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The Influence of Aggregate Mineralogy and Chemical Properties on Imaging Based Morphological Shape Indices

--Manuscript Draft--

Full Title:	The Influence of Aggregate Mineralogy and Chemical Properties on Imaging Based Morphological Shape Indices
Abstract:	<p>Coarse aggregate sources must possess sufficient level of quality to meet both initial design as well as long-term and life-cycle performance requirements for pavement construction. Morphological shape properties, mineralogy, and chemical properties of the aggregate particles can significantly influence their quality and performance in terms of both durability and mechanical properties. As part of this study, a survey was sent out to different highway agencies to collect representative coarse aggregate samples as well as information regarding different practices used by them for morphological, petrographic, and chemical characterizations of aggregate sources. Morphology analysis using machine vision technology was incorporated to identify shape properties of the collected aggregate samples. Additionally, thin section optical petrographic analysis using an Axioscan 7 full slide scanner was utilized to identify mineral composition of the aggregates. Finally, chemical testing and analysis was conducted using Inductively Coupled Plasma Mass Spectrometry (ICP-MS) to detect major element compositions in epoxy impregnated sample of aggregate particles. Statistical analysis including Pearson correlation and multiple regression were deployed to investigate the relationship between the parameters representing mineralogy, chemical, and morphological shape properties. The findings of this study indicated 12 minerals and seven chemical elements with statistical significance to impact the imaging-based shape indices of aggregates. Subsequently, regression-based prediction models were developed to estimate the aggregate shape indices using mineralogy and chemical properties with a relatively satisfactory performance. The improvements in objectively characterizing aggregate chemical, mineralogical, and shape properties can be used to develop improved and sustainable aggregate production methods and specifications.</p>
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1 **The Influence of Aggregate Mineralogy and Chemical Properties**
2 **on Imaging Based Morphological Shape Indices**

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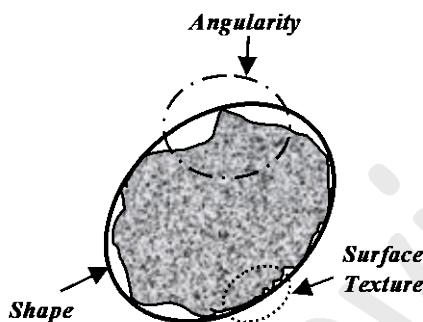
1 ABSTRACT

2 Coarse aggregate sources must possess sufficient level of quality to meet both initial design
3 as well as long-term and life-cycle performance requirements for pavement construction.
4 Morphological shape properties, mineralogy, and chemical properties of the aggregate
5 particles can significantly influence their quality and performance in terms of both durability
6 and mechanical properties. As part of this study, a survey was sent out to different highway
7 agencies to collect representative coarse aggregate samples as well as information regarding
8 different practices used by them for morphological, petrographic, and chemical
9 characterizations of aggregate sources. Morphology analysis using machine vision
10 technology was incorporated to identify shape properties of the collected aggregate samples.
11 Additionally, thin section optical petrographic analysis using an Axioscan 7 full slide scanner
12 was utilized to identify mineral composition of the aggregates. Finally, chemical testing and
13 analysis was conducted using Inductively Coupled Plasma Mass Spectrometry (ICP-MS) to
14 detect major element compositions in epoxy impregnated sample of aggregate particles.
15 Statistical analysis including Pearson correlation and multiple regression were deployed to
16 investigate the relationship between the parameters representing mineralogy, chemical, and
17 morphological shape properties. The findings of this study indicated 12 minerals and seven
18 chemical elements with statistical significance to impact the imaging-based shape indices of
19 aggregates. Subsequently, regression-based prediction models were developed to estimate the
20 aggregate shape indices using mineralogy and chemical properties with a relatively
21 satisfactory performance. The improvements in objectively characterizing aggregate
22 chemical, mineralogical, and shape properties can be used to develop improved and
23 sustainable aggregate production methods and specifications.

24 **Keywords:** Aggregates, Morphology, Petrography, Mineralogy, Angularity, Imaging

1 INTRODUCTION

2 Mineral aggregates are granular materials such as gravel, sand, and/or crushed stone
3 that are widely used as construction materials. Analysis of aggregate morphology,
4 mineralogy, and chemical composition is increasingly essential as aggregate continues to be
5 utilized for a myriad of applications. Coarse aggregates occupy by far the highest weight or
6 volume in both bound and unbound pavement layers. Key morphological or shape properties
7 of a coarse aggregate particle (see **Figure 1**) significantly affect the performance of the
8 unbound/bound layers of highway/airfield pavements as well as railroad ballast under the
9 traffic loading in terms of shear strength, modulus, and permanent deformation characteristics
10 (1-3).



21 **Figure 1 Key morphological or shape properties of a coarse aggregate particle (4)**

22 With the introduction of advanced machine vision technology in terms of both
23 software and hardware components, it is now possible to measure the shape properties of
24 aggregates in a quantitative and objective manner. AIMS (Aggregate Image Measurement
25 System) can be used as an objective and repeatable tool compared to the traditional visual
26 inspection methods to characterize aggregate shape properties (5).

