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ESTABLISHING RELEVANT ADC-BASED TEXTURE ANALYSIS METRICS FOR QUANTIFYING EARLY TREATMENT-INDUCED CHANGES IN HEAD AND NECK SQUAMOUS CELL CARCINOMA

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PURPOSE

The purpose of this study is to identify texture analysis metrics from apparent diffusion coefficient (ADC) maps that would provide quantifiable changes with treatment in patients with head and neck squamous cell carcinoma (HNSCC). We discerned which imaging metrics were relevant using baseline agreement and variations during early treatment.

MATERIALS AND METHODS

We retrospectively analyzed diffusion-weighted MRI scans in 9 patients with stages II-IV HNSCC. ADC maps were generated (see Panel G) from two baseline scans, performed 1 week apart, and one early treatment scan, obtained during the 2nd week of chemoradiation. Regions of interest (ROI) consisting of primary and nodal disease were drawn on the resampled ADC maps. Four 3D texture matrices describing local and regional relationships between voxel intensities in the ROIs were generated (Panel A). From these, 38 texture metrics and 7 histogram features were calculated for each patient, including the mean and median ADC. To identify metrics with good agreement between baseline studies, we compared all metrics using the intra-class correlation coefficient (ICC, Panel H). For metrics with ICC ≥ 0.80, the Wilcoxon signed-rank test was used to test if the difference between the mean of the baselines and the early treatment was non-zero.

A MATLAB Graphical User Interface (GUI) called Duke FIRE (Functional Imaging Research Environment, see Panel F) was developed by Jeff Nawrocki for a similar study in order to calculate four mathematical matrices representing the spatial distribution of pixels in an image: gray level co-occurrence matrix (GLCM, Panel B), gray level run length matrix (GLRLM, Panel C), gray level size zone matrix (GLSZM, Panel D), and the neighborhood gray level difference matrix (NGLDM, Panel E). Features representing characteristics of the image are derived from these texture matrices: 12 local features from the GLCM, 11 regional features from the GLRLM, 11 regional features from the GLSZM, and 5 local features from the NGLDM.

RESULTS

Nine of the 45 metrics had an ICC ≥ 0.80. Six of these 9 metrics had a p-value < 0.05: run length non-uniformity, ADC median, texture strength, ADC mean, zone percentage, and variance (panel I). Only 1 of the 9 metrics remained of interest, after applying the Holm correction to the alpha levels: run length non-uniformity (p = 0.004) in the Gray Level Run Length Matrix.
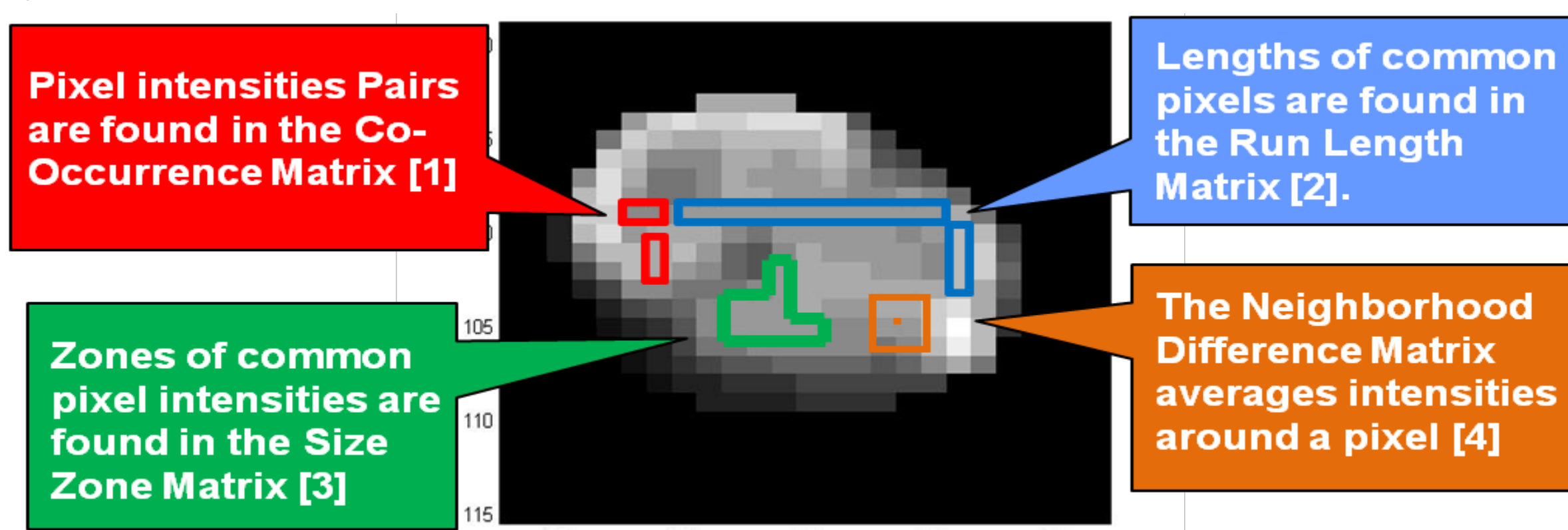
CONCLUSION

