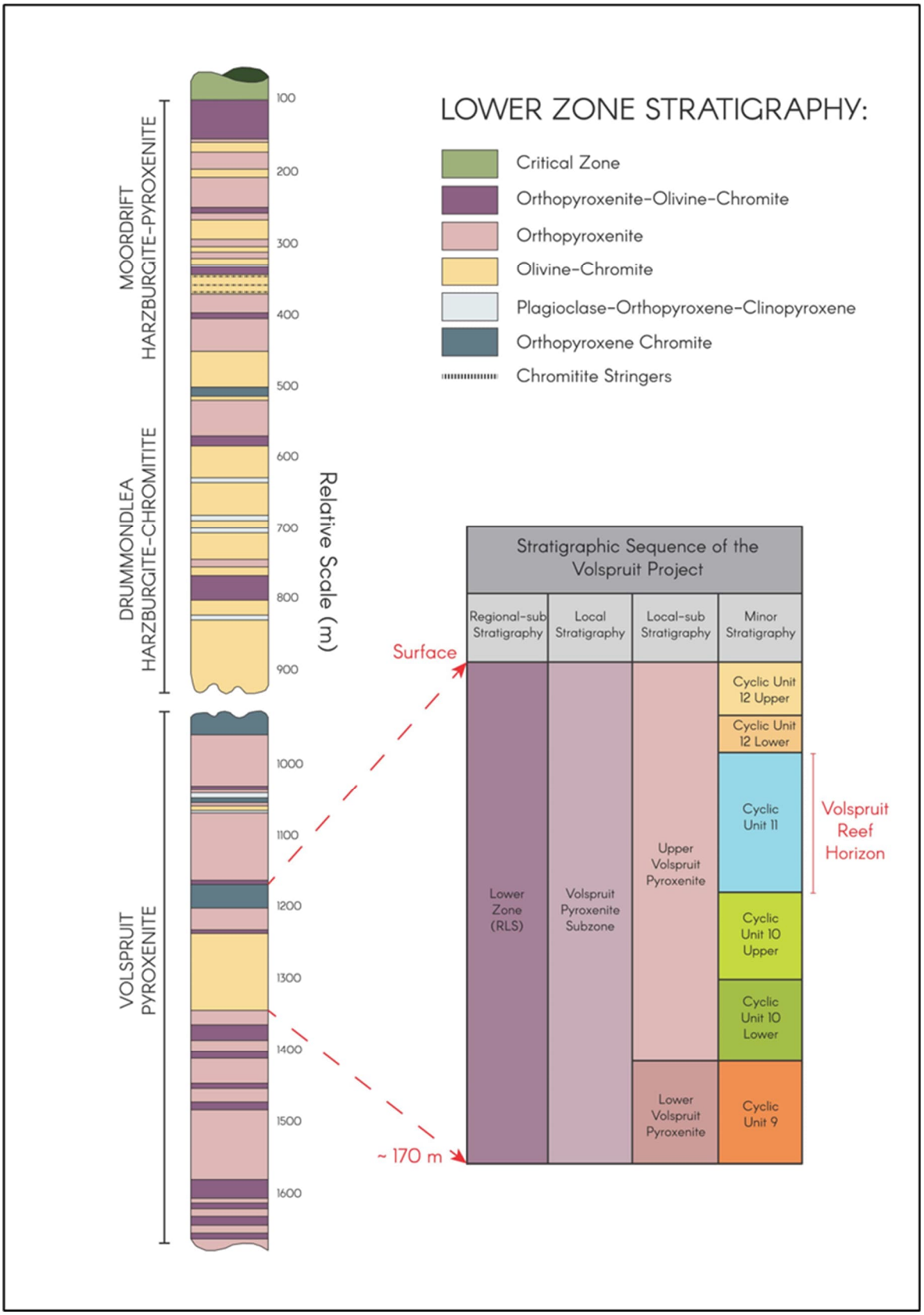

Figure 2 Lower Zone stratigraphy representing the Volspruit Project Area. Image modified after Hulbert (1983).

2.3 Summary of Results

The relogging campaign of 2022 was conducted based on a new stratigraphic understanding generated by Earthlab from the work of Hulbert (1983) and Tanner et al. (2019) (Figure 3), to better define the Volspruit Reef. In this model it was established that the Volspruit Reef is only confined to Cyclic Unit 11 Upper hosted by pyroxenites (Figure 3).

Cyclic Unit 12 Upper comprises homogeneous ortho-pyroxenites with minor chromite and no sulphides observed.

Cyclic Unit 12 Lower comprises a relatively small unit of harzburgites containing olivine, varying from poikilitic to inequigranular texture. This unit occasionally has sulfides but no significant PGMs are concentrated here. This unit marks the top contact of the hanging wall in the Volspruit Reef which is confined in the Cyclic Unit 11 Upper.

The Volspruit Reef (VR) is confined to the Cyclic Unit 11 Upper. Sulphide mineralisation observed in the cyclic units surrounding Cyclic Unit 11 Upper did not show any significant PGM (Pt and Pd) and Au grades according to historic downhole assay grade profiles of 2E and Au. The unit comprises homogeneous ortho-pyroxenites with minor chromite. It can be sub-divided into several mineralised units, most prominently three units i.e., VR1, VR2 and VR3 along with internal waste zones defined as VR middling units (VRMID) which can be barren or have insignificant scattered mineralisation. These mineralised units are characterised by their base metal sulphide content.

Cyclic Unit 11 Lower forms the basal layer of Cyclic Unit 11 Upper and can be compared to Cyclic Unit 12 Lower as it consists of the olivine-bearing harzburgites which vary from poikilitic to inequigranular in texture and are sometimes strongly serpentinised at certain intervals. Serpentinisation increases with depth and poikilitic harzburgites to equigranular fine-grained dunites form the dominant lithologies. The sulphides in this cyclic unit do not have significant PGM mineralisation according to historic downhole assay grade profiles of 2E and Au.

