

Correlating imaging parameters with molecular data: a novel approach to improve the management of oncological patients



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Biomarcatori e Tecniche di Diagnostica per Immagini nella Valutazione dell'Infiammazione in Oncologia

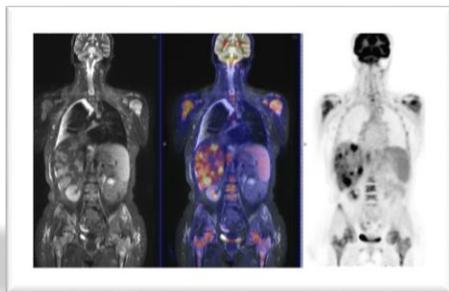
Mariarosaria Incoronato

IRCCS SDN MISSION

INTEGRATING the imaging results with molecular biology results in order to improve the management and the "clinical decision making" of the BC patient.

Hi, I'm IMAGING

Hi, I'm a BIOMARKER



BIOMARKERS DISCOVERY



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Review

Radiogenomic Analysis of Oncological Data: A Technical Survey

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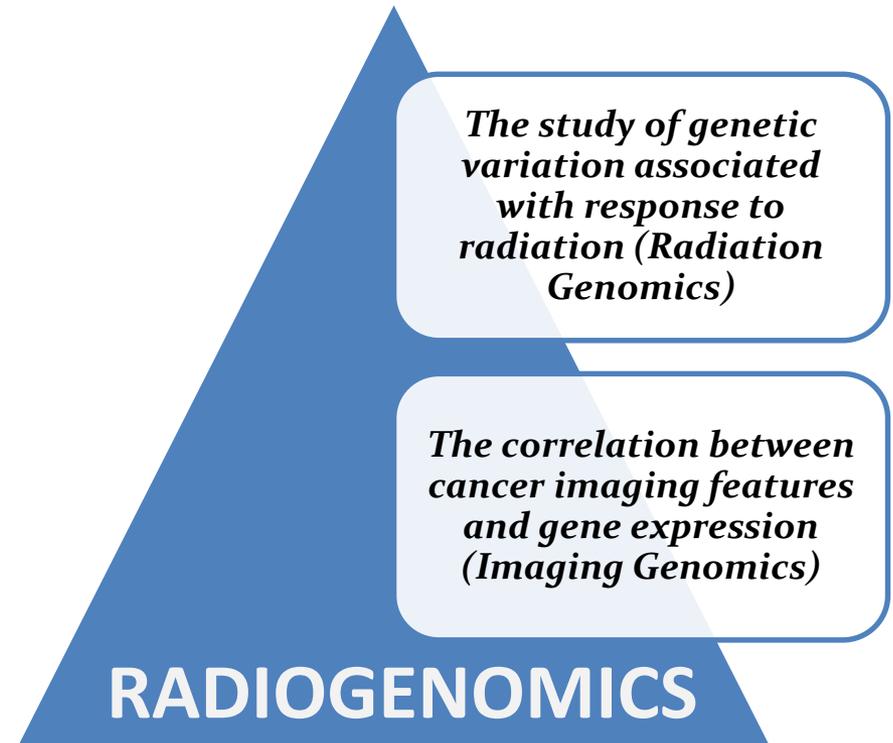
***Could the integration of imaging parameters
and biological markers improve the management
of oncological patients?***

Radiation genomics

Genetic variation, such as single nucleotide polymorphisms, is studied in relation to a cancer patient's risk of developing toxicity following radiation therapy. It is also used in the context of studying the genomics of tumor response to radiation therapy