The feasibility of texture analysis is dependent on the baseline agreement of each metric, which disqualifies many texture characteristics. Agreement of texture metrics without treatment intervention must be considered when the intention is to use such metrics for treatment response evaluation. Consequently, only a few metrics are reproducible and qualify for future studies that provide quantitative assessment of early treatment changes for HNSCC.
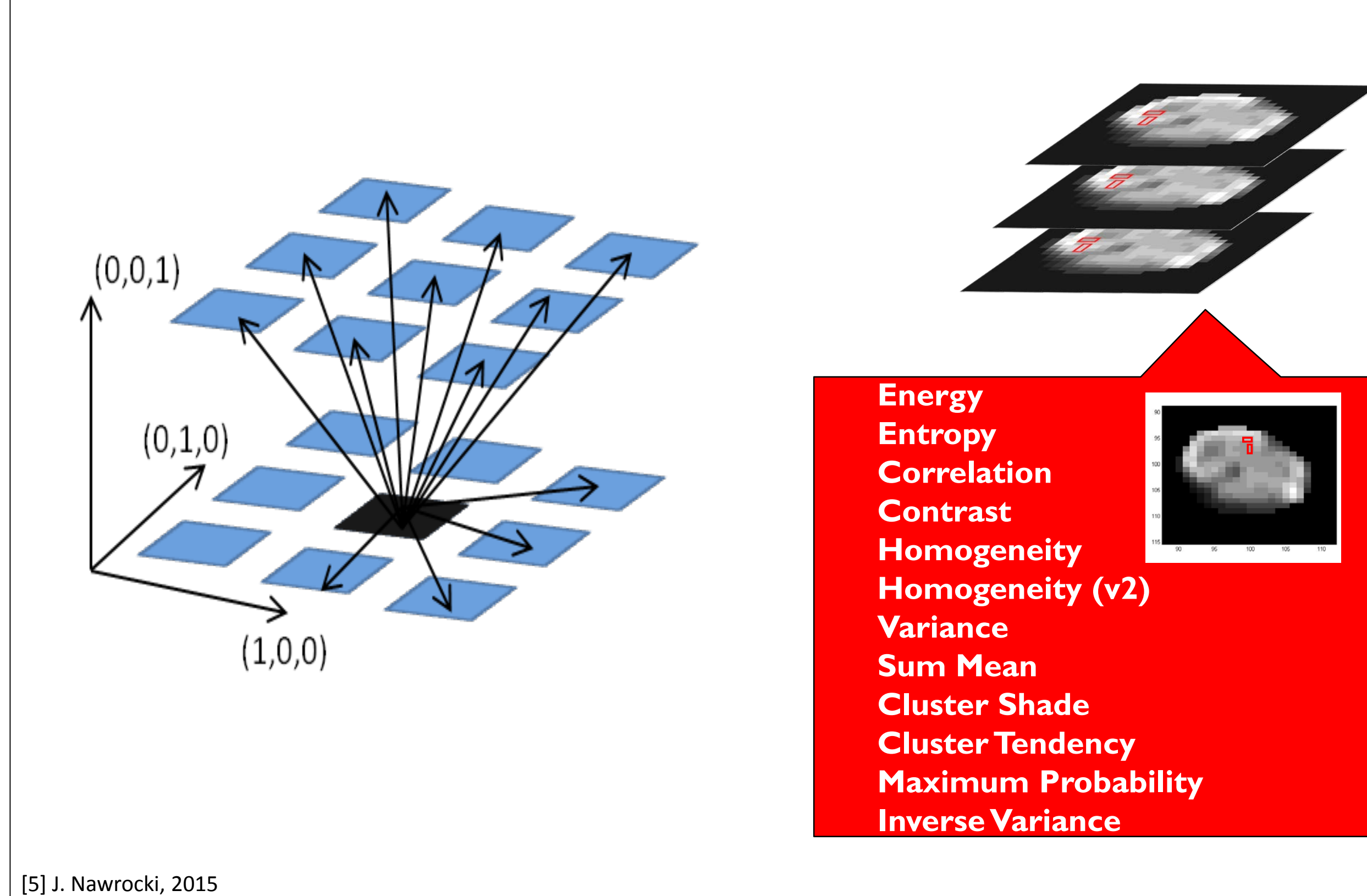
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Panel A: Texture analysis is used to quantitatively classify the homogeneity, or lack thereof, used to characterize gray-scale images based on spatial information of pixel pairs.
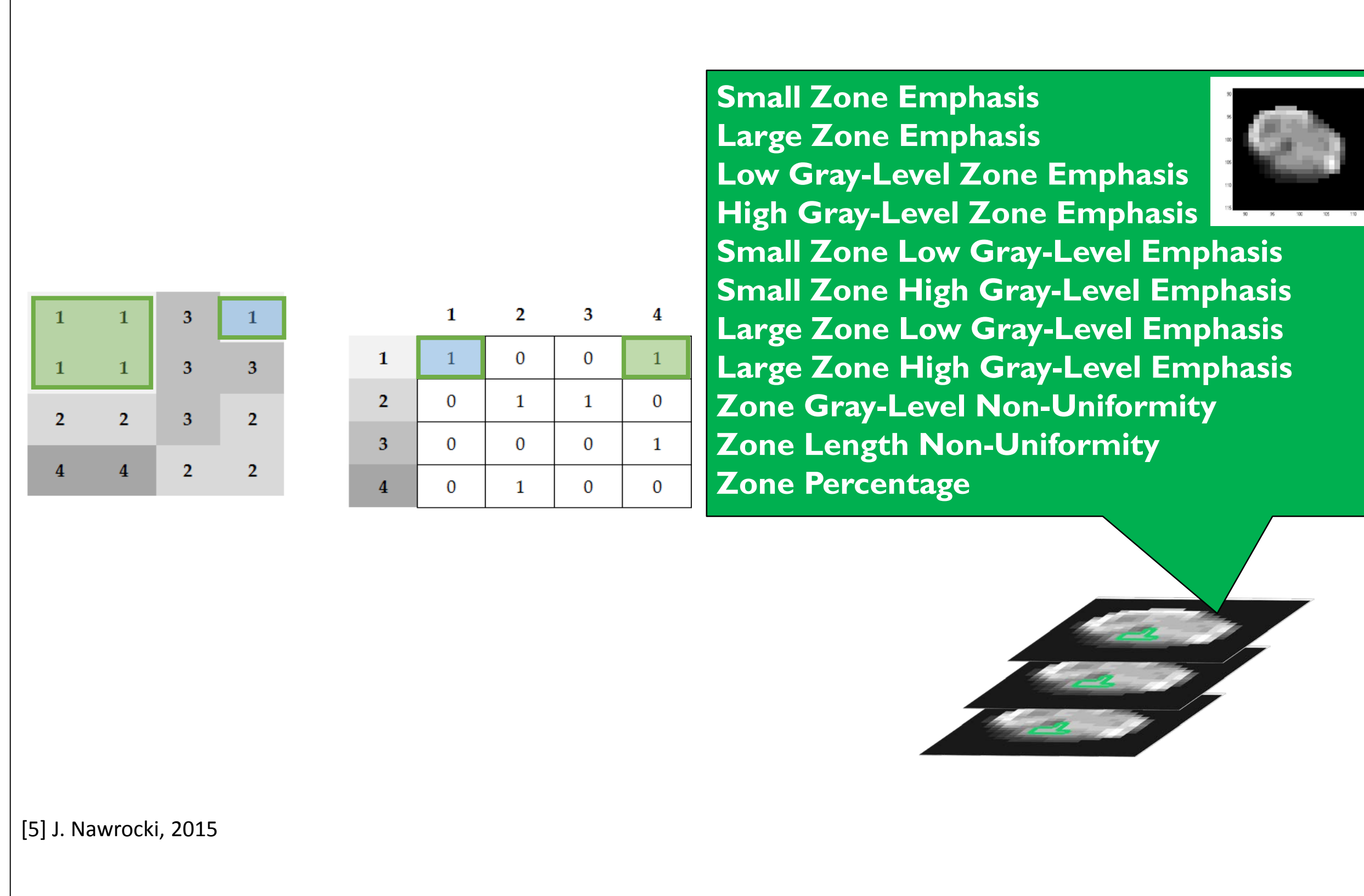