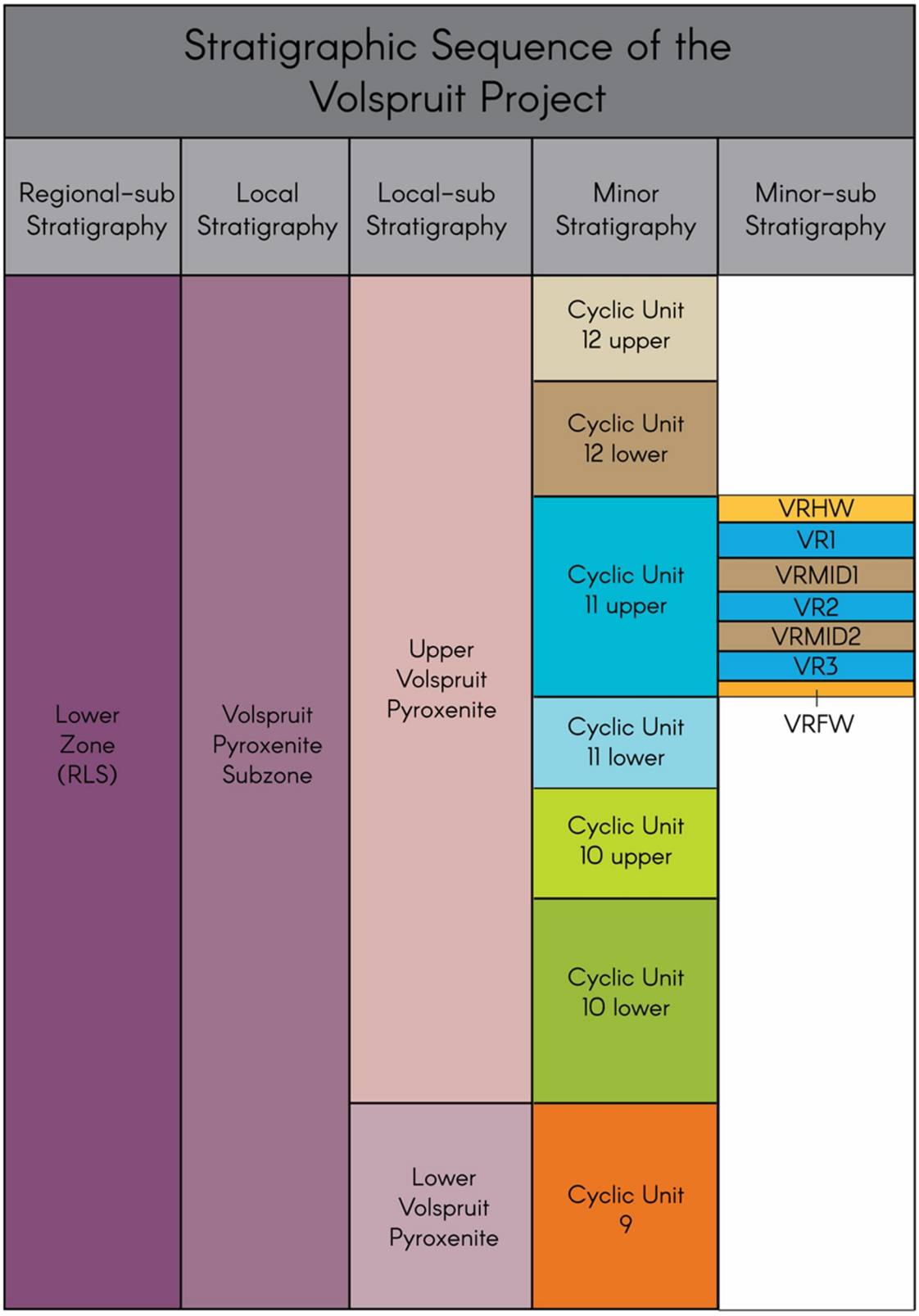

Figure 3 Redefined stratigraphy used by Earthlab for the relogging of GVS drill holes in 2022.

3 HISTORICAL CORE SAMPLING

3.1 Sub-sampling Techniques and Sample Preparation

3.1.1 Sample selection

A summary of the drill holes and sample intervals selected for the Rh and Ru regression sampling is displayed in Table 2. The sample selection for Rh and Ru regression was based on the following criteria:

- Spatial representativity of the entire mineralized domain perimeter as illustrated in Figure 4.
- To be representative of the spread of the 2E+Au grade downhole within the mineralized domain as seen in Figure 5.

Table 2. Summary of drill holes sampled for Rh and Ru regression.

BHID	From	To	Strat	Weathering zone	Percentage of sampled interval = mineralised domain	length	Amount of Samples
GVS004	36.00	75.00	CU11U	Fresh	77.7%	39.00	39
GVS008	180.00	225.00	CU11U	Fresh	71.7%	45.00	45
GVS010	95.00	128.00	CU11U	Fresh	84.8%	33.00	33
GVS023	91.00	132.00	CU11U	Fresh	75.6%	41.00	41
GVS028	108.00	153.00	CU11U	Fresh	75.6%	45.00	45
						Total	203

