

Optimization of sensitivity to disease-associated cortical metabolic abnormality by evidence-based quantification of in vivo ^1H MRS data from 3 T and 7 T

Kelley M. Swanberg, M.Sc.¹

Advisor: Professor Christoph Juchem, Ph.D.^{1,2}

¹Biomedical Engineering, Columbia University School of Engineering and Applied Science, New York, NY, USA

²Radiology, Columbia University Vagelos College of Physicians and Surgeons, New York, NY, USA



Doctoral Dissertation Defense
3 February 2022

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

CHAPTER I

Spectral Quantification:

What are the effects of spectral quality and baseline on the precision and accuracy of relative metabolite concentrations drawn from ^1H MRS data, and how do we minimize them?

CHAPTER II

Absolute Quantification:

Can disease-related differences in metabolite T_2 introduce systematic errors to the derivation of absolute from relative metabolite concentrations, and how do we minimize them?

CHAPTER III

Statistical Analysis:

Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of ^1H MRS data alone classify disease states (case application multiple sclerosis)?

CHAPTER IV

Generalization:

Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

CHAPTER V

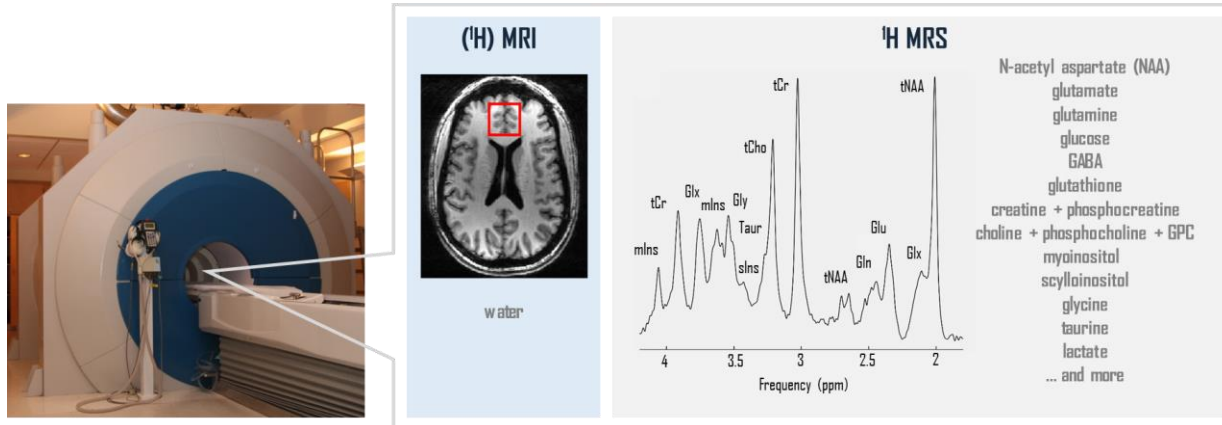
Back to the Big Picture:

General conclusions and outlook

CHAPTER VI

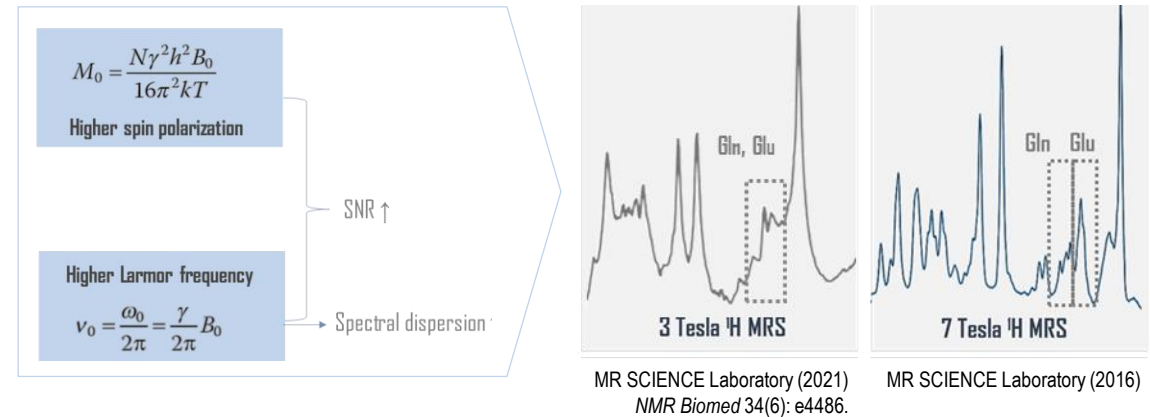
CHAPTER 1: INTRODUCTION

Noninvasive small-molecule metabolic profiling of tissue

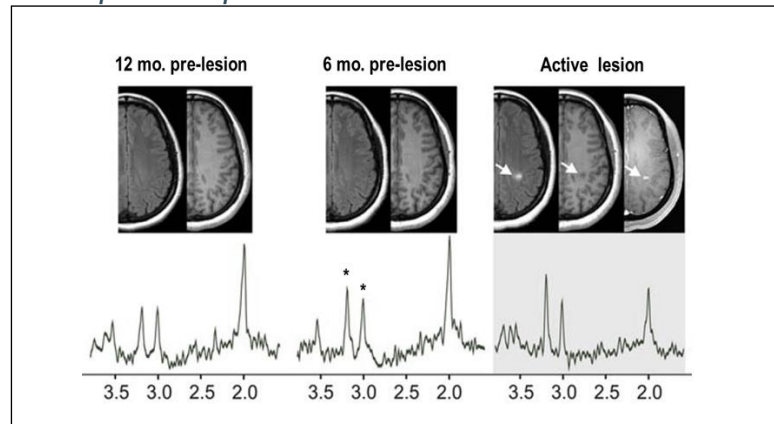


Swanberg, Prinsen, Bailey, Destefano, Pitt, Fulbright, and Juchem. *Proc Int Soc Magn Reson Med* 2017; 2970.

Magnet field strength ↑ → data quality ceiling ↑

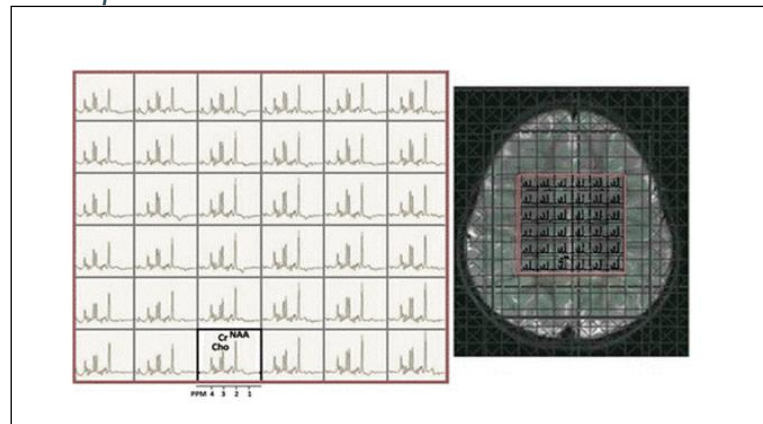


Multiple time points



Kirov, Liu, Tal, Wu, Davitz, Babb, Rusinek, Herbert, and Gonen. *Human Brain Mapping* 2017; 38: 4047-63.

Multiple voxels



Zhu and Barker. *Methods Mol Biol* 2011; 711: 203-26.

Multiple metabolites

TABLE 4 | F1-scores for all nine classification tasks (rows) after training LDA using only metabolic ratios.

	NAA/Cho	NAA/Cr	Cho/Cr	All 3 metabolic ratios
HC vs. CIS	35	33	43	36
HC vs. RR	6	16	—	14
HC vs. PP	47	45	19	49
HC vs. RR+SP	8	19	—	16
HC vs. PP+SP	21	26	—	28
CIS vs. RR	15	—	—	21
CIS vs. RR+SP	3	—	—	19
RR vs. PP	75	78	75	74
RR vs. SP	60	67	58	69

Values above 75 are colored in light gray.

Ion-Margineau, Kocevar, Stamile, Sima, Durand-Dubief, Huffel, and Sappey-Mariner. *Front Neurosci.* 2017; 11:398.

CHAPTER 1: INTRODUCTION



January 2020

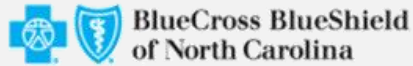
policy update bulletin

UnitedHealthcare West Medical Management Guideline Updates

Magnetic
Resonance
Spectroscopy
(MRS)

Aug. 1, 2018

- Updated non-coverage rationale:
 - Replaced language indicating "[the listed service] is unproven *and* not medically necessary" with "[the listed service] is **unproven and/or not medically necessary**"
 - Replaced reference to "patients" with "individuals"
- Updated supporting information to reflect the most current clinical evidence, FDA information, and references



An independent licensee of the Blue Cross and Blue Shield Association

Corporate Medical Policy

Policy

Magnetic Resonance Spectroscopy is considered investigational. BCBSNC does not provide coverage for investigational services or procedures.

Magnetic Resonance Spectroscopy

File Name: magnetic_resonance_spectroscopy
Origination: 12/1997
Last CAP Review: 5/2020
Next CAP Review: 5/2021
Last Review: 5/2020



Aetna considers magnetic resonance spectroscopy (MRS) (also known as NMR spectroscopy) experimental and investigational for all other indications, including the following (not an all-inclusive list) **because there is a lack of evidence of its efficacy in the medical literature.**

- Adrenoleukodystrophy
- Breast cancer
- Cerebrovascular diseases/disorders/injuries
- Dementia and movement disorders (e.g., Alzheimer's disease, dementia with Lewy bodies, frontotemporal dementia, Huntington disease, motor neuron disease, normal-pressure hydrocephalus, Parkinson disease/Parkinsonian syndromes, vascular dementia)
- Dermatomyositis
- Detection and quantification of hepatic steatosis in living liver donors
- Detection of esophageal squamous cell carcinoma
- Differentiation of primary central nervous system lymphoma (PCNSL) from other focal brain lesions
- Epilepsy (including juvenile myoclonic epilepsy, and temporal lobe epilepsy)
- Evaluation of migraine pathophysiology and identification of biomarkers in migraine

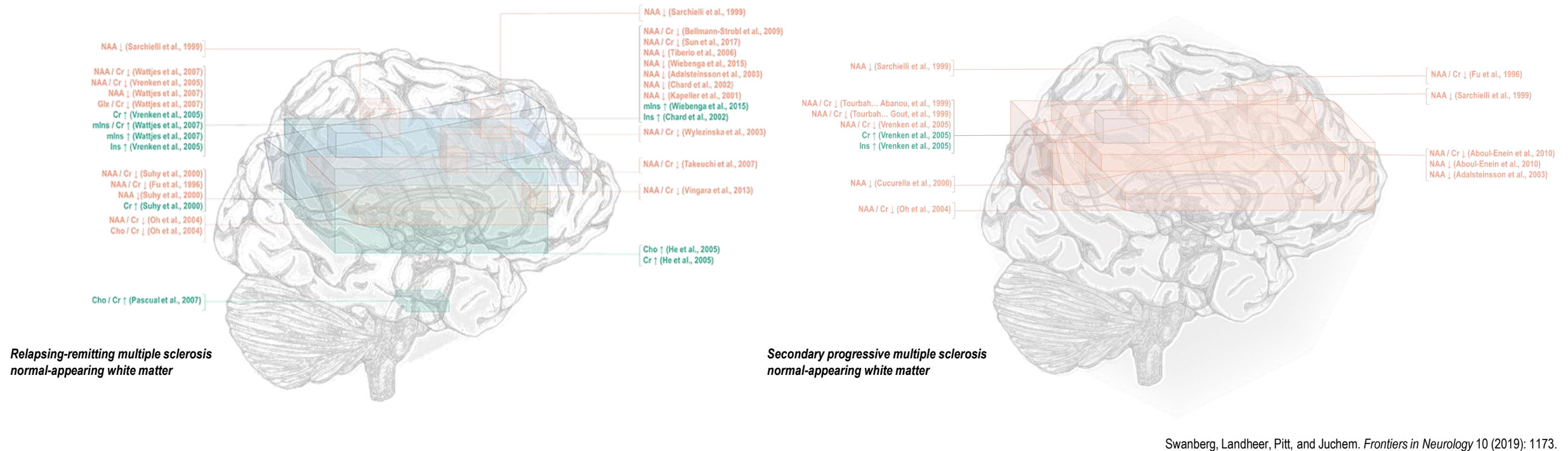
- Head trauma
- Low back pain
- Lyme neuroborreliosis
- Metabolic and mitochondrial diseases
- Monitoring hepatocellular carcinoma and liver cirrhosis development
- Mucopolysaccharidosis
- Multiple sclerosis
- Polymyositis
- Prognosis of consciousness recovery in individuals with vegetative state
- Prostate cancer
- Psychiatric disorders (e.g., attention-deficit/hyperactivity disorder, autism spectrum disorders, bipolar disorder, depression, emotional dysregulation, obsessive-compulsive disorder, and schizophrenia)
- Radiation encephalopathy
- Sport-related concussion
- Substance use disorders
- Traumatic brain injury

Policy

Aetna considers magnetic resonance spectroscopy (MRS) (also known as NMR spectroscopy) medically necessary for the following indications:

- Assessing prognosis in hypoxic ischemic encephalopathy
- Distinguishing low grade from high grade gliomas
- Evaluate a brain lesion of indeterminate nature when the MRS findings will be used to determine whether biopsy/resection can be safely postponed
- Distinguishing recurrent brain tumor from radiation-induced tumor necrosis.

CHAPTER 1: INTRODUCTION

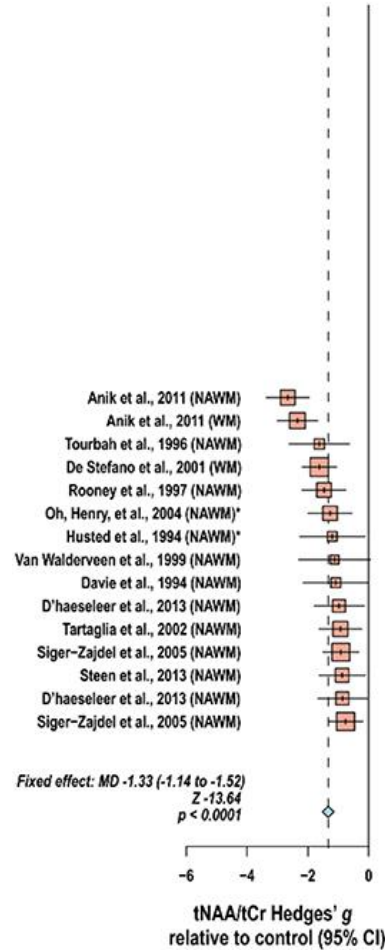


Swanberg, Landheer, Pitt, and Juchem. *Frontiers in Neurology* 10 (2019): 1173.

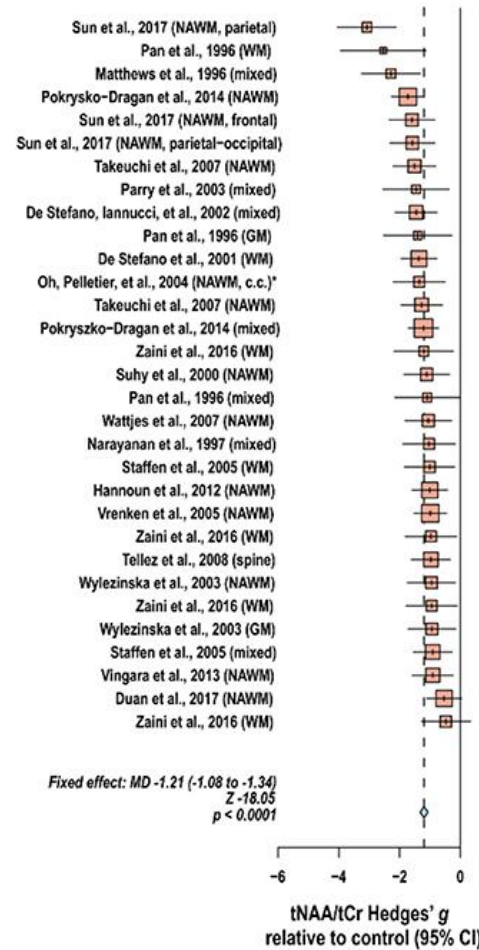
Classification of multiple sclerosis by single ^1H -MRS-visible metabolites lacks diagnostically useful sensitivity and especially specificity.

CHAPTER 1: INTRODUCTION

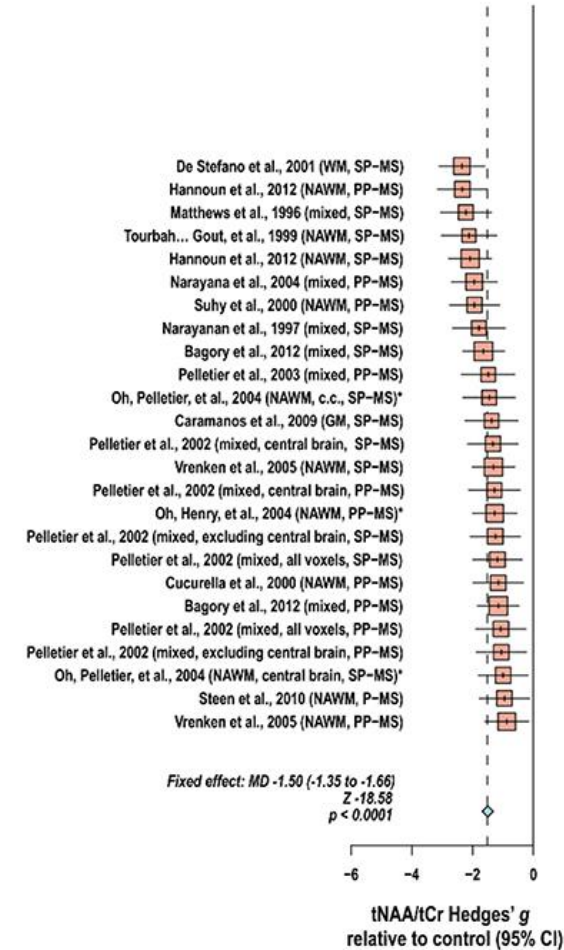
Mixed or unspecified MS



Relapsing-remitting MS



Progressive MS



Swanberg, Landheer, Pitt and Juchem. *Frontiers in Neurology* 10 (2019): 1173.

