


Cite this: *Nanoscale*, 2026, **18**, 20774

Exploring the potential of image feature extraction for catalyst layer characterization

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The progress of energy conversion devices such as fuel cells or electrolyzers is critical for integration of green hydrogen into the energy system. However, the catalyst layer (CL) poses a significant challenge to both technologies as their performance and durability depend on the nature of the CL produced. In most studies, the CL structure remains unknown or is presented superficially. Methods to access and quantify the CL structure are limited but necessary to enable advanced CL architectures, such as low iridium loadings in polymer electrolyte membrane water electrolysis (PEMWE). The path to progress involves advancing our understanding of the production–structure–property triangle (PSPT) for the CL. Proper implementation of quality control measures can lead to reduced production costs and increased longevity of the technologies. The objective of this study is to investigate the production–structure relationship by analyzing the impact of different production variables on the formed structure and quantifying the physical characteristics of CLs. The fabrication of CLs involved the use of an ultrasonic spray coater, with an in-depth exploration of different machine parameters. A confocal laser scanning microscope is used to analyze the produced CLs to obtain surface texture parameters (STPs) corresponding to a microscopy image. Additionally, image features (IFs) were extracted from the obtained images by using the *PyRadiomics* library. Correlation between the STPs and IFs is evaluated with Pearson correlation. Analysis of 89 CLs and 443 microscopy images showed that the 19 standardized STPs reduce to three non-redundant descriptors, each of which is reproduced by a specific image feature, yielding a compact and instrument-independent parameter set for CL quality control.

Received 25th March 2026,
Accepted 1st September 2026

DOI: 10.1039/d6nr01185c

rsc.li/nanoscale

Introduction

The large scale deployment of proton exchange membrane water electrolyzers (PEMWE) and fuel cells requires reliable, industrially scalable fabrication of catalyst layers (CLs).^{1–3} The structure of the CL critically determines performance, durability, and material utilization, particularly under the constraint of reduced iridium loadings.^{4–11} As catalyst loadings decrease, the sensitivity of device performance to structural inhomogeneities increases, making precise control and monitoring of CL morphology essential for manufacturing at scale.^{12–15} Several studies emphasized the importance of

understanding how electrolyzer durability relates to catalyst integration, CL formation, and operational behavior. Consequently, manufacturing technologies such as laboratory-scale ultrasonic spray coating,^{16–18} must be evaluated alongside approaches more relevant for industrial production, including slot-die coating^{19–21} or inkjet printing.^{22,23}

The CL structure forms during deposition and drying, and the resulting architecture spans multiple length scales, from macroscopic features such as porosity and ionomer distribution to microscopic characteristics including catalyst–ionomer interactions and surface functionalities.^{7,24,25} Microscopy techniques, such as scanning electron microscopy (SEM) or transmission electron microscopy (TEM) provide valuable insight into particle morphology^{26–28} and agglomeration but rarely yield standardized, quantitative descriptors of the overall layer architecture.

Advanced image analysis approaches attempt to extract structural information automatically using segmentation algorithms and pattern recognition techniques.^{6,29–31} These methods, however, require sufficient contrast between the different components of the image. Image processing techniques such as thresholding, edge detection, and segmenta-

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tion strongly depend on contrast to distinguishing features of interest from the background. Artificial contrast enhancement can introduce additional uncertainties, particularly for fine textures where image manipulation may lead to information loss.^{6,32}

Another challenge arises from the inherent structural complexity of CLs. They typically consist of densely packed particles with broad size distributions, irregular agglomerates, overlapping domains, pores, and multi-component regions composed of catalyst particles, supports, and ionomer. This structural density complicates the identification of meaningful geometric descriptors using conventional microscopy analysis. As a result, many studies focus on isolated particles or agglomerates rather than capturing the architecture of the entire CL. Consequently, alternative approaches for describing the appearance or texture of the CL are required.

Texture represents a fundamental characteristic of surface appearance and is closely linked to functional properties such as contact behavior, friction, and adhesion.^{32–35} In general, surface texture describes the periodic or non-periodic variation of patterns around a reference surface. Various techniques exist for assessing surface texture, including atomic force microscopy, confocal laser scanning microscopy (CLSM), SEM, and charge-coupled device imaging systems.^{36,37} While profile-based surface texture parameters (2D) have been widely used, increasing attention has been directed towards areal surface texture parameters (3D) for investigating functional relationships.^{38,39} These parameters are standardized in ISO 25178. However, selecting the most relevant descriptors remains challenging because the significance of individual parameters depends strongly on the investigated system and application.

An alternative perspective originates from computational image processing, where textures are classified into first-order and higher-order statistical features. First-order (FO) texture describes the distribution of grey-level intensities and is typically characterized by statistical measures such as variance, skewness, or kurtosis.⁴⁰ These image features provide information about intensity distributions but do not capture spatial relationships within the image.^{32,40,41} Higher-order texture descriptors quantify spatial relationships between pixels and are commonly derived from statistical matrices representing pixel intensity combinations.

One of the most influential approaches in this field is the gray-level co-occurrence matrix (GLCM), introduced by Haralick *et al.*⁴² This method enables the extraction of statistical descriptors that characterize spatial intensity relationships within images and has had a profound impact on quantitative texture analysis, accumulating more than 30 000 citations by 2025.^{42,43} Beyond GLCM, several additional methods have been developed, including the gray-level run length matrix (GLRLM),⁴⁴ gray-level size zone matrix (GLSZM),⁴⁵ neighboring gray tone difference matrix (NGTDM),⁴⁶ and gray-level dependency matrix (GLDM).⁴⁷ These techniques have been applied across diverse research areas, including terrain^{48–50} or cell classification,^{45,51,52} visual perception studies,^{53–56} paleography,^{57,58} and tool condition monitoring.^{59–61} In recent

years, the medical field has particularly advanced these methods within radiomics, where high-throughput imaging features are used for cancer detection.^{32,62–67}

An early application of statistical image analysis in electrochemistry was reported by Artyushkova *et al.* in 2012, who investigated the structure–property relationships of electrocatalysts using microscopy images.⁶⁸ In this work, SEM images were analyzed by calculating roughness, skewness, and four GLCM features (homogeneity, contrast, correlation, and angular second moment) to characterize catalyst morphology. These four features are among those originally proposed by Haralick *et al.*⁴² and were commonly used before a broader range of texture features became accessible and their definitions were standardized. Subsequent studies applied similar approaches to investigate carbon corrosion behavior and catalyst layer structures in PEM fuel cells.^{69,70} Advances in computational power and the growing availability of open-source analysis tools have significantly expanded the possibilities for extracting structural descriptors from microscopy images. Such descriptors enable access to the production–structure–property triangle (PSPT), where production parameters, structural characteristics, and functional properties are interconnected. In this framework, each corner represents one domain, while the edges describe the relationships between them. The present work focuses on the production–structure relationship. Establishing which structural descriptors are non-redundant and how they respond to fabrication variables is a prerequisite for relating structure to device behavior, since a descriptor set that is redundant or unreproducible cannot support a meaningful structure–property analysis.

Concerns within the radiomics community about the reproducibility of image features led to the creation of the Image Biomarker Standardization Initiative, which brought together 25 research teams to standardize and validate 169 radiomics features.⁷¹ One of the participants was the group around van Griethuysen *et al.* who developed the open-source platform *PyRadiomics*, which was utilized in this work.⁷²

Using established and validated software frameworks, such as *PyRadiomics*,⁷² is advantageous because they provide standardized implementations of texture features and reduce the risk of unintended data manipulation. IFs quantify the distribution of gray levels and the spatial relationships between pixels within an image. They therefore describe image texture, which is not the same as the surface texture of the object imaged, and they carry no inherent physical meaning. Therefore, correlation analyses are required to establish potential relationships between IFs and measurable structural characteristics.

Pearson correlation analysis provides a straightforward approach for quantifying the strength and direction of linear relationships between variables. While the interpretation of correlation strength depends on the specific dataset and observation range, such analyses allow the identification of potentially relevant descriptors within large feature sets.^{73–77} In complex datasets, initial strategies such as feature prioritization, redundancy reduction, and trend analysis provide an

effective starting point for identifying meaningful relationships. Establishing causal relationships between IFs and physical properties remains significantly more challenging and is beyond the scope of the present study.

This work addresses the production–structure edge of the PSPT for spray-coated CLs and makes three contributions. First, it establishes which of the standardized areal STPs are independent for this material class. Across 89 CLs and 443 CLSM measurements, the 19 parameters of ISO 25178 reduce to four correlation groups, from which three non-redundant descriptors are sufficient to describe the layer texture: the arithmetical mean height (S_a), the autocorrelation length (S_{al}), and the skewness (S_{sk}). S_a alone represents almost half of the parameter set and can therefore serve as a primary quality indicator. Second, it links these height-based descriptors to intensity-based IFs extracted with PyRadiomics.⁷² Because the IFs correlate with the STPs across all six production datasets, topographic information becomes accessible from any image, irrespective of the capturing device. The correlations do not provide absolute height values, as the scaling between an IF and its associated STP depends on the dataset, but they allow CLs to be compared and ranked relative to each other. Texture

quantification is therefore no longer restricted to instruments that deliver calibrated height data. Third, it reports a production-variable map for ultrasonic spray coating, relating four machine parameters and two composition variables to quantified texture changes with confidence intervals. CL structure is commonly reported qualitatively or through representative micrographs. Here the structural response to each production variable is given as a measured quantity. The structure–property edge is not addressed: establishing a non-redundant and reproducible descriptor set is a prerequisite for relating structure to device behavior, and is treated here as a separate step.

Materials and methods

This work covers the production of CLs, their structural characterization, and the correlation between the surface texture parameters measured from the height data and the image features computed from the intensity image. The methodical workflow, visualized in Fig. 1, encompassed three main stages.

The first stage, Data acquisition, involves using an ultrasonic spray-coater and a confocal laser scanning microscope

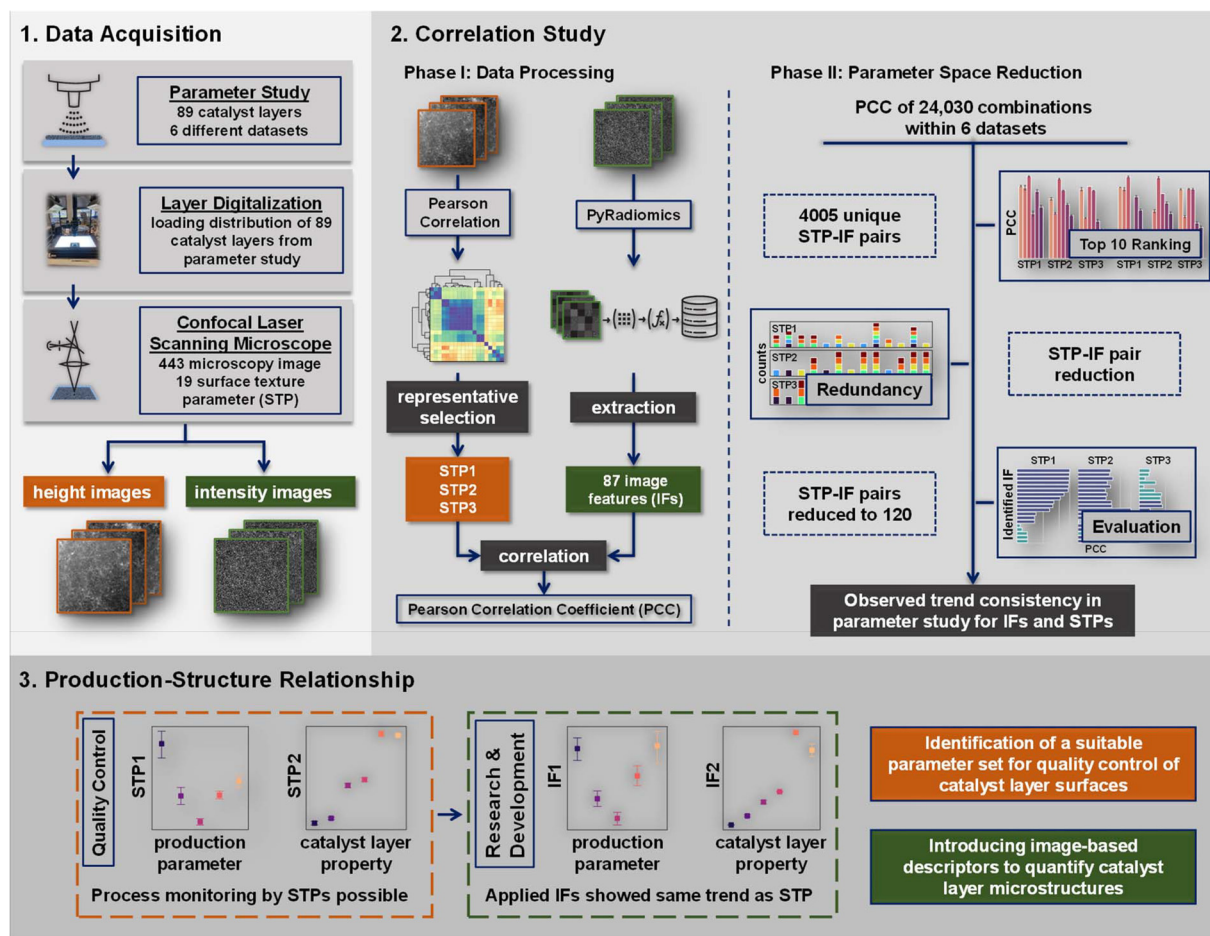


Fig. 1 Workflow of the developed methodology for correlating statistical IFs with physical STPs across multiple stages, from data acquisition to production–structure analysis.