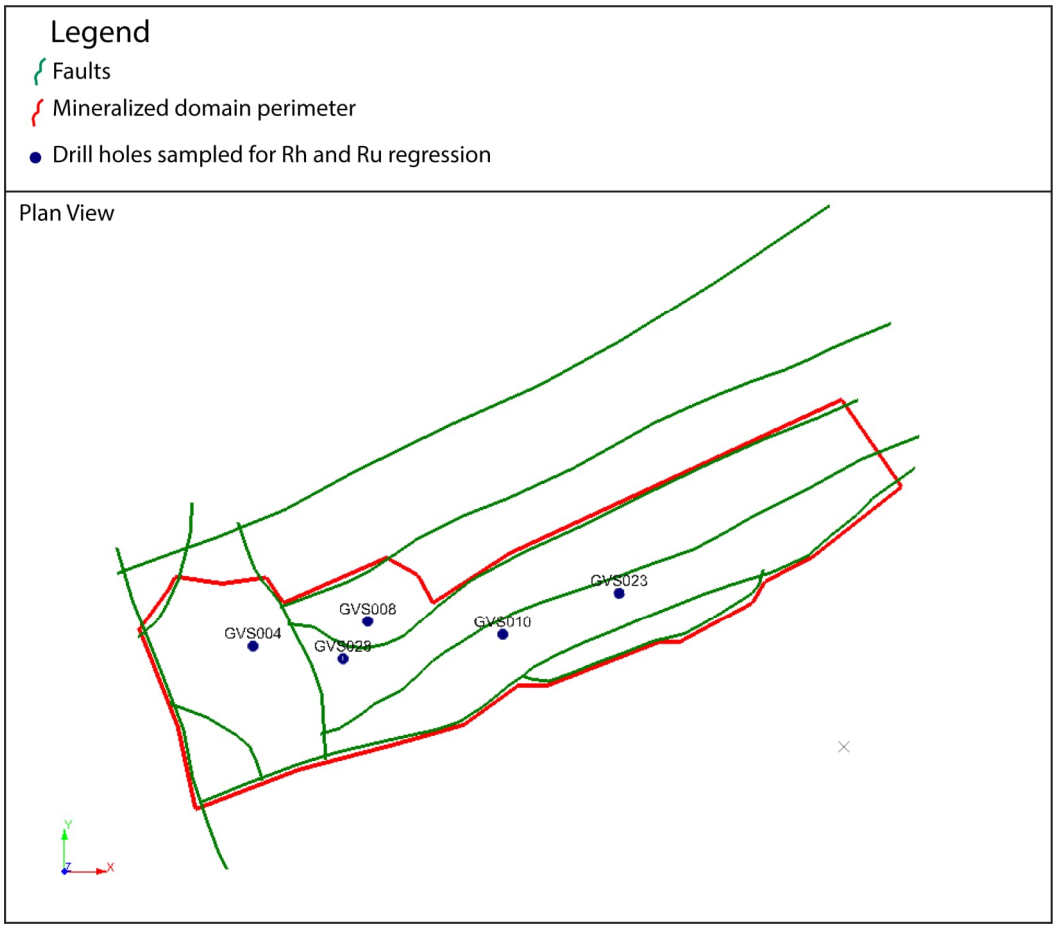

Figure 4. Location of drill holes sampled for Rh and Ru regression relative to faults and the mineralized domain perimeter.

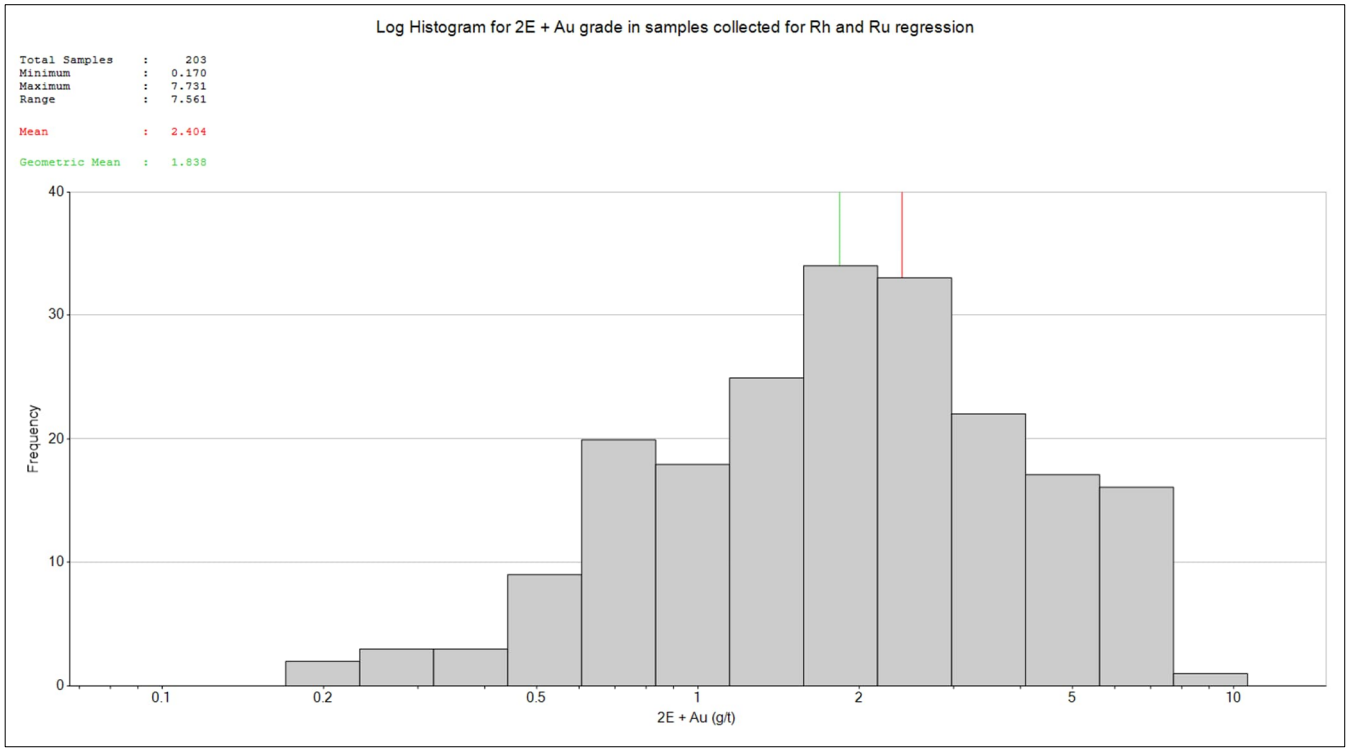

Figure 5. 2E + Au grade in sample collected for Rh and Ru regression.

3.1.2 Sample Marking

Steps that were followed for marking out sample locations on the drill core:

- A blue wax marker was used to draw in the orientation line on the remaining half core that was used to guide the core cutter to split the core into two equal pieces of quarter core.
- A yellow wax marker was used to mark out the 1 m quarter core primary assay samples, indicating the sample ID of the primary sample in yellow at the "from" depth of the primary sample.
- A white wax marker was used to mark out the position of an inserted QAQC sample in between primary samples. Note that the QAQC (Blank, standard, or pulp duplicate sample) has the same sample-ID naming convention as the primary samples. The sample ID of the QAQC sample was indicated in white at the "to" depth of the previous primary sample after which the QAQC sample was inserted in the sequence.
- Assay Sample Naming Convention:
    - GVS###001
        - GVS – Grassvalley South Rh Sample
        - ### – Drill hole ID
        - 001 – Sample Number

3.1.3 Laboratory Sample Preparation Procedure

This comprises steps followed by SGS in their laboratory to ensure that samples were in a format that would allow for reliable data analysis (Figure 6). Sample splitting was performed to reduce the sample size to form a homogeneous sub-sample, representative of the material submitted to the laboratory. Quality control procedures were followed in this regard. Furthermore, SGS used industry standard procedures along with their technical expertise in the preparation of all the samples.