27 Mechanical properties of aggregates vary widely. This variation can be attributed to
28 the variations in their petrographic characteristics, which can be measured through
29 microscope studies of thin sections. Petrographic thin section studies provide a reliable
30 forecast of the durability of rocks than a macroscopic study or a single mechanical test.
31 Especially in the exploration of rock sources for aggregate production, petrographic analysis
32 results can often be used to estimate aggregate quality without the need to conduct
33 mechanical tests. A research study by Raisanen (6) reported on how quantitative petrography
34 with optical microscopy could assist in aggregate quality estimation thus leading to
35 exploration of high-quality aggregate sources. The differences in aggregate mineralogy
36 determined from petrographic analyses were successfully used to interpret the results of
37 mechanical tests and establish their usefulness and validity. Eroğlu and Çalik (7) also
38 demonstrated a substantial relationship between the mechanical properties of aggregates and
39 their major mineral composition (plagioclase, quartz, and amphibole). Uniaxial compressive
40 strength, tensile strength, and Schmidt hardness tests all showed positive association with the
41 ratio of quartz to feldspar, and overall quartz content. Later, Kamani et al. (8) investigated the
42 effects of petrographic properties of carbonate aggregates on their engineering properties.
43 They concluded that opaque mineral contents and meso-scale porosity seemed to have a more
44 significant impact on the mechanical properties such as Los Angeles Abrasion Value
45 (LAAV), Aggregate Crushing Value (ACV), and magnesium Sulfate Soundness (SS). Wang
46 et al. (9) studied the influence of variation in Vertical Shaft Impactor (VSI) rotational speed
47 on shape properties of crushed granite particles. They used X-Ray diffraction analysis (XRD)
48 to identify the mineral composition of aggregates and AIMS to measure the shape properties
49

1 of the particles. They found that high content of quartz made granite aggregates perform well
2 in abrasion resistance and have a great distribution of angularity after VSI crushing.

3 McCann et al., (10) studied the relationship between aggregate physical and chemical
4 properties with the moisture sensitivity of aggregate-binder mixtures. Acid insolubility with
5 calcium content, silicon content, iron, aluminum, and potassium content as well as surface
6 area were found to impact moisture sensitivity of the mixtures. Later, Zhang et al., (11)
7 studied the effect of chemical composition on the properties of coarse aggregates. They found
8 that Al_2O_3 and SiO_2 can improve the properties of coarse aggregates, whereas CaO had a
9 negative effect on aggregate performance. They concluded that aggregates with higher Al_2O_3
10 and SiO_2 content can be selected for pavements with high strength requirements.

11 While there is a general understanding of the influence of aggregates' shape and
12 mineralogy on mechanical performance, the specifics including intercorrelation of the
13 mineralogical properties and their relation to shape indices have been still somewhat elusive.
14 A thorough study is needed to link morphological shape properties, mineralogy, and chemical
15 properties of aggregate sources as well as to the available performance data.

16 The primary goal in this research study was to analyze and catalogue physical shape,
17 mineralogical, and chemical properties of representative coarse aggregates used by different
18 North American highway agencies in pavement construction and to identify possible
19 relationships within those properties using statistical analysis techniques. Those petrographic
20 and/or chemical characteristics with significant correlations with shape properties are
21 considered the most useful predictive properties. The outcomes of this research have the
22 potential to assist in better understanding of material quality related aggregate type and
23 selection factors, providing more efficient and controlled rock crushing operations at the
24 quarries, and ultimately implementation in sustainable and cost-effective pavement
25 construction practices.

27 OBJECTIVE

28 The objective of this study is to establish linkage between three databases including
29 imaging-based shape indices, optical based mineral proportions, and percentage of major
30 concentration of chemical elements identified for representative coarse aggregates used by
31 North American transportation agencies.

33 DESCRIPTIONS OF TESTING AND DATA COLLECTION METHODS

34 Highway Agencies Survey and Aggregate Samples Collection

35 A questionnaire including four sections and 25 questions were distributed to 50 U.S.
36 State DOTs and 13 Canadian agencies. The goal of the questionnaire was to document
37 practices implemented by highway agencies to examine aggregate sources in terms of
38 physical shape, mineralogy, and chemical properties of aggregates. The response rate was
39 over 60% with 34 total agencies completing the survey from various regions across North
40 America, thereby ensuring a diverse representation from different regions.

41 Transportation agencies were asked to identify whether they check the morphological
42 properties of the aggregates used for pavement construction applications. The survey results
43 showed that 26 agencies characterize the physical shape properties of their aggregate sources.
44 Additionally, 22 agencies reported that they use manual/visual methods for morphological
45 characterizations while only four agencies use aggregate imaging systems for shape property
46 evaluations. The agencies were also requested to report whether they collect information
47 regarding the mineralogy and petrography of the aggregates. It was found that only 13 survey
48 respondents perform petrographic analysis on their aggregates sources to use for highway
49 constructions. Note that mineralogical composition may have a direct effect on the durability
50 of the aggregate, which might adversely affect the performance.

1 Coarse aggregate samples were requested from the surveyed agencies. Six agencies
 2 provided one or several 5-gallon buckets containing aggregate samples accompanied by basic
 3 descriptions of the samples. In total, 17 unique samples from six agencies were collected that
 4 are listed in **Table 1**. The descriptions for each letter assigned to individual samples are
 5 included at the bottom of **Table 1**. Note that the second sample from agency U4 included
 6 both sedimentary and metamorphic aggregates particles.

7

8 **TABLE 1 Inventory of the Aggregate Samples Collected from Different Agencies**

Agency Designation	Aggregate Sample ID
U1	GS1, GS2, GS3, GM4
U2	HM2, HM3, HM4, HM5, HM7
U3	JS1, JS2
U4	KM1, KSM2
U5	LS1, LS2, LS3
C1	PM1

*Notes:
U: Sample collected from a U.S. DOT
C: Sample collected from a Canadian Province
S: Sedimentary rock
M: Metamorphic rock
G, H, J, L, P: Sample unique letter corresponding to each agency

9

10 **Aggregate Morphological Characterization Using AIMS**

11 All the aggregate samples were fractionated into different particle sizes using 1.0 in.
 12 (25.4 mm), 0.75 in. (19.0 mm), 0.5 in. (12.7 mm), 0.375 in. (9.5 mm), 0.25 in. (6.35 mm),
 13 and No. 4 (4.75 mm) sieves. Two trials from each source including approximately 50
 14 aggregate particles from each sieve size were scanned. The AIMS performed image analysis
 15 on the grains of each sample, enabling the determination of angularity, surface texture, and
 16 Flatness & Elongation (F&E Ratio). Particle sizes available in each aggregate sample that
 17 were scanned using AIMS are marked with a cross sign in **Table 2**.