(CLSM). A total of 89 CLs were fabricated using the spray-coater and were then systematically grouped into six different datasets based on the defined parameter study. The uniformity of the deposited layer was checked optically for each CL. These measurements showed that the deposit is not uniform across the layer, and therefore that a single measurement position would not be representative. Five positions per sample were consequently measured, as shown in Fig. S1. Next, the samples were analyzed using a CLSM, which produces intensity-based microscopy images and height maps. From the latter, 19 STPs were extracted to quantitatively describe the microstructure of the produced CL.

In the second stage of the workflow, the Correlation study, two main phases were carried out: data processing and parameter space reduction. In the first phase, the STPs from the CLSM are transferred into an appropriate data structure, and the intensity images are processed with the *PyRadiomics* library⁷² to extract the IFs. Pearson correlation analysis was then applied to detect linear relationships between the extracted STPs. This analysis identified three representative STPs (S_a , S_{ab} , S_{sk}) that effectively characterized the entire parameter set. Additionally, 87 IFs were extracted using the open-source platform *PyRadiomics*.⁷² In the second phase, the selected STPs were correlated with the extracted IFs by calculating the Pearson correlation coefficient (PCC) for each parameter combination. To reduce the parameter space, a combination of strategies was employed to prioritize and eliminate redundant IFs. This two-step process established a link between the STPs measured from the height data and the IFs computed from the intensity images. The criteria by which one IF was selected per STP are given under Phase II. The third stage involved a detailed analysis of the Production–structure relationship for CLs, considering optical density measurements, STPs, and IFs. This framework was used to evaluate the feasibility of using IFs for CL texture quantification. To validate the viability of this method, production variables must lead to consistent and measurable structural trends in the CL, as determined by both STPs and IFs analyses.

Data acquisition

CL production. Initially, the dispersion production started with adding the iridium oxide catalyst (Premion, Alfa Aesar) into a 100 mL laboratory bottle. Deionized water (Milli-Q, Merck Millipore) was added, followed by *n*-propanol (Merck). The catalyst concentration was 3.3 mg mL^{−1} for all datasets.

The dispersion was ice-cooled for 5 min prior to the addition of the water-based Nafion dispersion (D1021, Ion Power) and subsequently treated with an ultrasonic horn while maintained in the ice bath. The CLs were produced using an ultrasonic spray-coater system (*ExactaCoat*, Sono-Tek) with an integrated AccuMist nozzle operating at 48 kHz. The dispersion was injected by syringes (25 mL, Hamilton) and a syringe pump (Sono-Tek) which was operated from the *ExactaCoat* software. The temperature of the heated vacuum plate was 90 °C. The loading of the CLs was controlled by spraying on a metal plate and weighing with a balance (AG204, Mettler Toledo). The CLs were sprayed onto an N117 membrane (Chemours). The same catalyst batch, Nafion dispersion, solvents and equipment were used for all 89 CLs.

Parameter study. The standard production variables are found in the grey area of Table 1, while the blue boxes show the production variable studied. The presented parameter study consisted of four datasets focusing on the production variables (pressure, nozzle height, flow rate, alcohol content) and two which focused on the CL properties (Nafion content, Ir loading).

To investigate the impact of different production variables, one dataset focused on the alcohol content of the dispersion. The alcohol content is given relative to the total solvent mass. The other datasets focused on spray parameters, such as the gas pressure adjusted by the nitrogen gas supply or the nozzle height, which measures the distance of the nozzle tip to the vacuum plate. The nitrogen gas supply serves as both the carrier gas and the shaping gas. The flow rate is a key process variable, because it determines the amount of material delivered over time. This affects both the coating thickness and the total production time. The presented datasets refer to typical input variables of a CL fabrication process. The plate temperature was held at 90 °C for all datasets, which was identified as the optimum in a study covering 40 to 110 °C.⁸ The drying conditions were kept constant, as the exhaust of the spray coater operates at a fixed rate, so that the convective removal of solvent vapor could not be varied independently. Drying nonetheless enters the parameter study through several of the studied variables: it begins as soon as the dispersion leaves the nozzle, so that the nozzle height and gas pressure determine how much solvent is removed in flight, while the alcohol content sets the evaporation rate and the flow rate the amount of solvent delivered per unit time. Compared with doctor blade or slot-die coating, the wet film arriving at the

Table 1 Overview of the main production variables chosen per dataset

	Variables	Pressure (Pa)	Nozzle height (mm)	Flow rate (mL min ^{−1})	Alcohol content (wt%)	Nafion content (wt%)	Loading (mg _{Ir} cm ^{−2})
Datasets	Pressure	1034–55 160	40	0.2	67	11	0.2
	Nozzle height	10 342	10–60	0.2	67	11	0.2
	Flow rate	10 342	40	0.1–0.8	67	11	0.2
	Alcohol content	10 342	40	0.2	33–91	11	0.2
	Nafion content	10 342	40	0.2	67	5–30	0.2
	Loading	10 342	40	0.2	67	11	0.05–1.00

substrate is very thin, so that solvent removal occurs largely in flight and immediately upon deposition. At high flow rates, or when combined with a small nozzle height, more solvent reaches the membrane than can evaporate, which leads to swelling and irregularities.

The dispersion (“alcohol content”) is processed by adjusting machine parameters (“gas pressure”, “nozzle height”, “flow rate”), interacting with each other and consequently affect the resulting CL properties. Some CL properties (“Nafion content”, “iridium loading”) are output variables, which are conceptualized at the beginning of production. On the other hand, the Nafion content and the catalyst can be treated as input variables, since both are related to dispersion. Both influence the dispersion stability and interact with the solvent ratio and each other. This work focuses on the CL texture. Therefore, the Nafion content and iridium loading are considered output variables and CL properties. Further CL properties, such as thickness, porosity, and ionomer distribution, emerge from the interaction between input and output variables and are not addressed here. This work focuses on the CL surface texture.

Characterization. The characterization was carried out with a confocal laser scanning microscope (LEXT OLS4000, Olympus) possessing a height resolution of 10 nm and an *x-y* resolution of 120 nm. The utilized objective lens was the MPLAPON100XLEXT with $(129 \times 129) \mu\text{m}^2$ field of view at a working distance of 0.35 mm. Each CL was fixed onto a disassembled hard disk drive that had a uniform surface and thickness (25 mm). For fixation, a 190 μm thick double-sided adhesive tape (VHBTMGPT-020F50, 3MTM) was used. Every sample was measured at five different locations. An exemplary schematic of the probing locations on the CLs is presented in Fig. S1. The arrangement consisted of three equidistant points on a diagonal, with one location placed in the middle of the sample. The other two measurements were taken perpendicular to the initial three measurements, with one placed at the outer corner and the other positioned between that corner and the remaining three measurements. It was assumed that the symmetry of the square CL would not require additional measurements. Intensity and height images are generated during the measurement process. Intensity images record the amount of light reflected or emitted from each point on the specimen's surface. They provide contrast based on the specimen's reflectivity. These images reveal surface features with varying optical properties and are useful for distinguishing different material phases or structures.^{78,79} A height image is derived from the *z*-position at which the maximum intensity is detected for each lateral point. It provides precise measurements of the sample surface topography. Together, these two types of images offer complementary information. The intensity image reveals material or structural contrasts, while the height image maps the actual three-dimensional surface morphology. Both are essential for comprehensive surface analysis.^{79–81} CLSM was selected because it provides a calibrated height map and a co-registered intensity image from the same measurement over a field of view large enough to sample the layer heterogeneity. Techniques such as AFM offer

higher resolution and would resolve nanoscale features inaccessible here, but over fields of view too small to obtain representative areal parameters for a CL without a large number of measurements per sample.

The intensity signal reflects local reflectivity and may therefore respond to compositional differences within the layer as well as to topography. The two contributions cannot be separated with the measurements used here.

Since the height is taken from the *z*-position of maximum intensity at each lateral point, the intensity image and the height map derive from the same measurement. The IFs extracted from the former and the STPs calculated from the latter are therefore two statistical summaries of the same surface, which is the basis for the correlation analysis carried out here. The same applies to imaging techniques in which intensity responds to topography, although the specific IF-STP pairing and its scaling depend on how intensity relates to height in each case.

For all measurements, the brightness was kept constant, while the number of *z*-stack steps (focal planes) and the step width (vertical distance between planes) were adjusted for each specimen so that the full height range of the surface was captured. The 2D laser intensity image was exported as a tagged image file (tif) in a square format of 1024×1024 pixels and as a 24-bit grayscale image. Prior to Gaussian filtering, which was used to reduce noise, the surface level was adjusted and a cut-off wavelength (λ_c) was set in the LEXT software. A preliminary experiment indicated that $\lambda_c = 25 \mu\text{m}$ provided the best results, and this value was applied to all specimens.

Correlation study

The correlation study served two distinct purposes. The PCC was used as a screening tool, to reduce the extracted IFs to a tractable set and to rank them by how consistently they associate with an STP across independently produced datasets. Whether an IF can be used in place of an STP was then assessed separately, by comparing the response of each to the production variable studied. This second step does not rest on the magnitude of the coefficient and is described under Production–structure relationship. Both steps remain fully inspectable: the reduction follows from stated criteria, and the agreement between an IF and its STP is read directly from the measured data rather than through a fitted model with parameters that cannot be examined individually.

The PCC quantifies linear association only, and its magnitude depends on the shape of the underlying response and on the variability present in the observations. There is no absolute scale on which a coefficient can be judged strong or weak, as this depends on the case studied and the range of observations.^{73,74} Datasets with near-identical summary statistics can have entirely different distributions, as demonstrated by Anscombe's Quartet⁷⁵ and the Datasaurus Dozen.^{76,77} The coefficients reported here are therefore interpreted alongside the corresponding trends rather than in isolation.

Phase I: data processing. In Phase I, standardized procedures are applied to extract relevant features and compute

the full set of correlations. In conjunction with the computed height image, 19 STPs were calculated using the LEXT software. The definition and classification of the obtained parameters are listed in Table 2. All further data processing utilized parts of the open-source Python libraries *pandas*,^{82,83} *matplotlib*,⁸⁴ *scipy*,⁸⁵ and *seaborn*.⁸⁶

Table 2 contains several commonly used surface textures according to ISO 25178. The data sets were merged to avoid the redundant use of STPs. The PCC was calculated for all possible combinations of STPs.

A cluster map was used to visualize the dependency patterns among the STPs, which resolved into four groups. Three representative STPs were selected, one from each of the groups describing amplitude, lateral texture, and height distribution. The fourth group comprises the extrema parameters, which are sensitive to noise and were therefore not represented. S_{tr} was excluded separately, as all samples were isotropic and the parameter carries no discriminating information for this material system. The 95% confidence interval of the calculated PCC was computed by applying the Fisher transformation.⁸⁷

From the 2D light intensity images, 87 IFs were extracted from each image using the open-source platform *PyRadiomics*.⁷² The calculated image features were derived from different matrices. In particular, 23 parameters were derived from the GLCM computed, 15 from the GLRLM, 15 from the GLSZM, 13 from the GLDM, four from the NGDTM, as well as 17 first-order (FO) texture parameters.