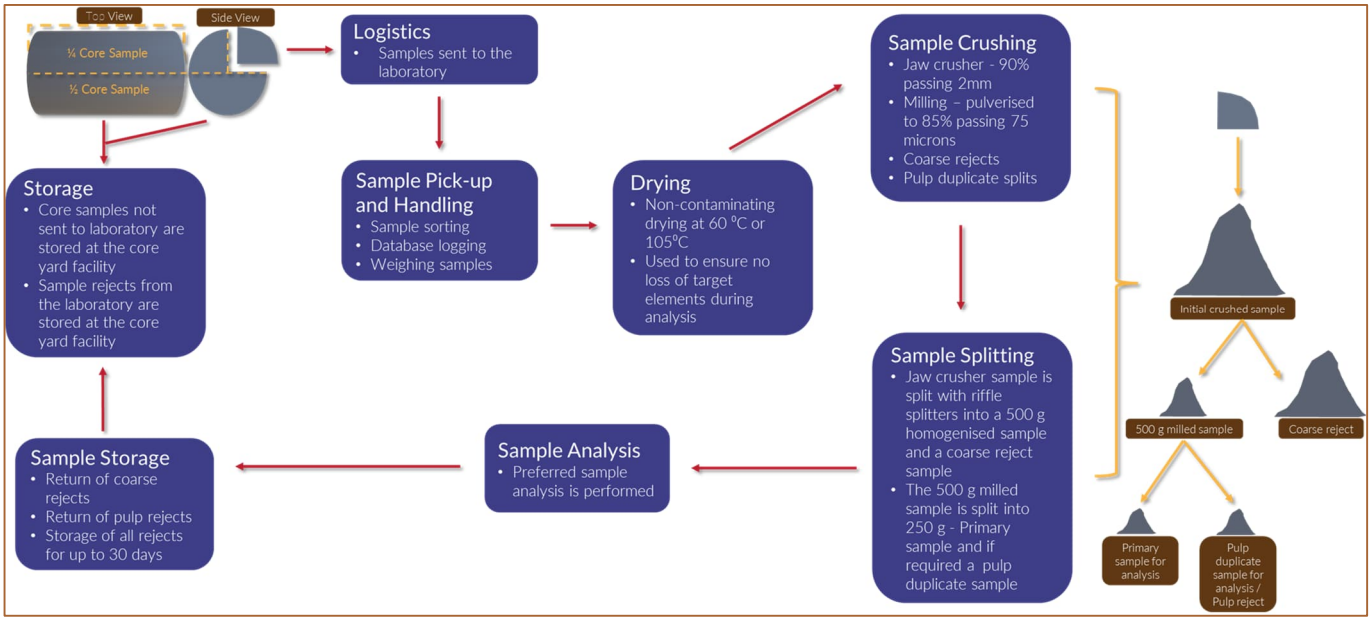

Figure 6. Flow chart for SGS sample preparation before conducting elemental determination methods.

3.1.4 Determination of 6E Analytes by Nickel Sulphide

The NiS method covers the determination of Au, Pd, Pt, Rh, Ir, and Ru in ores, rocks, soils and metallurgical products (Table 3).

Table 3. Determination of Gold, Platinum, Palladium, Rhodium, Iridium and Ruthenium by Ni Sulphide Fusion – (FAI41V10 scheme)

Item	Description					
Analytes	Au, Pd, Pt, Rh, Ir, Ru					
Units	g/t					
Analytes	Au	Pd	Pt	Rh	Ir	Ru
Lower Report Limit	0.01	0.01	0.01	0.01	0.01	0.01
Upper Report Limit	100	1000	1000	100	100	100
Analysis Detection Limit (SLIM)	0.01					
Statistical Detection Limit (SLIM)	0.025					
Limiting Repeatability (SLIM)	7.5%					
Sample Size	30 g variable					
Matrix	Pulverised/screened ore-grade samples (mucks, chips, drill core, test holes)					

The quality assurance was monitored by placing a duplicate, replicate, in-house and/or standard reference material and blank sample for every batch of 25 samples. The precision was monitored by SGS Laboratory as per the following formula based on their method capability in the lab:

$$\text{Tolerance (\%)} = [(100 * SDL) / EV] + LR$$

Where:

- SDL = Statistical Detection Limit (by default = 2.5 x Detection Limit)
- LR = Limit of Repeatability of the Method
- EV = Expected Value Concentration/average of data pair

3.1.5 Sample Security

Samples that were being sent for laboratory analysis, were transported from the core yard near Mokopane to the SGS laboratory in Rustenburg by a senior geologist. The samples were checked into the facility and signed for in the sample security register by a facility representative. It was the responsibility of the person delivering the samples, to ensure that the facility representative or their assistants sign on the receipt of the samples and check to see all sub-batch bags were present and accounted for. The remaining quarter core was stored in a locked core shed for any future relogging, or sampling requirements should they arise.

3.1.6 Sample Assay Methods

Samples are prepared using the appropriate nickel flux type depending on the type of material analysed. The fusion process promotes the separation of precious metals. Pt, Pd, Rh, Ru and Ir are collected in a NiS sulphide button by fire assay procedure. The technique is used to separate NiS from PGM and Au sulfides and tellurides. NiS dissolves readily in hot concentrated Hydrochloric acid while Pt, Pd, Rh, Ru, Ir residue and Au sulfides remain reasonably undissolved and can be separated from the acidic $NiCl_2$ solution by filtration. Tellurium is added to precipitate any dissolved PGM and Au as tellurides, Stannous chloride is added to reduce Te^{6+} to lower oxidation states for tellurides and elemental tellurium to form. The PGMs and Au collected via filtration are digested in aqua regia and makeup to a specific volume. After the dissolution of the residue, the precious metal solutions are then analysed for Au, Pt, Pd, Rh, Ru, and Ir by ICP-OES. Traditionally, the recovery of PGMs by fire assay involves the fusion of the sample with lead, and some Rh is lost in the dissolution of the silver bead and some ruthenium is absorbed into the cupel during the cupellation stage. Therefore, the NiS method was preferred to analyse for Pt, Pd, Ir, Ru, Rh, and Au.