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CHAPTER 1: INTRODUCTION

References	MS	Tissue	Effect	References	MS	Tissue	Effect
Aboul-Enein et al. (80)	SP	NAWM	↓ in MS	Pan et al. (54)	R	mixed	↓ in MS
Aboul-Enein et al. (80)	R	NAWM	NS	Parry et al. (74)	R	mixed	↓ in MS
Anik et al. (41)	M	WM	↓ in MS	Pascual et al. (141)	R	NAWM	NS
Anik et al. (41)	M	NAWM	↓ in MS	Pelletier et al. (85)	PP	mixed, supratentorial	↓ in MS
Arnold et al. (47)	M	mixed	↓ in MS	Pelletier et al. (85)	PP	mixed, excluding central	↓ in MS
Bagory et al. (84)	SP	mixed	↓ in MS	Pelletier et al. (85)	PP	mixed, central	↓ in MS
Bagory et al. (84)	PP	mixed	↓ in MS	Pelletier et al. (85)	SP	mixed, supratentorial	↓ in MS
Bagory et al. (84)	R	mixed	NS	Pelletier et al. (85)	SP	mixed, excluding central	↓ in MS
Bellmann-Strobl et al. (65)	R	NAWM	↓ in MS	Pelletier et al. (85)	SP	mixed, central	↓ in MS
Brass et al. (43)	M	NAWM	↓ in MS	Pelletier et al. (85)	R	mixed, supratentorial	NS
Caramanos et al. (83)	SP	GM	↓ in MS	Pelletier et al. (85)	R	mixed, excluding central	NS
Caramanos et al. (83)	R	GM	NS	Pelletier et al. (85)	R	mixed, central	NS
Casanova et al. (204)	R	NAWM, peduncles	NS	Pelletier et al. (89)	PP	mixed	↓ in MS
Casanova et al. (204)	R	NAWM, pons	NS	Pokryszko-Dragan et al. (63)	R	mixed	↓ in MS
Cucurella et al. (78)	SP	NAWM	NS	Pokryszko-Dragan et al. (63)	R	WM	↓ in MS
Cucurella et al. (78)	PP	NAWM	↓ in MS	Reddy et al. (59)	R	WM	↓ in MS*
Davie et al. (24)	M	NAWM	↓ in MS	Rooney et al. (37)	M	NAWM	↓ in MS
De Stefano et al. (86)	RP	mixed	↓ in MS*	Ruiz-Peña et al. (143)	R	NAWM	NS
De Stefano et al. (36)	M	WM	↓ in MS	Sarchielli et al. (53)	R	NAWM	NS
De Stefano et al. (36)	R	WM	↓ in MS	Sarchielli et al. (88)	SP	mixed	↓ in MS
De Stefano et al. (36)	SP	WM	↓ in MS	Siger-Zajdel et al. (44)	M _{sp}	NAWM	↓ in MS
De Stefano et al. (72)	R	mixed	↓ in MS	Siger-Zajdel et al. (44)	M _f	NAWM	↓ in MS
De Stefano et al. (61)	R	WM	↓ in MS	Staffen et al. (58)	R	mixed	↓ in MS
D'Haeseleer et al. (42)	M	NAWM	↓ in MS	Staffen et al. (58)	R _{nl}	NAWM	NS
Duan et al. (64)	R	WM	↓ in MS	Staffen et al. (58)	R _f	WM	↓ in MS
Fu et al. (52)	SP	NAWM	↓ in MS	Steen et al. (81)	P	NAWM	↓ in MS
Fu et al. (52)	R	NAWM	↓ in MS	Steen et al. (39)	M	NAWM	↓ in MS
Fu et al. (60)	SP	WM	↓ in MS	Suhly et al. (50)	PP	NAWM	↓ in MS
Fu et al. (60)	R	WM	↓ in MS	Suhly et al. (50)	R	NAWM	↓ in MS
Hannoun et al. (62)	SP	WM	↓ in MS	Sun et al. (68)	R	NAWM, frontal	↓ in MS
Hannoun et al. (62)	PP	WM	↓ in MS	Sun et al. (68)	R	NAWM, parietal	↓ in MS
Hannoun et al. (62)	R	WM	↓ in MS	Sun et al. (68)	R	NAWM, parietal-occipital	↓ in MS

Husted et al. (30)	M	NAWM	↓ in MS
Kimura et al. (32)	M	NAWM	NS
Leary et al. (82)	PP	NAWM	↓ in MS
Maffei et al. (76)	R	spine	↓ in MS*
Maffei et al. (76)	SP	spine	NS*
Mathiesen et al. (144)	R	GM	NS
Mathiesen et al. (144)	R	mixed	NS
Mathiesen et al. (144)	R	NAWM	NS
Matthews et al. (55)	M	NAWM	NS
Matthews et al. (71)	SP	mixed	↓ in MS
Matthews et al. (71)	R	mixed	↓ in MS
Narayanan et al. (73)	SP	mixed	↓ in MS
Narayanan et al. (73)	R	mixed	↓ in MS
Narayana et al. (87)	PP	mixed	↓ in MS
Obert et al. (172)	SP	NAWM	NS
Obert et al. (172)	R	NAWM	NS
Oguz et al. (148)	R	NAWM	NS
Oh et al. (45)	M	NAWM	↓ in MS
Oh et al. (45)	PP	NAWM	↓ in MS
Oh et al. (66)	SP	NAWM, c.c.	↓ in MS
Oh et al. (66)	SP	NAWM, central	↓ in MS
Oh et al. (66)	SP	NAWM, not c.c.	NS
Oh et al. (66)	R	NAWM, c.c.	↓ in MS
Oh et al. (66)	R	NAWM, central	NS
Oh et al. (66)	R	NAWM, not c.c.	NS
Pan et al. (54)	R	GM	↓ in MS
Pan et al. (54)	R	WM	↓ in MS

*Single-subject MS case report.

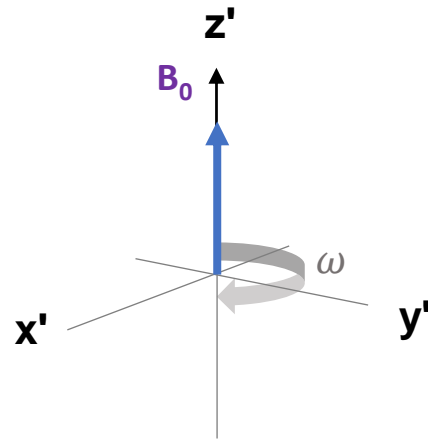
MS: multiple sclerosis; P: progressive; SP: secondary progressive; PP: primary progressive; R: relapsing-remitting; M: mixed or unspecified MS phenotype(s); c.c.: corpus callosum; M_{sp}: sporadic MS; M_f: familial MS; R_{nl}: relapsing-remitting with no lesions in region of interest; R_f: relapsing-remitting with lesions in region of interest; R_{nl}: relapsing-remitting with any or high fatigue; R_f: relapsing-remitting with no or low fatigue.

Takeuchi et al. (51)	R	NAWM	↓ in MS
Tartaglia et al. (25)	M	NAWM	↓ in MS
Tedeschi et al. (34)	M	NAWM	↓ in MS
Téllez et al. (75)	R _{nl}	mixed, lentiform nucleus	↓ in MS
Téllez et al. (75)	R _{nl}	WM, frontal	NS
Téllez et al. (75)	R _f	mixed, lentiform nucleus	NS
Téllez et al. (75)	R _f	WM, frontal	NS
Tourbah et al. (40)	M	NAWM	↓ in MS
Tourbah et al. (46)	M	NAWM	↓ in MS
Tourbah et al. (46)	R	NAWM	NS
Tourbah et al. (46)	SP	NAWM	↓ in MS
Tourbah et al. (79)	R	NAWM	NS
Tourbah et al. (79)	SP	NAWM	↓ in MS
van Walderveen et al. (22)	M	NAWM	↓ in MS
Vingara et al. (48)	R	NAWM	↓ in MS
Vrenken et al. (69)	PP	NAWM	↓ in MS
Vrenken et al. (69)	SP	NAWM	↓ in MS
Vrenken et al. (69)	R	NAWM	↓ in MS
Wattjes et al. (67)	R	NAWM	↓ in MS
Wood et al. (38)	M	NAWM	↓ in MS
Wu et al. (145)	R	mixed	NS
Wylezinska et al. (70)	R	GM	↓ in MS
Wylezinska et al. (70)	R	NAWM	↓ in MS
Yetkin et al. (56)	R	NAWM	NS
Zaini et al. (57)	R _{nl}	WM	↓ in MS
Zaini et al. (57)	R _f	WM	↓ in MS

Swanberg, Landheer, Pitt, and Juchem. *Frontiers in Neurology* (2019): 10.

Classification of multiple sclerosis by single ¹H-MRS-visible metabolites lacks diagnostically useful sensitivity and especially specificity.

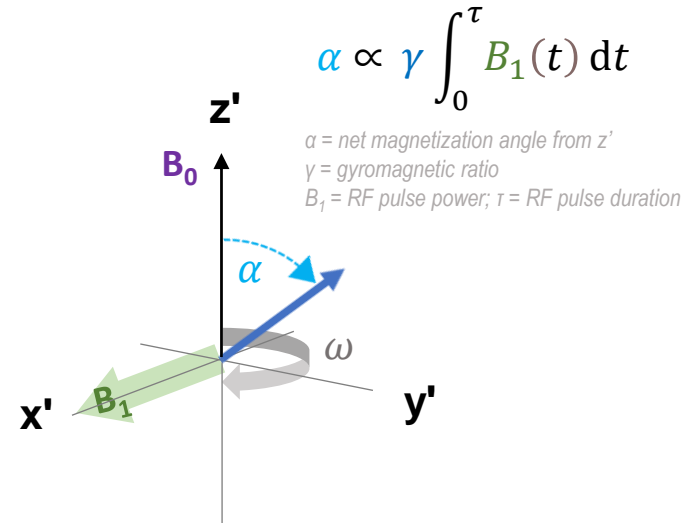
CHAPTER 1: INTRODUCTION



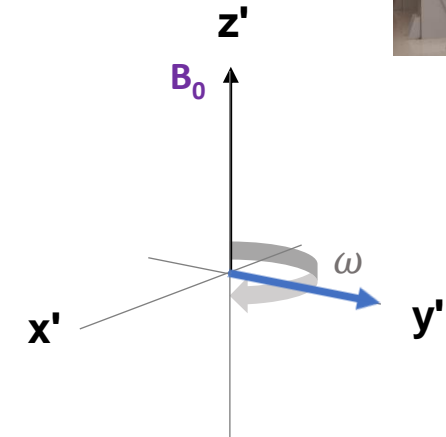
Net magnetization vector along z from nuclear spin **polarization** at thermal equilibrium and **precession** about z at **Larmor frequency**

$$\omega = -\gamma(B_0 + \Delta B)$$

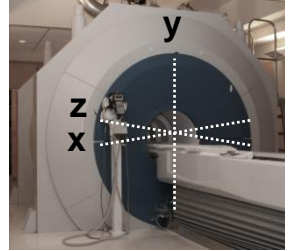
ω = Larmor frequency; γ = gyromagnetic ratio
 B_0 = scanner field; B = local field



Excitation in z and **phasing in xy** of spins by **radiofrequency pulse** application



Precession about z on **xy plane** detected by radiofrequency **receive coils**



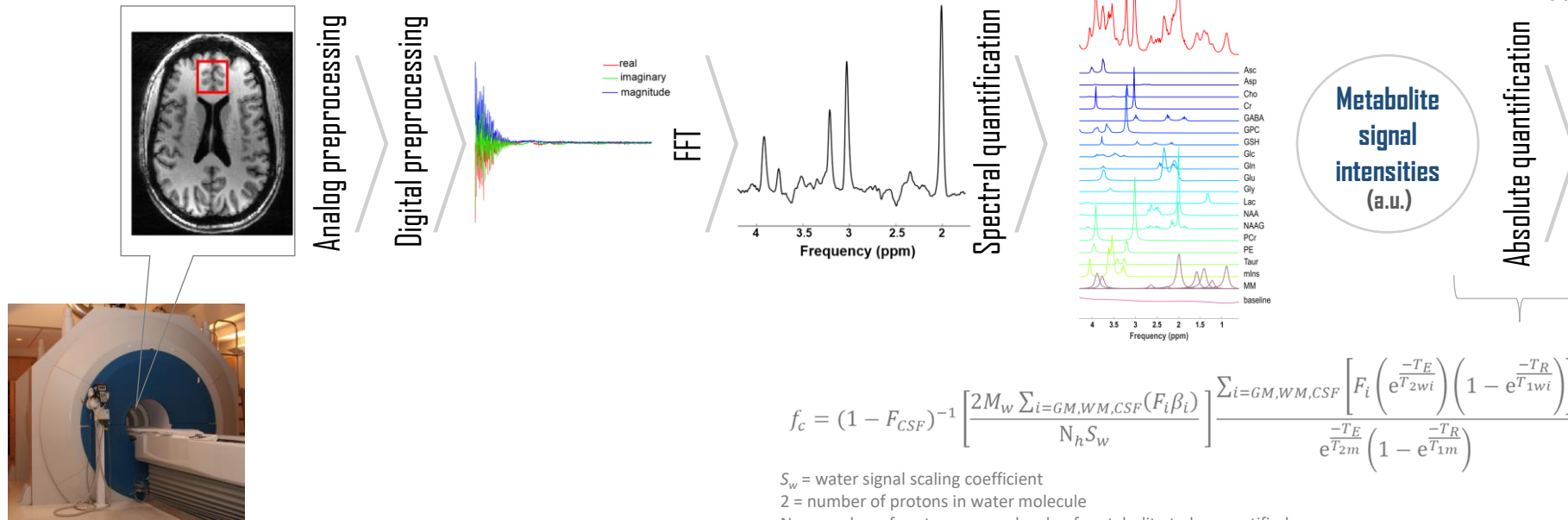
¹H-MRS signals represent radiofrequency field-induced changes in receive coil voltage, not metabolite concentration or proton density.

CHAPTER 1: INTRODUCTION

$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of baseline splines
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 S_n = metabolite basis function lineshape coefficients
 ν = frequency domain value
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$$\widehat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

Metabolite concentrations by tissue
 Intracellular vs. extracellular metabolite concentration
 Intracellular metabolite concentrations within cell types of interest
 Biological functions of metabolite with respect to cell types of interest
 ...And more



$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

S_w = water signal scaling coefficient
 2 = number of protons in water molecule
 N_h = number of protons per molecule of metabolite to be quantified
 M_w = molarity of pure water
 β_i = molarity of water as a fraction of pure water in either grey matter (GM), white matter (WM), or CSF
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 T_{2wi} = T_2 of water in grey matter (GM), white matter (WM), or CSF
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 T_{2m} = T_2 of metabolite
 T_{1m} = T_1 of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

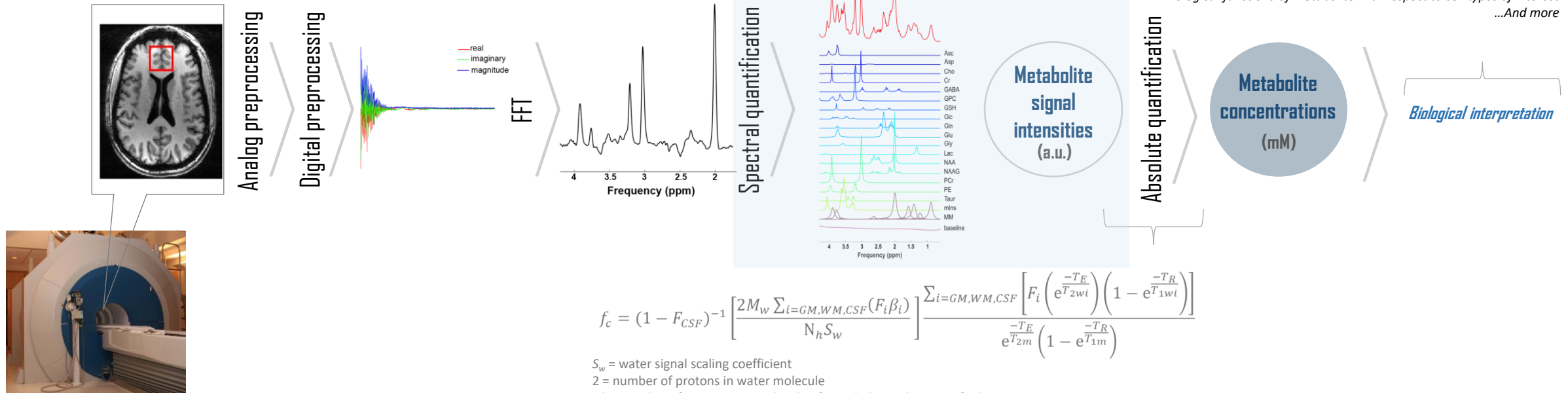


Chapter II

Spectral Quantification: What are the effects of spectral quality and baseline on the precision and accuracy of relative metabolite concentrations drawn from ^1H MRS data, and how do we minimize them?

$\Phi_{0,1}$ = zero-, first-order phase
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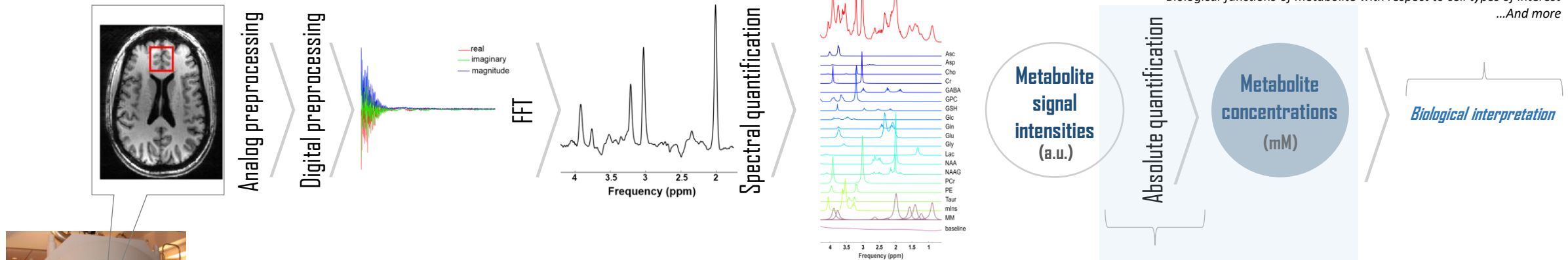


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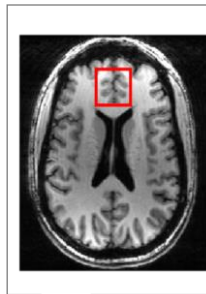
Chapter III

Absolute Quantification: Can disease-related differences in metabolite T_2 introduce systematic errors to the derivation of absolute from relative metabolite concentrations, and how do we minimize them?

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

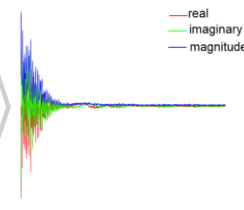
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CHAPTER 1: INTRODUCTION

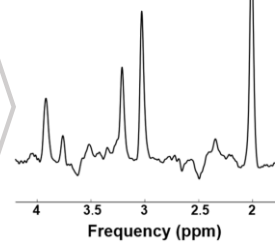


Analog preprocessing

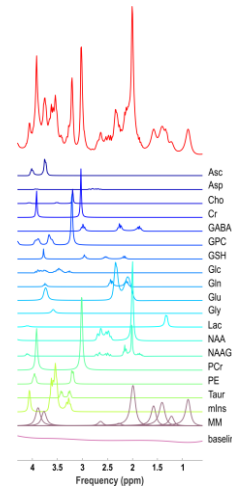
Digital preprocessing



FFT



Spectral quantification



$$\hat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

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Statistical Analysis: Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of 1H MRS data alone classify disease states (case application multiple sclerosis)?