Phase II: parameter space reduction. In this work, the reduced variable set included 87 IFs and 3 selected STPs, resulting in 90 variables. The STPs could be reduced beforehand, as ISO 25178 defines what each parameter describes and the redundancy among them can therefore be assessed independently of the data. No comparable standard exists for

the IFs, and their relevance to the CL surface is not known *a priori*. Reducing them at this stage would risk discarding features whose relationship to the surface texture had not yet been established, which is why the IF reduction follows the correlation analysis rather than preceding it. Applying the equation yields 4005 correlations per dataset, or 24 030 total correlations across all six datasets. If all 19 available STPs had been used instead, the number of variables would increase to 106, resulting in 5565 correlations per dataset, and 33 390 across all datasets. This comparison illustrates the substantial increase in computational and analytical complexity that would result from using the full set of parameters. As part of this work, a multi-stage reduction strategy was developed to ensure a traceable and systematic selection process. First, the absolute value of the PCC was used to identify the ten strongest correlations per dataset and per STP, yielding 180 IF-STP pairs across all six datasets and three selected STPs. This initial filtering prioritized the most relevant relationships while significantly reducing the computational load and processing time. Next, the redundancy of the selected image features was examined. Only features that appeared among the top correlations in more than one dataset were retained. This consistency-based filtering excluded features with isolated or dataset-specific importance, highlighting those with stable, cross-dataset relevance. This refined subset of correlations, now reduced to a manageable number (120), enabled a more targeted evaluation. From this pool, one IF was retained per STP according to the following criteria, applied in order: (i) the IF must appear among the ten strongest correlations for that STP in more than one dataset; (ii) candidates are ranked by the number of datasets in which they occur, this being the property most directly related to transferability; (iii) among equally ranked candidates, the higher mean absolute PCC is preferred; (iv) the three retained IFs are drawn from different texture matrices, so that the descriptor set does not rest on a single matrix; (v) where the preceding criteria do not discriminate, the IF with the more directly interpretable textural meaning is preferred. The candidates entering this selection and their mean coefficients are listed in Table S3.

These IFs were then used to determine if similar conclusions could be drawn by substituting them for the original STP. This step provides insight into the practical potential of using statistical IFs as alternative to physical STPs.

Production–structure relationship. The IFs will contribute only to the progress of electrode development if they can show similar trends regarding structural characteristics as the STPs. Therefore, the datasets were evaluated, interpreted and discussed with both textural feature classes, the STPs and the IFs.

Results and discussion

Phase I: data processing

The six datasets were merged at the beginning of this study part. The PCC was calculated for each possible STP combination. A $|\text{PCC}| > 0.70$ is interpreted as a very strong linear

Table 2 List of surface texture parameters (STP) calculated by the LEXT software

Classification	Symbol	Unit	Definition
Height parameters	S_q	μm	Root mean square height
	S_{sk}	—	Skewness
	S_{ku}	—	Kurtosis
	S_p	μm	Maximum peak height
	S_v	μm	Maximum pit depth
	S_z	μm	Maximum height
	S_a	μm	Arithmetical mean height
Space parameters	S_{al}	μm	Autocorrelation length
	S_{tr}	—	Texture aspect ratio
Functional parameters	S_k	μm	Core height
	S_{pk}	μm	Reduced peak height
	S_{vk}	μm	Reduced valley height
	S_{Mr1}	%	Material ratio in peak
	S_{Mr2}	%	Material ratio in valley
	S_{xp}	μm	Peak extreme height
Volume parameters	V_{mp}	$\mu\text{m}^3 \mu\text{m}^{-2}$	Peak material volume
	V_{mc}	$\mu\text{m}^3 \mu\text{m}^{-2}$	Core material volume
	V_{vv}	$\mu\text{m}^3 \mu\text{m}^{-2}$	Valley void volume
	V_{vc}	$\mu\text{m}^3 \mu\text{m}^{-2}$	Core void volume

relationship between two variables. The correlation is interpreted as strong correlation, if the PCC ranges between $0.50 < |PCC| \leq 0.70$.

Therefore, the clustermap of the PCC results (Fig. 2) showed that the STPs can be grouped into several classes, as ISO 25178 suggested (Table 2). The dendrogram and clustermap analysis reveal four main groups of STPs. The level at which branches merge in the dendrogram reflects the degree of dissimilarity between STPs. Lower levels indicate greater similarity or higher correlation, while higher levels indicate greater dissimilarity.

The first group corresponds to the height parameter class extremes and comprises S_v , S_p , and S_z . Specifically, S_v represents the maximum pit depth, or the distance from the mean plane to the lowest surface point. S_p denotes the maximum peak height, which is the distance from the mean plane to the highest peak. S_z captures the maximum height

difference, which is defined as the vertical distance between the deepest valley and the highest peak on the surface. While these parameters effectively describe extreme surface features, they are sensitive to noise and prone to outliers. They may not always accurately represent the general surface profile, particularly when measurement artifacts or irregularities are present. Consequently, none of the STPs in the first group were included in the correlation analysis.

The second group, consisting of S_{vk} , V_{vv} , S_k , V_{mc} , V_{vc} , S_q , S_a , and S_{xp} , was the largest group identified. It exhibited a minimum observed $|PCC|$ of 0.73, with only two STPs showing $|PCC| < 0.93$. The third group was identified as comprising S_{al} , S_{pk} , and V_{mp} , while the fourth group includes parameters that describe the general height distribution, namely S_{sk} , S_{ku} , S_{Mr1} , and S_{Mr2} . The texture aspect ratio, S_{tr} , showed for all relationships a negative $|PCC| \leq 0.22^{+0.11}_{-0.11}$. This was due to the fact that this parameter describes the spatial isotropy, which

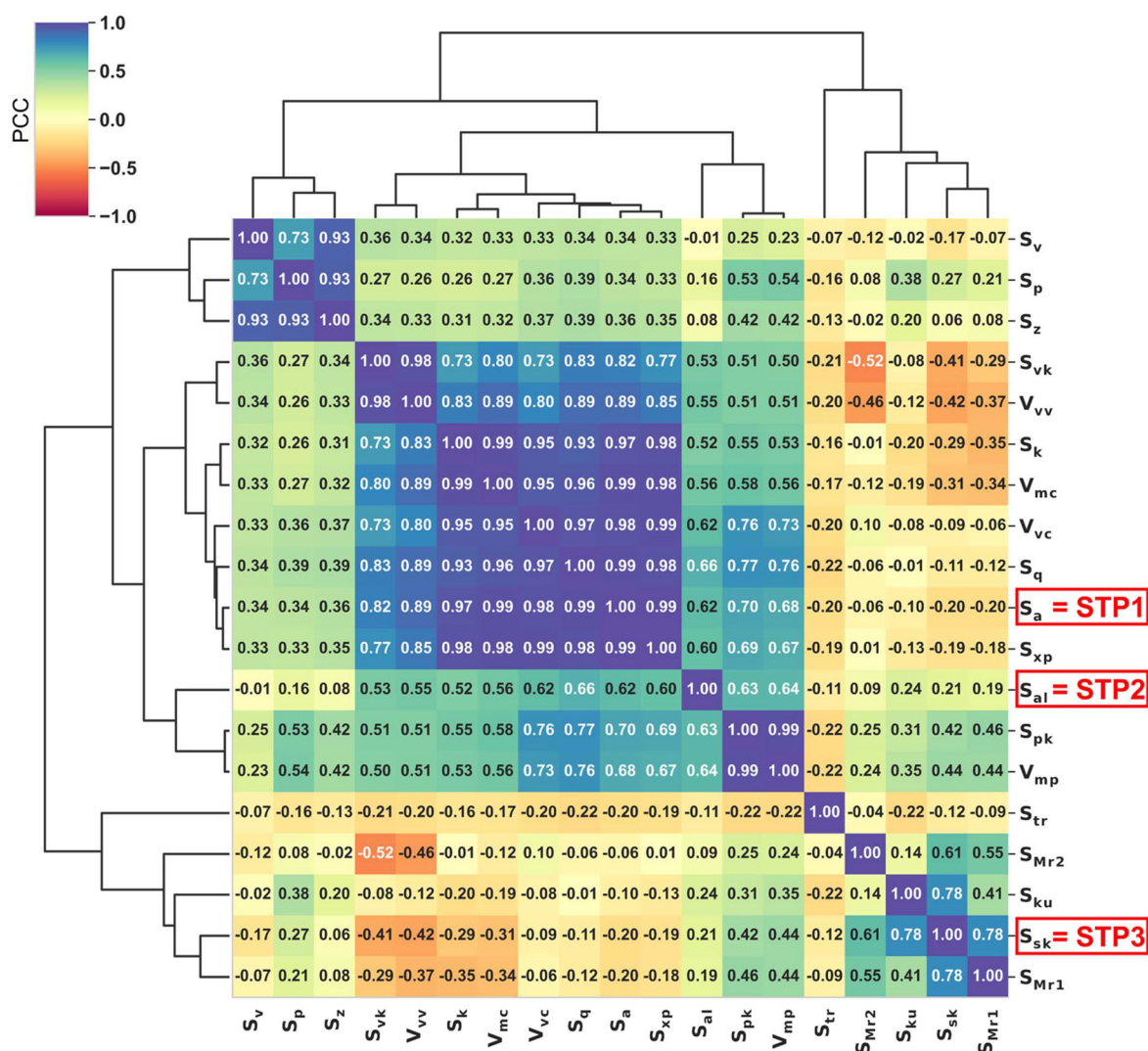


Fig. 2 Visualization of the correlation matrix and the computed Pearson correlation coefficient (PCC) as clustermap.

remained relatively unchanged for all samples. In total, 100% of the studied CL possessed a S_{tr} value of >0.40 , while for 98% a value of >0.70 was obtained. This indicated that all samples studied possessed a high isotropy with no directional orientation. S_{tr} was hence omitted from further analysis.

Three representative STPs were selected based on the clustermap (Fig. 2), and their detailed relationship to the other STPs is presented in Fig. 3. One STP was selected per group, except for the group comprising the extrema parameters, which was not represented for the reason given above. The arithmetical mean height (S_a), which ranged from $0.20\ \mu\text{m}$ to $0.46\ \mu\text{m}$ across the studied CLs, was chosen as first representative STP as it showed a PCC of $\geq 0.97^{+0.01}_{-0.01}$ (S_{xp} , S_q , V_{mc} , V_{vc} , S_k) in six out of nineteen combinations. Further, a strong correlation was observed between S_a and V_{vv} ($\text{PCC} = 0.89^{+0.02}_{-0.03}$) as well as to S_{vk} ($\text{PCC} = 0.82^{+0.03}_{-0.04}$). The correlation between S_a and reduced peak height, S_{pk} ($\text{PCC} = 0.70^{+0.05}_{-0.06}$), or peak material volume, V_{mp} ($\text{PCC} = 0.68^{+0.06}_{-0.06}$), marked the boundary where S_a could be used to represent the other STPs. These strong relationships originate partly from inherent mathematical dependencies between the parameters, as several are averages over the same height field. S_a and S_q , for example, differ only in whether the deviations from the mean plane are averaged as absolute values or as squares. Using only S_a for all applications may not be appropriate, as certain parameters could be more sensitive to particular processes. From a quality control perspective, S_a is therefore the primary candidate for monitoring CL production, as it represents almost 50% of the STPs studied. Analyzing the computed confidence interval at a level of 95% showed that they increased with decreasing PCC. That

was due to the increased variance with decreased PCC and showed why the 95% computed confidence interval was higher for the other representative STPs than for S_a .

The other two chosen representative STPs were the autocorrelation length S_{al} and the skewness S_{sk} . The autocorrelation length describes the spatial surface texture and is equal to the lateral length with the fastest decay to a given value, here $s = 0.2$. This parameter is used to describe the contact behavior of rough surfaces or adhesion properties.^{34,35} Analysis of the PCC showed that S_{al} correlated to all parameters represented by S_a within a range of $0.52^{+0.08}_{-0.09} < \text{PCC} \leq 0.66^{+0.06}_{-0.07}$, but correlated weakly to the remaining parameters ($|\text{PCC}| \leq 0.24^{+0.10}_{-0.11}$) as well. A moderate correlation between S_{al} and the parameters represented by S_a is expected, since rougher surfaces tend to have coarser lateral features. The clustering nevertheless resolves S_{al} into a separate group, and the two parameters describe different properties. S_a quantifies the amplitude of the height variation, whereas S_{al} quantifies the lateral length scale over which it occurs. The skewness describes the symmetry of the height distribution. A value near zero indicates a symmetric distribution, positive values a surface dominated by peaks, and negative values one dominated by plateaus with pits. The skewness correlated weakly to most of the STPs ($|\text{PCC}| \leq 0.44^{+0.09}_{-0.09}$), and strongly to S_{ku} ($\text{PCC} = 0.78^{+0.04}_{-0.05}$), S_{Mr1} ($\text{PCC} = 0.78^{+0.04}_{-0.05}$), and S_{Mr2} ($\text{PCC} = 0.61^{+0.07}_{-0.07}$). Finally, one identified STP group is not represented, as the three STPs S_v , S_p , and S_z describe the extrema of the surface texture and are, therefore, prone to noise and measurement errors.