3.2 Quality Assurance

3.2.1 Sampling

Earthlab performed a sampling programme on five (5) Grassvalley South drill holes. The sampling was conducted on 1 m intervals. The sampling intervals were marked out on the core before cutting after which sampling occurred. Quarter samples were sampled and the remaining quarter was left behind as reference samples. The sample bags were sealed directly after packing with one sample name ticket inside the bag and one stapled to the top of the bag. The samples were divided into batches of 53 samples (of which forty were primary samples and thirteen were quality control samples). The samples were transported to SGS laboratories in Rustenburg by an Earthlab Geologist and the chain of custody was handed over to the SGS for the analysis of the samples for their 5E and Au content.

A total of 268 samples were sampled including quality control samples, of which 203 samples were primary samples. The quality control samples consisted of blanks, standards, and duplicate samples (Table 4).

Table 4. Quality Control samples used during the sampling of the 5 Grassvalley South drill holes.

Sample Type	Name	Number
Blank	AMIS0577	25
Certified Reference Material	AMIS0499	8
Certified Reference Material	AMIS0498	8
Certified Reference Material	AMIS0486	4
Pulp Duplicates	-	20

All the data was captured into SABLE® upon completion of the sampling. The data was then validated and signed off by the Database Manager if all was in order.

3.2.2 Database Storage and Management

The physical hardcopy logs and sampling books are stored at the Volspruit core yard facility. These were used as a reference for any data quality queries. Additionally, it provides a physical backup of the data.

All data was captured onto a dedicated electronic SABLE®7.2 database which runs on an SQLite server where security and access to the database were managed.

The databases were managed by a dedicated geologist (geological database manager) to ensure data quality, integrity, and security. Various data logs exist on the database. The drill hole databases include the stratigraphy, lithology, mineralisation, sampling, and assay data logs. Each drill hole has a collar, lithology, stratigraphy, sampling, and assay data as a minimum requirement. The dataset includes 'From' and 'To' metre fields, rock types, stratigraphic nomenclature used on the project area, mineralisation, alteration, and additional comments where applicable. Quality control data, such as inserted CRMs and twin stream data was housed in the database in the sampling log and assay results tables. The sampling dataset includes the methods used for sampling, the laboratory used for the analysis and units of measure. The assay result datasets include all the grade values available for each sample. All additional information was populated in the 'Comments' field of the associated data log.

3.2.2.1 Database Integrity

The SABLE®7.2 database contains a series of built-in customised as well as default active validations which were run concurrent to the time of data capture. This ensured the quality of the data being captured by preventing faulty data entries from being captured through security and appending rules specified by the

database manager. The database manager produced a final system validation print out which flags any erroneous or suspect data entries, which were then subsequently queried and resolved accordingly.

Manual validations undertaken by the database manager include the following checks:

- All required logs and fields within the logs have been populated
- The appropriate lithological and stratigraphic coding has been used and was in sequence
- There were no overlaps, gaps or zero lengths in the lithological and sampling logs
- All the relevant fields within the sampling log have been populated correctly
- Quality assurance of the inserted certified reference materials has been correctly populated
- Check that the grade content was aligned with the stratigraphy

Once validations were completed and issues had been attended to by the geological database manager, the data was signed off to be analysed for assay quality control and extracted for geological modelling and MRE.

4 ASSAY QUALITY CONTROL

4.1 Accuracy Analysis

The South Body sampling has been subjected to quality control standards by assessing the accuracy of the control samples submitted to the laboratories. This includes blanks and certified reference materials and, in some instances, non-certified reference materials. Blank samples that fall above 10x the detection limit and certified reference samples that fall outside the third standard deviation upper and lower limits of statistical control will be flagged and labelled as a failed sample. Each control sample is separated by element and will undergo this procedure to produce a list of failed samples. The failed samples are then used to produce a final list of primary samples that can be used for the resource estimation process.

4.1.1 Summary of Accuracy Analysis

A total of 47 control samples were used in this sampling campaign and the results have been separated into their respective analytes and displayed in Table 5 below. The overall results show good accuracy across Pt, Pd, Au and Rh. Pd and Au displayed perfect accuracy with 100% of the samples falling within tolerance limits. Pt and Rh also show great accuracy with 93.62% and 97.87% of samples falling within tolerance limits respectively. Ru displayed less accurate results with only 85.11% of the samples falling within tolerance limits. The poorer performance of the Ru results may be due to multiple reasons: the CRM's material used may not accurately resemble the material found in this sampling campaign; the low number of samples may have exaggerated the number of failures one would expect to see in a larger sample population; the upper and lower standard deviations relating to the accepted value for Ru in the CRMs used are very restrictive due to the acceptance value being so small (near detection limit of the analysis hardware).

The results show no contamination in any of the analytes, meaning that contamination did not play a role in the failure of any of the samples.

Table 5. Summary of GVS project's control samples analyses for accuracy analysis indicating the total percentage of failed samples per element.

CRM		Pt			Pd			Au			Rh			Ru		
		N	Outliers		n	Outliers		n	Outliers		n	Outliers		n	Outliers	
			n	%		n	%		n	%		n	%		n	%
Standards	AMIS0486	4.00	2.00	50.00	4.00	0.00	0.00	4.00	0.00	0.00	4.00	0.00	0.00	4.00	0.00	0.00
	AMIS0498	8.00	0.00	0.00	8.00	0.00	0.00	8.00	0.00	0.00	8.00	0.00	0.00	8.00	3.00	37.50
	AMIS0499	10.00	1.00	10.00	10.00	0.00	0.00	10.00	0.00	0.00	10.00	1.00	10.00	10.00	4.00	40.00
BLANK		25.00	0.00	0.00	25.00	0.00	0.00	25.00	0.00	0.00	25.00	0.00	0.00	25.00	0.00	0.00
TOTAL		47.00	3.00	6.38	47.00	0.00	0.00	47.00	0.00	0.00	47.00	1.00	2.13	47.00	7.00	14.89

4.2 Precision Analysis

The pulp duplicates used in this analysis were generated internally by the laboratory's twinstream process as part of their QAQC protocols. The twinstream results have been analysed graphically through XY plots showing regressions with 95% confidence intervals. Twinstream results have also been analysed using the Half Absolute Relative Difference method. The graphs used in the analysis of these results will be made available upon request. Analyses have been separated into their respective elements including Gold (Au), Rhodium (Rh), Rutinium (Ru), Platinum (Pt), and Palladium (Pd).