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 Biological functions of metabolite with respect to cell types of interest
 ...And more

Metabolite
signal
intensities
(a.u.)

Absolute quantification

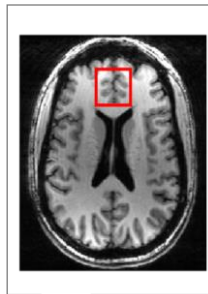
Metabolite
concentrations
(mM)

Biological interpretation

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

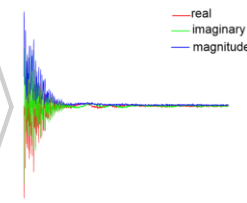
S_w = water signal scaling coefficient
 2 = number of protons in water molecule
 N_h = number of protons per molecule of metabolite to be quantified
 M_w = molarity of pure water
 β_i = molarity of water as a fraction of pure water in either grey matter (GM), white matter (WM), or CSF
 F_i = voxel fraction occupied by grey matter (GM), white matter (WM), or CSF
 T_{2wi} = T_2 of water in grey matter (GM), white matter (WM), or CSF
 T_{1wi} = T_1 of water in grey matter (GM), white matter (WM), or CSF
 T_{2m} = T_2 of metabolite
 T_{1m} = T_1 of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

CHAPTER 1: INTRODUCTION

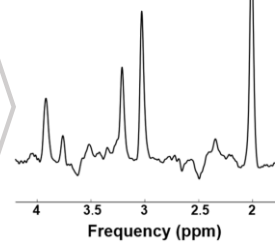


Analog preprocessing

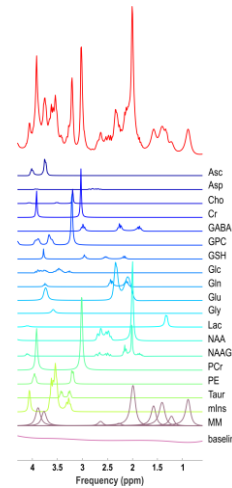
Digital preprocessing



FFT



Spectral quantification



Metabolite
signal
intensities
(a.u.)

Absolute quantification

Metabolite
concentrations
(mM)

Biological interpretation

Chapter V

Generalization: Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via 1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of baseline splines
 B = baseline spline

S_n = metabolite basis function lineshape coefficients
 ν = frequency domain value
 γ = line broadening parameter
 ϵ = frequency shift parameter

$$\widehat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

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 T_{2m} = T_2 of metabolite
 T_{1m} = T_1 of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

Metabolite concentrations by tissue
 Intracellular vs. extracellular metabolite concentration
 Intracellular metabolite concentrations within cell types of interest
 Biological functions of metabolite with respect to cell types of interest
 ...And more

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

CHAPTER I

Spectral Quantification:

What are the effects of spectral quality and baseline on the precision and accuracy of relative metabolite concentrations drawn from ^1H MRS data, and how do we minimize them?

CHAPTER II

Absolute Quantification:

Can disease-related differences in metabolite T_2 introduce systematic errors to the derivation of absolute from relative metabolite concentrations, and how do we minimize them?

CHAPTER III

Statistical Analysis:

Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of ^1H MRS data alone classify disease states (case application multiple sclerosis)?

CHAPTER IV

Generalization:

Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

CHAPTER V

Back to the Big Picture:

General conclusions and outlook

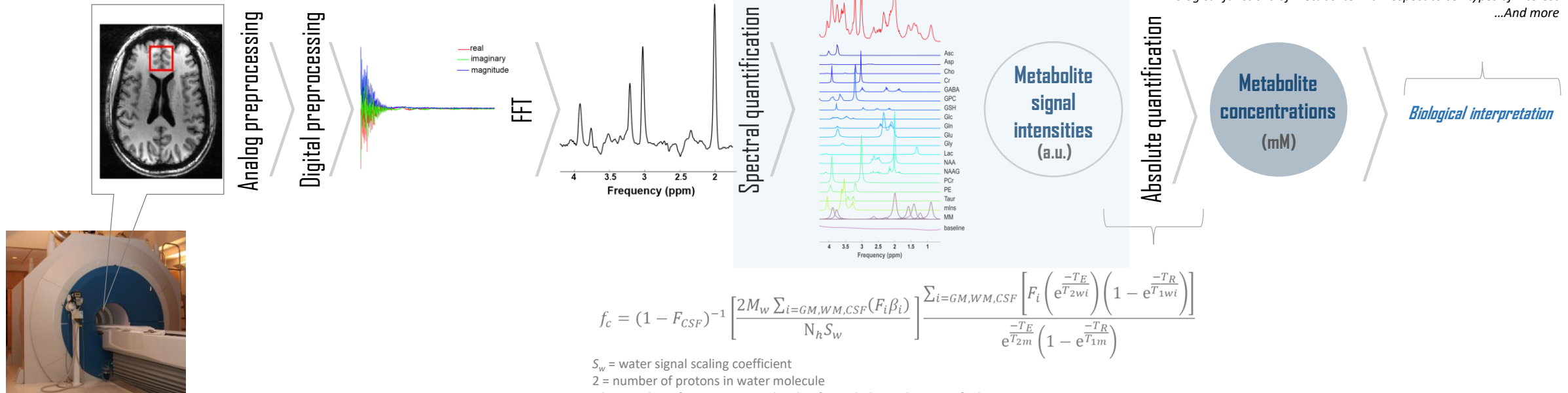
CHAPTER VI

Chapter II

Spectral Quantification: What are the effects of spectral quality and baseline on the precision and accuracy of relative metabolite concentrations drawn from ^1H MRS data, and how do we minimize them?

$$\hat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

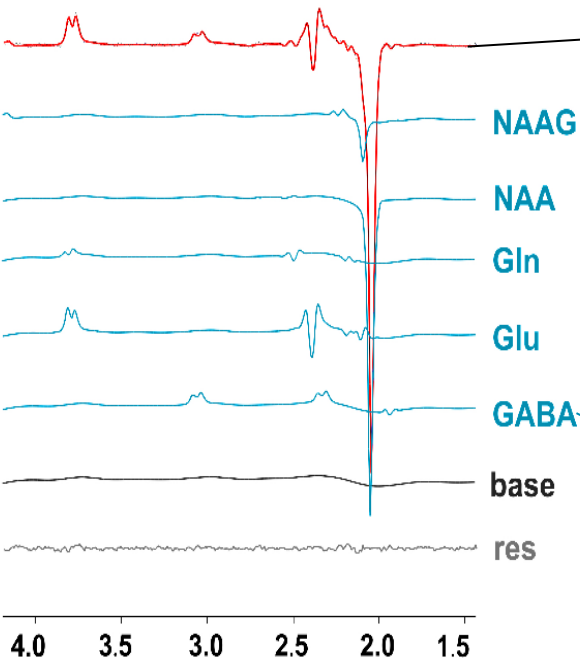
$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of baseline splines
 B = baseline spline
 S_n = metabolite basis function lineshape coefficients
 ν = frequency domain value
 γ = line broadening parameter
 ϵ = frequency shift parameter



$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

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 T_{2wi} = T_2 of water in grey matter (GM), white matter (WM), or CSF
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 T_{2m} = T_2 of metabolite
 T_{1m} = T_1 of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

CHAPTER 2: SPECTRAL QUANTIFICATION



Frequency (ppm)

Swanberg, Prinsen, Kurada, Bailey, Destefano, Pitt, Fulbright, and Juchem. *NMR in Biomedicine* (2021); 34(11).

Zero- and first-order phase correction Baseline term Metabolite scalings Metabolite basis shapes

$$\widehat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

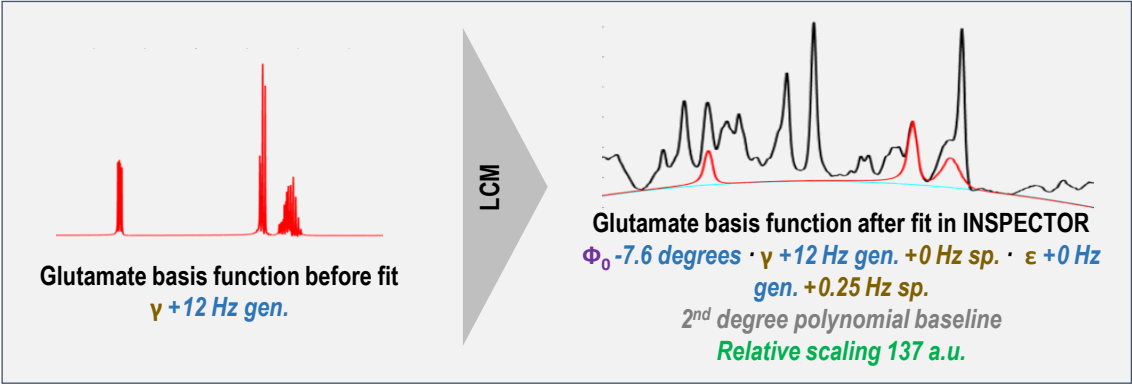
$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of spline knots
 B = baseline spline
 β = spline coefficient

S_n = metabolite basis function lineshape coefficients
 N_s = Number of signal points
 ν = frequency domain value
 γ = line broadening parameter
 ϵ = frequency shift parameter
 m = simulated or measured basis metabolite FID

M_l = metabolite basis function: $M_l(\nu, \gamma_l, \epsilon_l) = F(m_l(t))e^{-(\gamma_l + i\epsilon_l)t}$

$\Phi_0, \Phi_1, \beta_j, C_l, S_n, \gamma_l, \epsilon_l$ adjusted to minimize regularized least-squares error between model and data

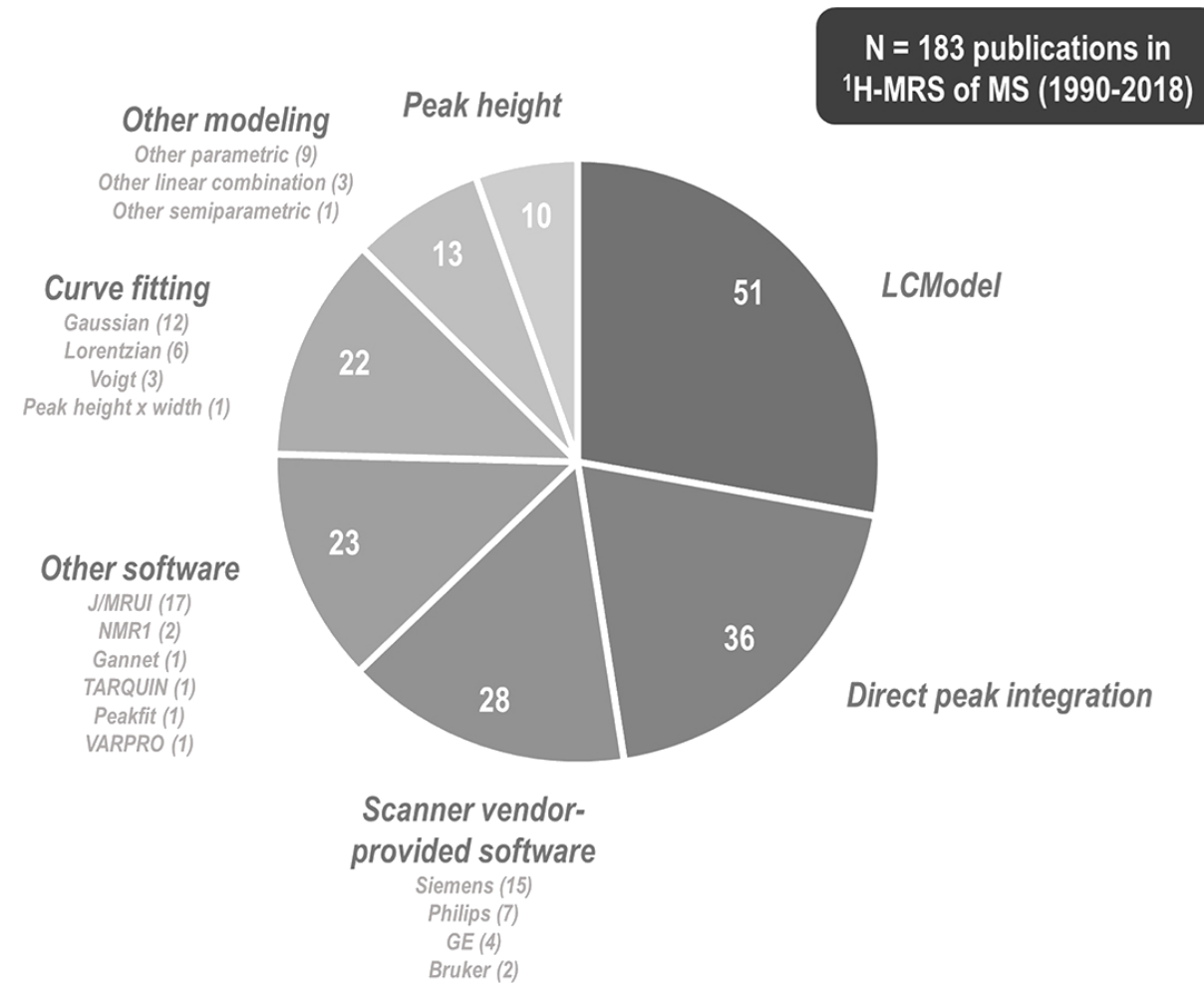
Provencher, S. *MRM* (1993); 30.



LCM

Glutamate basis function before fit
 $\gamma + 12 \text{ Hz gen.}$

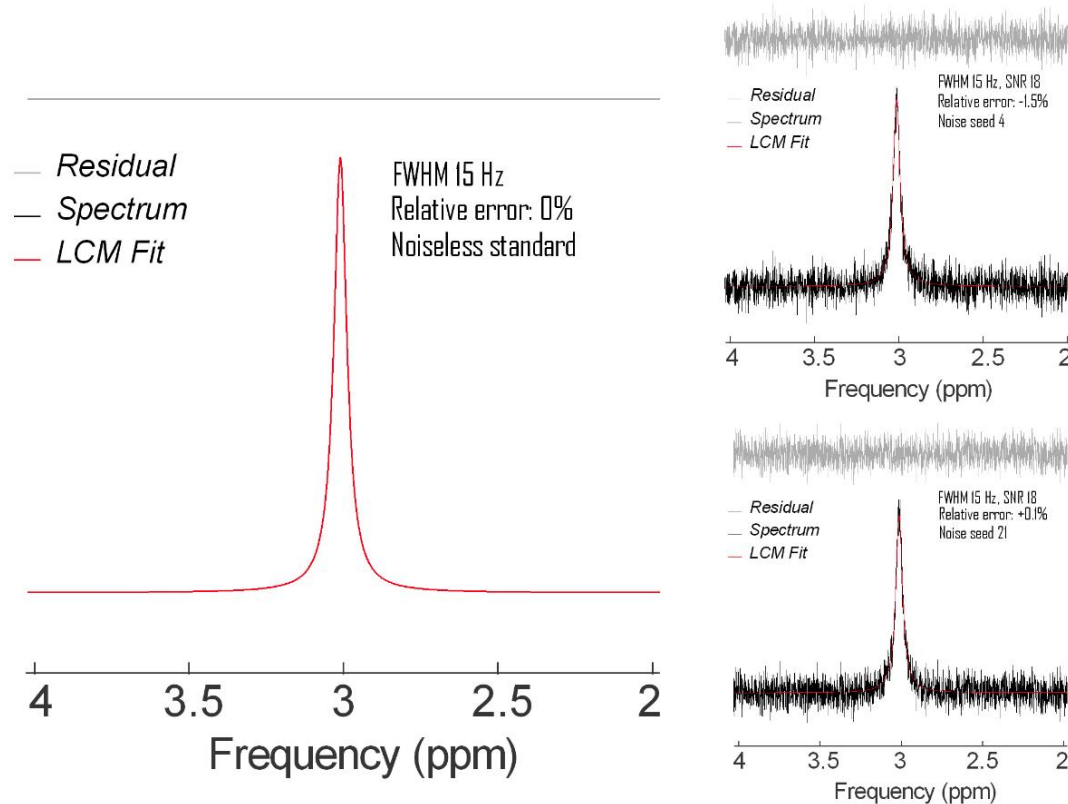
Glutamate basis function after fit in INSPECTOR
 $\Phi_0 - 7.6 \text{ degrees} \cdot \gamma + 12 \text{ Hz gen.} + 0 \text{ Hz sp.} \cdot \epsilon + 0 \text{ Hz gen.} + 0.25 \text{ Hz sp.}$
2nd degree polynomial baseline
Relative scaling 137 a.u.



Swanberg, Landheer, Pitt, and Juchem. *Frontiers in Neurology* (2019); 1173.

Characterizing and optimizing the accuracy and precision of ^1H MRS quantification methods is a prerequisite for standardizing them.

CHAPTER 2: SPECTRAL QUANTIFICATION

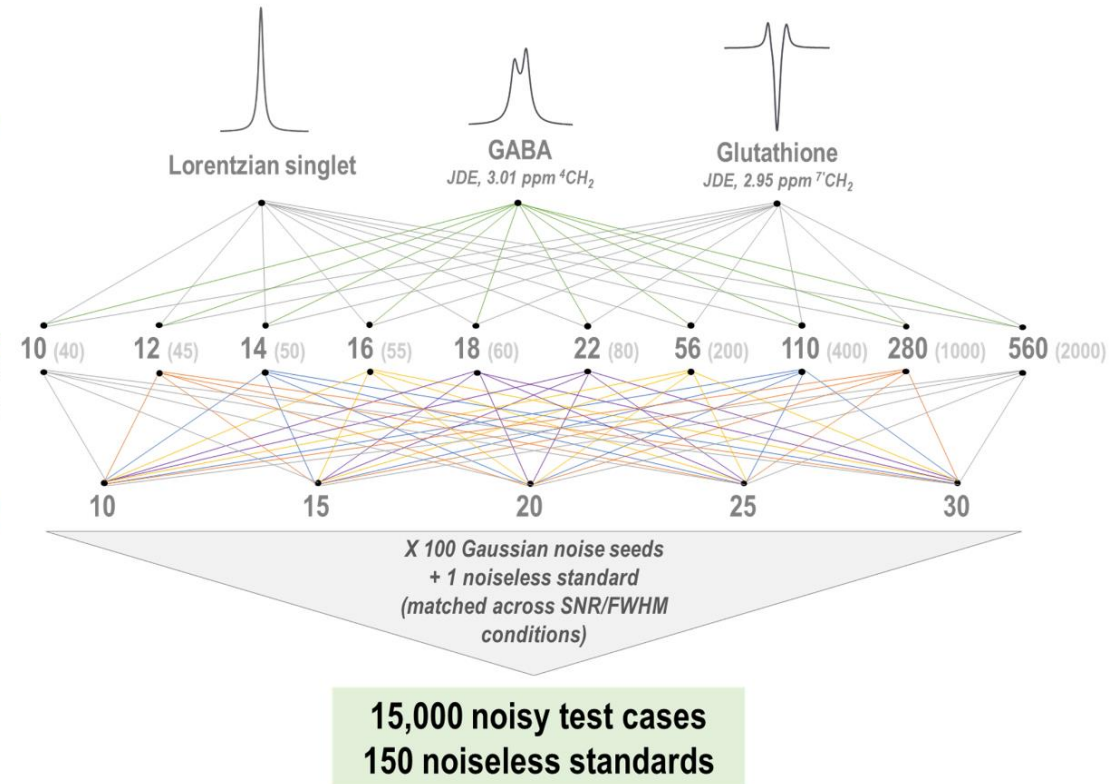


Resonance

Starting SNR

3.03 ppm singlet
3.01 ppm GABA $^4\text{CH}_2$
(2.95 ppm GSH $^7\text{CH}_2$)

FWHM (Hz)



Swanberg, Prinsen, and Juchem. *Proc Intl Soc Mag Reson Med.* (2019); 4237.