The correlation analysis revealed that many surface texture parameters describe similar height-related information, allow-

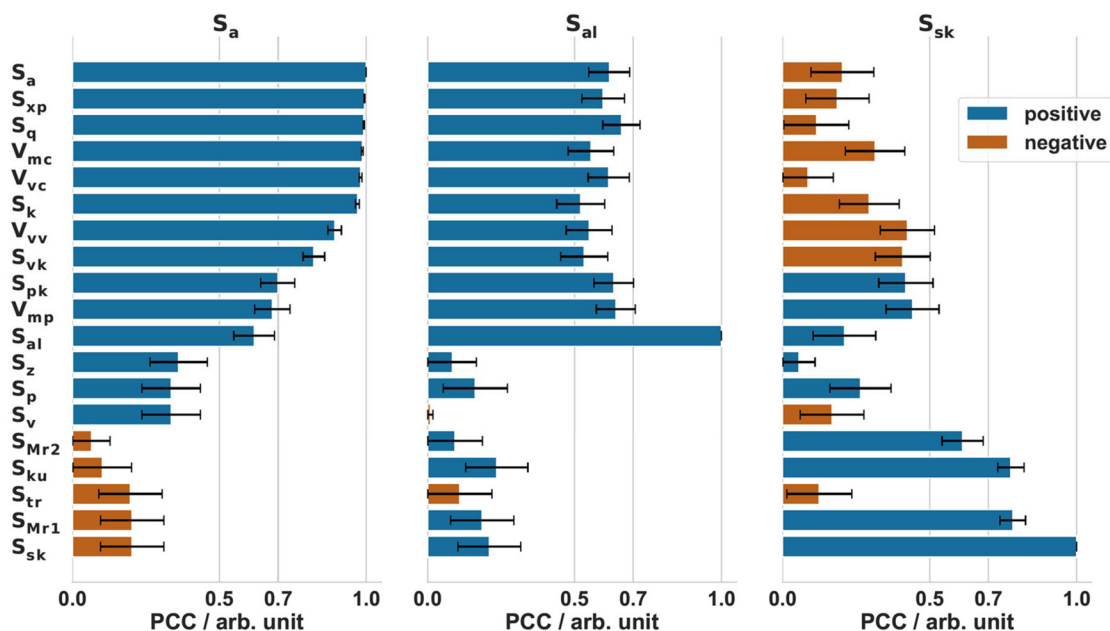


Fig. 3 Relationship between the representative STP's, noted at the top of each graph, and the corresponding STP written on the y-axis. The three representative STPs are the arithmetical mean height (S_a), the autocorrelation length (S_{al}), and the skewness (S_{sk}). Bar color indicates the sign of the correlation, blue for positive and orange for negative, with the PCC presented as absolute value. The definition of the acronyms can be found in Table 2.

ing the parameter set to be reduced to a few representative descriptors. In particular, S_a captures most height-related variations and can serve as a primary quality indicator for catalyst layer production, while S_{al} and S_{sk} provide complementary information on lateral texture characteristics and height distribution symmetry.

Phase II: Parameter space reduction

For each dataset presented in Table 1, the PCC was calculated between each selected STP and the 87 extracted IFs. To reduce the number of IFs and to prioritize the relevant parameter set, the ten strongest correlations of the absolute PCC were selected for each dataset and STP. It became apparent that the obtained PCCs depended on the selected dataset. Averaging the absolute PCC per dataset showed that the “gas pressure” dataset had the weakest correlation with (0.49 ± 0.10), followed by the “nozzle height” dataset (0.61 ± 0.15) and the “flow rate” dataset (0.61 ± 0.15). The strongest correlations were obtained from the “iridium loading” (0.91 ± 0.06), “alcohol content” (0.78 ± 0.15) and “Nafion content” (0.70 ± 0.14) data sets. The mean absolute PCC of the ten strongest correlations per STP is reported for each dataset as a descriptive summary of the overall correlation strength of the respective dataset, with the stated interval being the standard deviation across these correlations. As the prioritized IFs are not independent of one another, this value is descriptive and is not interpreted as a statistical estimate.

Fig. 4a shows the averaged PCCs sorted with respect to the different datasets and reference STPs. The negative PCCs are shown as absolute values to facilitate comparison. After sorting the PCCs, the maximum standard deviation obtained was ± 0.09 for the positive correlation between IFs and S_a in the case of the “Nafion content” dataset (0.52 ± 0.09). At the same time, this was the weakest correlation obtained for the respective dataset and the correlation between prioritized IFs and S_a . Except for this particular case, S_a correlated more strongly than S_{al} and S_{sk} with the extracted IFs for every other dataset. The strongest correlations between S_a and IFs were obtained from the “iridium loading” dataset, which showed both positive and negative correlations, with averaged PCC of 0.96 ± 0.01 . S_{al} correlated more strongly with the prioritized IFs than S_{sk} in four out of six datasets. In the Nafion content dataset, the IFs showed a stronger correlation for S_{sk} compared to S_a and S_{al} . The strength of the correlation depended on the dataset, probably due to underlying information and dependencies within the dataset used. However, these parameters must not affect the STPs or IFs linearly. A low coefficient can therefore reflect how the data are distributed rather than how well the descriptors correspond. As mentioned above, the obtained correlation strength depends on the range of observation.⁷⁴ This can lead to low correlation values for certain datasets. Another selection criterion is redundancy, as it reflects how versatile and robust a given parameter is. For each dataset, the ten prioritized IFs were analyzed for redundancy across all datasets examined, as shown in Fig. 4b. In total, 38 out of 87 IFs met the criterion of occurring more than once across datasets, thereby reducing the parameter space by 56%.

Redundancy analysis revealed that per STP, 26 IFs correlated with S_a and S_{sk} , while 22 correlated with S_{al} . Among the IFs, six parameters described the FO parameter space, while seven were derived from the GLCM, eight from the GLDM, six from the GLRLM, nine from the GLSZM, and two from the NGTDM. The retained features therefore comprise 7 of 23 GLCM, 8 of 13 GLDM, 9 of 15 GLSZM, 6 of 15 GLRLM, 2 of 4 NGTDM, and 6 of 17 FO texture parameters. The abbreviations of all IFs are listed in Table S1. No tendency was observed for the correlation between the IFs and S_a . However, none of the GLCM features correlated with S_{al} , while only two of the nine GLSZM features correlated with S_{sk} . Analysis of the different datasets showed that only GLDM9 (large dependence high gray level emphasis) correlated strongly enough with S_a across all datasets and GLRLM6 (long run high gray level emphasis) correlated within five datasets. All other IFs correlated across at most four datasets with S_{al} (GLDM8, GLRLM15, GLRLM5, GLSZM12, GLSZM13). Meanwhile, S_{sk} exhibited correlations with three IFs (GLCM14, GLDM1, GLDM2) present in three datasets at maximum. None of the extracted IFs correlated for the same dataset and simultaneously with all STPs, showing that the IFs represent different aspects of surface texture. Consequently, additional examinations concentrated on the most frequently observed IFs across the datasets and their correlation with a specific STP. These parameters were evaluated in more detail in the next step and compared with the other PCCs calculated, shown for each dataset in Fig. S2–S7. The relationship between IFs and STPs showed a clear dependence on the specific STP, as S_{sk} showed an inverse directional dependence, unlike the other two STPs. This tendency was also observed in the other datasets evaluated. For the “iridium loading” dataset, shown in Fig. S7, both S_a and S_{al} obtained 14 PCCs >0.80 , while the trend of the confidence interval was similar to that observed in Fig. 3 evaluating the correlation between the different STPs. The lower the PCC, the wider the confidence interval. In the case of S_{sk} , only four relationships were obtained that had a PCC greater than 0.80. As explained, the respective datasets affected the correlation strength of the obtained PCCs. This made it difficult to highlight a clear tendency regarding the correlated IFs and their corresponding correlation strength. Therefore, only the three selected IFs after the redundancy analysis were considered for further explanation of the datasets. The corresponding visual representations for each of the six datasets (Fig. S2–S7) can be found in the supplement, together with an in-depth discussion of the observed correlations. The resulting connection between the selected STPs and IFs is summarized in Fig. 5.

Fig. 5 summarizes which IF was selected for each STP and the strength of the underlying correlation. The selection followed the criteria defined in the methods section, applied in order. Occurrence across datasets was weighted above correlation strength, since an IF that recurs in independently produced datasets is more likely to transfer than one with a high coefficient in a single dataset. GLDM10, for instance, reaches a higher mean coefficient for S_a than GLDM9 (0.88 against 0.77) but occurs in only three of the six datasets, whereas GLDM9

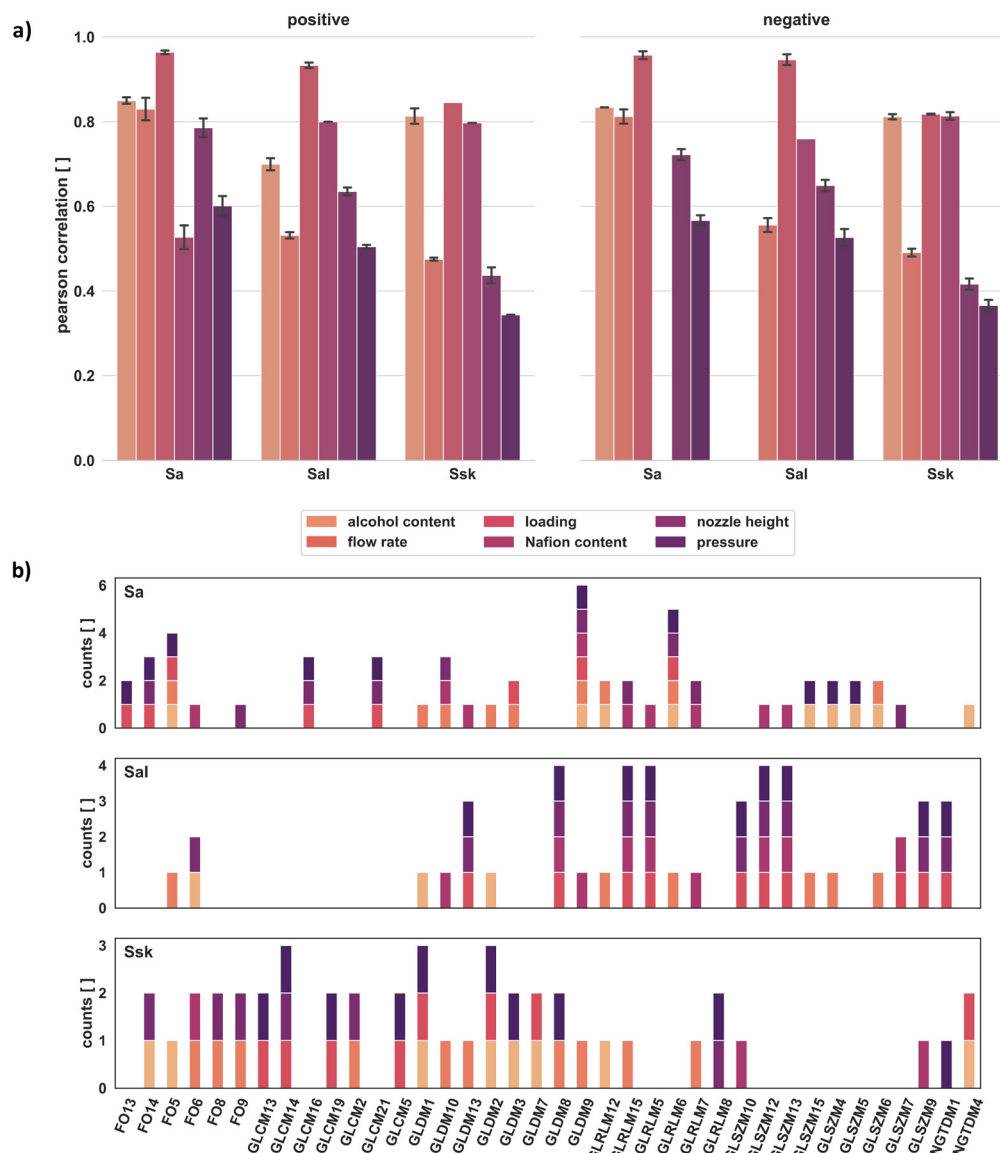


Fig. 4 Results of the first two steps of the parameter space reduction (a) selecting the ten strongest correlations for each dataset and (b) checking the redundancy of the prioritized IFs. Where no value is given for a sign, no correlation of that sign was among the ten strongest for that STP and dataset. The acronyms referring to the respective IFs calculated by the different matrices, such as the gray-level co-occurrence matrix (GLCM), gray-level run length matrix (GLRLM), gray level size zone matrix (GLSZM), neighboring gray tone difference matrix (NGTDM), gray level dependency matrix (GLDM), and the first-order texture parameter. The exact definition of the parameters can be found in Table S1.

occurs in all six and was therefore selected. Where candidates could not be separated on these grounds, the remaining criteria applied. For S_{al} , five IFs occur in the same four datasets with mean coefficients between 0.64 and 0.69. GLRLM5 was selected rather than the marginally higher-ranked GLDM8, since GLDM9 is already selected for S_a and drawing all descriptors from a single texture matrix would reintroduce the redundancy the reduction is intended to remove. Long run emphasis, which quantifies the extent of contiguous same-intensity runs, also corresponds more directly to the lateral length scale that S_{al} describes than large dependence emphasis does. For S_{sk} , GLDM1 and GLDM2 occur in the same three datasets and correlate with one another at $PCC = 1.00$ across all datasets, so

the two carry the same information and GLDM2 was selected. The candidates entering the selection and their mean coefficients are listed in Table S3. The selection of the IFs and the physical meaning they carry are discussed in more depth, with exemplary CL surface features, in the SI.