18 According to ASTM D4791 (12), the F&E Ratio of an aggregate particle is defined as
 19 the ratio of the maximum dimension to the minimum dimension of a particle. Projections of a
 20 particle placed on the lighting table are captured by the camera in AIMS and used to generate
 21 the binary image. Eigenvector analysis (13) on the binary images identifies the major and
 22 minor axes of the particle. The third dimension or depth of a particle is measured by
 23 determining the distance between the camera's lens and surface of particle relative to the
 24 original location of the camera. Gradient method is used as the image processing technique
 25 for angularity measurements. The gradient method starts by calculating the inclination of
 26 gradient vectors on particle boundary points from the x-axis (horizontal axis in an image).
 27 The average change in the inclination of the gradient vectors is considered as an indicator of
 28 angularity and can be calculated using **Equation 1** (14).

29

30
$$\text{Angularity Index} = \frac{1}{N-1} \sum_{i=1}^{N-3} |\theta_i - \theta_{i+3}| \quad (1)$$

31 where subscript i denotes the i^{th} point on the boundary of a particle and N is the total number
 32 of points on the boundary. The average rather than the summation is considered in **Equation**
 33 **1** so that the angularity calculation is not biased by particle size. The step size used in

1 calculating gradients is 3 since it minimizes the effect of noise created during image
 2 acquisition on the results (15). Note that the angularity index can have a numerical value
 3 between 0 to 10,000.

4

5 **TABLE 2 Particles Sizes Available in Each Aggregate Sample Scanned Using AIMS**

Aggregate Sample ID	Particle Sizes (inch) or Sieve No.					
	1	0.75	0.5	0.325	0.25	No.4
GS1		×	×	×	×	
GS2		×	×	×	×	
GS3					×	
GM4			×	×	×	
HM2		×	×	×		
HM3					×	×
HM4	×	×	×	×		
HM5					×	×
HM7			×	×		×
JS1			×	×	×	
JS2			×	×	×	
KM1			×	×	×	
KSM2			×	×	×	
LS1					×	×
LS2						×
LS3						×
PM1			×	×		

6

7 Surface texture is measured using the wavelet technique. Texture details are identified
 8 in the horizontal, vertical, and diagonal directions in three separate images. Finally, the
 9 texture index at the desired decomposition level is considered as the arithmetic mean of the
 10 squared values of the wavelet coefficients for all three directions. **Equation 2** is used for
 11 texture analysis (15). Note that the texture index can have a numerical value between 0 to
 12 1,000.

13
$$Texture\ Index = \frac{1}{3N} \sum_{i=1}^3 \sum_{j=1}^N [D_{ij}(x, y)]^2 \quad (2)$$

14 where,

15 N = number of coefficients;

16 $i = 1, 2, 3$ for the three directions of texture;

17 j = wavelet coefficient index; and

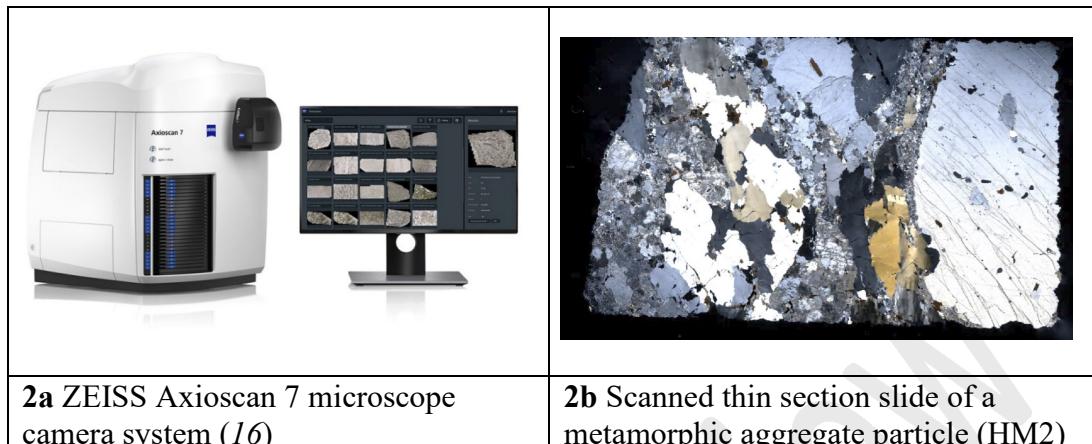
18 D = wavelet coefficient.

19

20 Petrographic Characterization Using Axioscan 7 Full Slide Scanner

21 1 in. by 2 in. (25 mm by 50 mm) thin section slides with microprobe polishing of
 22 randomly selected particles from each aggregate source were prepared. In total 48 thin
 23 section slides were prepared from 17 aggregate sources listed in **Table 1**. The entire surface
 24 of each slide was scanned using ZEISS Axioscan 7 microscope camera system (See **Figure**
 25 **2a**) located at Kansas State University. This device allows for complete petrographic
 26 information to be digitized across entire samples which provides full replication of the
 27 petrographic microscope within a digital environment. Multi-channel and multi-polarized
 28 petrographic data can be visualized using the ZEN blue poll viewer with capability for

1 switching between brightfield, plain polarization, circular polarization, and crossed
 2 polarization data channels (16). **Figure 2b** shows an example scan of a thin section slide
 3 prepared from a metamorphic aggregate particle in HM2 aggregate source.



4 **Figure 2 Axioscan 7 slide scanner with an example of a scanned aggregate thin section**
 5

6 The images of each scanned slide were manually analyzed using point counting
 7 method to provide precise mineral composition information for each slide. Point counting is a
 8 method for estimating the composition of rocks, based on identifying the mineral or grain
 9 present at a large number (usually 300 to 500) of points in a petrographic slide (17). The
 10 petrographic microscope was capable of accurately identifying 27 different minerals, all of
 11 which were identified in at least some of the samples. The rock type, e.g., sedimentary,
 12 igneous, or metamorphic were also identified. The results of the petrographic analysis are
 13 presented later in this paper.