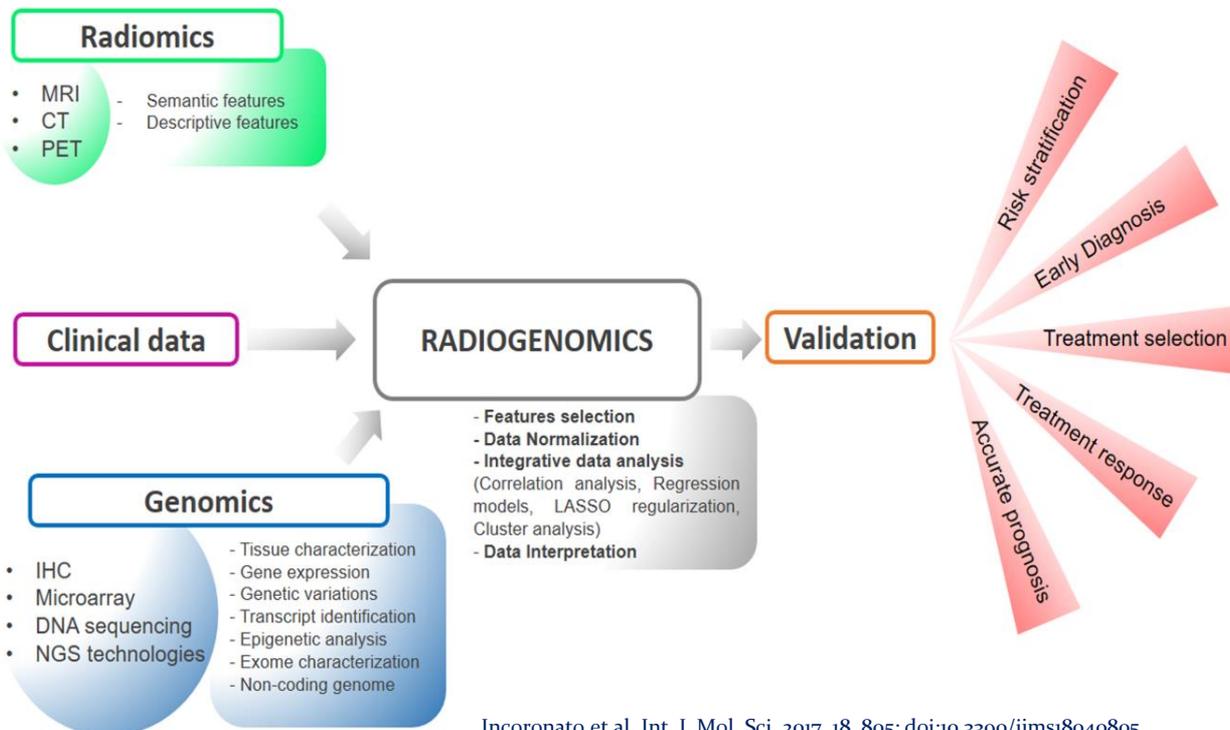
Imaging genomics

In imaging genomics, radiogenomics can be used to create imaging biomarkers that can identify the genomics of a disease, especially cancer without the use of a biopsy.



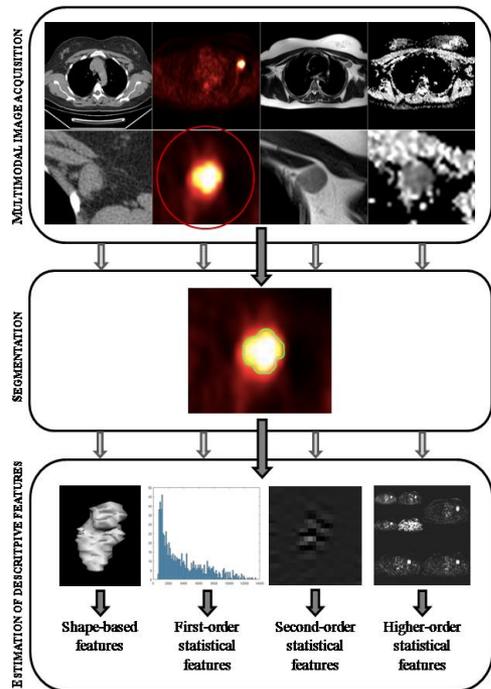
Radiogenomics

Technological improvements in the field of imaging and molecular biology have led to the “Radiogenomics” or “Imaging Genomics”. Literally, Radiogenomics refers to the analytical processes aimed to correlate cancer imaging features (Radiomics) with Genomic data.