Pixel intensities Pairs are found in the Co-Occurrence Matrix [1].

Lengths of common pixels are found in the Run Length Matrix [2].

The Neighborhood Difference Matrix averages intensities around a pixel [4]

Zones of common pixel intensities are found in the Size Zone Matrix [3]

Panel B: Gray Level Co-Occurrence Matrix (GLCM). 12 local features.

Energy
Entropy
Correlation
Contrast
Homogeneity
Homogeneity (v2)
Variance
Sum Mean
Cluster Shade
Cluster Tendency
Maximum Probability
Inverse Variance

[5] J. Nawrocki, 2015

Panel C: Gray Level Run Length Matrix (GLRLM). 11 regional features.

Short Run Emphasis
Long Run Emphasis
Low Gray-Level Run Emphasis
High Gray-Level Run Emphasis
Short Run Low Gray-Level Emphasis
Short Run High Gray-Level Emphasis
Long Run Low Gray-Level Emphasis
Long Run High Gray-Level Emphasis
Gray-Level Non-Uniformity
Run Length Non-Uniformity
Run Percentage

[5] J. Nawrocki, 2015

Panel D: Gray Level Size Zone Matrix (GLSZM). 11 regional features.

Small Zone Emphasis
Large Zone Emphasis
Low Gray-Level Zone Emphasis
High Gray-Level Zone Emphasis
Small Zone Low Gray-Level Emphasis
Small Zone High Gray-Level Emphasis
Large Zone Low Gray-Level Emphasis
Large Zone High Gray-Level Emphasis
Zone Gray-Level Non-Uniformity
Zone Length Non-Uniformity
Zone Percentage

[5] J. Nawrocki, 2015

Panel E: Neighborhood Gray Level Difference Matrix. 5 local features.