Production–structure relationship

The IFs are analyzed alongside the STPs to determine if interpreting the STP leads to the same conclusions as analyzing the respective IF. The IFs can only be considered reliable descriptors of the CL texture in future experiments, such as monitoring the CL structure across different magnification scales, if both the STPs and IFs lead to consistent conclusions. Another

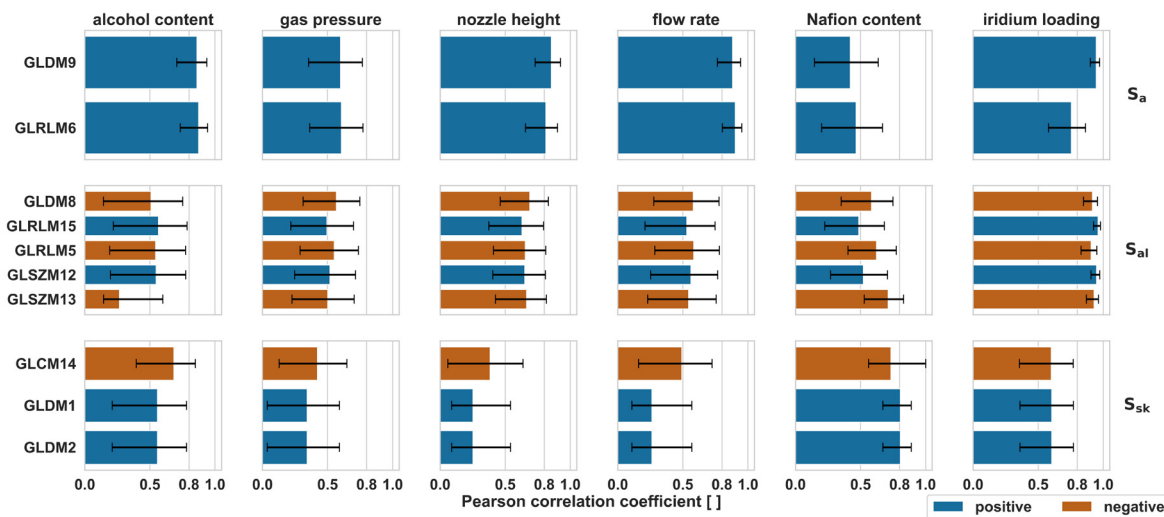


Fig. 5 Overview of the connection between the selected STPs and IFs based on the redundancy analysis. The STPs are the arithmetical mean height (S_a), the autocorrelation length (S_{al}), and the skewness (S_{sk}). The IFs are large dependence high gray level emphasis (GLDM9), long run high gray level emphasis (GLRLM6), large dependence emphasis (GLDM8), long run emphasis (GLRLM5), small area low gray level emphasis (GLSZM13), small area high gray level emphasis (GLSZM12), short run high gray level emphasis (GLRLM15), dependence non-uniformity (GLDM2), dependence entropy (GLDM1), and informational measure of correlation 1 (GLCM14).

important aspect is that IFs enable the quantitative analysis of CLSM intensity images. This allows for more sophisticated comparisons between different samples and enhances objectivity. This is shown exemplary in Fig. 6. The nozzle height was varied from 10 mm to 60 mm, and corresponding images were acquired. A visual comparison of these images makes it difficult to draw clear conclusions. However, applying IFs allows the objective quantification and interpretation of image data, making the underlying structural information accessible through statistical analysis, as presented in Fig. 7a–c. The following explanations use the three selected pairs: GLDM9 with the arithmetical mean height (S_a), GLRLM5 with the autocorrelation length (S_{al}), and GLDM2 with the skewness (S_{sk}).

The selected IFs used in this chapter for explanation and trend monitoring are as follows: GLDM9 characterizes the joint distribution of large dependencies associated with higher gray-level

values. GLDM9 quantifies the spatial relationship of each pixel to its neighbors within a given distance with lower values tending to more homogeneity within the image. GLRLM5 measures the distribution of long run lengths, with higher values indicating longer sequences of similar gray levels and a coarser texture overall. Finally, GLDM2 assesses the similarity of pixel dependencies across the image, where lower values reflect greater consistency and uniformity in structural patterns. The three selected IFs follow the criteria described in the methods section, and the candidates entering the selection are listed in Table S2. First, the datasets relating to the production variables are analyzed and displayed in Fig. 7. The x-axis represents the production parameter studied. The doubled y-axis displays the information of the respective STP (S_a , S_{al} , S_{sk}) together with its linked IF.

Adjusting the production variables lead to variations of S_a in the range between 0.20 μm and 0.46 μm while its counter-

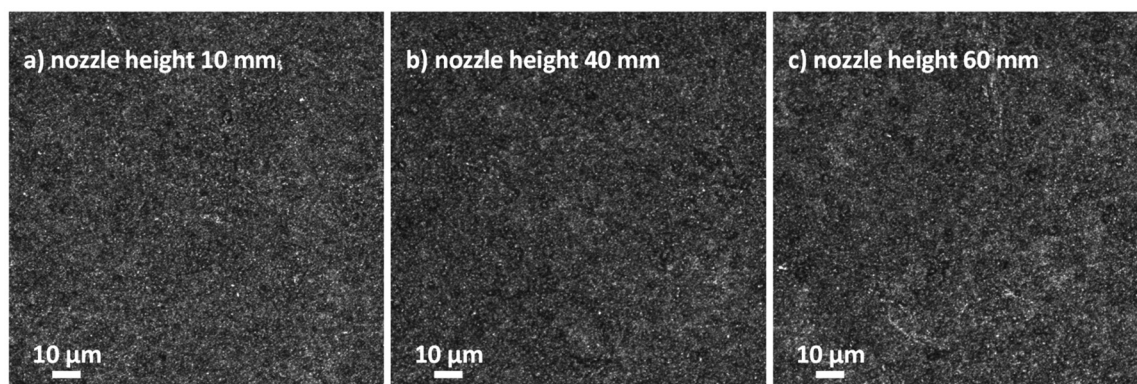


Fig. 6 CLSM intensity images of CL surfaces at varying nozzle heights (a–c), illustrating the challenge of visual comparison and the value of using IFs for quantitative analysis.

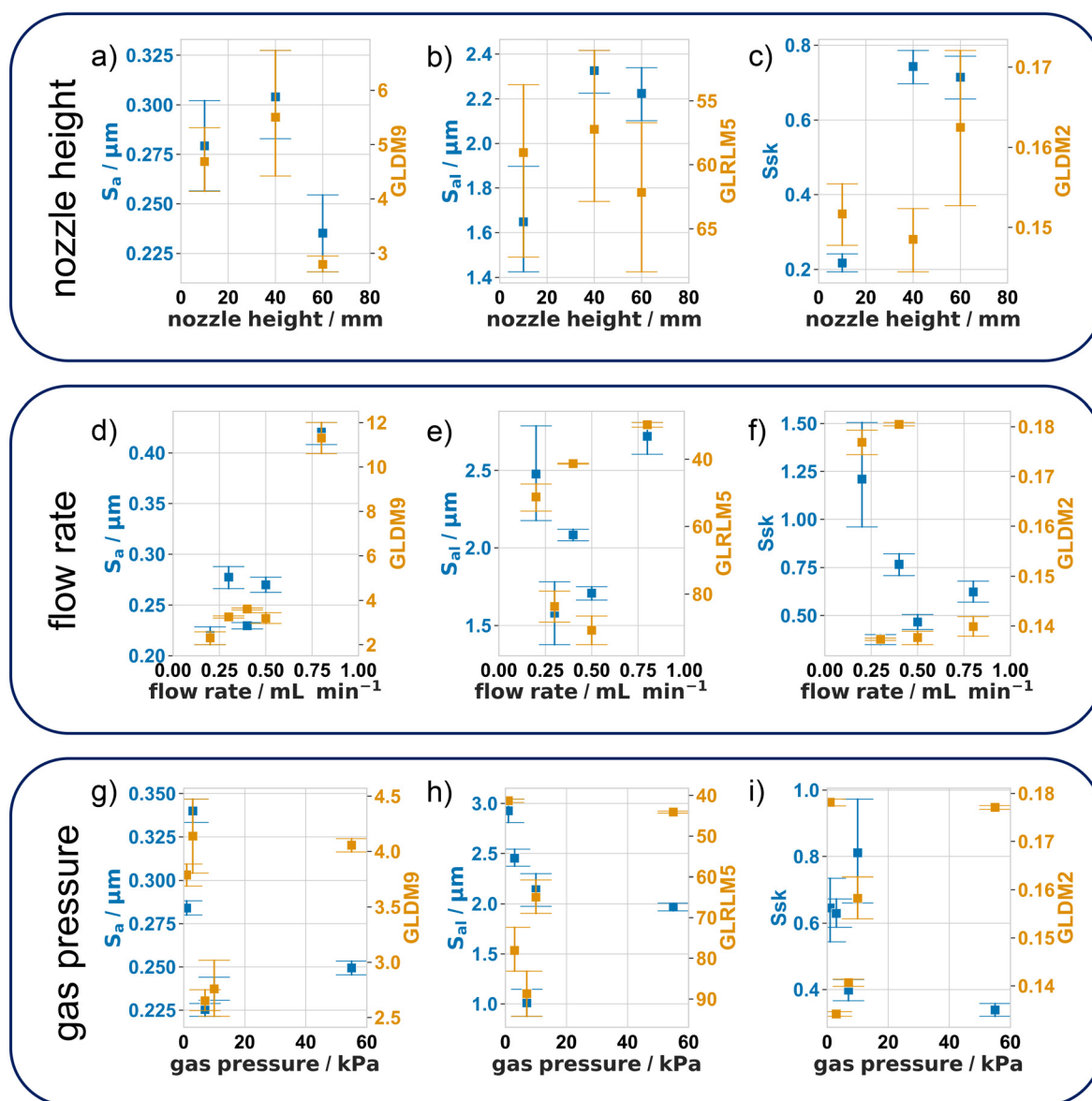


Fig. 7 Impact of the production variables on the surface texture. The surface texture was evaluated by studying the surface texture parameter monitored by the CLSM characterization and the extracted image features of the obtained laser intensity images. The y-axis of GLRLM5 was inverted to facilitate the comparison to autocorrelation length (S_a). GLDM9: large dependence high gray level emphasis, GLRLM5: long run emphasis, GLDM2: dependence non-uniformity. The panels show nozzle height (a–c), flow rate (d–f), and gas pressure (g–i), each with S_a and GLDM9 (a, d, g), S_{al} and GLRLM5 (b, e, h), and S_{sk} and GLDM2 (c, f, i).

part GLDM9 ranged from 1.87 to 9.48. Depending on the dataset examined, the GLDM9 scaled differently compared to S_a by a factor ranging from 10 to 35. However, for all datasets, the observed trends mirrored the trend observed in the analysis of S_a .