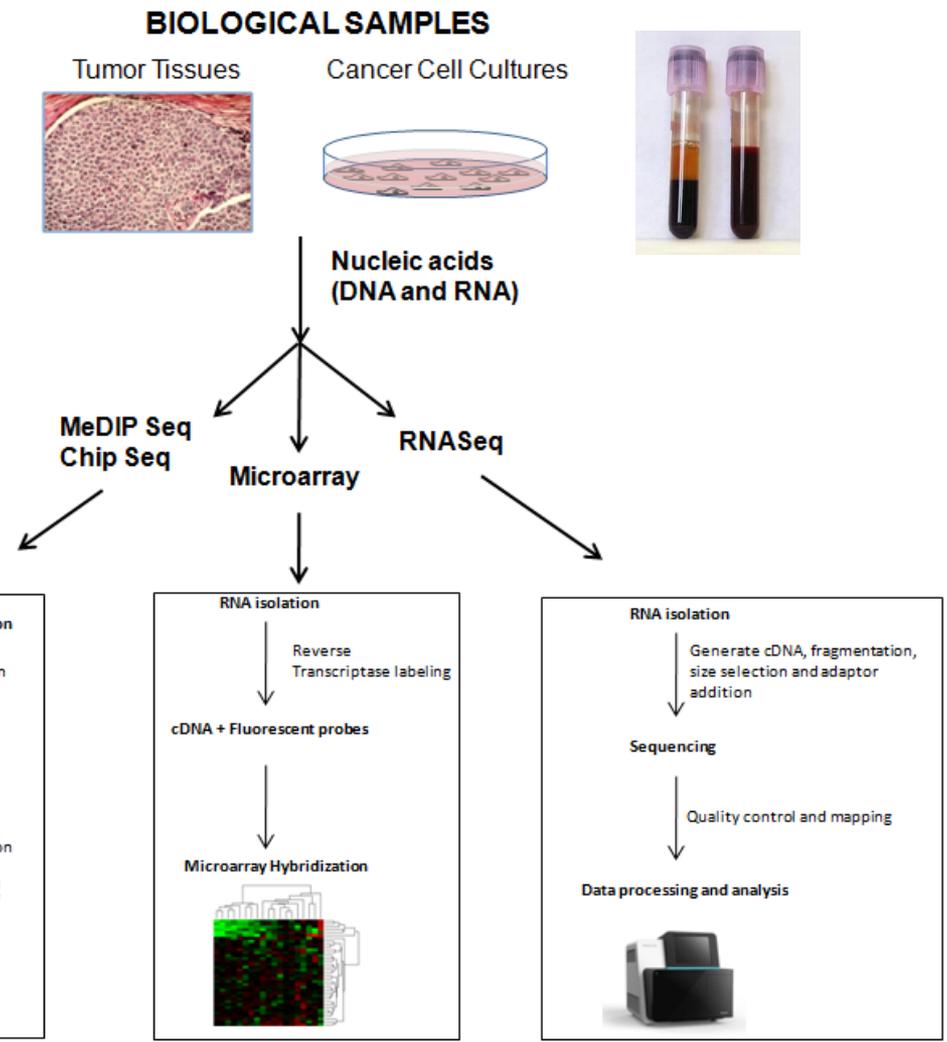
Radiomics refers to the comprehensive quantification of tumor phenotypes by the extraction of a large amount of quantitative features from medical images. This high-throughput extraction of quantitative imaging features is the result of a workflow composed of three main steps

- Acquiring the images
- Segmenting the regions of interest (ROIs)
- Estimating descriptive features