Coarseness
Contrast
Busyness
Complexity
Texture Strength

[5] J. Nawrocki, 2015
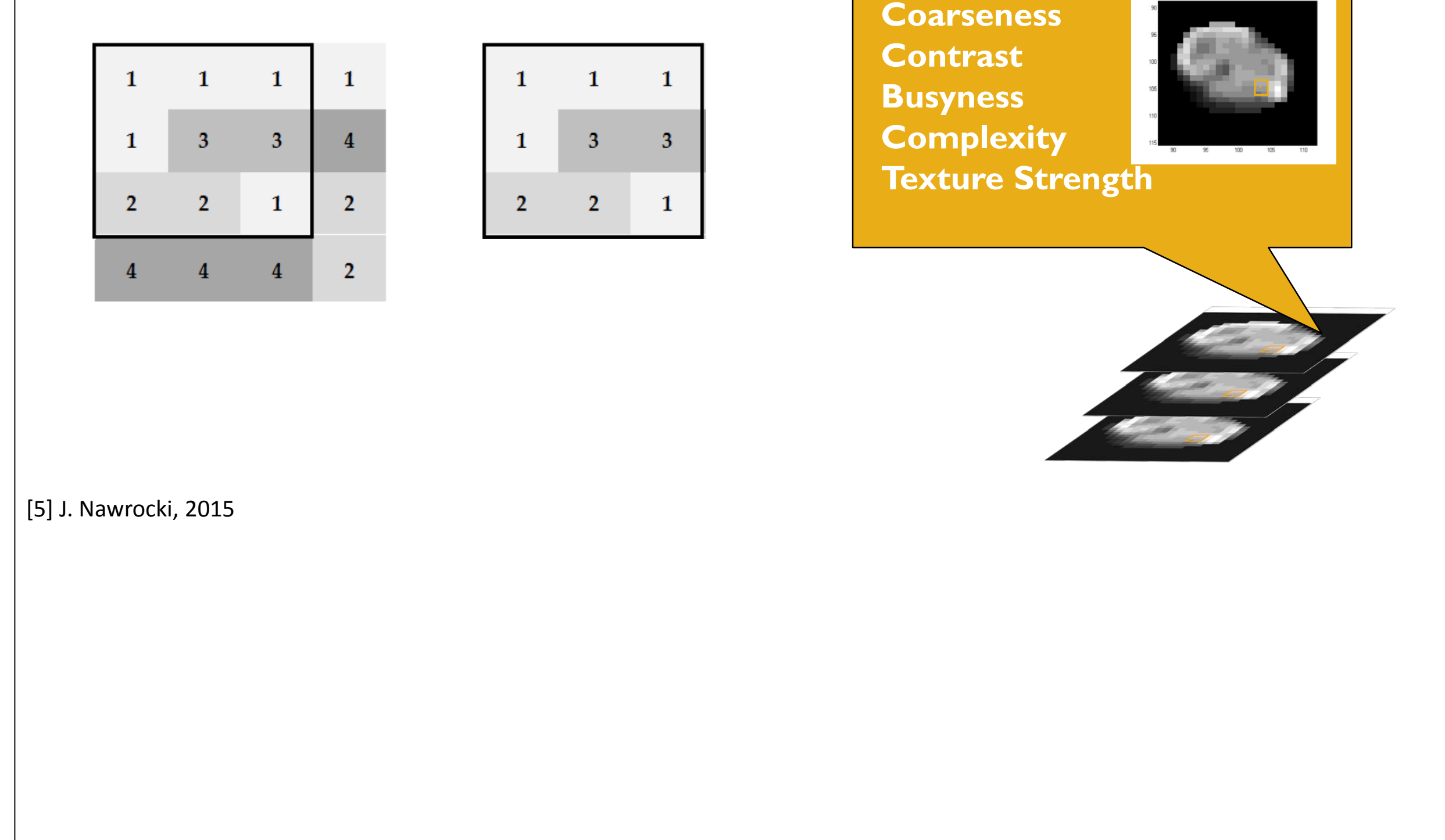
Panel F: The in-house developed Texture Analysis Matlab-based platform, used to calculate tumoral texture metrics for local and regional relationships for co-occurrence, run length, size zone, and neighborhood difference.