Spectral quantification method is an important but testable source of inaccuracy and imprecision in ^1H MRS data.

INSPECTOR: Batch Simulation and LCM

Data

Processing

T1/T2

Synthesis

MARSS

LCM

Batch

Manual

Exit

Batch Mode

☒ Simulation only

☐ LCM only

☐ Simulation and LCM

Simulation Mode

☒ Lorentzian only

☐ Custom simulation

Export Root

C:\Users\ibaham\Desktop\Batch_Spectral_Quant_Validation_Tool\test_export\test.mat

Select

Protocol Template

C:\Users\ibaham\Desktop\Batch_Spectral_Quant_Validation_Tool\test_export\test

Select

Import Root

C:\Users\ibaham\Desktop\Batch_Spectral_Quant_Validation_Tool\test_export\test.mat

Select

Sim Template

C:\Users\ibaham\Desktop\Batch_Spectral_Quant_Validation_Tool\test_export\test

Select

Batch Simulation Parameters

SF

123.262

Calib

4.65

BW

4000

Pts

2048

Signal Amps

[500 1000 2000 5000 10000]

Signal LB

[10 15 20 25 30]

Noise Amps

[0.01]

Noise Seeds

5

Noise Mode

☒ Correlated

☐ Uncorrelated

Run Batch Process

---► **SIMULATION ONLY**

Define Simulation

Define Quality Vectors

Batch Simulate

Spectra output to
user-defined directory

SIMULATION AND LCM

Input:
INSPECTOR
protocol
template

*Automated Protocol
Generation and
Data I/O*

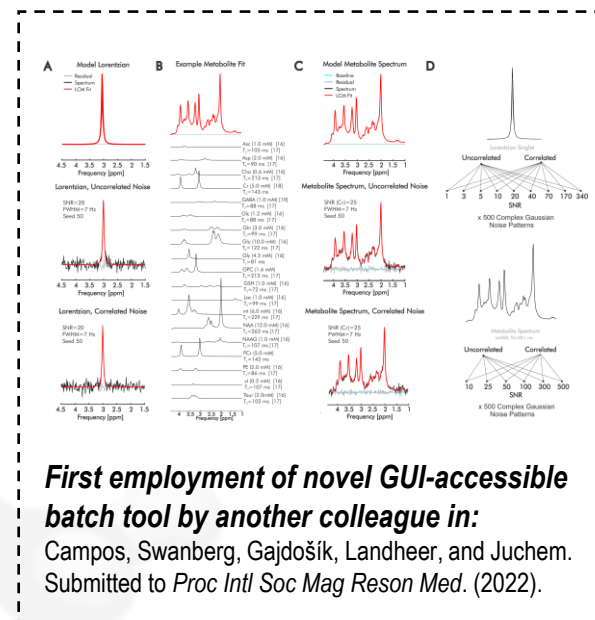
*Batch LCM**

*LCM results output to
user-defined directory*

LCM ONLY

Input:
Directory
of spectral
data to fit

Tool 1: GUI-supported automated batch spectral simulation and quantification pipeline development and validation

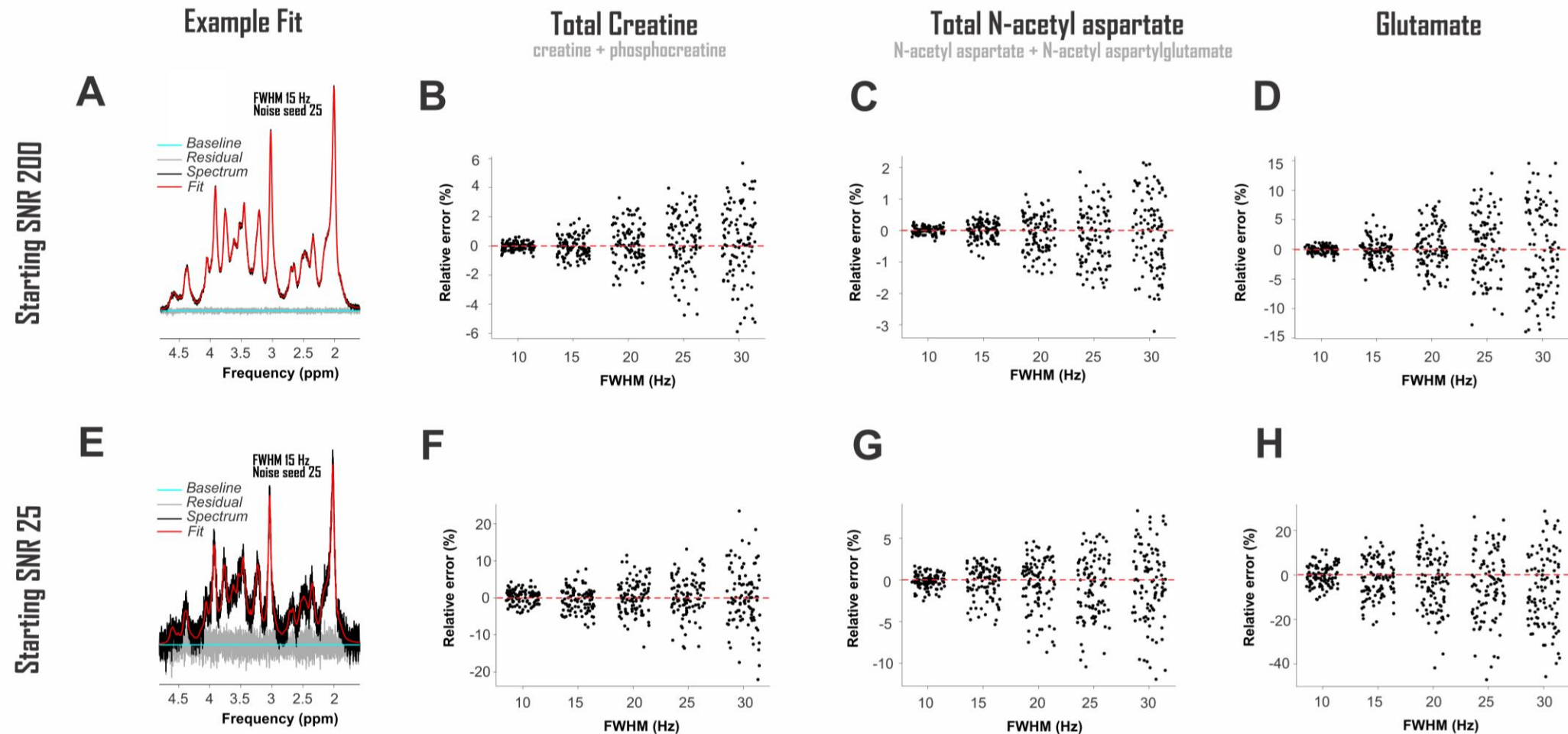


First employment of novel GUI-accessible batch tool by another colleague in:
Campos, Swanberg, Gajdošík, Landheer, and Juchem.
Submitted to *Proc Intl Soc Mag Reson Med.* (2022).

*Statistical analysis
pipeline of choice*

Master CSV: Concentration estimates and errors for all fits

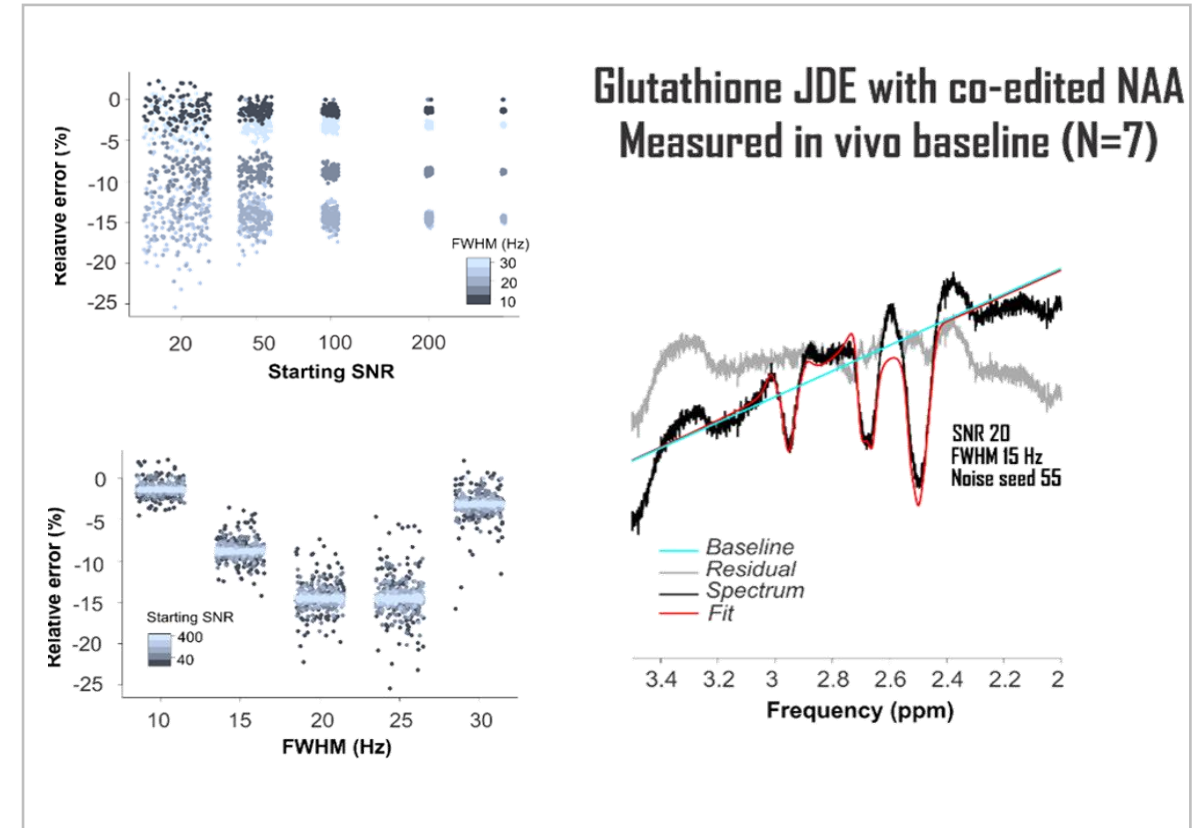
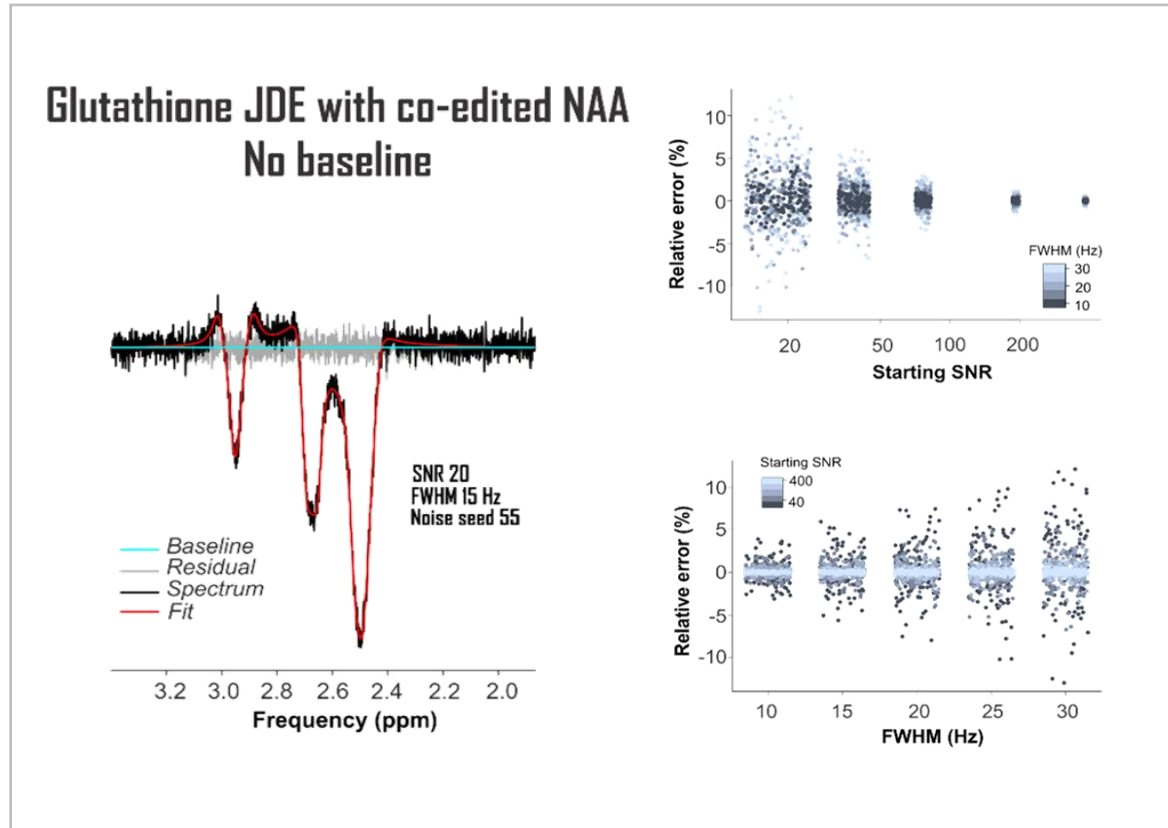
CHAPTER 2: SPECTRAL QUANTIFICATION



Swanberg, Prinsen, and Juchem. *Proc Intl Soc Mag Reson Med.* (2019); 4237.

Spectral line width and signal-to-noise ratio alone affect spectral quantification precision but not accuracy.

CHAPTER 2: SPECTRAL QUANTIFICATION

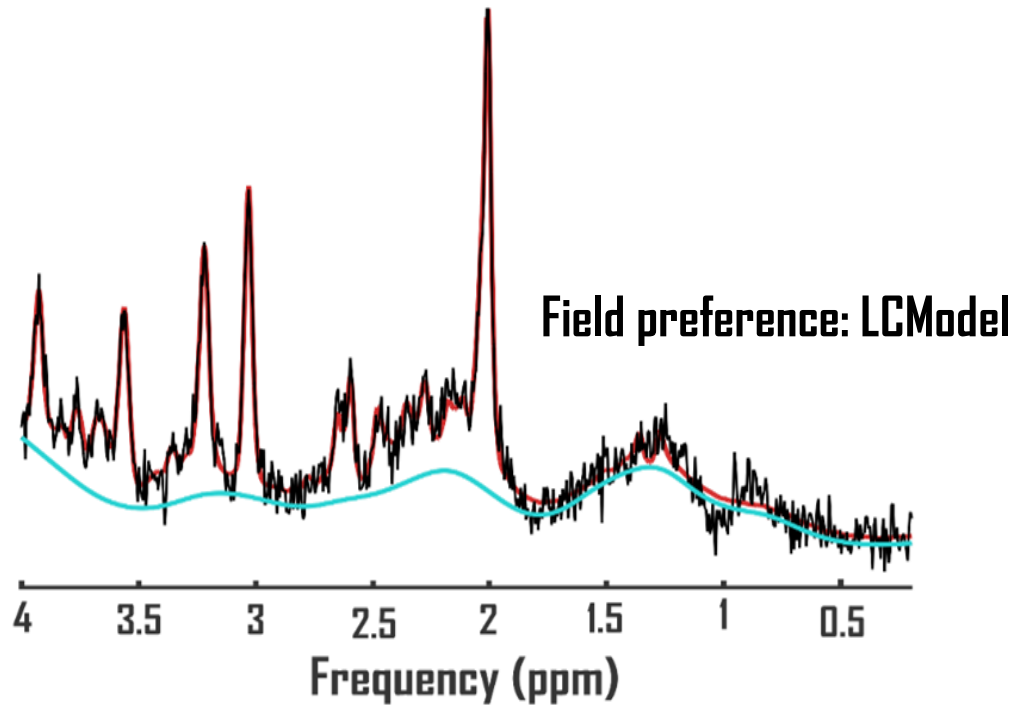


Swanberg, Prinsen, and Juchem. *Proc Intl Soc Mag Reson Med.* (2019); 4237.

Data quality can interact with spectral baselines to induce additional systematic effects on spectral fit accuracy.