14

15 Chemical Characterization Using Inductively Coupled Plasma-Mass Spectrometer 16 (ICP-MS)

17 ICP-MS is a type of mass spectrometry that uses an inductively coupled plasma to
 18 ionize the sample. This device atomizes the sample and creates atomic and small polyatomic
 19 ions, which are then detected. ICP-MS equipment (see **Figure 3a**) in Geology department at
 20 the University of Illinois-Urbana was used to test 48 epoxy impregnated aggregate particles
 21 (see **Figure 3c**) corresponding to each thin section to identify chemical elements. Laser
 22 sampling technique was performed using a GeoLas 2005 System (see **Figure 3b**). The laser-
 23 generated aerosol containing aggregate powder was transported from the ablation cell to the
 24 ICP-MS instrument using a transfer tube with an internal diameter of 3.0 mm. Detailed
 25 operating conditions for the laser and the ICP-MS instrument can be found elsewhere (18).
 26 The outcome of ICP-MS was a large dataset of elemental compositions for each aggregate
 27 source.

28

29 DATA ANALYSIS RESULTS AND DISCUSSIONS

30 **Figure 4** presents the morphological shape property results. The results show that the
 31 average angularity values vary in the range of 2172 to 3341, the average surface texture
 32 values vary between 172 and 551, and the F&E Ratios are between 2 and 3.95. Note that
 33 relatively low standard deviation values were recorded which verifies that the morphological
 34 data are clustered around the mean. **Figure 4a** and **4b** show that relatively higher variations
 35 were recorded for angularity and surface textures compared to F&E Ratio which can be
 36 attributed to variations in the size of scanned aggregate particles.

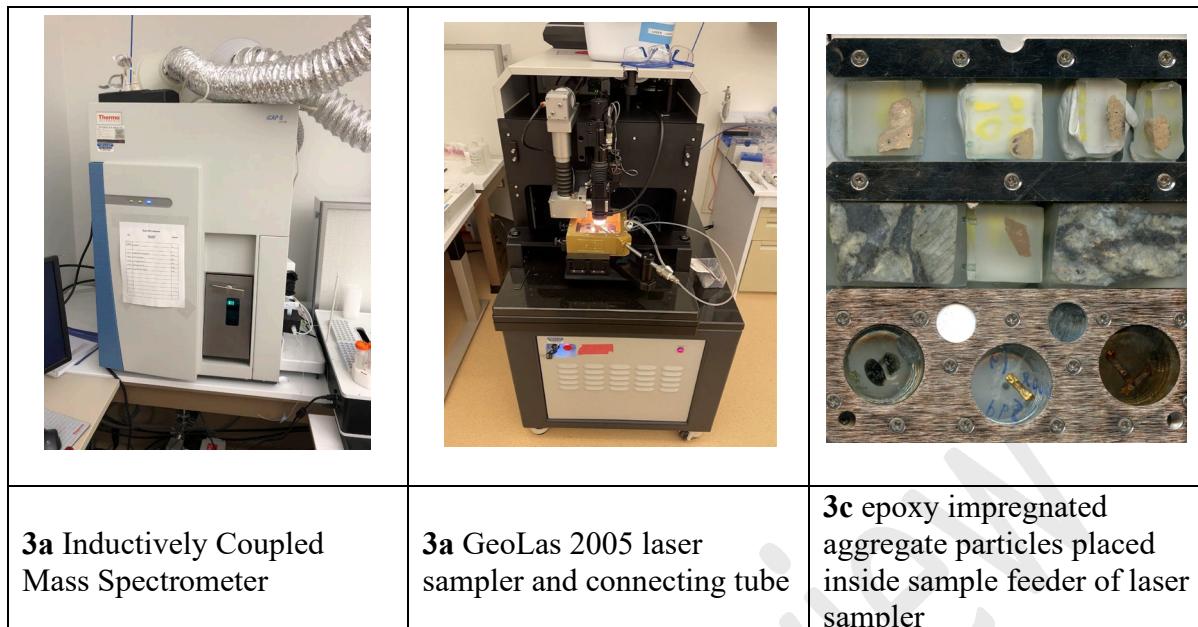
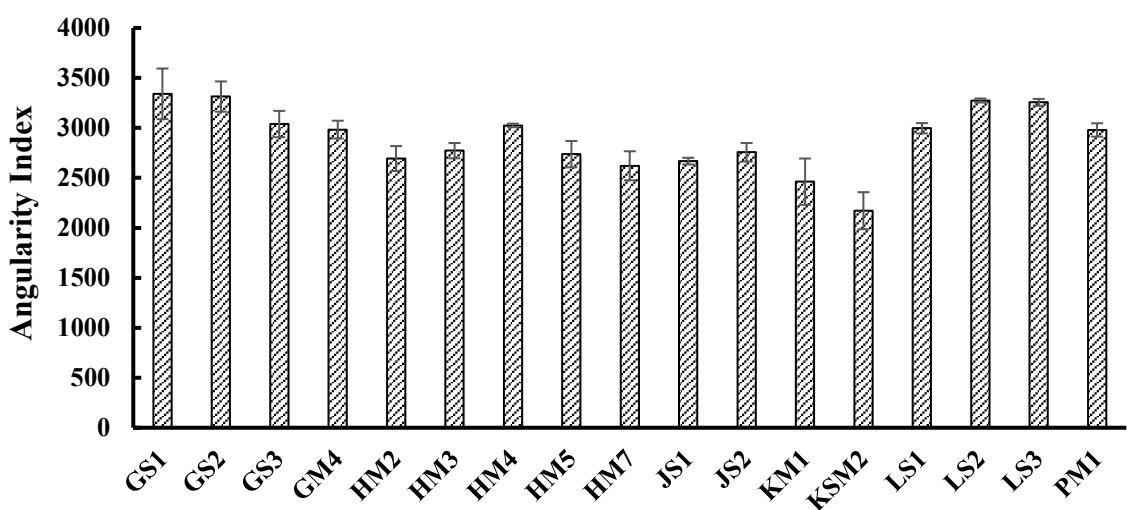