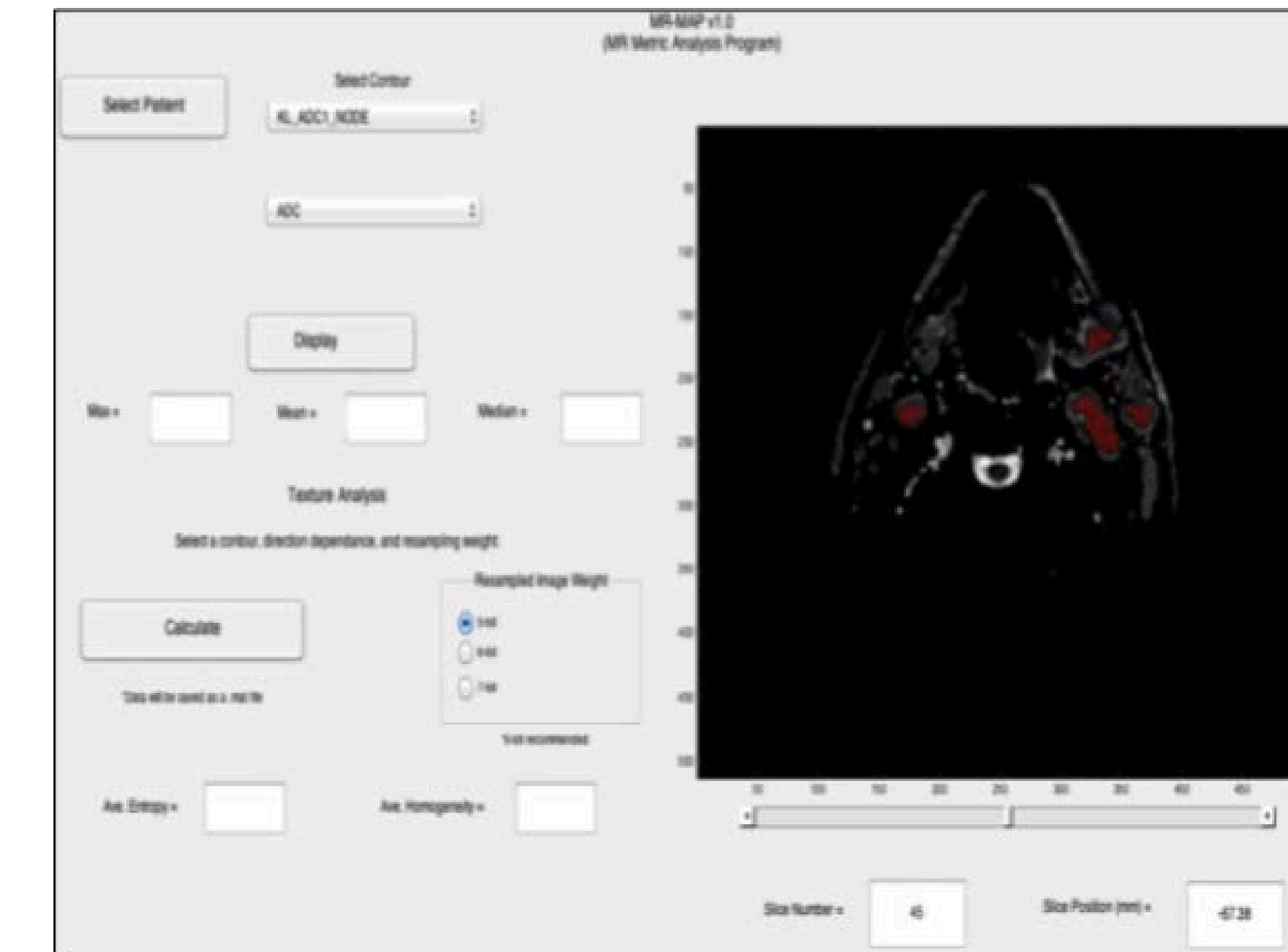
Panel G: ADC maps superimposed on the corresponding CT images for the 3 time points, as well as masked ADC for primary and nodal ROIs. These maps were rigidly registered and then resampled to the temporally corresponding CT scan.