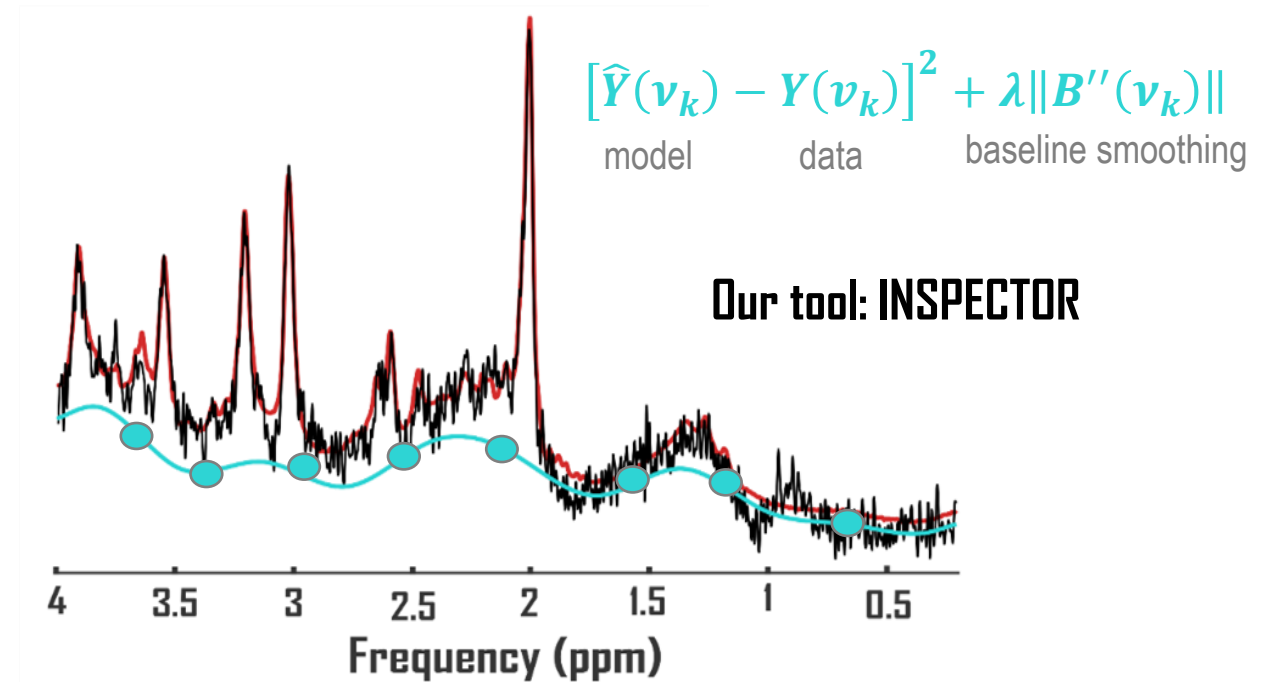
CHAPTER 2: SPECTRAL QUANTIFICATION

Absolute knot interval not fixed by user (*DKNTMN is not knot interval*)
 Λ not fixed by user (*determined by spectral line width*)



Test data set provided by LCModel package

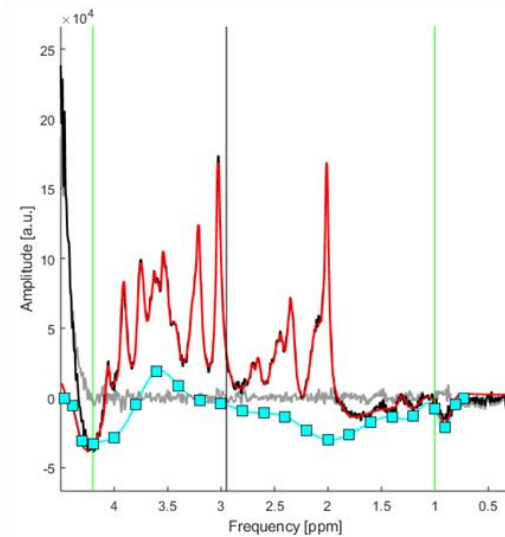
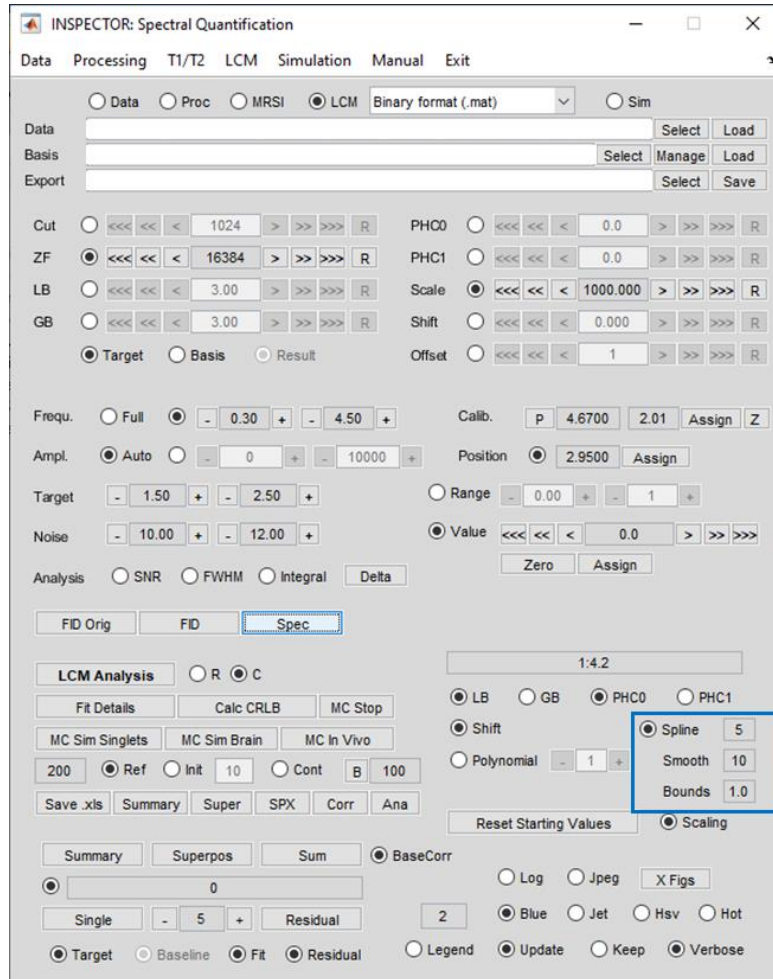
Absolute knot interval = 0.3
 $\Lambda = 20$



Swanberg, Landheer, Gajdošik, Treacy, and Juchem. *Proc Intl Soc Mag Reson Med.* (2020); 2856.

^1H MRS spectral baseline modeling by smoothed cubic splines is common but understudied, partly due to lack of available tools.

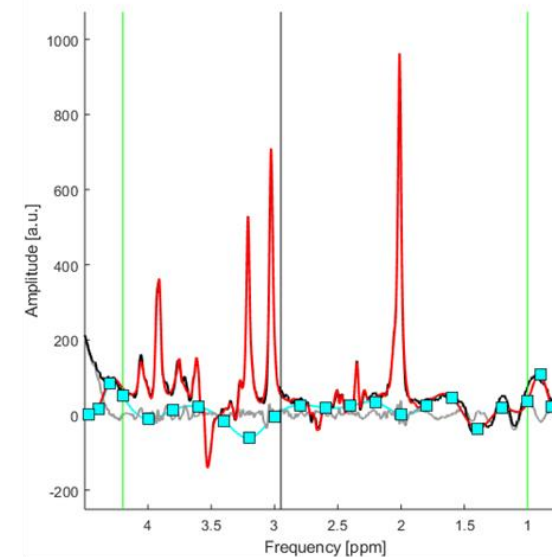
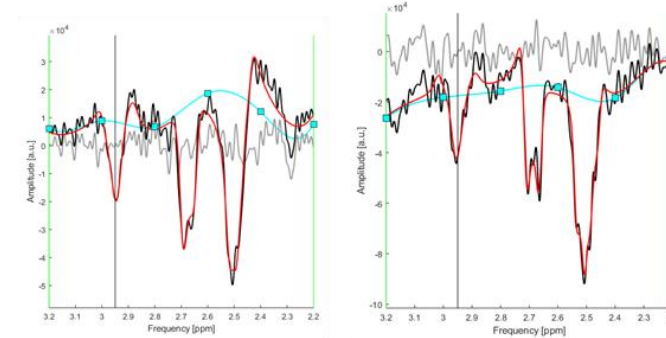
CHAPTER 2: SPECTRAL QUANTIFICATION



Spline: Number of knot points/ppm

Smooth: Lambda value on cost function (l^2 norm of spline second derivative)

Bounds: Upper and lower bound of spline knots (% of residual on initial 0th-degree polynomial fit)



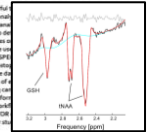
Tool 2: GUI-supported regularized cubic spline definition for spectral baseline modeling

scientific reports

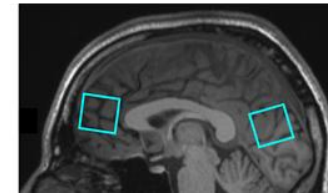
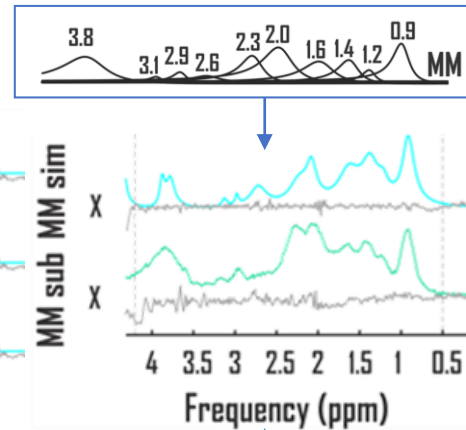
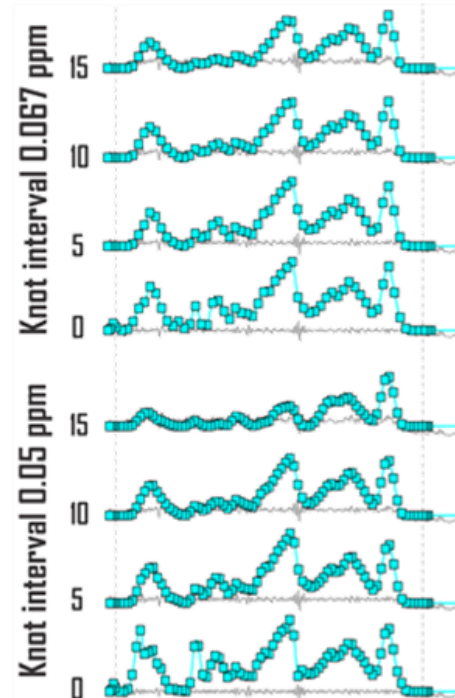
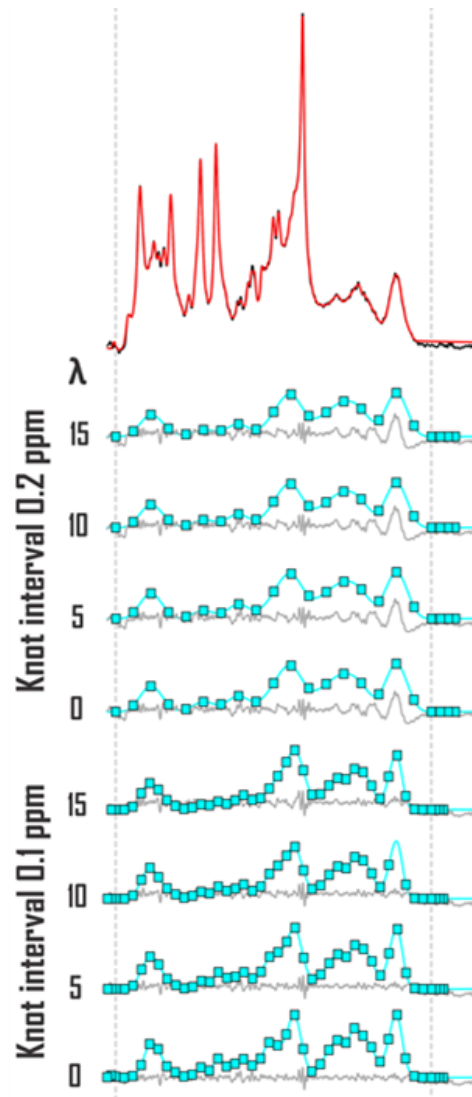
OPEN INSPECTOR: free software for magnetic resonance spectroscopy data inspection, processing, simulation and analysis

Martin Gajdošik¹, Karl Landheer², Kelley M. Swanberg³ & Christoph Juchem^{1,2}

In vivo magnetic resonance spectroscopy (MRS) is a powerful diagnostic, allowing for non-invasive measurement and analysis. However, currently available MRS processing and analysis tools often lack the depth of quality management, access to the user interface, and the ability to handle large datasets. The INSPECTOR software provides a comprehensive, open-source, and user-friendly platform for MRS data inspection, processing, simulation and analysis. The software includes a graphical user interface (GUI) for data inspection, processing, simulation and analysis. The software is designed to be user-friendly and easy to use, and it provides a comprehensive set of tools for MRS data inspection, processing, simulation and analysis. The software is available for free download and use, and it is designed to be user-friendly and easy to use.



First full-length publication showing results of novel spline baseline tool as featured by a colleague in:
Gajdošik, Landheer, Swanberg, and Juchem. *Sci Rep* (2021); 11, 2094.



In collaboration with:



Martin Gajdošik,
Ph.D.



Karl Landheer,
Ph.D.



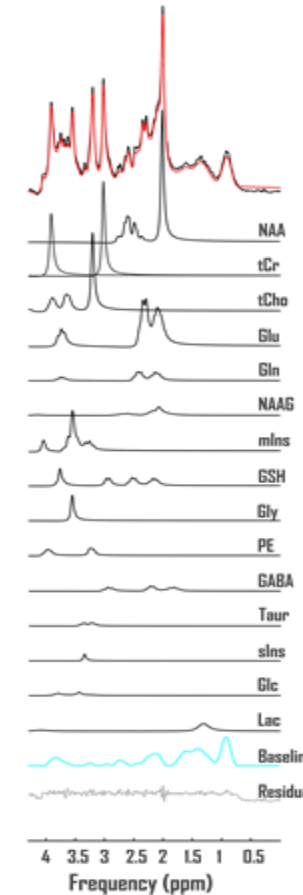
Michael Treacy,
B.A.

sLASER¹ (T_E 20.1 ms; T_R 2 s)
DOTCOPS-optimized crushers²
16-step phase cycling³
3 T Siemens MAGNETOM Prisma

¹Landheer et al. (2020). *NMR Biomed* e4324

²Landheer et al. (2020). *MRM* 81(4).

³Landheer et al. (2019). *MRM*. 83(2).



Swanberg, Landheer, Gajdošik, Treacy, and Juchem. *Proc Intl Soc Mag Reson Med*. (2020); 2856.

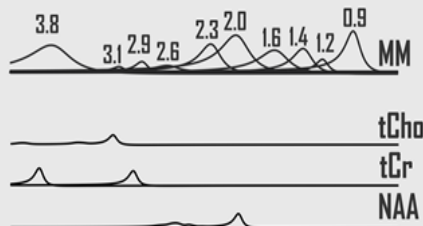
CHAPTER 2: SPECTRAL QUANTIFICATION

Macromolecule prediction error

Metabolite-nulled acquisition



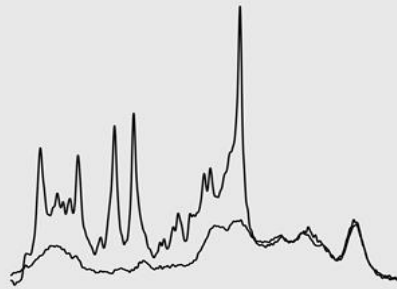
Step 1: Fit simulated MM; scrub residual metabolites



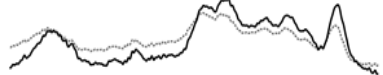
Scrubbed metabolite-nulled acquisition



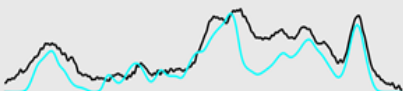
Step 2: Align to metabolite acquisition



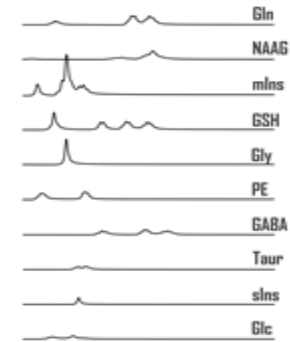
Aligned, scrubbed metabolite-nulled acquisition



Step 3: Subtract modeled baseline; sum over fit range

Modeled baseline error w.r.t.
metabolite-nulled acquisition

Metabolite quantification error



Simulated metabolites

+



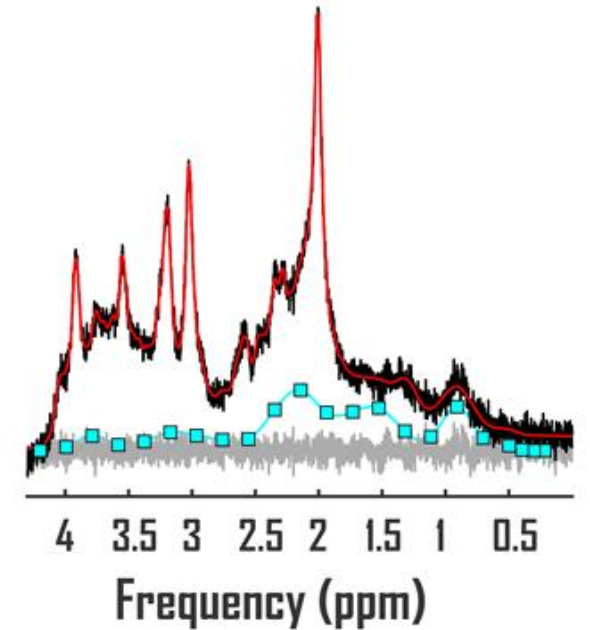
Gaussian noise

(10 fixed patterns)

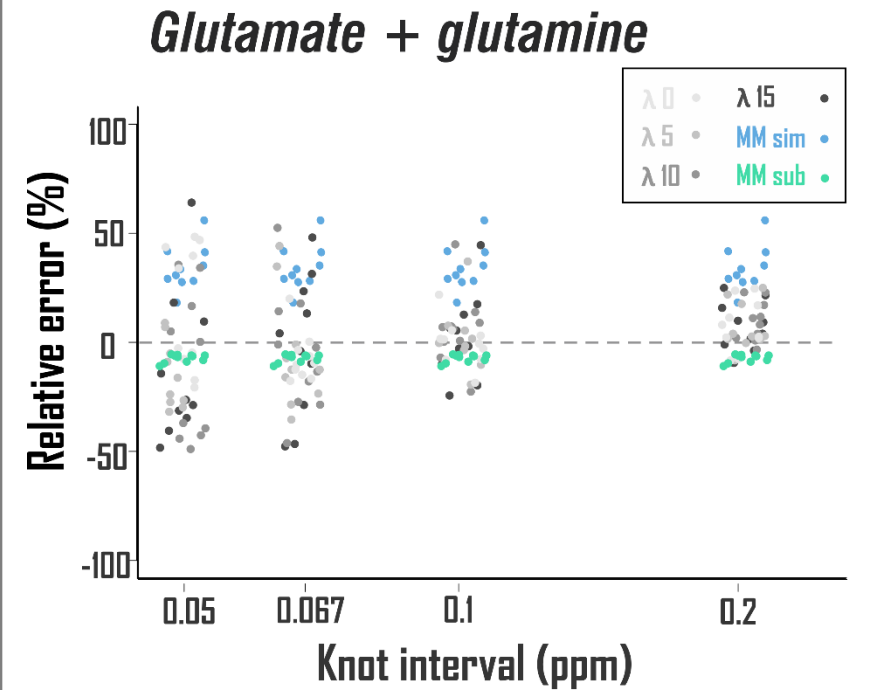
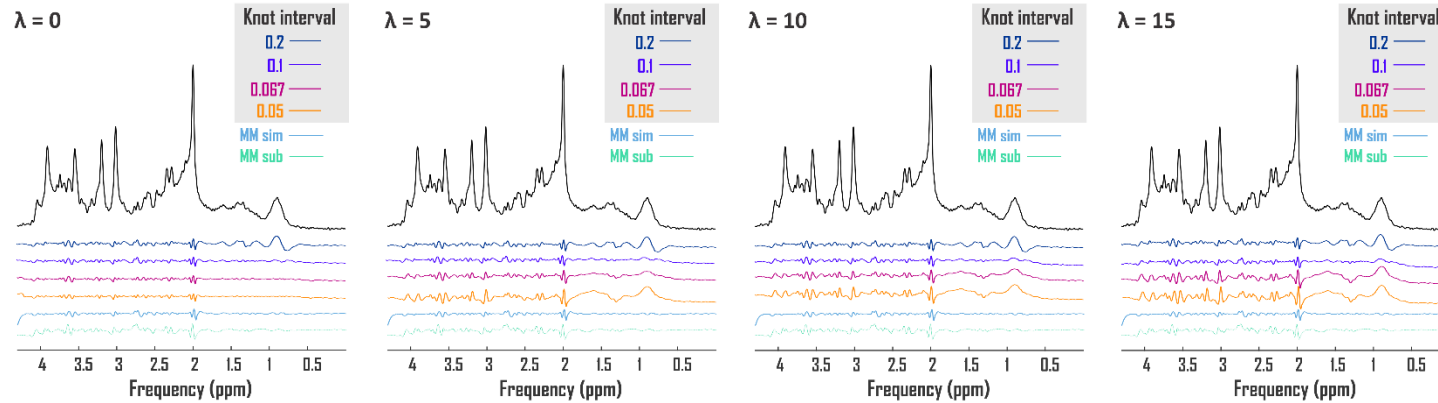
+

Metabolite-nulled acquisition
(aligned + scrubbed)

=

Modeled metabolite
concentration error w.r.t.
simulated gold standardSwanberg, Landheer, Gajdošik, Treacy, and Juchem. *Proc Intl Soc Mag Reson Med.* (2020); 2856.