The flow rate (Fig. 7d–f) showed that the higher the flow rate, the higher S_a and GLDM9. However, no conclusive trend could be identified for the other surface properties studied. Surface characterization indicated that gas pressure (Fig. 7g–i) resulted in minimized S_a and S_{sk} if the pressure was between 3 kPa and 10 kPa. S_{al} for this dataset behaved similarly, but showed a distinct minimum at 7 kPa. As the response to gas

pressure is not monotonic, the linear correlation coefficients for this dataset remain low irrespective of how closely the IFs follow the STPs. The agreement between the two descriptor families is instead partly reflected in the course of the points, including the position of the minima.

To fully understand the relationship, it is critical to consider the flow rate in relation to pressure and nozzle distance. A combined descriptor such as a deposition rate could capture this interdependence, but defining one would require varying these parameters in combination rather than individually, as was done here. When the pressure was too low and the flow rate too high, the CL structure exhibited irregularities. The

reason was most likely that the resulting inhomogeneous spray cone distributed the dispersion non-uniformly over the membrane surface. A higher flow rate can be employed depending on the nozzle height. On the other hand, if the nozzle distance is too small, using a high flow rate can result in swelling of the non-homogeneous CLs of the membrane. When comparing the microscopy images in Fig. 6, no clear conclusion can be drawn. However, analysis using STPs or IFs revealed that the nozzle height influenced the arithmetical mean height (S_a), which was minimized at the greater distance of 60 mm. Both S_{al} and S_{sk} obtained a clear minimum at a nozzle distance of 20 mm.

The study of the associated IFs led to the same conclusion across all classical spray-coating parameter investigated. The relationship between the production variables and their effect on surface texture was not purely linear, which explains the comparatively lower PCC values. Nevertheless, GLDM9, GLRLM5, and GLDM2 describe the surface texture in a manner comparable to their respective STPs, indicating more complex, non-linear interactions between the variables studied.

The production parameters systematically influence the catalyst layer surface texture, although their relationships are not purely linear due to the complex interactions governing spray coating. Within the investigated parameter window, more homogeneous catalyst layers were obtained using a larger nozzle distance (≈ 60 mm) together with moderate gas pressures (≈ 3 – 10 kPa) and lower flow rates (≤ 0.2 mL min $^{-1}$), highlighting the importance of balancing these parameters during laboratory-scale spray coating.

The alcohol content is one important property of dispersion and is therefore crucial for the resulting CL structure. To determine whether IFs can capture the structural changes induced by varying alcohol content, the *n*-propanol concentration was systematically varied, and the results are presented in Fig. 8. Adjusting the alcohol content had strong effects on the S_a and GLDM9. For both S_a and GLDM9, the smallest value was

observed at an alcohol content of 67%. Reducing the *n*-propanol content of the dispersion well below the azeotropic point to 33% had a drastic effect on S_a , as the value increased from $0.26\ \mu\text{m}$ to $0.46\ \mu\text{m}$, which were simultaneously the maximum of all the data sets studied.

A maximum GLRLM5 value of 55.4 was observed at 67% *n*-propanol content, but the S_{al} did not show much difference between $2.41\ \mu\text{m}$ at 66% and $2.33\ \mu\text{m}$ at 91% *n*-propanol content. S_{sk} reached its maximum of 0.71 at 67% *n*-propanol content, like GLDM2 which was 0.178. Interestingly, S_{sk} was comparatively high as the water/*n*-propanol was close to its azeotropic point at 67% *n*-propanol. The reasons for this could be manifold, as the interaction between the dispersion, its processing and the resulting CL structure depends on various factors. It has been reported that for the dispersion system studied, higher *n*-propanol content resulted in stronger catalyst-ionomer interaction and better dispersed particles with fewer agglomerates.¹¹ Another study suggested that the ionomer-catalyst interaction prevents catalyst agglomeration in the dispersion.¹⁰ This could explain why changes in alcohol content lead to an altered CL texture. The lower the *n*-propanol content, the less stabilized the dispersion was. Therefore, larger agglomerates formed a rougher surface texture, indicated by higher S_a values. The accompanying decrease in S_{sk} indicates that the surface is dominated by broad raised regions separated by deeper gaps, rather than by isolated peaks. High alcohol contents (91%) could lead to similar behavior, as dispersion stability is a critical and complex factor influencing the resulting CL structure.

The datasets related to the CL components are shown in Fig. 9. The Nafion content dataset (Fig. 9a) was non-linear and the PCC values for all IFs considered were below 0.50. Nevertheless, both S_a and GLDM9 showed that increasing Nafion content had no effect on surface roughness as long as the Nafion content was larger than 10 wt%. With little variation in roughness above this content, there is little for the correlation to resolve, so the coefficients for this dataset are

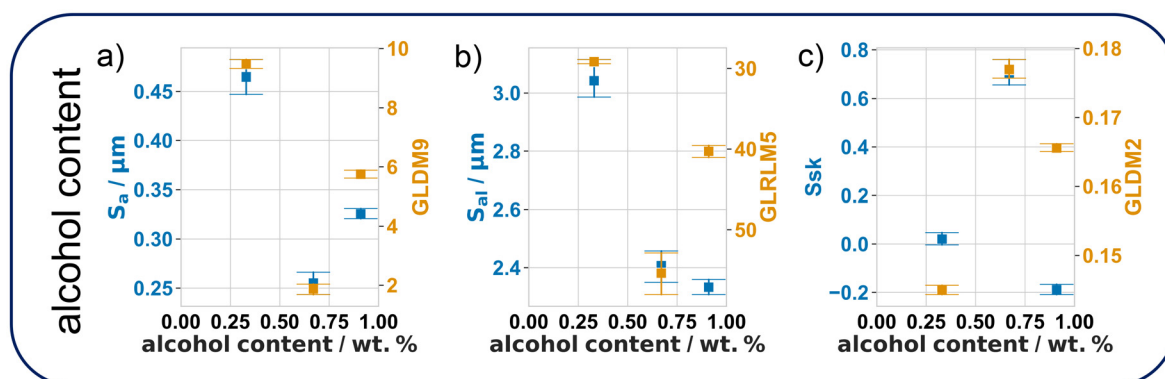


Fig. 8 Impact of the alcohol content on the surface texture. The surface texture was evaluated by studying the surface texture parameter monitored by the CLSM characterization and the extracted image features of the obtained laser intensity images. The y-axis of GLRLM5 was inverted to facilitate the comparison to S_{al} . GLDM9: large dependence high gray level emphasis, GLRLM5: long run emphasis, GLDM2: dependence non-uniformity. The panels show S_a and GLDM9 (a), S_{al} and GLRLM5 (b), and S_{sk} and GLDM2 (c).

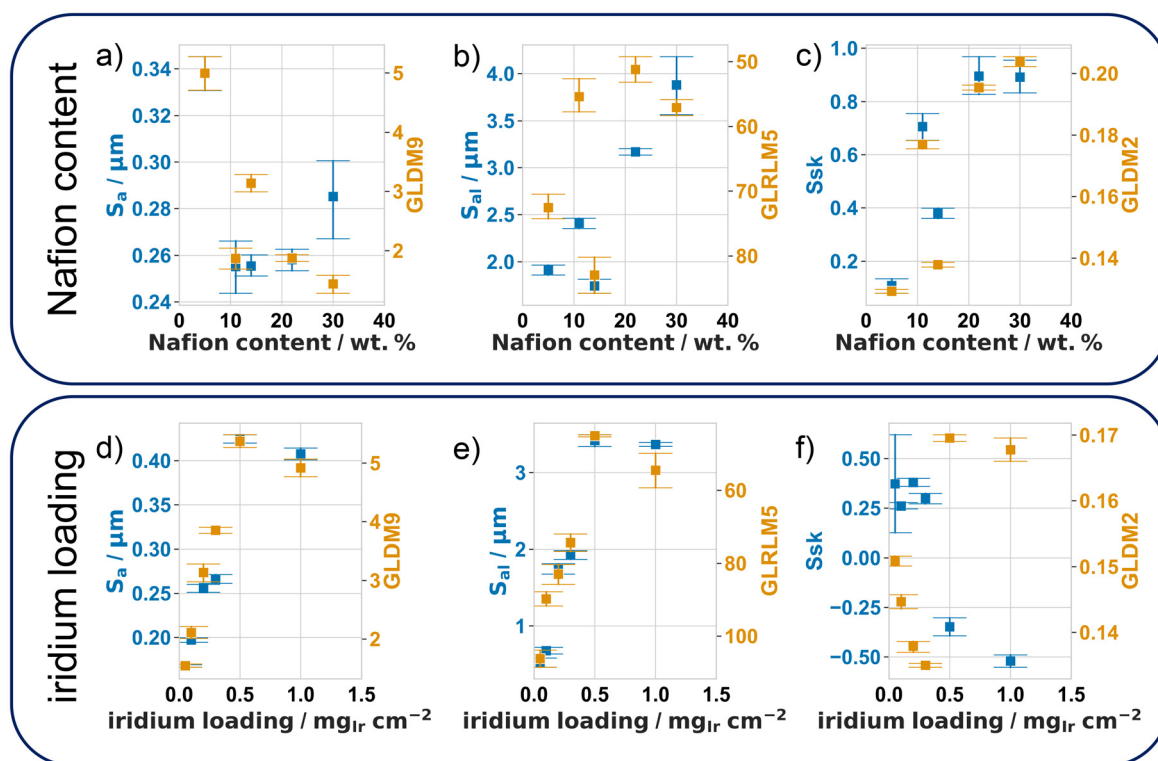


Fig. 9 Analysis of the surface texture in dependency to basic CL properties as the Nafion content or iridium loading. The y-axis of GLRLM5 was inverted to facilitate the comparison to autocorrelation length (S_{al}). GLDM9: large dependence high gray level emphasis, GLRLM5: long run emphasis, GLDM2: dependence non-uniformity. The panels show Nafion content (a–c) and iridium loading (d–f), each with S_a and GLDM9 (a, d), S_{al} and GLRLM5 (b, e), and S_{sk} and GLDM2 (c, f).

low independently of how closely the IFs follow the STPs. The plateau also bears on the remaining datasets: all other CLs were produced at 11 wt% Nafion and therefore lie within it, so the texture variations reported for the other five production variables are not confounded by ionomer content.

One possible reason could be the lower dispersion stability, because the Nafion content affects the dispersion behavior. The ionomer adsorbs onto the catalyst particles and stabilizes the dispersion, so that at low Nafion contents the particles are less well stabilized and larger agglomerates form.^{10,11} The dispersion properties themselves were not characterized in this work. Rheology, viscosity, dispersion stability and agglomerate size distribution govern droplet formation at the nozzle and the state of the dispersion on arrival at the substrate, and therefore sit upstream of the production variables studied here. Combining their systematic characterization with the descriptors identified in this work would allow the link between ink formulation, machine parameters, and the resulting CL structure to be quantified rather than inferred. This is similar to the effects observed for the alcohol content, where reduced alcohol levels led to the formation of larger agglomerates. S_{al} increased at high Nafion content, but the counterpart GLRLM5 behaved differently and did not show the same trend. S_{sk} and GLDM2 showed a similar trend, as both increased with increasing Nafion content in the CL. This indicates that the

surface becomes smoother as Nafion spreads across the surface, reducing the sharpness of the emerging surface features. The larger S_a at low Nafion contents indicates that the surface features are more pronounced, which is consistent with larger catalyst domains being less covered by ionomer. With increasing Nafion content, S_{sk} shifts from a more symmetrical height distribution toward one in which peaks are more prevalent, while S_a remains unchanged. Together with the increase in S_{al} , this indicates that the lateral features become coarser and the surface is dominated by fewer raised regions, rather than that the roughness itself changes. The Iridium loading dataset (Fig. 9b) possessed the highest PCC, *i.e.* the strongest correlation between the studied STPs and IFs. S_a was the lowest for 0.1 mgIr cm^{-2} and increased along with the loading up to 0.5 mgIr cm^{-2} . Beyond this loading, a doubling of the loading had nearly no effect on S_a . This trend was also obtained for S_{al} and both IFs (GLDM9, GLRLM6). However, the relative impact of the roughness gets smaller as the thickness of the CL gets higher. This could indicate that a threshold was observed for loadings $>0.5 \text{ mgIr cm}^{-2}$, similar to observations made by Rozain *et al.*⁸⁸ and Bernt *et al.*⁸⁹ The autocorrelation length (S_{al}) and GLRLM5 obtained a PCC of -0.91 , and the trend observed for this dataset represented this strong correlation. This emphasized the importance of underlying dataset structure while applying correlation studies.