Baseline 1 — Baseline 2 — Early treatment
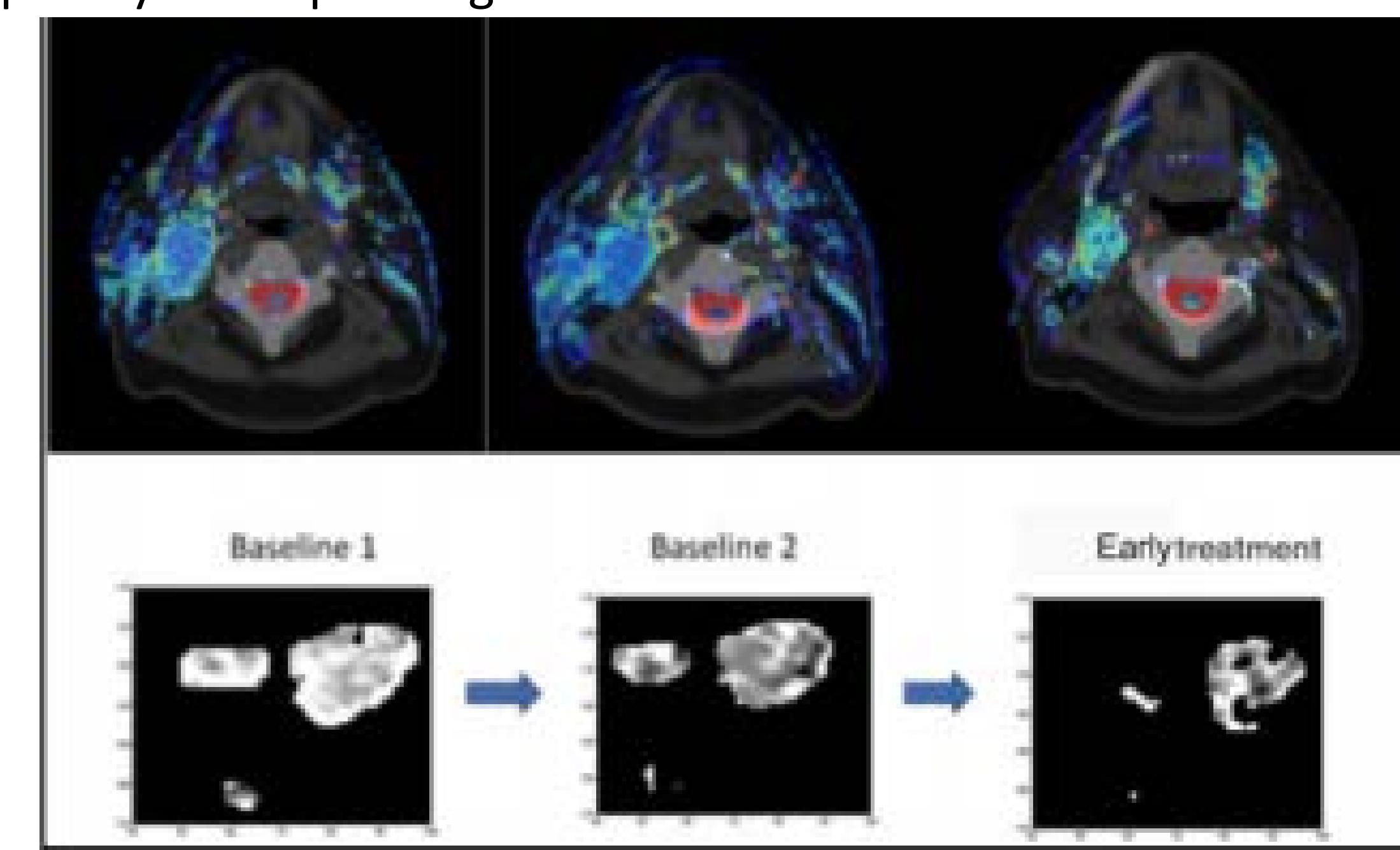
Panel H: Bland-Altman plots showing two metrics with high ICC (Coarseness & Run Length Non-Uniformity) and low ICC (Entropy & Busyness).
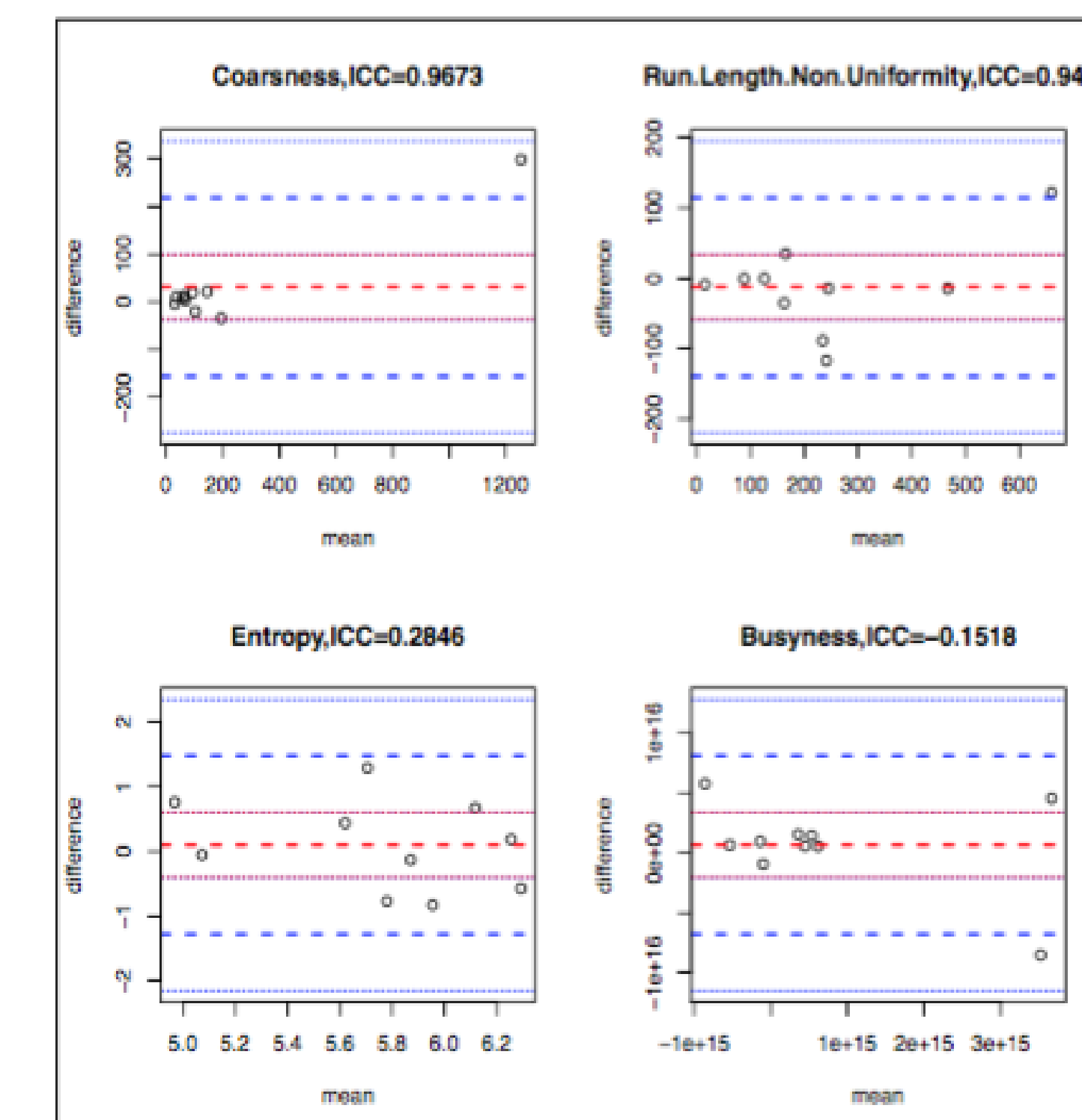
Panel I: Observed ICC values and the results of the Holmcorrected, signed rank test of the change from baseline to intratreatment for each metric. ‡ Run length was the only test that achieved significance using a Holm-corrected alpha.

Metric	Matrix	P-value	Holm's Alpha ‡	ICC
Run length Non-Uniformity	GLRLM	0.004	0.0056	0.97
ADC Median	Histogram	0.01	0.0063	0.95
Texture Strength	NGLDM	0.01	0.0071	0.93
ADC Mean	Histogram	0.02	0.0083	0.95
Zone Percentage	GLZLM	0.04	0.01	0.84
Variance	Histogram	0.04	0.0125	0.84
Coarseness	NGLDM	0.05	0.0167	0.83
Long Zone	GLZLM	0.2	0.025	0.84
Cluster Shade	GLCM	0.3	0.05	0.8