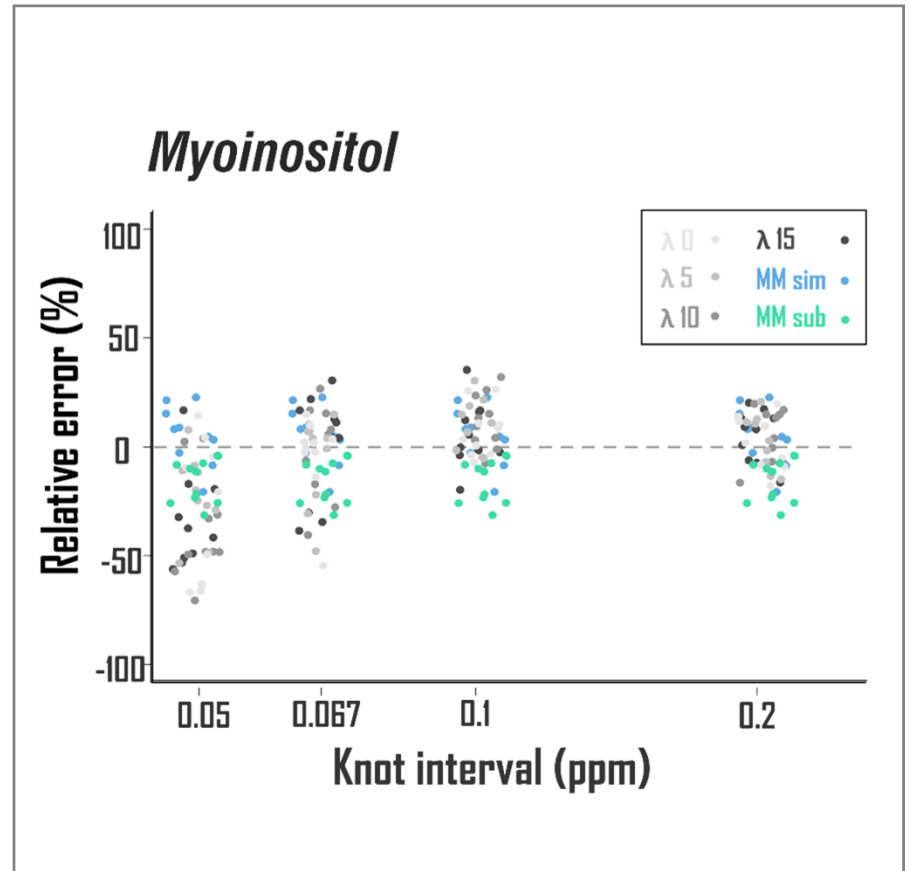
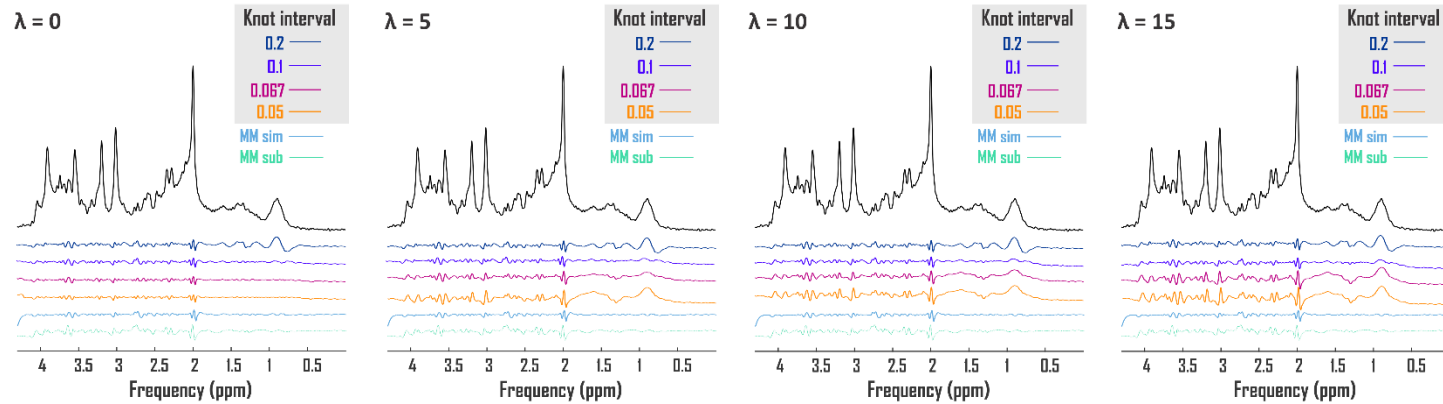
CHAPTER 2: SPECTRAL QUANTIFICATION

Metabolite fit residuals (averaged $N=20$)

Swanberg, Landheer, Gajdošík, Treacy, and Juchem. *Proc Intl Soc Mag Reson Med.* (2020); 2856.

Fit residual is not a reliable proxy for metabolite quantification accuracy.

CHAPTER 2: SPECTRAL QUANTIFICATION

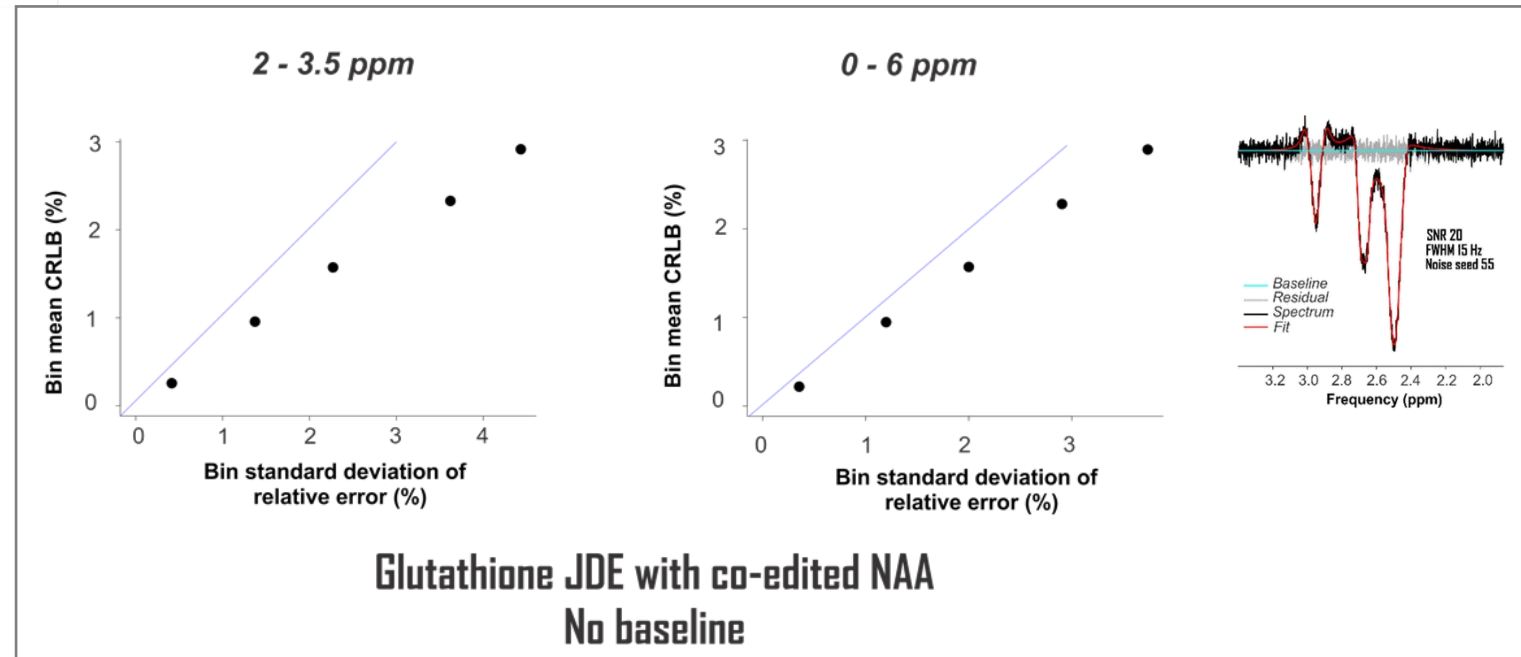
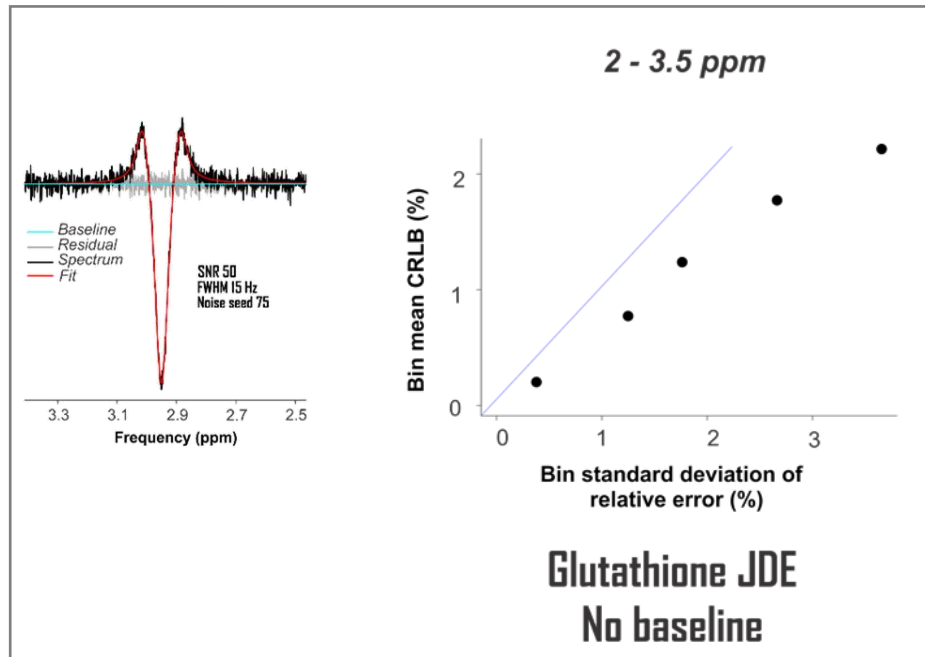
Metabolite fit residuals (averaged $N=20$)

Swanberg, Landheer, Gajdošík, Treacy, and Juchem. *Proc Intl Soc Mag Reson Med.* (2020); 2856.

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CHAPTER 2: SPECTRAL QUANTIFICATION

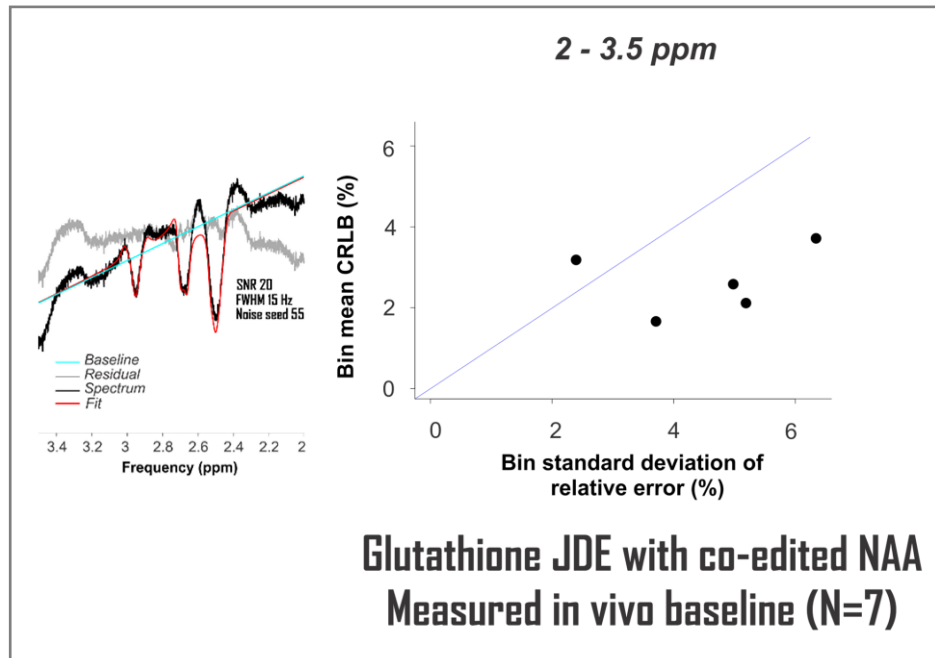
$$\sigma_{p_l} \geq \text{CRB}_{p_l}$$



Swanberg, Prinsen, and Juchem. *Proc Intl Soc Mag Reson Med.* (2019); 4237.

In the absence of a gold standard, the Cramér-Rao Lower Bound can help to approximate in vivo fit errors.

CHAPTER 2: SPECTRAL QUANTIFICATION



Swanberg, Prinsen, and Juchem. *Proc Intl Soc Mag Reson Med.* (2019); 4237.

Metabolite	a_m^{true} (a.u.)	a_m^{est} (a.u.)	$2 \times \text{CRB}_{a_m}^{\text{est}}$ (a.u.)	$2 \times \text{CRB}_{a_m, \theta}^{\text{est}}$ (a.u.)
NAA	13.00	12.00	0.77	1.10
Cr_PCr	6.00	5.95	0.46	0.59
Cho	2.00	1.82	0.48	0.52
mI	5.50	6.10	2.20	2.31
Glx	13.50	16.89	2.70	3.20

Ratney et al. *MAGMA* 16 (2004); 284.

But this relationship between Cramér-Rao Lower Bound and fit error depends on inclusion of baseline terms.

OPTIMIZING ^1H MRS: SPECTRAL QUANTIFICATION

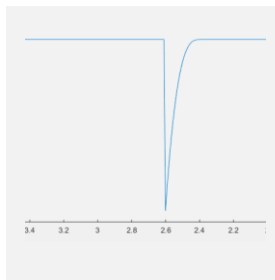
CHAPTER 2: SPECTRAL QUANTIFICATION

$$\sigma_{p_l} \geq \text{CRB}_{p_l} = \sqrt{(F^{-1})_{ll}} \longleftarrow F = \frac{1}{\sigma^2} \Re(P^T D^H D P)$$

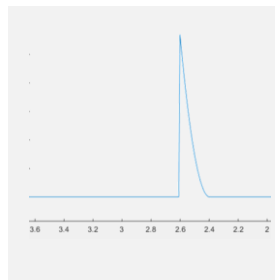
σ S.D. of noise amplitude
 D Partial derivative of model w.r.t. each parameter
 P Prior knowledge matrix

D (example columns for spline baseline amplitudes; real part shown)

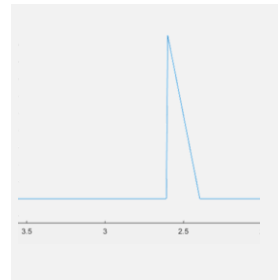
2.4-2.6 ppm



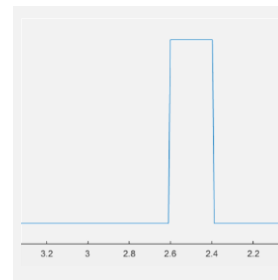
Model P.D. w.r.t. degree 3
baseline component amplitude



Model P.D. w.r.t. degree 2
baseline component amplitude

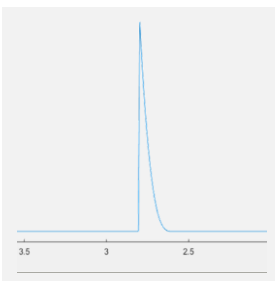


Model P.D. w.r.t. degree 1
baseline component amplitude

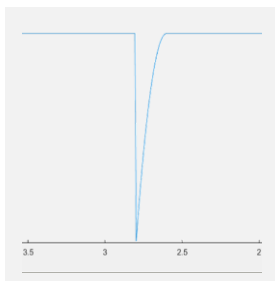


Model P.D. w.r.t. degree 0
baseline component amplitude

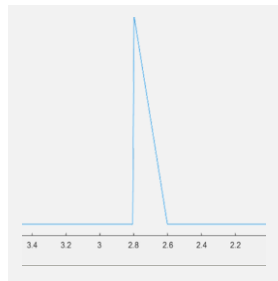
2.6-2.8 ppm



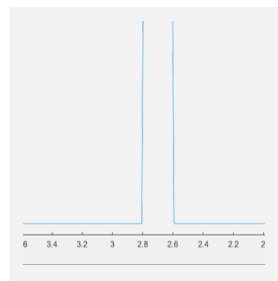
Model P.D. w.r.t. degree 3
baseline component amplitude



Model P.D. w.r.t. degree 2
baseline component amplitude



Model P.D. w.r.t. degree 1
baseline component amplitude



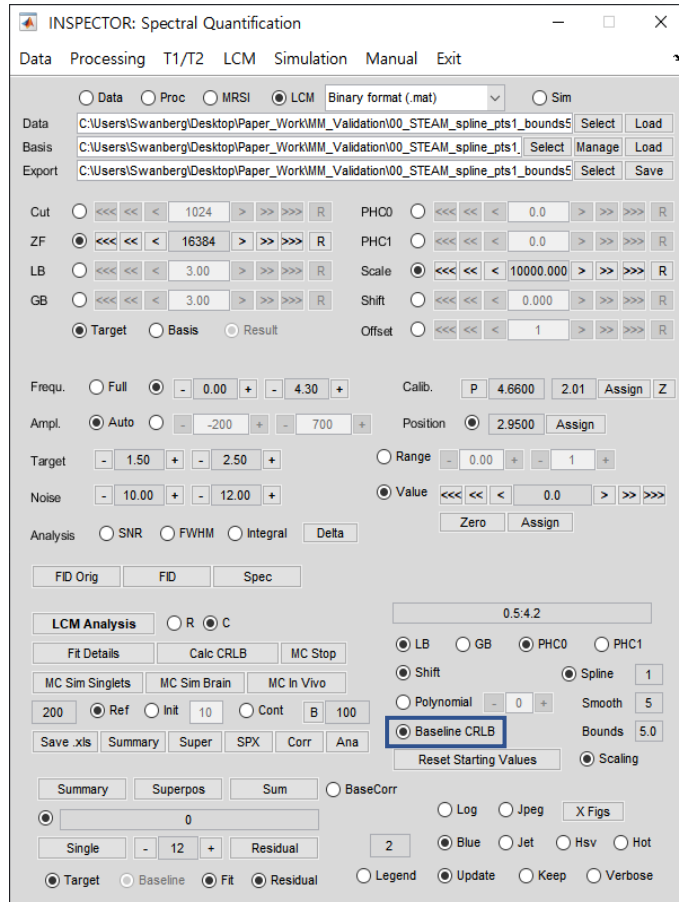
Model P.D. w.r.t. degree 0
baseline component amplitude

P (incorporating baseline terms)

	Metab1 (IP)	Metab2 (IP)	BL (IP)	GP						
	Prior knowledge P:									
Metab1 (IP + GP)	1	0	0	0	0	0	0	0	0	0
	0	1	0	0	0	0	0	0	0	0
	0	0	1	0	0	0	0	0	0	0
Metab2 (IP + GP)	0	0	0	0	0	0	0	0	0	1
	0	0	0	1	0	0	0	0	0	0
	0	0	0	0	1	0	0	0	0	0
	0	0	0	0	0	1	0	0	0	0
	0	0	0	0	0	0	0	0	0	1
BL (IP)	0	0	0	0	0	0	1	0	0	0
	0	0	0	0	0	0	0	1	0	0
	0	0	0	0	0	0	0	0	1	0

Baseline terms can be included in Cramér-Rao Lower Bound calculations as scaled polynomial shapes.