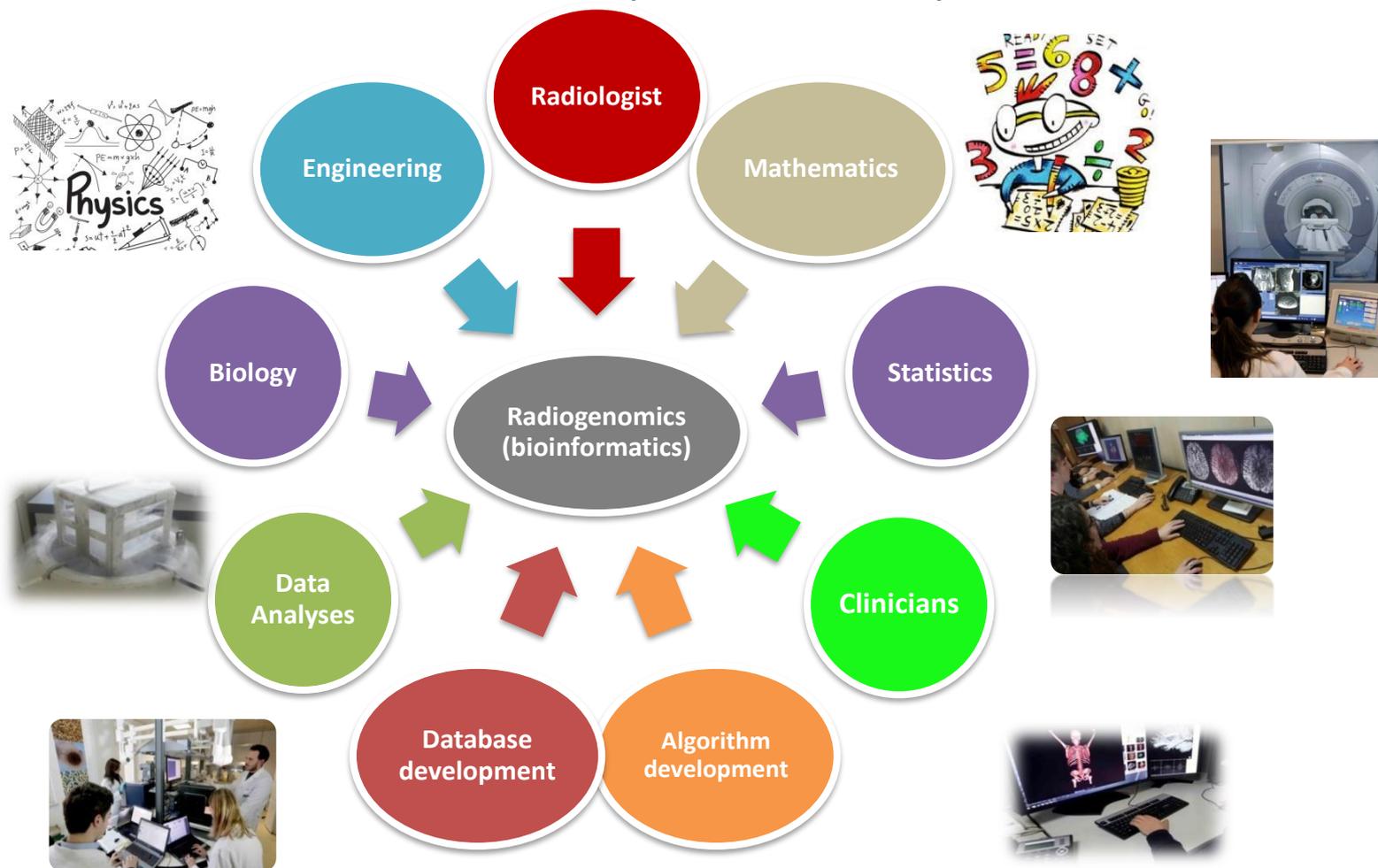


A great advantage of radiomic analyses is their feasibility with conventional clinical images (PET, CT, MRI). The first step of radiomic pipeline, in fact, involves the acquisition of images that are typically part of diagnostic or treatment planning protocols for oncological patients

Genomics is the study of the entirety of an organism's genes actually performed by the combination of high-throughput molecular biology technologies with complex computing and math techniques (bioinformatic analysis). Generally, two technologies are critical for genomics analysis: 1) **microarray**; and 2) **next generation sequencing** (NGS)



Once both radiomic and genomic features are extracted, radiogenomic analysis will be performed. Radiogenomic approaches are extensively based on numerical calculus and computer science methods, allowing the management and analysis of a huge number of variables for each sample and modality.



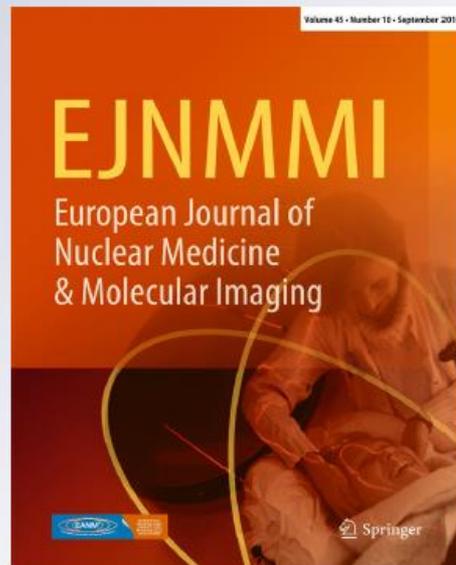
Relationship between functional imaging and immunohistochemical markers and prediction of breast cancer subtype: a PET/MRI study

Mariarosaria Incoronato, Anna Maria Grimaldi, Carlo Cavaliere, Marianna Inglese, Peppino Mirabelli, Serena Monti, Umberto Ferbo, et al.

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PURPOSE: The aim of this study was to determine if functional parameters extracted from the hybrid system positron emission tomography/magnetic resonance imaging (PET/MRI) correlated with the immunohistochemical markers of breast cancer (BC) lesions, to assess their ability to predict BC subtypes.