Figure 3 Illustration of ICP-MS, laser sampling, and epoxy impregnated aggregate samples

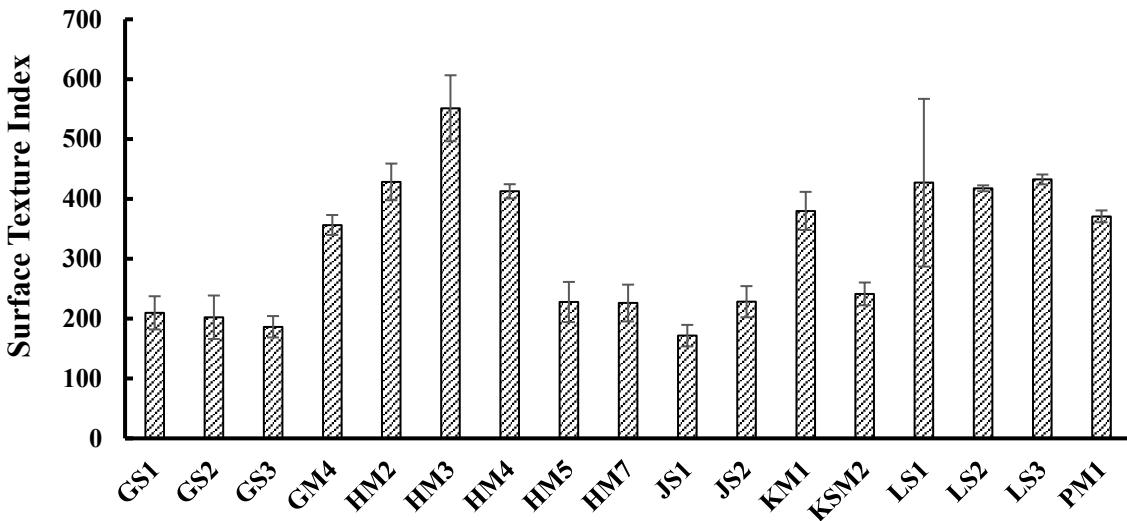
Petrographic analysis results are presented in **Table 3**. In total 27 different minerals were identified. The mineralogy composition showed that the Quartz, Calcite, Plagioclase as well as Orthoclase were found in most of the samples. Only GS3 sample was found to have Peloids while Albite and Clinopyroxene were present in KM1 aggregate sample. JS1 and LS3 samples were found to have homogeneous minerals with only two minerals detected in each.

Figure 5 presents the chemical analysis results. ICP-MS detected 9 elements in the aggregate samples. As expected, Calcium and Silicon were the two governing elements in the aggregate samples. Aluminum and Magnesium were the other two elements which were detected in relatively higher percentages. Phosphorus and Titanium were the two elements with the lowest concentrations in the samples.

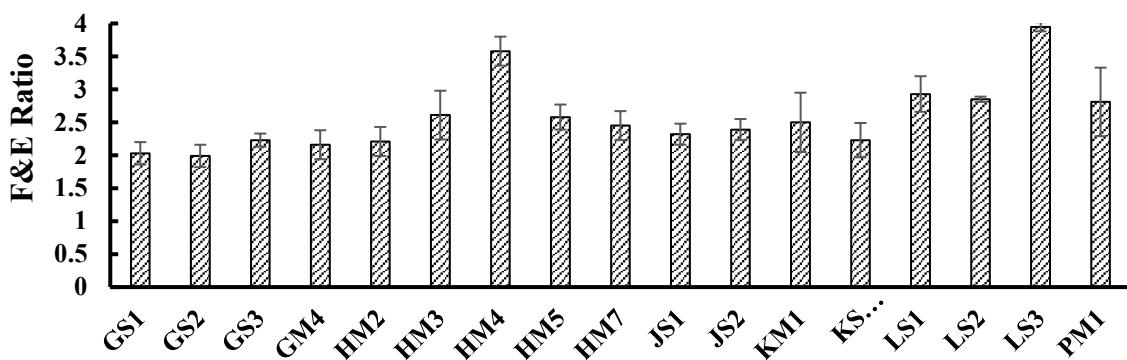
The petrographic, chemical, and morphological data were amalgamated into a unified master data file. A matrix of computed relationships was generated to identify possible data relationships that may exist for further study that compared across morphology, petrography, and chemistry of the samples. A Pearson correlation analysis was performed using SPSS software (19) to identify the strength and direction of the linear relationship between different variables. Particularly, the influence of percentages of various minerals and chemical elements on the three main morphological shape indices were investigated. Note that the rock type and the sizes of particles were also considered an independent variable in the analysis. Statistically significant variables which had *p*-values (2-tailed) less than 0.05 for at least two of the shape indices were identified. Additionally, the Pearson Correlation Coefficients (PCC) were obtained and reported for the variables (see **Table 4**). In total six elements and 12 mineral types in addition to the rock type were found to be statistically significant variables impacting at least two of the imaging-based shape indices.