CHAPTER 2: SPECTRAL QUANTIFICATION



Full D: 2 metab * 4 metab-specific pars + 41 polynomial baseline coefficients = 49

After P: 2 metab * 3 metab-specific pars + 1 global pars + 41 polynomial baseline coefficients = 48 fit pars (CRLB)

Summary of amplitude CRLBs:

GSH: 4.610%

NAA: 1.092%

CRLB(amplitude)

= [4.609992 1.091928]%

CRLB(LB)

= [0.549687 0.124653] Hz

CRLB(Shift)

= [0.143785 0.060952] Hz

CRLB(PHC0)

= 0.629687 deg

CRLB(Spline, 1.97 - 2.03 ppm)

= [29.645544]%

CRLB(Spline, 2.03 - 2.10 ppm)

= [47.097105 53.157634 43.573187 32.961269]%

CRLB(Spline, 2.10 - 2.20 ppm)

= [47.024316 22.876282 9.182262 2.528464]%

CRLB(Spline, 2.20 - 2.40 ppm)

= [37.387031 26.199661 36.470409 0.793382]%

CRLB(Spline, 2.40 - 2.60 ppm)

= [79.686996 55.116961 50.446840 0.972640]%

CRLB(Spline, 2.60 - 2.80 ppm)

= [219.076590 122.924176 85.723342 0.869879]%

CRLB(Spline, 2.80 - 3.00 ppm)

= [643.838396 519.757889 134.353913 0.800714]%

CRLB(Spline, 3.00 - 3.20 ppm)

= [336.323145 728.388733 168.856288 0.793278]%

CRLB(Spline, 3.20 - 3.30 ppm)

= [14.314476 151.906508 38.210219 1.333068]%

CRLB(Spline, 3.30 - 3.37 ppm)

= [50.064434 35.881835 13.488720 2.995382]%

CRLB(Spline, 3.37 - 3.43 ppm)

= [379.114049 211.640147 101.542109 40.847510]%

LCMODEL ANALYSIS SUMMARY:

(errors as CRLB / Hessian of LSQ)

GSH: 2.36 mM (3.845, 4.6/9.5%) / LB 11.9 Hz (0.5/1.2 Hz) / Shift -3.58 Hz (0.1/0.3 Hz)

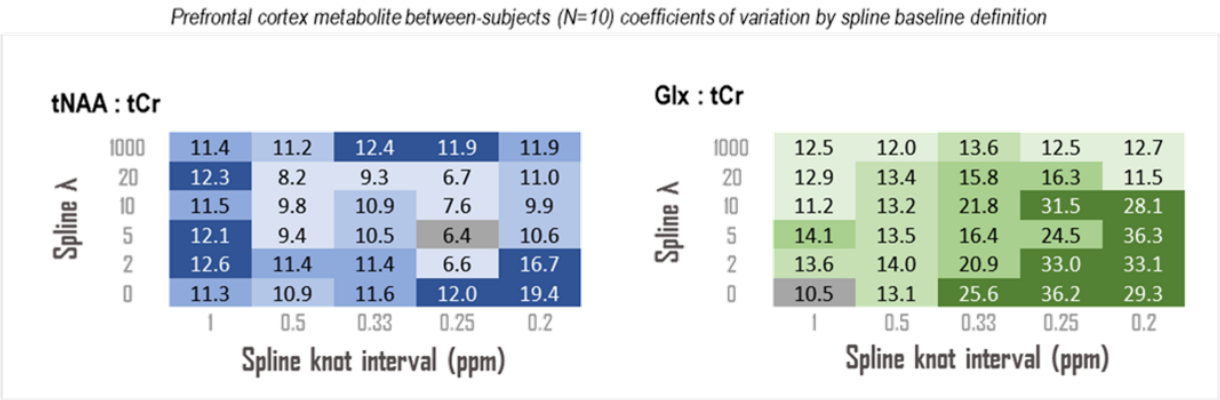
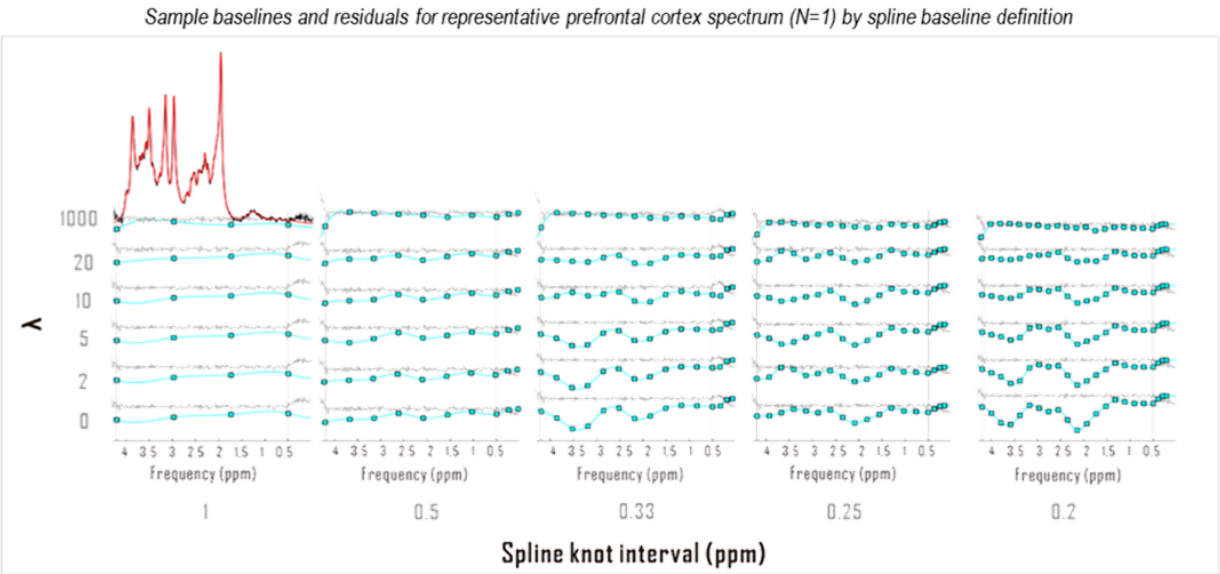
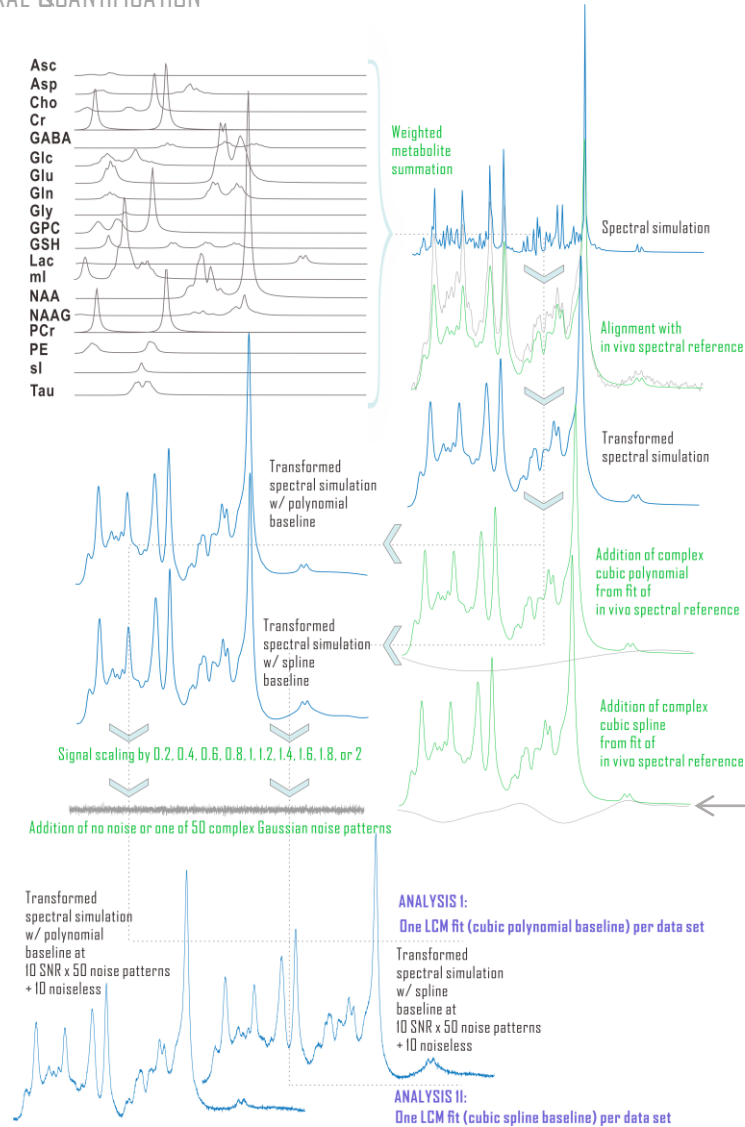
NAA: 10.00 mM (16.316, 1.1/2.2%) / LB 7.2 Hz (0.1/0.3 Hz) / Shift -1.06 Hz (<0.1/0.1 Hz)

PHC0: 5.9 deg (0.6/1.2 deg)

Tool 3: GUI-supported polynomial and cubic spline baseline error definitions by geometry-based calculation of Cramer-Rao Lower bound

Baseline terms can be included in Cramér-Rao Lower Bound calculations as scaled polynomial shapes.

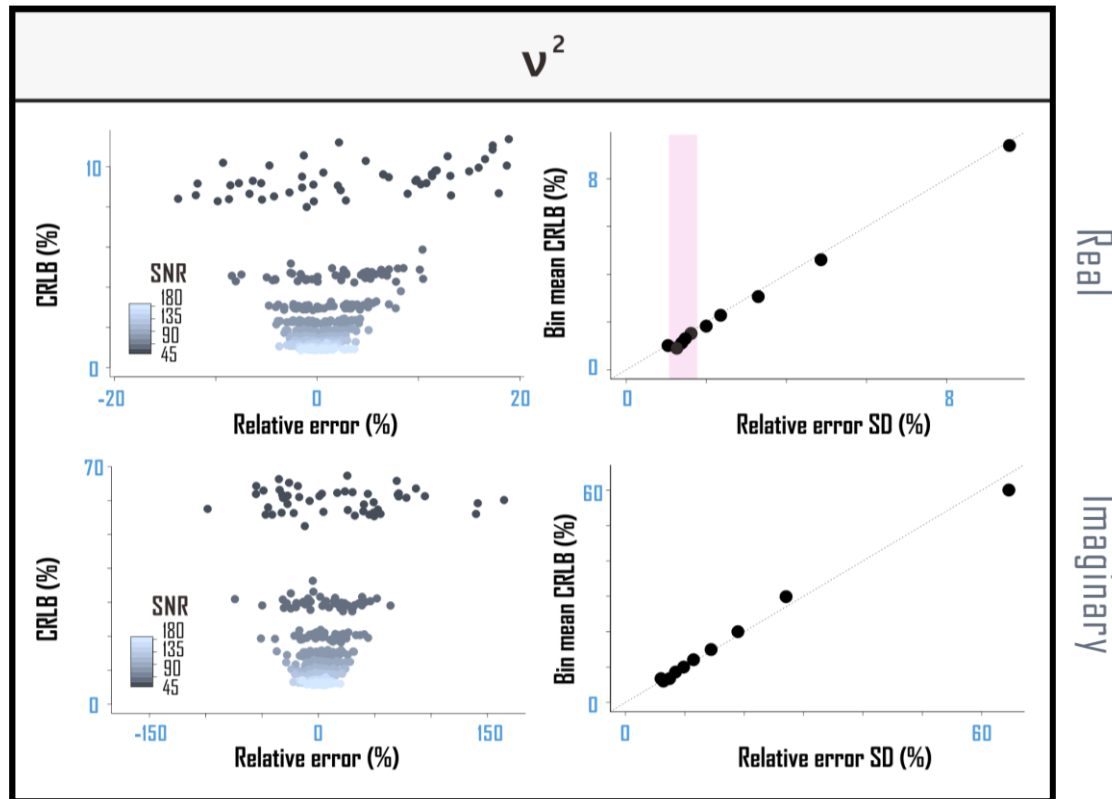
CHAPTER 2: SPECTRAL QUANTIFICATION



Swanberg, Gajdošík, Landheer, and Juchem. *Proc Intl Soc Mag Reson Med.* (2021); 2010.

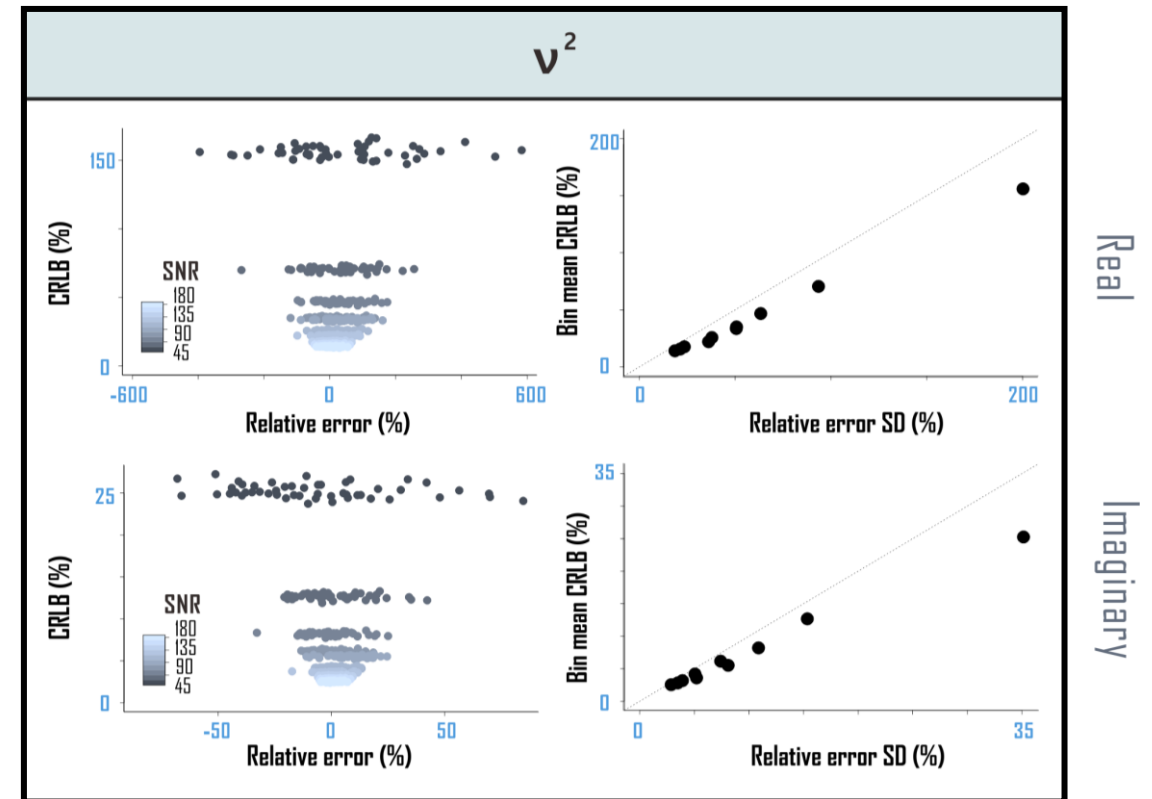
CHAPTER 2: SPECTRAL QUANTIFICATION

Cubic polynomial baselines



Shapiro-Wilk test indicates that fit error distribution significantly differs from normality

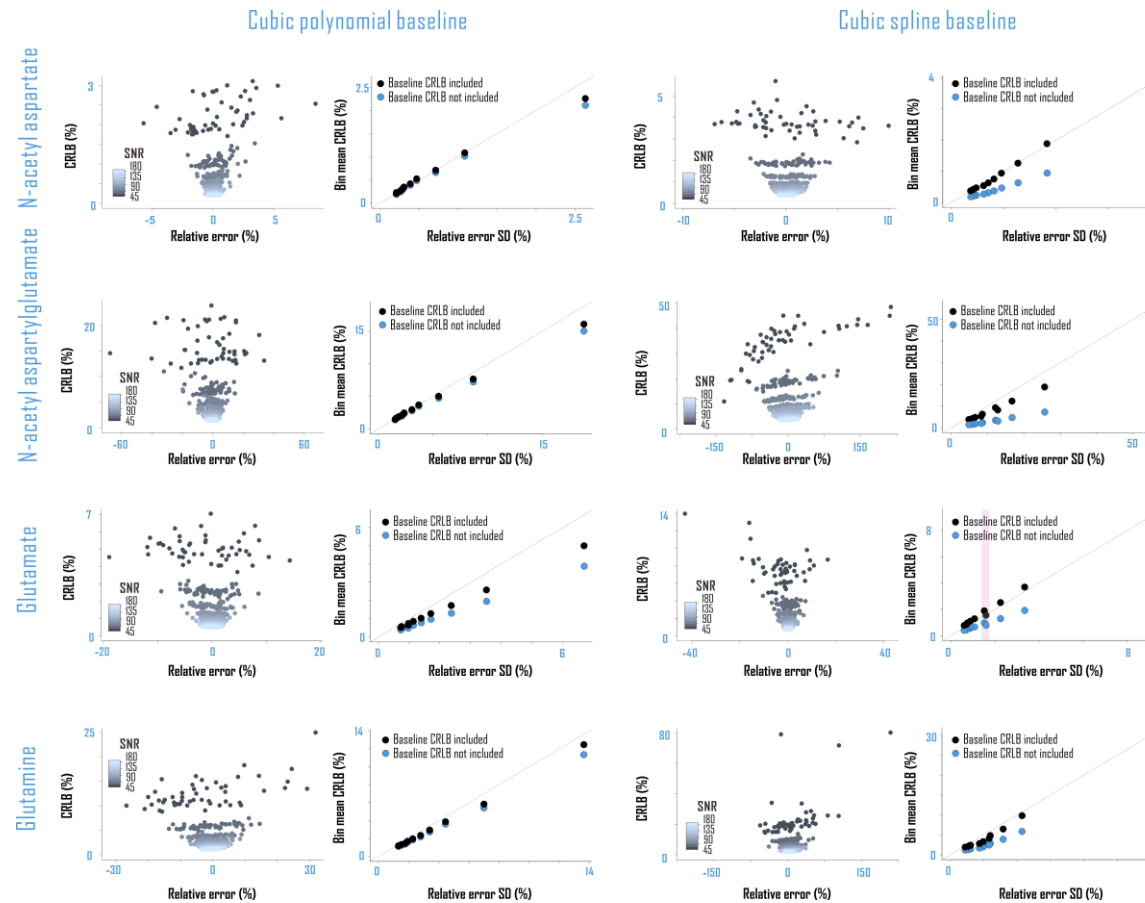
Cubic spline baselines (2.35-2.61 ppm shown)



Swanberg, Gajdošík, Landheer, and Juchem. *Proc Intl Soc Mag Reson Med.* (2021); 2010.