N° patients	50
Age	52.5 (35-80)
Receptor status	Number
ER+	42
ER-	8
PR+	43
PR-	7
HER+	19
HER-	31
Proliferation index	
Ki-67 <20%	12
Ki-67 ≥20%	38
Grade	
G1	1
G2	27
G3	22

Table 1. Clinical features of tumour lesions.

		Luminal A	Luminal B	HER2 enriched	Basal like
Subtype					
Number		13	29	4	3
Lesion size (cm)		3.8 (0.7-5.0)*	4.1 (2.3-7.8)*	4.2 (2.9-6.6)*	4.2 (2.6-7.1)*

Table 2. Molecular subtype and relative lesion size.

*Mean and size range in parenthesis.

Luminal A	ER+, PR≥20%, Her2-, Ki67<20%
Luminal B	- ER+, Her2-, PR<20% or Ki67 ≥20%; - ER+, Her2+, Ki67 and PR any value
Basal-like	ER-, PR-, Her2-
Her2-like	ER-, PR- and Her2+

CORRELATION ANALYSIS

Perfusion, diffusion and metabolic imaging parameters

- **Ktrans**: forward volume transfer constant
- **Ve**: extravascular extracellular space volume
- **Kep**: reverse efflux volume transfer constant
- **SUV**: metabolic standardized uptake value
- **SUL**: lean body mass
- **ADC**: apparent diffusion coefficient
- **Lesion size**