The composition of the catalyst layer affects the surface texture differently depending on the component considered. While increasing Nafion content (>10 wt%) has little influence on overall roughness but smoothens sharp surface features, increasing iridium loading raises the absolute roughness up to $\approx 0.5 \text{ mg}_{\text{Ir}} \text{ cm}^{-2}$, beyond which the surface structure approaches a saturation regime. This might seem surprising, as discontinuous coverage at low iridium loadings could be expected to give a rougher surface. However, this observation can be explained by the substantially lower thickness of the catalyst layers at low loadings, where the absolute height variations remain small. Consequently, their absolute roughness values are smaller, although the roughness is larger relative to the catalyst layer thickness.

The datasets were designed as controlled parameter studies rather than for predictive modeling, and the agreement between an IF and its STP was assessed on the same samples from which both were computed. Surfaces with a directional texture were not examined, all layers in this study being isotropic with $S_{\text{Ir}} 0.40$.

Relation to device-relevant properties

The descriptors identified here quantify the CL surface, and it is useful to indicate how they may relate to device-relevant properties, although no electrochemical measurements were performed in this work. At the anode, the CL is contacted mechanically by the PTL, and the resulting interfacial resistance is a recognized contributor to cell resistance at reduced iridium loadings.¹³ Contact resistance describes the deviation of a real contact from an ideal one.⁹⁰ For two solids in mechanical contact, this deviation arises because the real contact area is only a fraction of the apparent area and the current is constricted through discrete contact spots. Two of the descriptors relate to this directly: S_{a} quantifies the amplitude of the height variation, while S_{sk} distinguishes plateau-dominated from peak-dominated height distributions, so that surfaces with comparable S_{a} may establish different real contact areas under compression. S_{al} describes the lateral length scale over which the height varies and therefore indicates whether the CL surface is structured on a scale comparable to the pore and fiber dimensions of the PTL, which would determine how uniformly the layer is contacted. These relationships are expectations rather than results and testing them requires device-level measurements outside the scope of this study. The present work provides the basis for this. Three descriptors that are reproducible and independent of each other can be related to device performance without the overlap that using all 19 parameters would introduce.

The relationships reported here were established on spray-coated IrO_2 with Nafion, deposited at a plate temperature of 90 °C under constant drying conditions and measured on a single CLSM under fixed acquisition settings. The workflow is general, and the redundancy structure of the STP set should hold wherever surface texture is measured by the same standard, but the specific STP-IF assignments should be verified for other material systems, imaging techniques, and proces-

sing conditions. The three descriptors cover the amplitude, the lateral length scale, and the symmetry of the height distribution, and are therefore a reasonable starting point for other systems, whereas a more specific question may require checking which of the parameters they represent is the relevant one. The associated IFs offer a corresponding starting point, as each was selected for tracking its STP across independently produced datasets. Since the IFs are computed from gray levels, the relationship between pixel intensity and topography determines the sign of the correlation. In the images used here, high intensity corresponds to raised material, where this relationship is reversed, the correlations would be expected to change sign rather than to disappear.

Conclusion

This work quantified the surface texture of 89 spray-coated CLs from 443 CLSM measurements and reduced the standardized ISO 25178 parameter set to three non-redundant descriptors: S_{a} , S_{al} , and S_{sk} . Each was linked to a specific IF (GLDM9, GLRLM5, and GLDM2) that reproduces its response to the studied production variables. The outcome is a compact descriptor set for CL texture that can be obtained either from calibrated height data or from intensity images alone. The magnitude of the correlation coefficient depends on the distribution of the data and on the variability present in each dataset, rather than on the quality of the descriptor, which is why the trends are reported alongside the coefficients throughout.

Adjusting the alcohol content significantly affected surface roughness, with the smoothest layers obtained at 67 wt% *n*-propanol and rougher textures at both lower and higher alcohol contents. Spray-coating variables, such as gas pressure and flow rate, also influenced S_{a} , revealing complex, non-linear interactions, with higher flow rates resulting in increased surface roughness. Variation in the Nafion content and iridium loading affected the surface roughness of the CL and showed that higher iridium loading resulted in rougher surfaces.

IFs are currently applied mainly outside electrode research. This work showed that CL texture can be quantified using IFs derived from the GLDM and GLRLM, and that interpreting the IFs led to the same conclusions as interpreting the corresponding STPs, with one exception in the Nafion content dataset. The strength of the correlation varied considerably between datasets: coefficients were high for iridium loading and alcohol content and low for the spray-coating parameters, where the structural response is not linear, while the trends agreed in most cases. This relationship is not specific to the instrument. IFs and STPs correlate because both quantify the texture of the same surface, one from the intensity distribution and one from the height map. STPs remain straightforward to obtain wherever a calibrated topographic instrument is available, but they are restricted to such instruments. IFs are computed from intensity data alone and are therefore accessible

from imaging techniques that provide no height information, including techniques offering higher lateral resolution than CLSM, such as SEM. Which IF serves as the closest proxy for a given STP, and how the two scales, depends on the imaging technique and remains to be established beyond CLSM. Quantifying microscopy images in combination with automated image acquisition therefore offers a route to monitoring CL structure across length scales, and to a more systematic understanding of the PSPT in electrode engineering.

Author contributions

Nikolai Utsch: conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, writing – original draft. Dieter Froning: methodology, software, formal analysis, writing – review & editing. Fabian Scheepers: methodology, writing – review & editing. Mohit Jain: investigation, writing – review & editing. Meital Shviro: writing – review & editing, supervision. Werner Lehnert: resources, funding acquisition, writing – review & editing. Anna K. Mechler: supervision, writing – review & editing.

Conflicts of interest

The authors declare no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request and can be accessed *via* JülichData upon request.

Supplementary information (SI) is available. See DOI: <https://doi.org/10.1039/d6nr01185c>.

Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the PROMET-H2 grant agreement no 862253.

References

- 1 C. R. Wang, *et al.*, Proton Exchange Membrane (PEM) Water Electrolysis: Cell-Level Considerations for Gigawatt-Scale Deployment, *Chem. Rev.*, 2025, **125**, 1257–1302.
- 2 D. Segets and U. Apfel, Special Collection: Holistic Development of Electrochemical Processes for Industrial Systems, *ChemCatChem*, 2024, e202400678, DOI: [10.1002/cctc.202400678](https://doi.org/10.1002/cctc.202400678).
- 3 X.-Z. Yuan, *et al.*, A review of functions, attributes, properties and measurements for the quality control of proton exchange membrane fuel cell components, *J. Power Sources*, 2021, **491**, 229540.
- 4 R. Borup, *et al.*, Scientific Aspects of Polymer Electrolyte Fuel Cell Durability and Degradation, *Chem. Rev.*, 2007, **107**, 3904–3951.
- 5 P. Schneider, *et al.*, Impact of Platinum Loading and Layer Thickness on Cathode Catalyst Degradation in PEM Fuel Cells, *J. Electrochem. Soc.*, 2023, **170**, 024506.
- 6 A. Colliard-Granero, *et al.*, Deep learning for the automation of particle analysis in catalyst layers for polymer electrolyte fuel cells, *Nanoscale*, 2022, **14**, 10–18.
- 7 J. Jankovic, S. Zhang, A. Putz, M. S. Saha and D. Susac, Multiscale imaging and transport modeling for fuel cell electrodes, *J. Mater. Res.*, 2019, **34**, 579–591.
- 8 S. M. Alia, K. S. Reeves, J. S. Baxter and D. A. Cullen, The Impact of Ink and Spray Variables on Catalyst Layer Properties, Electrolyzer Performance, and Electrolyzer Durability, *J. Electrochem. Soc.*, 2020, **167**, 144512.
- 9 C. V. Pham, D. Escalera-López, K. Mayrhofer, S. Cherevko and S. Thiele, Essentials of High Performance Water Electrolyzers – From Catalyst Layer Materials to Electrode Engineering, *Adv. Energy Mater.*, 2021, **11**, 2101998.
- 10 S. Khandavalli, *et al.*, Rheological Investigation on the Microstructure of Fuel Cell Catalyst Inks, *ACS Appl. Mater. Interfaces*, 2018, **10**, 43610–43622.
- 11 L. Osmieri, *et al.*, Utilizing ink composition to tune bulk-electrode gas transport, performance, and operational robustness for a Fe–N–C catalyst in polymer electrolyte fuel cell, *Nano Energy*, 2020, **75**, 104943.
- 12 Z. Taie, *et al.*, Pathway to Complete Energy Sector Decarbonization with Available Iridium Resources using Ultralow Loaded Water Electrolyzers, *ACS Appl. Mater. Interfaces*, 2020, **12**, 52701–52712.
- 13 M. Bernt, *et al.*, Effect of the IrO_x Conductivity on the Anode Electrode/Porous Transport Layer Interfacial Resistance in PEM Water Electrolyzers, *J. Electrochem. Soc.*, 2021, **168**, 084513.
- 14 J. Parra-Restrepo, *et al.*, Influence of the porous transport layer properties on the mass and charge transfer in a segmented PEM electrolyzer, *Int. J. Hydrogen Energy*, 2020, **45**, 8094–8106.
- 15 P. A. García-Salaberri, *et al.*, The critical role of the anode porous transport layer/catalyst layer interface of polymer electrolyte membrane water electrolyzers: A parametric analysis, *Chem. Eng. J.*, 2025, **509**, 160722.
- 16 Z. Kang, *et al.*, Studying Performance and Kinetic Differences between Various Anode Electrodes in Proton Exchange Membrane Water Electrolysis Cell, *Materials*, 2022, **15**, 7209.
- 17 E. Leonard, *et al.*, Interfacial analysis of a PEM electrolyzer using X-ray computed tomography, *Sustainable Energy Fuels*, 2020, **4**, 921–931.
- 18 Z. Kang, *et al.*, Discovering and Demonstrating a Novel High-Performing 2D-Patterned Electrode for Proton-