4a Variation of angularity values for aggregate samples scanned with AIMS



4b Variation of surface texture values for aggregate samples scanned with AIMS



4c Variations of F&E Ratio for aggregate samples scanned with AIMS

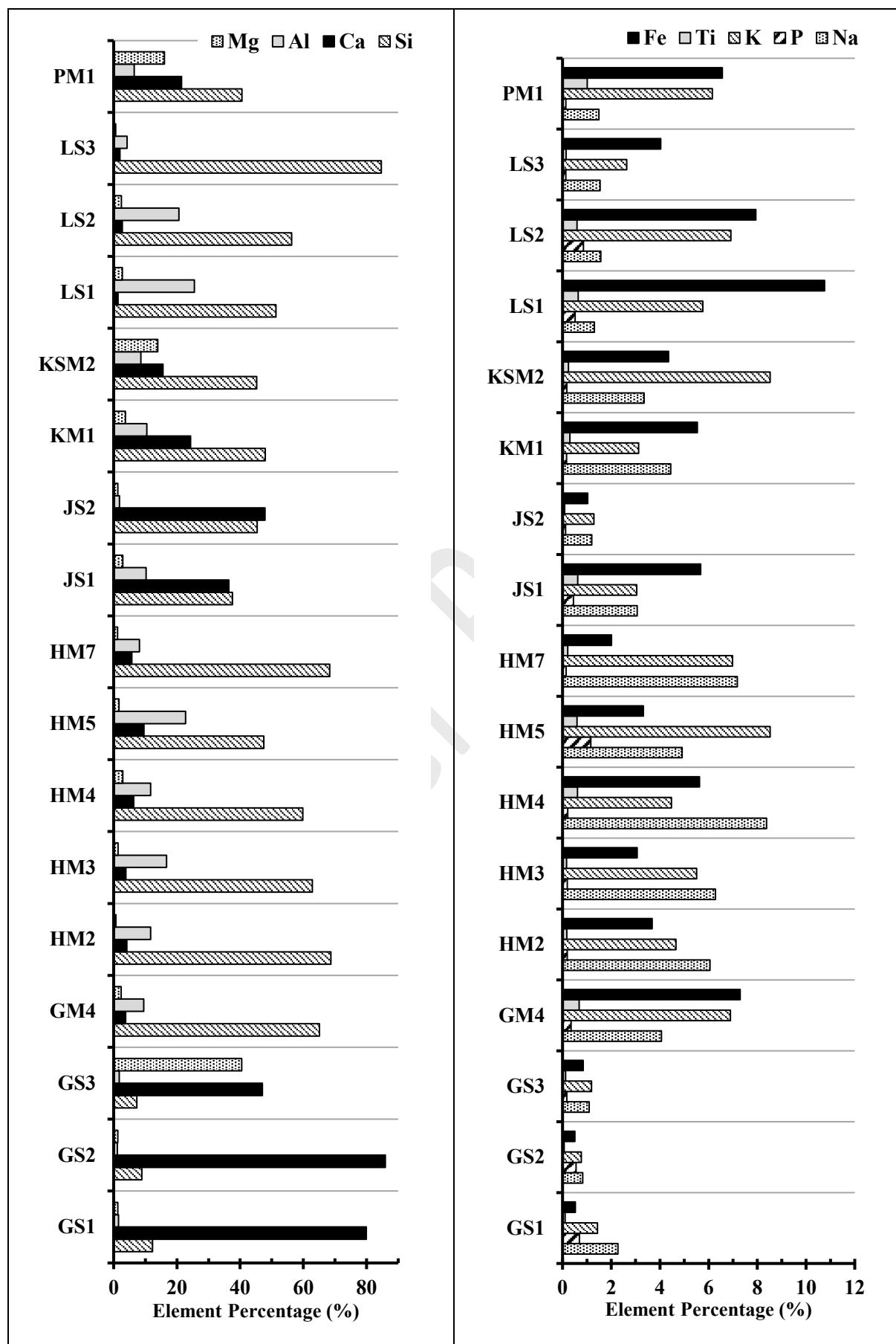
Figure 4 Morphological shape property indices measured with AIMS

1

TABLE 3 Petrographic Analysis Results Obtained from Scanned Aggregate Thin Section with Axioscan 7

Mineral Name	Percentages of Minerals in Each Aggregate Sample (%)																
	GS1	GS2	GS3	GM4	HM2	HM3	HM4	HM5	HM7	JS1	JS2	KM1	KSM2	LS1	LS2	LS3	PM1
Quartz	12.32	28.15	-	24.99	35.00	60.84	48.17	28.84	54.34	6.00	20.33	45.94	26.44	35.33	36.70	90.67	31.00
Calcite	33.78	34.79	76.45	-	1.67	0.33	-	-	-	94.00	53.84	4.00	55.17	38.34	10.14	-	56.67
Bioclasts	10.72	6.30	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Pores	5.90	3.44	8.66	-	-	-	0.33	-	-	-	-	-	-	-	-	-	-
Carbonate mud	38.82	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Plagioclase	0.33	0.33	-	49.51	4.00	2.33	9.84	13.67	8.00	-	-	30.31	18.34	-	-	-	2.67
Orthoclase	12.36	0.50	-	63.50	30.00	45.33	18.67	-	27.17	-	-	1.66	9.67	-	-	-	-
Opal	0.66	1.31	-	-	-	-	-	-	-	-	-	-	-	25.67	-	-	-
Micrite	23.48	26.35	44.81	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Microcline	0.32	-	-	-	-	-	-	-	10.17	-	-	0.50	18.67	-	-	-	-
Sulfides	-	-	-	11.15	-	-	-	-	-	-	-	2.67	-	-	-	-	-
Epidote	-	-	-	-	-	-	-	-	-	-	-	2.67	-	-	-	-	-
Peloids	-	-	1.66	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Pyroxene	-	-	-	20.98	-	-	-	-	-	-	-	-	-	-	-	-	-
Olivine	-	-	-	1.97	-	-	-	-	-	-	-	-	-	-	-	-	-
Chlorite	-	-	-	4.53	-	-	0.33	-	0.33	-	-	0.33	-	-	-	-	-
Oxides	-	-	-	3.34	-	-	-	-	-	-	-	-	1.33	-	-	9.33	-
K-Feldspar	-	-	-	56.33	11.00	7.33	-	78.00	1.33	-	-	48.33	-	-	-	-	4.67
Opaque	-	-	-	8.33	0.67	1.17	1.67	-	-	-	-	-	-	-	-	1.82	-
Sericite	-	-	-	-	11.67	3.00	-	-	-	-	-	7.78	-	-	-	-	-
Hornblende	-	-	-	-	5.00	4.67	0.33	-	-	-	-	-	-	-	-	-	-
Muscovite	-	-	-	-	-	11.67	1.67	23.34	0.33	-	16.00	3.67	0.67	15.17	-	-	-
Biotite	-	-	-	-	-	-	19.33	-	3.34	-	-	5.99	7.50	16.00	39.37	-	-
Garnet	-	-	-	-	1.00	1.33	2.00	4.00	-	-	-	-	-	-	-	-	-
Chalcedony	-	-	-	-	-	-	-	-	-	-	20.00	-	-	-	11.98	-	-
Albite	-	-	-	-	-	-	-	-	-	-	-	3.67	-	-	-	-	-
Clinopyroxene	-	-	-	-	-	-	-	-	-	-	-	39.33	-	-	-	-	-