Mann–Whitney U test

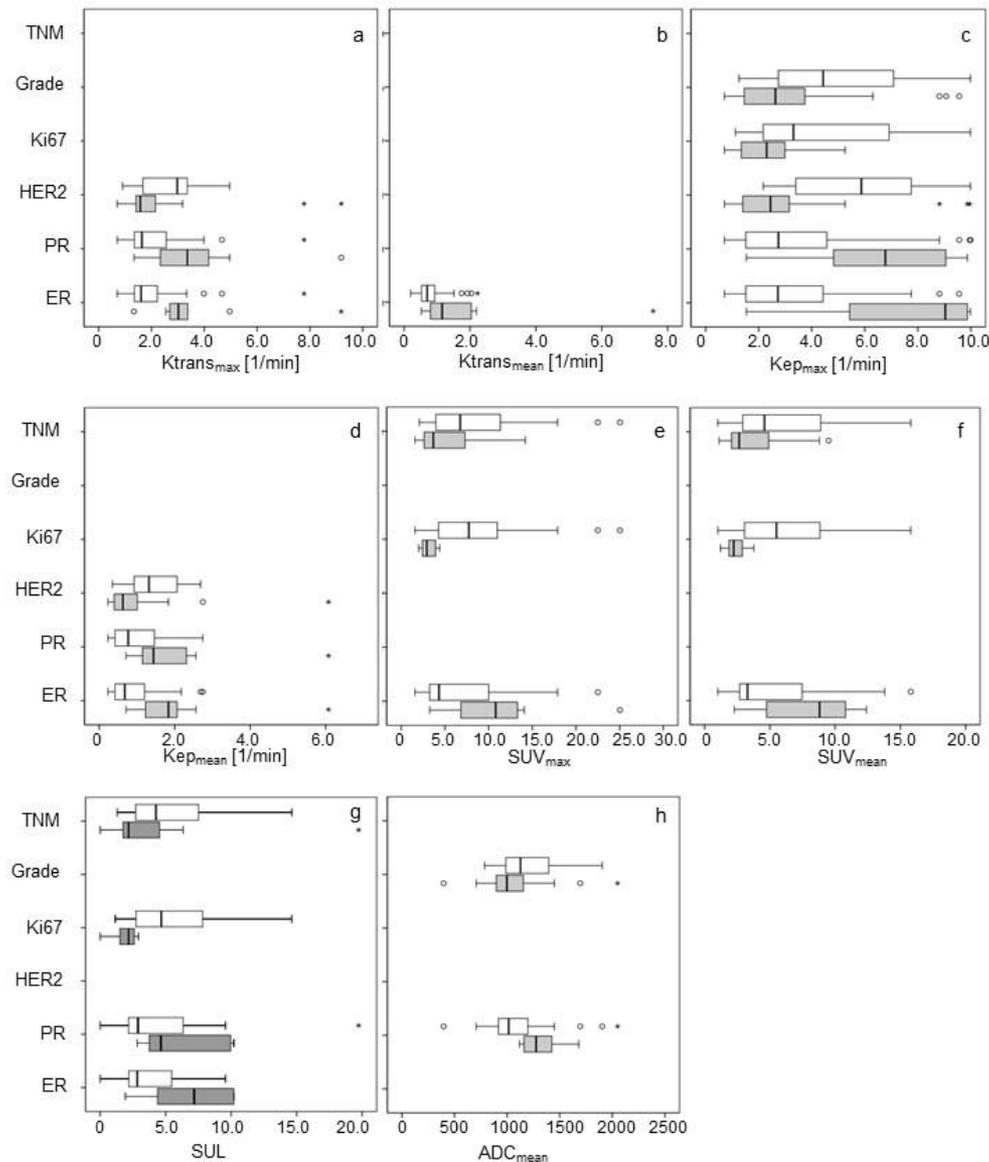


Fig. 3 Association study among IHC markers versus perfusions and diffusion imaging parameters. White colour refers to positive receptors status (ER, PR and HER2), high Ki67, Grade 3, and T3-4 staging; grey colour refers to negative receptors status (ER, PR and HER2), low Ki67, Grade 2, and T1-2 staging. Standard box plot, in which the vertical line represents the median, the thick line the interquartile range, and the thin line the maximum and minimum values. The circular and star dots represent the outliers.

ABILITY OF PET/MRI PARAMETERS TO DISCRIMINATE BETWEEN BC MOLECULAR SUBTYPES

Luminal A	ER+, PR \geq 20%, Her2-, Ki67<20%
Luminal B	- ER+, Her2-, PR<20% or Ki67 \geq 20%; - ER+, Her2+, Ki67 and PR any value
Basal-like	ER-, PR-, Her2-
Her2-like	ER-, PR- and Her2+