- Exchange Membrane Water Electrolysis Devices, *ACS Appl. Mater. Interfaces*, 2022, **14**, 2335–2342.
- 19 M. Stähler, A. Stähler, F. Scheepers, M. Carmo and D. Stolten, A completely slot die coated membrane electrode assembly, *Int. J. Hydrogen Energy*, 2019, **44**, 7053–7058.
- 20 J. Park, Z. Kang, G. Bender, M. Ulsh and S. A. Mauger, Roll-to-roll production of catalyst coated membranes for low-temperature electrolyzers, *J. Power Sources*, 2020, **479**, 228819.
- 21 A. Stähler, M. Stähler, F. Scheepers, W. Lehnert and M. Carmo, Scalable Implementation of Recombination Catalyst Layers to Mitigate Gas Crossover in PEM Water Electrolyzers, *J. Electrochem. Soc.*, 2022, **169**, 034522.
- 22 M. Mandal, A. Valls, N. Gangnus and M. Secanell, Analysis of Inkjet Printed Catalyst Coated Membranes for Polymer Electrolyte Electrolyzers, *J. Electrochem. Soc.*, 2018, **165**, F543–F552.
- 23 A. Willert, *et al.*, Multilayer additive manufacturing of catalyst-coated membranes for polymer electrolyte membrane fuel cells by inkjet printing, *Int. J. Hydrogen Energy*, 2022, **47**, 20973–20986.
- 24 S. F. Zaccarine, *et al.*, Multi-Scale Multi-Technique Characterization Approach for Analysis of PEM Electrolyzer Catalyst Layer Degradation, *J. Electrochem. Soc.*, 2022, **169**, 064502.
- 25 R. Girod, T. Lazaridis, H. A. Gasteiger and V. Tileli, Three-dimensional nanoimaging of fuel cell catalyst layers, *Nat. Catal.*, 2023, **6**, 383–391.
- 26 A. Bigdeli, M. R. Hormozi-Nezhad, M. Jalali-Heravi, M. R. Abedini and F. Sharif-Bakhtiar, Towards defining new nano-descriptors: extracting morphological features from transmission electron microscopy images, *RSC Adv.*, 2014, **4**, 60135–60143.
- 27 B. K. Kakati, V. K. Yamsani, K. S. Dhathathreyan, D. Sathiyamoorthy and A. Verma, The electrical conductivity of a composite bipolar plate for fuel cell applications, *Carbon*, 2009, **47**, 2413–2418.
- 28 A. Lanzini, P. Leone and P. Asinari, Microstructural characterization of solid oxide fuel cell electrodes by image analysis technique, *J. Power Sources*, 2009, **194**, 408–422.
- 29 M. J. Eslamibidgoli, *et al.*, Convolutional neural networks for high throughput screening of catalyst layer inks for polymer electrolyte fuel cells, *RSC Adv.*, 2021, **11**, 32126–32134.
- 30 K. P. Treder, *et al.*, nNPipe: a neural network pipeline for automated analysis of morphologically diverse catalyst systems, *npj Comput. Mater.*, 2023, **9**, 18.
- 31 R. Kumar, P. Kulashekar, B. Dhanasekar and B. Ramamoorthy, Application of digital image magnification for surface roughness evaluation using machine vision, *Int. J. Mach. Tools Manuf.*, 2005, **45**, 228–234.
- 32 P. Lambin, *et al.*, Radiomics: Extracting more information from medical images using advanced feature analysis, *Eur. J. Cancer*, 2012, **48**, 441–446.
- 33 A. Gebejes and R. Huertas, Texture Characterization based on Grey-Level Co-occurrence Matrix, in *ICTIC 2013*, 2013.
- 34 Y. Zhang and S. Sundararajan, The effect of autocorrelation length on the real area of contact and friction behavior of rough surfaces, *J. Appl. Phys.*, 2005, **97**, 103526.
- 35 A. Davis, Y. H. Yeong, A. Steele, I. S. Bayer and E. Loth, Superhydrophobic Nanocomposite Surface Topography and Ice Adhesion, *ACS Appl. Mater. Interfaces*, 2014, **6**, 9272–9279.
- 36 M. Iliyas Ahmad, *et al.*, Machine monitoring system: a decade in review, *Int. J. Adv. Manuf. Technol.*, 2020, **108**, 3645–3659.
- 37 A. Townsend, N. Senin, L. Blunt, R. K. Leach and J. S. Taylor, Surface texture metrology for metal additive manufacturing: a review, *Precis. Eng.*, 2016, **46**, 34–47.
- 38 K. K. Manesh, B. Ramamoorthy and M. Singaperumal, Numerical generation of anisotropic 3D non-Gaussian engineering surfaces with specified 3D surface roughness parameters, *Wear*, 2010, **268**, 1371–1379.
- 39 Q. Zeng, Y. Qin, W. Chang and X. Luo, Correlating and evaluating the functionality-related properties with surface texture parameters and specific characteristics of machined components, *Int. J. Mech. Sci.*, 2018, **149**, 62–72.
- 40 N. Aggarwal and R. K. Agrawal, First and, Second Order Statistics Features for Classification of Magnetic Resonance Brain Images, *J. Signal Image Process.*, 2012, **03**, 146–153.
- 41 T. Löfstedt, P. Brynolfsson, T. Asklund, T. Nyholm and A. Garpebring, Gray-level invariant Haralick texture features, *PLoS One*, 2019, **14**, e0212110.
- 42 R. M. Haralick, K. Shanmugam and I. Dinstein, Textural Features for Image Classification, *IEEE Trans. Syst. Man Cybern.*, 1973, **SMC-3**, 610–621.
- 43 P. Brynolfsson, *et al.*, Haralick texture features from apparent diffusion coefficient (ADC) MRI images depend on imaging and pre-processing parameters, *Sci. Rep.*, 2017, **7**, 4041.
- 44 M. M. Galloway, Texture analysis using gray level run lengths, *Comput. Graph. Image Process.*, 1975, **4**, 172–179.
- 45 G. Thibault, J. Angulo and F. Meyer, Advanced Statistical Matrices for Texture Characterization: Application to Cell Classification, *IEEE Trans. Biomed. Eng.*, 2014, **61**, 630–637.
- 46 M. Amadasun and R. King, Textural features corresponding to textural properties, *IEEE Trans. Syst. Man Cybern.*, 1989, **19**, 1264–1274.
- 47 C. Sun and W. G. Wee, Neighboring gray level dependence matrix for texture classification, *Comput. Vis. Graph. Image Process.*, 1983, **23**, 341–352.
- 48 F. Ulaby, F. Kouyate, B. Brisco and T. H. Williams, Textural Information in SAR Images, *IEEE Trans. Geosci. Remote Sens.*, 1986, **GE-24**, 235–245.
- 49 M. P. Bishop, J. F. Shroder, B. L. Hickman and L. Copland, Scale-dependent analysis of satellite imagery for characterization of glacier surfaces in the Karakoram Himalaya, *Geomorphology*, 1998, **21**, 217–232.
- 50 C. A. Coburn and A. C. B. Roberts, A multiscale texture analysis procedure for improved forest stand classification, *Int. J. Remote Sens.*, 2004, **25**, 4287–4308.
- 51 P. Foggia, G. Percannella, P. Soda and M. Vento, Benchmarking HEP-2 Cells Classification Methods, *IEEE Trans. Med. Imaging*, 2013, **32**, 1878–1889.

- 52 N. Fularczyk, *et al.*, A Learning Based Framework for Disease Prediction from Images of Human-Derived Pluripotent Stem Cells of Schizophrenia Patients, *Neuroinform*, 2022, **20**, 513–523.
- 53 W. H. Nisbett, A. Kavuri and M. Das, On the correlation between second order texture features and human observer detection performance in digital images, *Sci. Rep.*, 2020, **10**, 13510.
- 54 B. Julesz, A brief outline of the texton theory of human vision, *Trends Neurosci.*, 1984, **7**, 41–45.
- 55 B. Julesz, Textons, the elements of texture perception, and their interactions, *Nature*, 1981, **290**, 91–97.
- 56 A. Tyagi, V. P. Singh and M. M. Gore, Towards artificial intelligence in mental health: a comprehensive survey on the detection of schizophrenia, *Multimed. Tools Appl.*, 2023, **82**, 20343–20405.
- 57 I. Moalla, F. Lebourgeois, H. Emptoz and A. M. Alimi, Image analysis for palaeography inspection, in Second International Conference on Document Image Analysis for Libraries (DIAL'06) 8 pp. – 311 IEEE, Lyon, (2006). DOI: [10.1109/DIAL.2006.20](https://doi.org/10.1109/DIAL.2006.20).
- 58 I. Bar-Yosef, I. Beckman, K. Kedem and I. Dinstein, Binarization, character extraction, and writer identification of historical Hebrew calligraphy documents, *Int. J. Doc. Anal. Recognit.*, 2007, **9**, 89–99.
- 59 S. Dutta, S. K. Pal, S. Mukhopadhyay and R. Sen, Application of digital image processing in tool condition monitoring: A review, *CIRP J. Manuf. Sci. Technol.*, 2013, **6**, 212–232.
- 60 A. A. Kassim, M. A. Mannan and Z. Mian, Texture analysis methods for tool condition monitoring, *Image Vis. Comput.*, 2007, **25**, 1080–1090.
- 61 R. Datta, D. Joshi, J. Li and J. Z. Wang, Image retrieval: Ideas, influences, and trends of the new age, *ACM Comput. Surv.*, 2008, **40**, 1–60.
- 62 P. Lambin, *et al.*, Radiomics: the bridge between medical imaging and personalized medicine, *Nat. Rev. Clin. Oncol.*, 2017, **14**, 749–762.
- 63 X. Zheng, *et al.*, Deep learning radiomics can predict axillary lymph node status in early-stage breast cancer, *Nat. Commun.*, 2020, **11**, 1236.
- 64 A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz and H. J. W. L. Aerts, Artificial intelligence in radiology, *Nat. Rev. Cancer*, 2018, **18**, 500–510.
- 65 K. Bera, N. Braman, A. Gupta, V. Velcheti and A. Madabhushi, Predicting cancer outcomes with radiomics and artificial intelligence in radiology, *Nat. Rev. Clin. Oncol.*, 2022, **19**, 132–146.
- 66 S. Chen, *et al.*, Using neighborhood gray tone difference matrix texture features on dual time point PET/CT images to differentiate malignant from benign FDG-avid solitary pulmonary nodules, *Cancer Imaging*, 2019, **19**, 56.
- 67 N. W. Schurink, *et al.*, Sources of variation in multicenter rectal MRI data and their effect on radiomics feature reproducibility, *Eur. Radiol.*, 2022, **32**, 1506–1516.
- 68 K. Artyushkova, S. Pylypenko, M. Dowlapalli and P. Atanassov, Use of digital image processing of microscopic images and multivariate analysis for quantitative correlation of morphology, activity and durability of electrocatalysts, *RSC Adv.*, 2012, **2**, 4304.
- 69 K. Artyushkova, P. Atanassov, M. Dutta, S. Wessel and V. Colbow, Structural correlations: Design levers for performance and durability of catalyst layers, *J. Power Sources*, 2015, **284**, 631–641.
- 70 K. Artyushkova, S. Pylypenko, M. Dowlapalli and P. Atanassov, Structure-to-property relationships in fuel cell catalyst supports: Correlation of surface chemistry and morphology with oxidation resistance of carbon blacks, *J. Power Sources*, 2012, **214**, 303–313.
- 71 A. Zwanenburg, *et al.*, The Image Biomarker Standardization Initiative: Standardized Quantitative Radiomics for High-Throughput Image-based Phenotyping, *Radiology*, 2020, **295**, 328–338.
- 72 J. J. M. van Griethuysen, *et al.*, Computational Radiomics System to Decode the Radiographic Phenotype, *Cancer Res.*, 2017, **77**, e104–e107.
- 73 M. Kozak, What is Strong Correlation?, *Teach. Stat.*, 2009, **31**, 85–86.
- 74 R. J. Janse, *et al.*, Conducting correlation analysis: important limitations and pitfalls, *Clin. Kidney J.*, 2021, **14**, 2332–2337.
- 75 F. J. Anscombe, Graphs in Statistical Analysis, *Am. Stat.*, 1973, **27**, 17–21.
- 76 J. Matejka and G. Fitzmaurice, Same Stats, Different Graphs: Generating Datasets with Varied Appearance and Identical Statistics through Simulated Annealing, in Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems, 1290–1294 ACM, Denver Colorado USA, (2017). DOI: [10.1145/3025453.3025912](https://doi.org/10.1145/3025453.3025912).
- 77 A. Cairo, The Functional Art: An Introduction to Information Graphics and Visualization: Download the Datasaurus: Never trust summary statistics alone; always visualize your data. *The Functional Art*, <https://thefunctionalart.blogspot.com/2016/08/download-datasaurus-never-trust-summary.html> (2016).
- 78 C. A. Combs and H. Shroff, Fluorescence Microscopy: A Concise Guide to Current Imaging Methods, *Curr. Protoc. Neurosci.*, 2017, **79**(1), 2.1.1–2.1.25.
- 79 V. Panchal, *et al.*, Confocal laser scanning microscopy for rapid optical characterization of graphene, *Commun. Phys.*, 2018, **1**, 83.
- 80 A. D. Elliott, Confocal Microscopy: Principles and Modern Practices, *Curr. Protoc. Cytom.*, 2020, **92**(1), DOI: [10.1002/cpcy.68](https://doi.org/10.1002/cpcy.68).
- 81 M. Fabich, Advancing Confocal Laser Scanning Microscopy: The Advantage of Optical Metrology, *Opt. Photonik*, 2009, **4**, 40–43.
- 82 The pandas development team. pandas-dev/pandas: Pandas. (2020) DOI: [10.5281/zenodo.3509134](https://doi.org/10.5281/zenodo.3509134).
- 83 W. McKinney, Data Structures for Statistical Computing in Python. in 56–61 (Austin, Texas, 2010). DOI: [10.25080/Majors-92bf1922-00a](https://doi.org/10.25080/Majors-92bf1922-00a).
- 84 J. D. Hunter, Matplotlib: A 2D graphics environment, *Comput. Sci. Eng.*, 2007, **9**, 90–95.

- 85 P. Virtanen, *et al.*, SciPy 1.0 Fundamental Algorithms for Scientific Computing in Python, *Nat. Methods*, 2020, **17**, 261–272.
- 86 M. Waskom, Seaborn: statistical data visualization, *J. Open Source Software*, 2021, **6**, 3021.
- 87 G. Taraldsen, Confidence in Correlation, 2020. DOI: [10.13140/RG.2.2.23673.49769](https://doi.org/10.13140/RG.2.2.23673.49769).
- 88 C. Rozain, E. Mayousse, N. Guillet and P. Millet, Influence of iridium oxide loadings on the performance of PEM water electrolysis cells: Part I–Pure IrO₂-based anodes, *Appl. Catal., B*, 2016, **182**, 153–160.
- 89 M. Bernt, A. Siebel and H. A. Gasteiger, Analysis of Voltage Losses in PEM Water Electrolyzers with Low Platinum Group Metal Loadings, *J. Electrochem. Soc.*, 2018, **165**, F305–F314.
- 90 H. H. Berger, Contact Resistance and Contact Resistivity, *J. Electrochem. Soc.*, 1972, **119**(507), DOI: [10.1149/1.2404240](https://doi.org/10.1149/1.2404240).