2



1

TABLE 4 Pearson Correlation Analysis Results

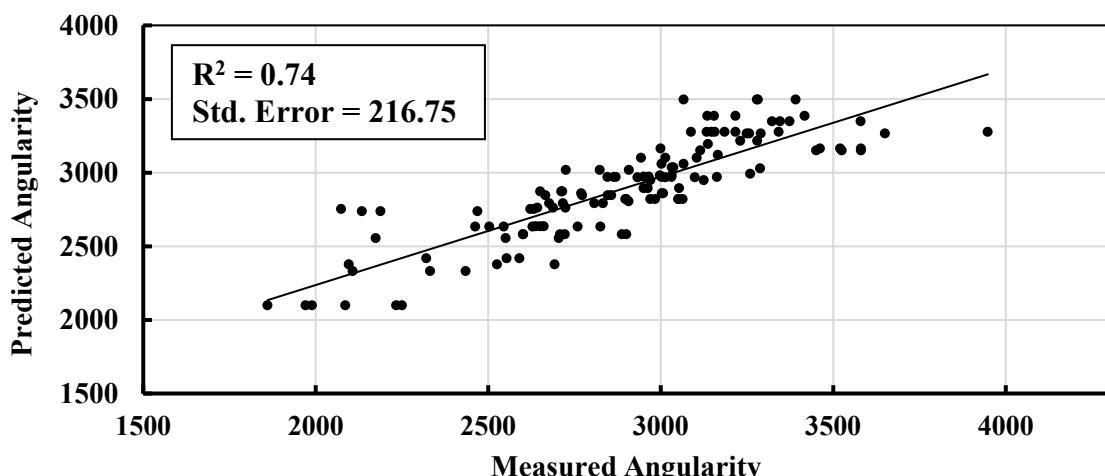
Variable	Angularity Index		Surface Texture Index		F&E Ratio	
	p-value	*PCC	p-value	PCC	p-value	PCC
Silicon (Si)	0	-0.429	0	0.483	0	0.368
Sodium (Na)	0.001	-0.282	0	0.422	0.027	0.194
Aluminum (Al)	0.001	-0.298	0	0.534	0	0.489
Potassium (K)	0	-0.487	0.01	0.224	0.004	0.253
Calcium (Ca)	0	0.506	0	-0.452	0	-0.434
Iron (Fe)	0.006	-0.238	0	0.393	0.012	0.219
Quartz	0.02	-0.111	0	0.333	0	0.341
Bioclasts	0	0.458	0	-0.341	0	-0.337
Pores	0	0.437	0	-0.354	0	-0.295
Carbonate mud	0.003	0.255	0.045	-0.0176	0.043	-0.178
Micrite	0	0.363	0	-0.340	0	-0.279
Calcite	0.398	0.075	0	-0.444	0.034	-0.186
Plagioclase	0	-0.387	0.001	0.288	0.571	0.050
Microcline	0	-0.558	0.014	-0.215	0.662	-0.039
Epidote	0.002	-0.275	0.036	0.184	0.397	0.075
K-Feldspar	0.870	-0.015	0.009	0.227	0.027	0.194
Biotite	0.047	-0.174	0	0.423	0.018	0.208
Garnet	0.730	0.031	0	0.379	0.001	0.291
Rock type	0	-0.498	0	0.524	0	0.240

2 *PCC: Pearson Correlation Coefficient

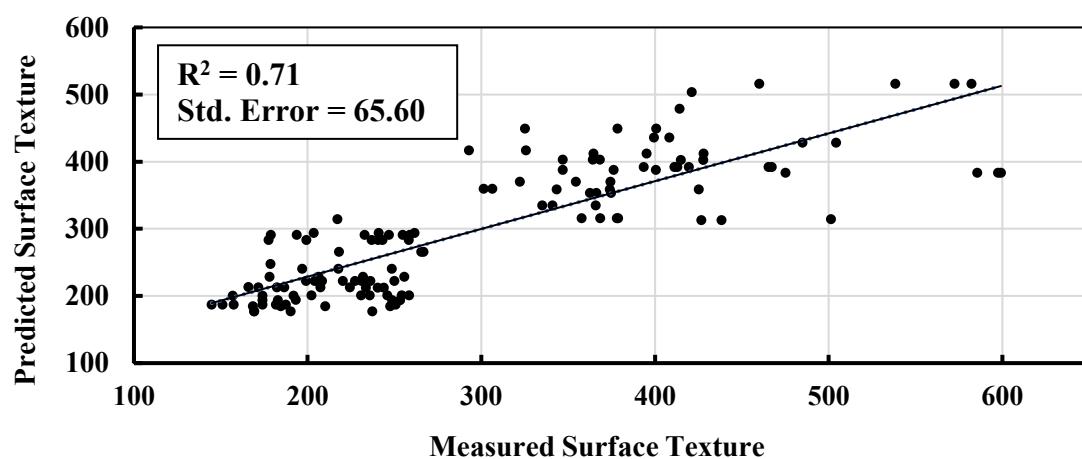
3

4 According to **Table 4**, the variables with PCC between ± 0.30 and ± 0.49 , show
 5 medium correlations on shape indices. When PCC values lie below ± 0.29 , it is an indicator
 6 of a small correlation. Note that Calcium, Microcline, Plagioclase, and rock type were among
 7 the variables that showed high degree of correlation since their corresponding PCC lies
 8 between ± 0.50 and ± 1 .