Kruskal–Wallis test and pairwise comparisons

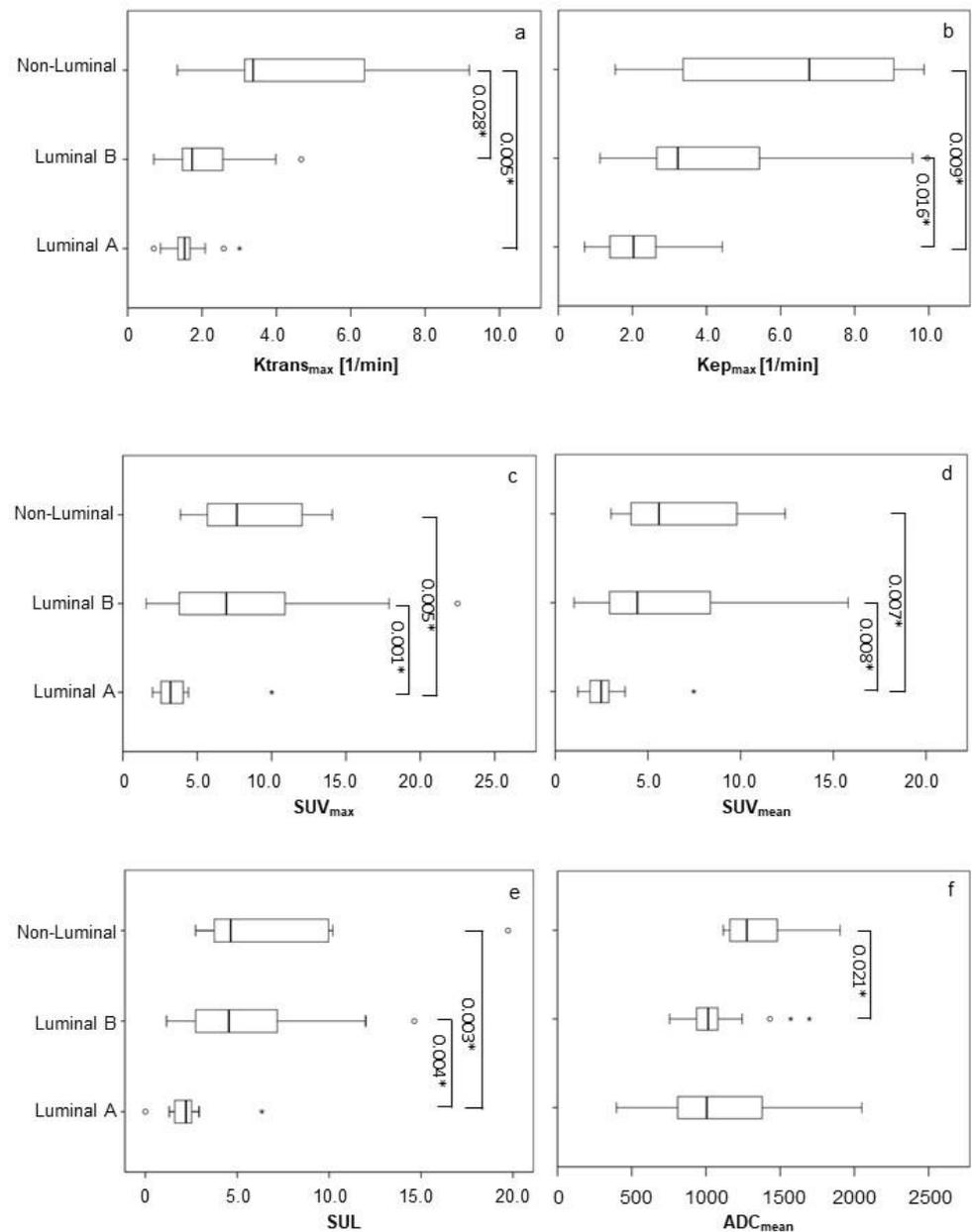
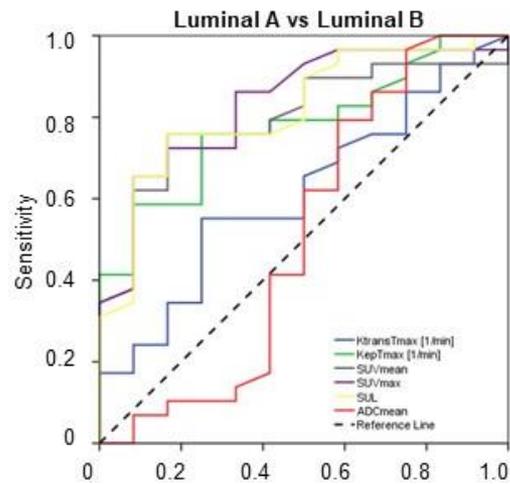
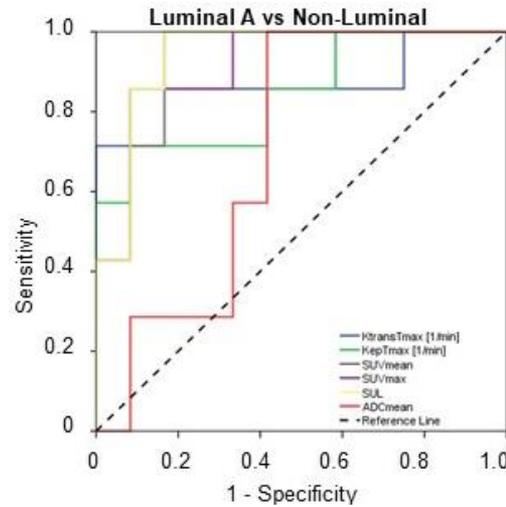


Fig. 4 Distribution of imaging parameters versus tumour subtypes. Standard box plot, in which the vertical line represents the median, the thick line represents the interquartile range, and the thin line represents the maximum and minimum values. The circular and star dots represent the outliers. *Indicates statistical significance achieved after correction for pairwise multiple comparisons.

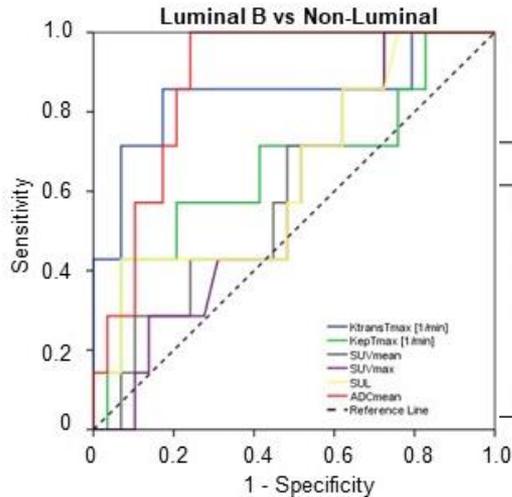
DIAGNOSTIC ACCURACY OF IMAGING PARAMETERS