4.2.1 Summary of Precision Analysis

A total of 20 duplicate samples were used in the precision analysis and the results for each analyte are represented in Table 6 below. The results show good repeatability overall with Pt, Pd, Au and Rh having 90%–95% of their samples falling within 15% absolute difference. Ru sits on the acceptance limit with only 85% of the samples falling within 15% absolute difference. The reason for the poor results seen for Ru may be due to the variable nature of the material as potentially due to inherent error that can easily occur when working with such low grades which approach the detection limit of the analysis hardware.

Table 6. Summary of South Body twinstream results using Half Absolute Relative Difference outlier method.

Project		Element	No. of Samples	Mean Original	Mean Duplicate	|Mean Difference|	Within 15%	No. of Outliers	Outliers (%)
Volspruit South	Pulp Duplicates	Pt	20	1.37	1.37	0.01	95.00	1.00	5.00
		Pd	20	1.61	1.62	0.01	95.00	1.00	5.00
		Au	20	0.08	0.08	0.01	95.00	1.00	5.00
		Rh	20	0.23	0.23	0.00	90.00	2.00	10.00
		Ru	20	0.09	0.09	0.00	85.00	3.00	15.00
	>90%								
	>85%								
	<85%								

5 RH & RU REGRESSION

The objective of this section is to provide a comprehensive overview of the assay regression process carried out using the scikit-learn Python library. The regression aims to derive reliable estimates of Rhodium and Ruthenium concentrations from the metallurgical drilling project samples. These estimated values are intended to augment the existing historic assays, enabling a holistic resource model which includes these fundamental metal contributors. This section comprehensively outlines the methodology employed, including the selection of appropriate regression models, parameter tuning, and evaluation error metrics.

When comparing the regression of rhodium using a straight-line equation versus utilising machine learning regression models in Python through scikit-learn, it becomes evident that the latter approach is significantly more effective. While a simple linear regression may provide a basic correlation, machine learning regressors offer a superior ability to capture complex non-linear relationships and patterns within the data. Scikit-learn, with its versatile algorithms, allows for more accurate predictions and improved model performance by adapting to the intricacies of the rhodium dataset. This advanced approach, bolstered by extensive libraries and optimisation techniques, enhances the precision and reliability of regression analysis for rhodium data in a way that a traditional linear equation cannot achieve.

5.1 Python Programming – Scikit-learn Library

Scikit-learn is a widely adopted machine-learning library in Python renowned for its simplicity, flexibility, and extensive functionality. It provides a user-friendly interface for implementing a wide range of regression techniques, including linear models, support vector machines, decision trees, and ensemble methods. Scikit-learn's implementation of these models incorporates efficient algorithms and best practices, making it highly suitable for regression tasks in diverse scientific and industrial domains. Moreover, its robust documentation and active community support ensure reliable and up-to-date guidance throughout the regression process.

5.2 Regression Requirements

The regression process aimed to estimate and train and regression model for the concentrations of Rhodium and Ruthenium from Platinum, Palladium, and Gold in the given set of samples obtained during the metallurgical drilling programme. This task necessitated the construction of a regression model capable of predicting the values of these additional elements accurately. The resulting regression model would then be integrated into the historic assays to enhance the metal evaluation by incorporating the predicted Rh and Ru concentrations into the existing resource model.

5.3 Regression Methodology

To accomplish the assay regression task, an iterative approach utilising algorithmic design and scikit-learn's regression models were employed. The following steps were followed:

5.3.1 Model Selection and Parameter Tuning

Various regression models available in scikit-learn were tested to identify the best-performing model for each individual element. The tested models included Linear Regression, RANSAC Regressor, Ridge Regression, Support Vector Regression (SVR), Decision Tree Regressor, Random Forest Regressor, Gradient Boosting Regressor, and AdaBoost Regressor. Each model was evaluated based on its ability to accurately predict the target element's concentration. The following subsections outline each of these models capabilities and functionalities at a high level.

5.3.1.1 Linear Regression:

A simple and widely used regression model that assumes a linear relationship between the predictor variables and the target variable. Suitable for scenarios where the relationship between the input variables and the output variable can be adequately approximated by a linear equation.

5.3.1.2 RANSAC Regressor:

Robust model that mitigates the impact of outliers in the data by iteratively fitting the model to a subset of inliers. Particularly useful when the dataset contains noisy or anomalous data points that could adversely affect the regression model's performance.

5.3.1.3 Ridge Regression:

Regression technique that incorporates regularisation by adding a penalty term to the loss function, encouraging smaller parameter values. Effective in handling multicollinearity issues and reducing overfitting by shrinking the regression coefficients.

5.3.1.4 Support Vector Regression (SVR):

Utilises support vector machines (SVMs) to perform regression tasks. Applies a non-linear mapping of the input variables to a high-dimensional feature space, where a linear regression model is constructed. Suitable for complex relationships between input and output variables and can handle datasets with high dimensionality.

5.3.1.5 Decision Tree Regressor:

Employs a decision tree structure to model the relationships between input variables and the target variable. Makes a series of binary decisions based on the feature values to predict the target variable's value. Provides interpretability and handles non-linear relationships effectively.

5.3.1.6 Random Forest Regressor:

Ensemble learning method that combines multiple decision trees to create a more robust and accurate regression model. Uses bootstrapping and random feature selection during model construction to improve generalisation and reduce overfitting.

5.3.1.7 Gradient Boosting Regressor:

Ensemble learning technique that combines weak regression models sequentially to build a strong predictive model. Each subsequent model is trained to correct the errors made by the previous models, gradually improving the overall predictive performance.