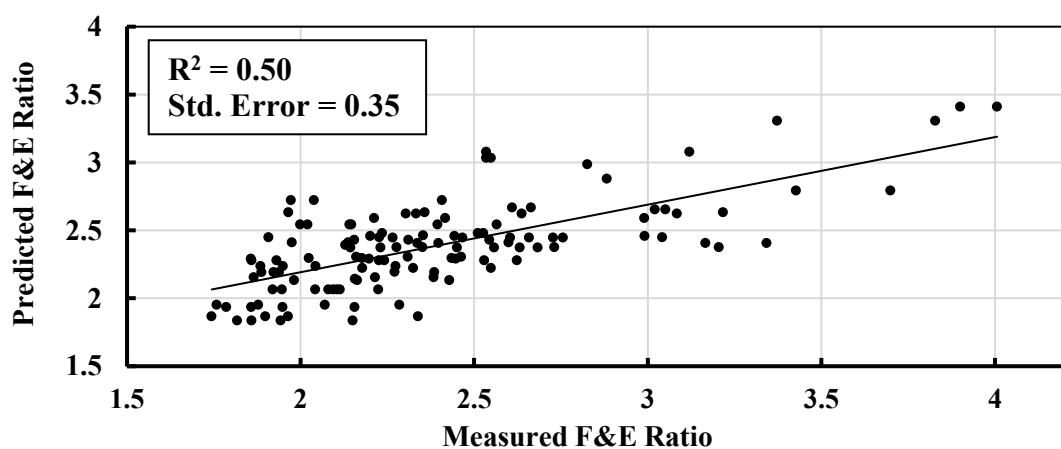
9 Using the variables that were marked significant in Pearson correlation analysis,
 10 multiple regression analysis was performed to develop models for predicting the imaging-
 11 based shape indices. Considering the sub-samples for each aggregate source as well as the thin
 12 section slides and epoxy impregnated particles that were prepared corresponding to each
 13 aggregate source, a total of 130 data points were compiled to be used in regression analysis.
 14 The results of the regression analysis, including model performance indicators for angularity
 15 index, surface texture index as well as F&E Ratio are presented in **Figure 6**. Higher
 16 coefficient of determination (R^2) values achieved for the angularity index and surface texture
 17 index prediction models compared to F&E Ratio model. This can be related to the fact that
 18 most of the particle sizes that were used in this study were 0.5 in. (12.7 mm) or smaller.
 19 Therefore, the variation of F&E Ratio is less pronounced which could affect the performance
 20 of the regression model. Nevertheless, additional data points including a larger variation of
 21 particle sizes and aggregate types is required to verify this hypothesis. Ultimately, the
 22 regression analysis shows promising results to estimate the morphological shape indices
 23 based on the mineralogy and chemical composition of the aggregate samples. Note that the
 24 database that was used in this study only included sedimentary and metamorphic rock types.
 25 Establishing a larger database including additional rock types/sizes might improve the
 26 accuracy of the prediction models.



6a Angularity index regression based prediction model



6b Surface texture index regression based prediction model



6c F&E Ratio regression based prediction model

Figure 6 Regression based models for predicting aggregate morphological shape indices based on minerals and chemical compositions

1 SUMMARY AND CONCLUSIONS

2 This study focused on investigating the influence of mineralogy and chemical
3 properties on morphological shape indices of 16 construction aggregates sources collected
4 from different North American highway agencies. The following conclusions can be drawn
5 within the scope of this study:

- 6 • A questionnaire was sent to U.S. State DOTs and Canadian agencies to document
7 their practices implemented for examining aggregate sources. The findings from the
8 survey indicated that 67% of agencies construct pavement layers with aggregate
9 materials without checking aggregate geology requirements. Moreover, only 4
10 agencies indicated that they use aggregate imaging systems for shape property
11 evaluations.
- 12 • A database of morphological shape indices including angularity index, surface texture
13 index and F&E Ratio for different collected aggregate sources/sizes were established
14 using AIMS aggregate imaging system.
- 15 • The Axioscan 7 high-performance full slide scanner was found to be an effective tool
16 for optical mineralogy catheterization and was used to scan 48 thin section slides
17 prepared from aggregate sources. 27 different mineral proportions were detected
18 using the point counting method. Quartz, Calcite, Plagioclase, and Orthoclase were
19 found in most of the aggregate samples.
- 20 • Inductively Coupled Plasma Mass Spectrometry (ICP-MS) was used to perform
21 chemical analysis and successfully identified trace amounts and major concentrations
22 of chemical elements on epoxy impregnated aggregate particles. Nine different
23 elements were detected with Calcium and Silicon as the two governing elements.
- 24 • Pearson correlation and multiple regression analysis were performed to find possible
25 influence of mineralogy and chemical properties on imaging-based shape indices.
26 Different variables including 12 minerals, six chemical elements as well as rock type
27 were found to be statistically significant variables impacting particle shape indices.
28 Three regression-based prediction models were developed with promising
29 performance to estimate shape properties of aggregate particularly angularity and
30 surface texture using mineralogy and chemical properties.

31 Further research is required to establish a comprehensive database of different
32 aggregate sources with broader variation of mineralogy, chemical composition, rock types,
33 and particle sizes. This larger database will provide the opportunity for better understanding
34 of the relationship between mineralogy, chemical and shape indices. The outcomes of this
35 research can be used as a quality control tool for aggregate industry to improve the aggregate
36 production practices and rock selection factors and can be implemented towards sustainable
37 and cost-effective utilization of aggregates in pavement design and construction.

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1 **AUTHOR CONTRIBUTIONS**

2 The authors confirm contribution to the paper as follows: study conception and design:
3 Maziar Moaveni, Craig Lundstrom; data collection: Maziar Moaveni, Brice Lacroix, Craig
4 Lundstrom; analysis and interpretation of results: Maziar Moaveni, Brice Lacroix, Craig
5 Lundstrom, Miles Wilford; draft manuscript preparation: Maziar Moaveni, Miles Wilford,
6 Akili Gonzales. All authors reviewed the results and approved the final version of the
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