Imaging parameters	AUC	Std. Error	p-value	Cut-off
Ktrans _{max} [1/min]	0.614	0.09	0.258	1.69
<u>Kep_{max} [1/min]</u>	<u>0.779</u>	<u>0.07</u>	<u>0.005*</u>	2.64
<u>SUV_{mean}</u>	<u>0.799</u>	<u>0.07</u>	<u>0.003*</u>	2.93
<u>SUV_{max}</u>	<u>0.833</u>	<u>0.07</u>	<u><0.001*</u>	4.43
<u>SUL</u>	<u>0.813</u>	<u>0.07</u>	<u>0.001*</u>	2.72
ADC _{mean}	0.509	0.12	0.931	770.50



Imaging parameters	AUC	Std. Error	p-value	Cut-off
<u>Ktrans_{max} [1/min]</u>	<u>0.881</u>	<u>0.10</u>	<u>0.007*</u>	2.76
<u>Kep_{max} [1/min]</u>	<u>0.845</u>	<u>0.10</u>	<u>0.014*</u>	3.70
<u>SUV_{mean}</u>	<u>0.929</u>	<u>0.06</u>	<u>0.002*</u>	2.97
<u>SUV_{max}</u>	<u>0.917</u>	<u>0.07</u>	<u>0.003*</u>	4.48
<u>SUL</u>	<u>0.945</u>	<u>0.50</u>	<u>0.001*</u>	2.72
ADC _{mean}	0.702	0.12	0.151	1076.00



Imaging parameters	AUC	Std. Error	p-value	Cut-off
<u>Ktrans_{max} [1/min]</u>	<u>0.842</u>	<u>0.10</u>	<u>0.005*</u>	2.90
Kep _{max} [1/min]	0.660	0.13	0.194	6.54
SUV _{mean}	0.616	0.11	0.349	2.97
SUV _{max}	0.589	0.11	0.472	3.83
SUL	0.643	0.12	0.246	9.648
<u>ADC_{mean}</u>	<u>0.877</u>	<u>0.06</u>	<u>0.002*</u>	1098.50

Fig. 5 ROC curve analyses. Diagnostic accuracy of imaging parameters were evaluated among breast cancer subtypes, as indicated: luminal A vs luminal B subtypes (panel a), luminal A vs Non-luminal subtypes (panel b) and luminal B vs Non-luminal subtypes (panel c), tables on the right summarize AUC, p-value and cut-off values of imaging parameters taken in account for ROC curve analyses (* indicates p-value statistically significant).

MULTIVARIATE ANALYSES FOR PREDICTION STUDIES

True: correctly predicted cases; False: not correctly predicted cases.

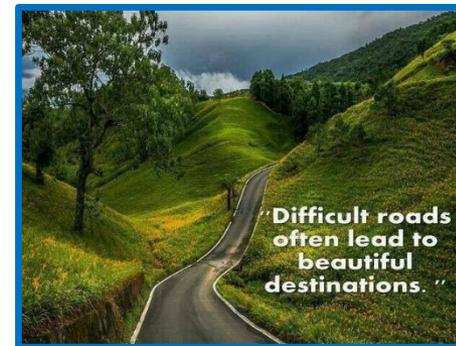
Logistic regression for predictive model

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Ktrans _{max}	1.169	0.368	10.073	1.00	0.002	0.447	1.890
SUV _{max}	0.234	0.081	8.283	1.00	0.004	0.075	0.394

Subtypes defined by IHC (n°)	Number of predicted subtype (%)		
	Luminal A	Luminal B	Non-luminal
Luminal A (13)	<u>True</u> 9 (69.2%)	<u>False</u> 4 (30.8%)	<u>False</u> 0 (0%)
Luminal B (29)	<u>False</u> 3 (10.3%)	<u>True</u> 25 (86.2%)	<u>False</u> 1 (3.5%)
Non-luminal (7)	<u>False</u> 0 (0%)	<u>False</u> 3 (42.9%)	<u>True</u> 4 (57.1%)

CONCLUSIONS: Using multivariate analyses of both PET and MR parameters, a prognostic model including Ktrans_{max} and SUV_{max} was able to predict 38/49 tumor subtypes (77.6%, p<0.001), with higher accuracy for the luminal B subtype (86.2%).

Could the integration of imaging parameters and biological markers improve the management of oncological patients?



tusind tak
謝謝 dakujem vám
ありがとう
ngiyabonga
dziękuję
merci
baie dankie
धन्यवाद molte grazie
suksema
danke
thank
you
gracias
obrigada
obrigado
takk
gràcies
tänan
teşekkür ederim
شكرا
tack så mycket
dank u
teşekkür edire
mahalo