5.3.1.8 AdaBoost Regressor:

Another ensemble learning algorithm that iteratively combines weak regression models. Focuses on adjusting the weights of training instances to give more emphasis to those that were previously mispredicted.

5.4 Error Metric Extraction

Two commonly used error metrics, Mean Absolute Error (MAE) and Mean Squared Error (MSE), were employed to quantify the performance of each regression model. The scikit-learn library facilitated the computation of these metrics, which provide insights into the magnitude and distribution of prediction errors. By extracting the error metrics for each model, a comprehensive evaluation of their performance could be obtained.

5.5 Iterative Testing with Different Parameters

To account for potential variations in model performance, iterative testing was conducted by systematically varying two parameters: test size and random state. Test sizes were selected from a list ranging from 0.1 to 0.9, allowing for an assessment of the impact of training data size on model performance. Test sizes are proportional in percentages based on the decimal indicated, where a test size of 0.1 indicates 10% of the original dataset is used to train the regression model. The random state values, ranging from 0 to 100, enabled the evaluation of model sensitivity to different random data shuffling scenarios. The total number of regression models tested using this iterative functionality amounted to 3,636 models being outputted by analysis.

5.6 Model Ranking and Selection

To determine the best-performing model for each element, a ranking scheme based on MAE and MSE was utilised over the 3,636 regression models. The error metrics are calculated using the predicted values versus the actual values of the analyte being predicted. The average rank between the two error metrics was computed for each model, facilitating an objective selection process. This approach ensured that both metrics were considered, allowing for a balanced assessment of the model's predictive capabilities.

5.6.1 Ranking and Selection Results

Ranking results achieved during the training of the regression models were conducted on results received by the laboratories which are strictly above the detection limit, so as not to add unnecessary noise to the regression model training. The error metrics MAE and RMSE are the actual measures in ppm for which the accuracy of the predicted analytes can be achieved by utilising the selected regression model and its parameters (Table 7 and Table 8).

Table 7. Rhodium regression model rankings (top 5 displayed)

Model	Test Size	Random State	MAE (ppm)	MSE (ppm^2)	RMSE (ppm)	MAE Rank	MSE Rank	Average Rank
RANSAC Regression	0.1	74	0.0168	0.0004	0.0202	1	1	1
RANSAC Regression	0.1	32	0.0196	0.0006	0.0245	2	2	2
RANSAC Regression	0.1	25	0.0215	0.0007	0.0271	4	3	3.5
Linear Regression	0.1	25	0.0226	0.0008	0.0283	6	5	5.5
RANSAC Regression	0.1	26	0.0238	0.0008	0.0279	9	4	6.5

Table 8. Ruthenium regression model rankings (top 5 displayed)

Model	Test Size	Random State	MAE (ppm)	MSE (ppm^2)	RMSE (ppm)	MAE Rank	MSE Rank	Average Rank
RANSAC Regression	0.1	31	0.0079	0.0001	0.0110	1	2	1.5
RANSAC Regression	0.1	53	0.0079	0.0001	0.0105	2	1	1.5
RANSAC Regression	0.1	85	0.0094	0.0002	0.0129	3	3	3
RANSAC Regression	0.1	15	0.0095	0.0002	0.0141	4	7	5.5
RANSAC Regression	0.1	20	0.0106	0.0002	0.0141	6	6	6

Based on the tables presented above, the best-ranking regression model for Rhodium regression is the RANSAC Regressor with a test size of 10% of the training dataset and a random state of 74, whereas the best regression model for Ruthenium regression is the RANSAC Regressor with a test size of 10% of the training dataset at a random state of 31. Both regressor models are able to predict their target analyte with an accuracy, based on the average between MAE and RMSE, below the detection limits capable by the laboratories, which is 0.02 ppm for both analytes.

5.7 Regression Results on the Volspruit South Body MRE

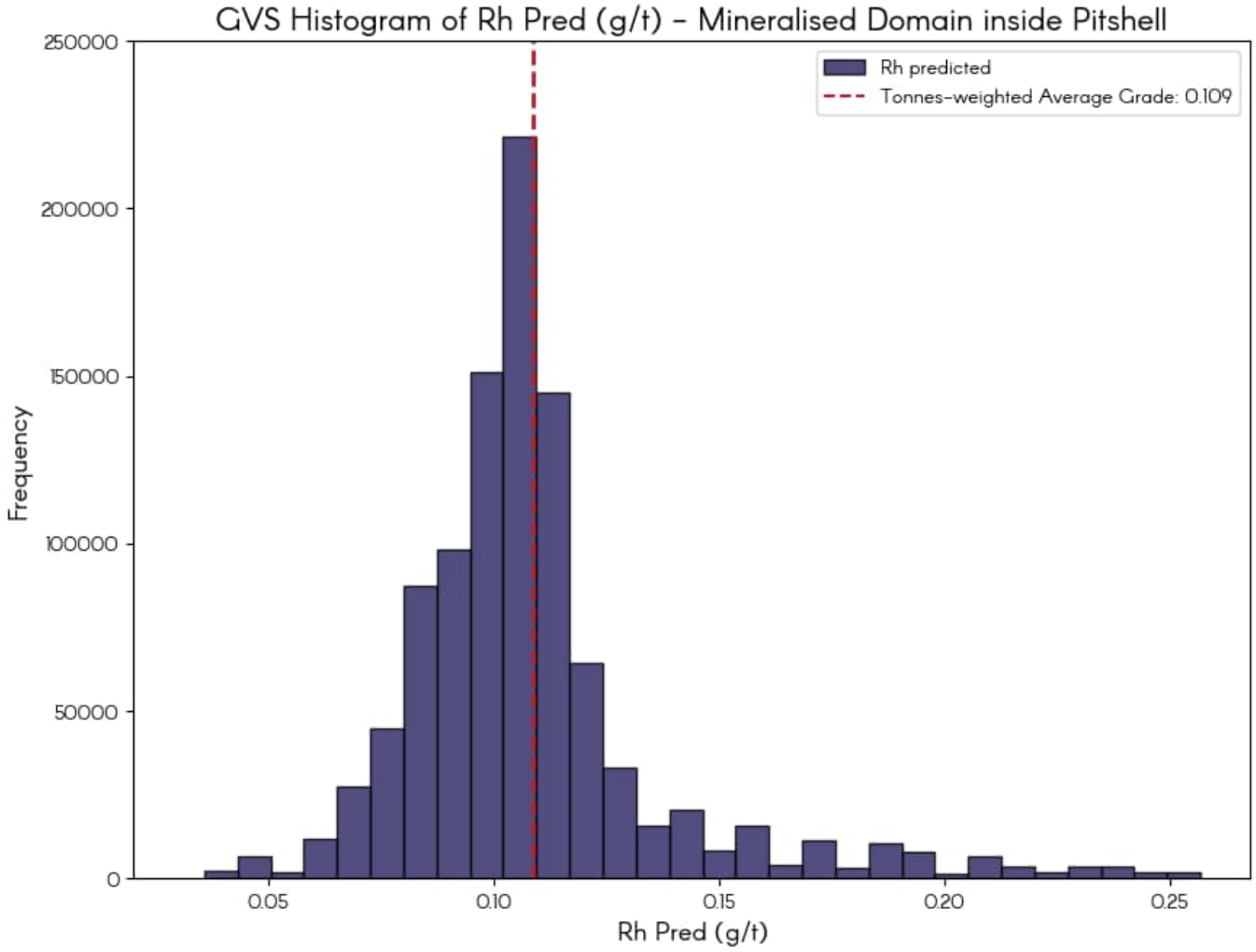

Figure 7. Histogram showing the distribution of predicted Rhodium concentrations within the block model.

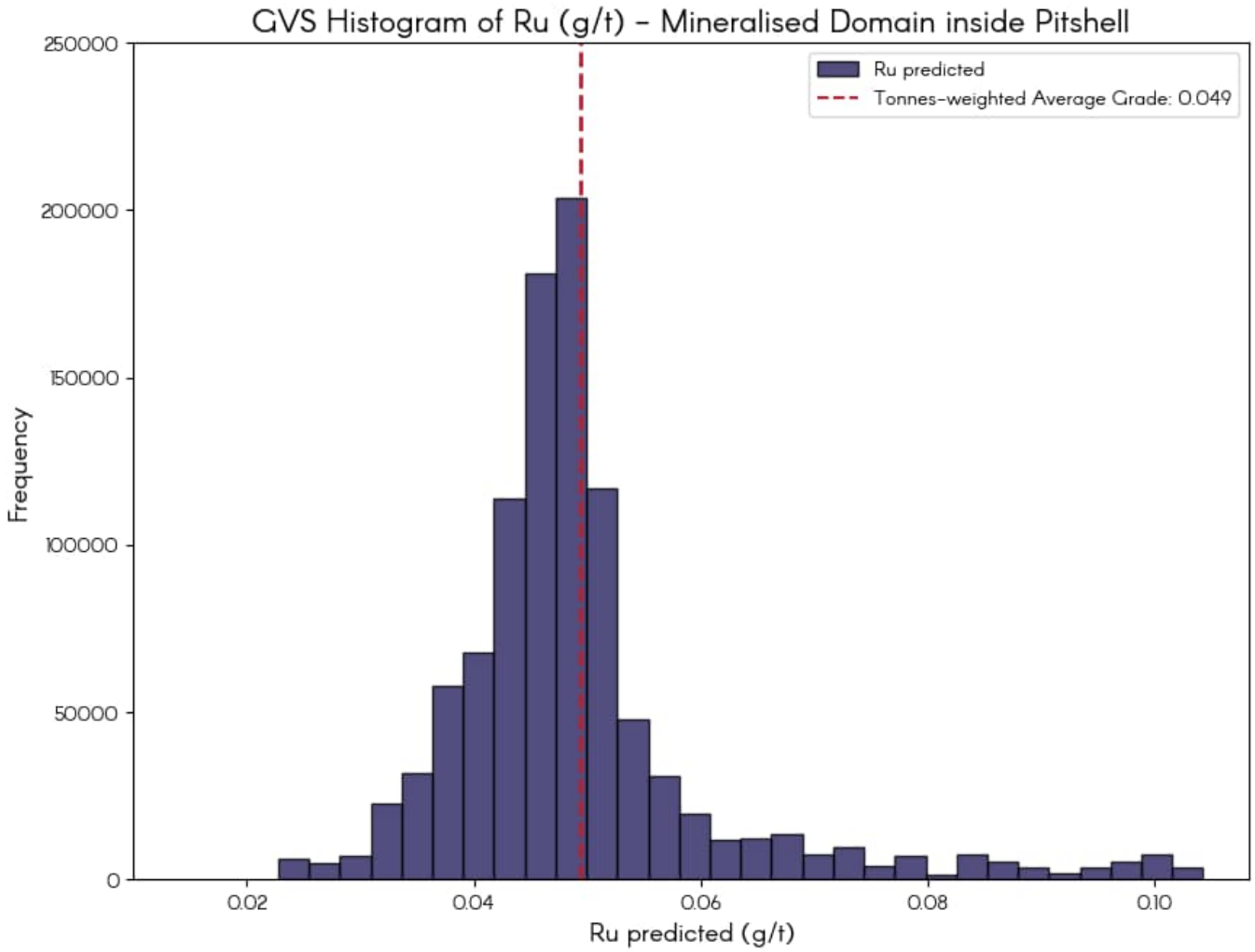

Figure 8. Histogram showing the distribution of predicted Ruthenium concentrations within the block model.

6 CONCLUSION

Earthlab has been successful in interpreting and defining the stratigraphic succession occurring in the Grassvalley South drill holes, during the detailed relogging campaign of the historical core. The Volspruit Reef is confined in the Cyclic Unit 11 Upper. These relogged drill holes were used to update the 2023 MRE technical report.

The five drill holes that were resampled were analysed for 5E and gold. These assay results were successfully used for Rh and Ru regression.

The regression application conducted on Rhodium (Rh) and Ruthenium (Ru) utilising Platinum (Pt), Palladium (Pd), and Gold (Au) as input variables has yielded highly successful results. Both regression models for Rh and Ru demonstrated exceptional performance, with Mean Absolute Errors (MAE) well below the laboratory's detection limit of 0.02 ppm. Specifically, the Rhodium model achieved a remarkable MAE of 0.0168 ppm, while the Ruthenium model exhibited an even lower MAE of 0.0079 ppm.