Inclusion of baseline terms in Cramér-Rao Lower Bound calculations as scaled polynomial shapes provides estimates of baseline fit error.

CHAPTER 2: SPECTRAL QUANTIFICATION



Shapiro-Wilk test indicates that fit error distribution significantly differs from normality

Swanberg, Gajdošík, Landheer, and Juchem. *Proc Intl Soc Mag Reson Med*. (2021); 2010.

Inclusion of baseline terms in Cramér-Rao Lower Bound calculations as scaled polynomial shapes improves CRLB estimates of metabolite fit error.

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

CHAPTER I

Spectral Quantification:

Data quality (FWHM and SNR) interacts with spectral baselines to affect metabolite fit accuracy.

Fit residual can be misleading when deciding whether a spectral baseline model supports accurate metabolite estimates.

Incorporating baseline terms to the Fisher information matrix improves utility of CRLB as a proxy for metabolite fit precision.

CHAPTER II

Absolute Quantification:

Can disease-related differences in metabolite T_2 introduce systematic errors to the derivation of absolute from relative metabolite concentrations, and how do we minimize them?

CHAPTER III

Statistical Analysis:

Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of ^1H MRS data alone classify disease states (case application multiple sclerosis)?

CHAPTER IV

Generalization:

Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

CHAPTER V

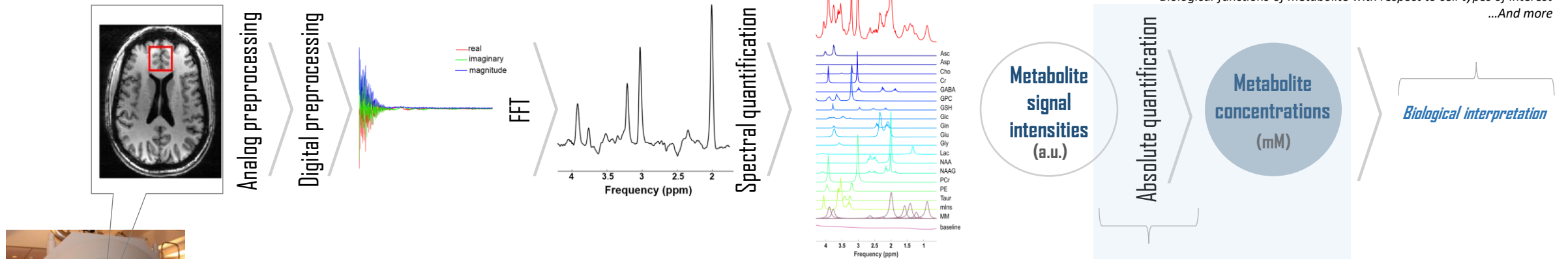
Back to the Big Picture:

General conclusions and outlook

CHAPTER VI

$$\hat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of baseline splines
 B = baseline spline
 S_n = metabolite basis function lineshape coefficients
 ν = frequency domain value
 γ = line broadening parameter
 ϵ = frequency shift parameter



Chapter III

Absolute Quantification: Can disease-related differences in metabolite T_2 introduce systematic errors to the derivation of absolute from relative metabolite concentrations, and how do we minimize them?

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

S_w = water signal scaling coefficient
 2 = number of protons in water molecule
 N_h = number of protons per molecule of metabolite to be quantified
 M_w = molarity of pure water
 β_i = molarity of water as a fraction of pure water in either grey matter (GM), white matter (WM), or CSF
 F_i = voxel fraction occupied by grey matter (GM), white matter (WM), or CSF
 $T_{2wi} = T_2$ of water in grey matter (GM), white matter (WM), or CSF
 $T_{1wi} = T_1$ of water in grey matter (GM), white matter (WM), or CSF
 $T_{2m} = T_2$ of metabolite
 $T_{1m} = T_1$ of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

CHAPTER 3: ABSOLUTE QUANTIFICATION

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

Final result

f_c

conversion factor from spectral quantification scaling coefficient to absolute concentration

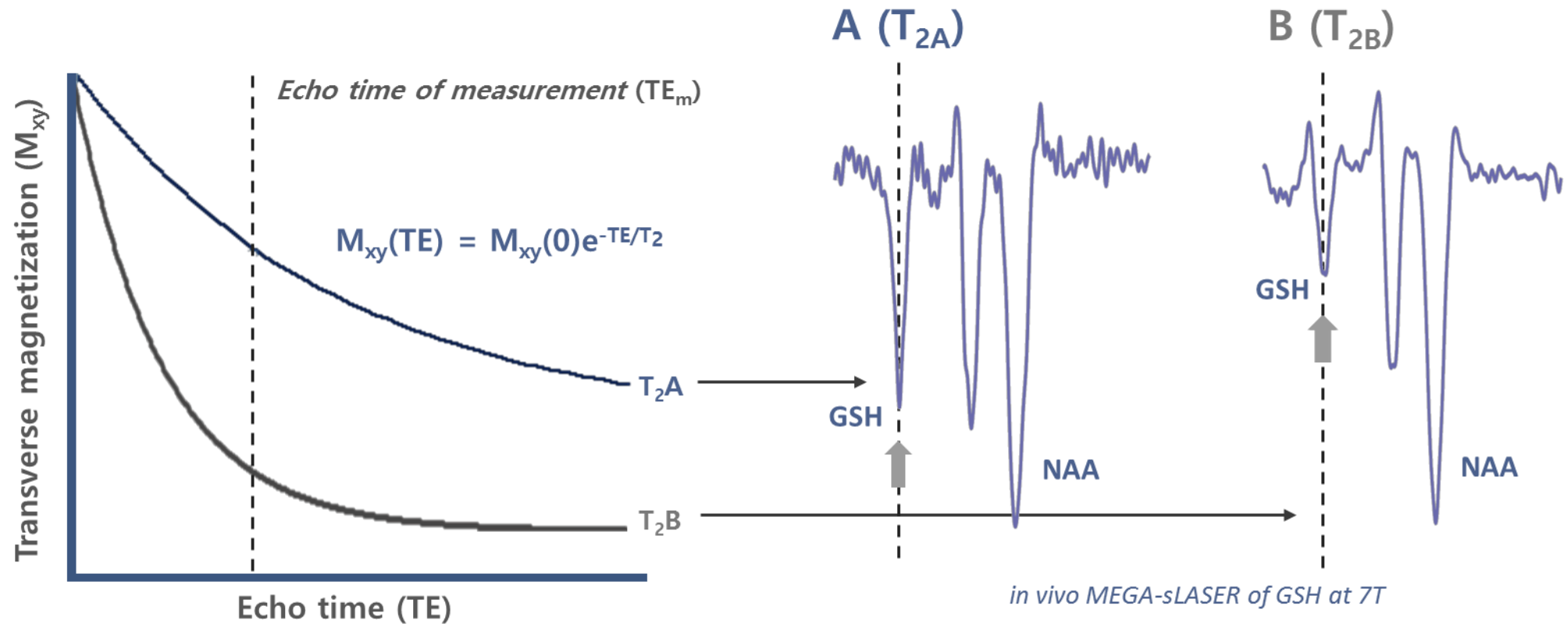
Accounting for proton number and estimating water molarity in voxel

S_w	water signal scaling coefficient
2	number of protons in water molecule
N_h	number of protons per molecule of metabolite to be quantified
M_w	molarity of pure water
β_i	molarity of water as a fraction of pure water in either grey matter (GM), white matter (WM), or CSF
F_i	voxel fraction occupied by grey matter (GM), white matter (WM), or CSF

Accounting for relaxation differences between water and metabolite

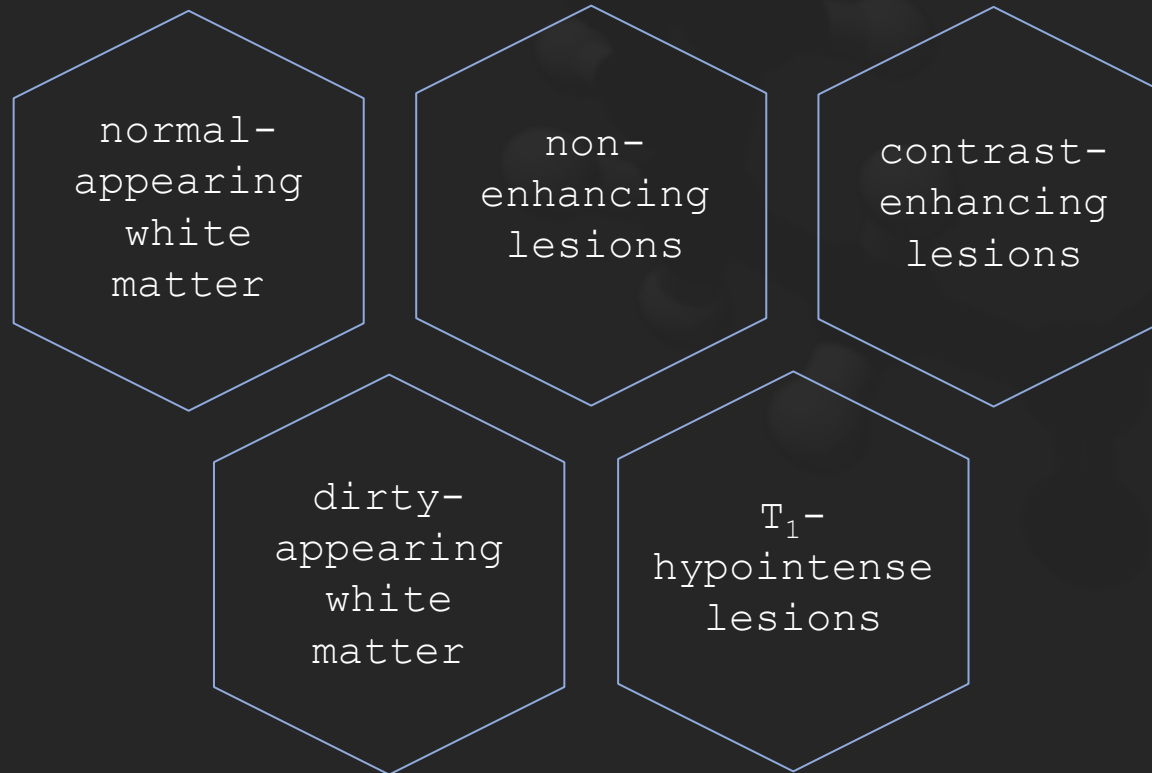
T_{2wi}	T_2 of water in grey matter (GM), white matter (WM), or CSF
T_{1wi}	T_1 of water in grey matter (GM), white matter (WM), or CSF
T_{2m}	T_2 of metabolite
T_{1m}	T_1 of metabolite
T_E	echo time of sequence
T_R	repetition time of sequence

CHAPTER 3: ABSOLUTE QUANTIFICATION

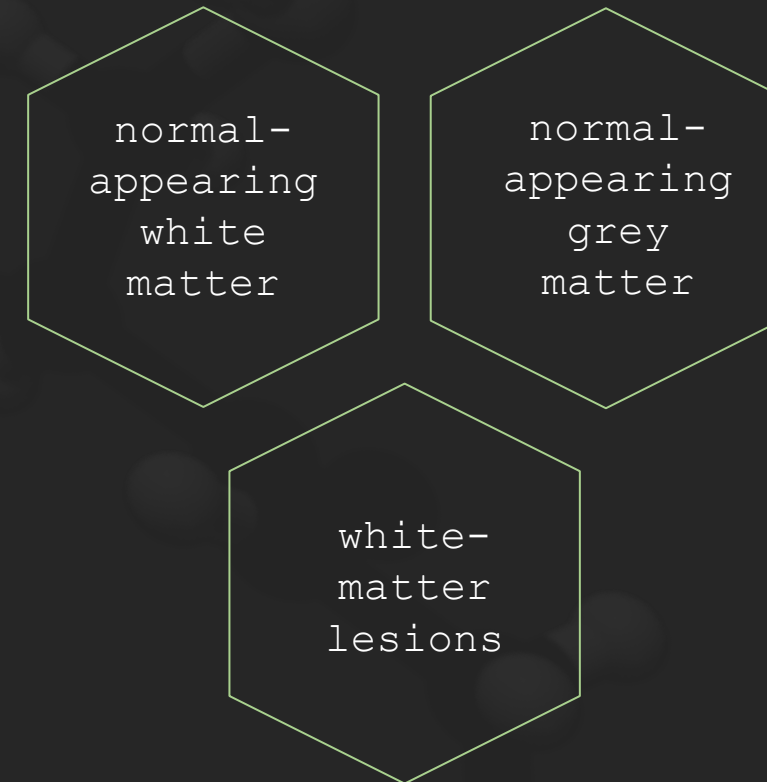


$$[A] = [B], \text{ but } T_{2A} > T_{2B}, \text{ so at } TE_M \quad M_{xy}A > M_{xy}B$$

MS \rightarrow increases in water T_2 for:

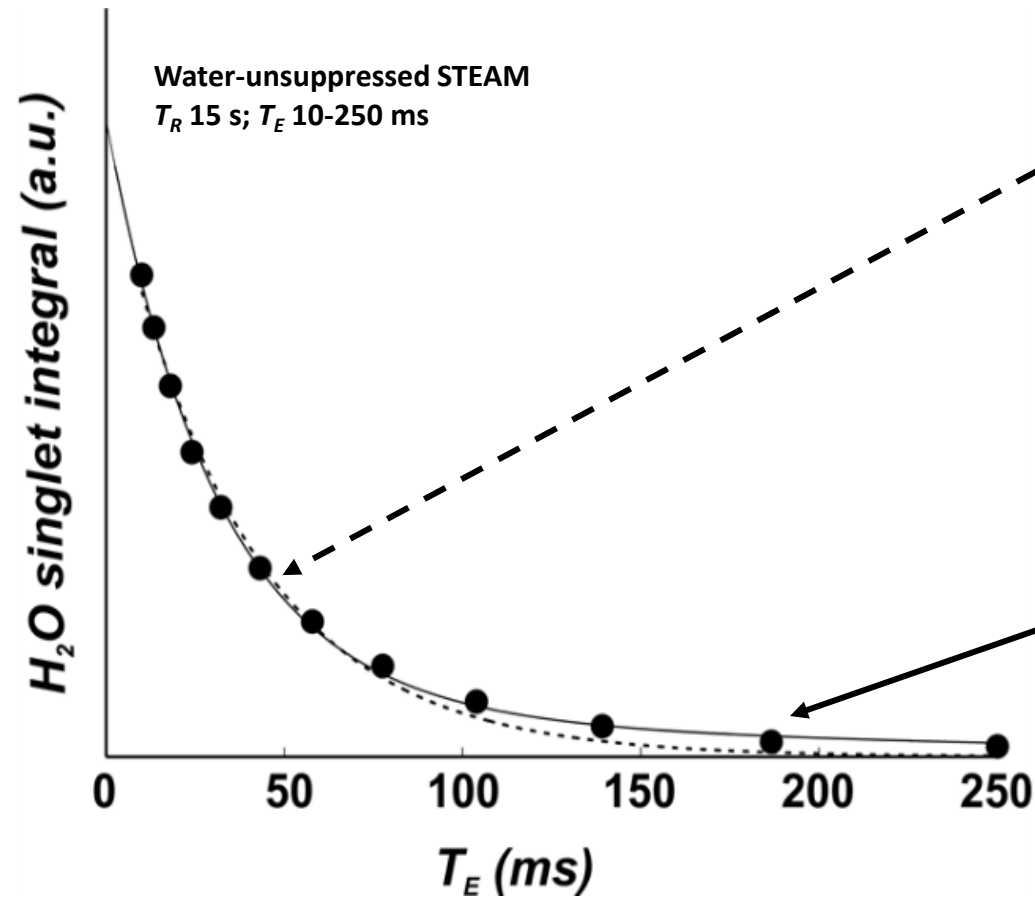


MS \rightarrow decreases in metabolite T_2 for:



Swanberg, Landheer, Pitt, and Juchem. *Frontiers in Neurology* 10 (2019): 1173.

A review has shown that water T_2 relaxation may change with multiple sclerosis disease state.



Monoexponential

$$M_{TE} = M_0 e^{\frac{-T_E}{T_2}}$$

Biexponential with fixed coefficients

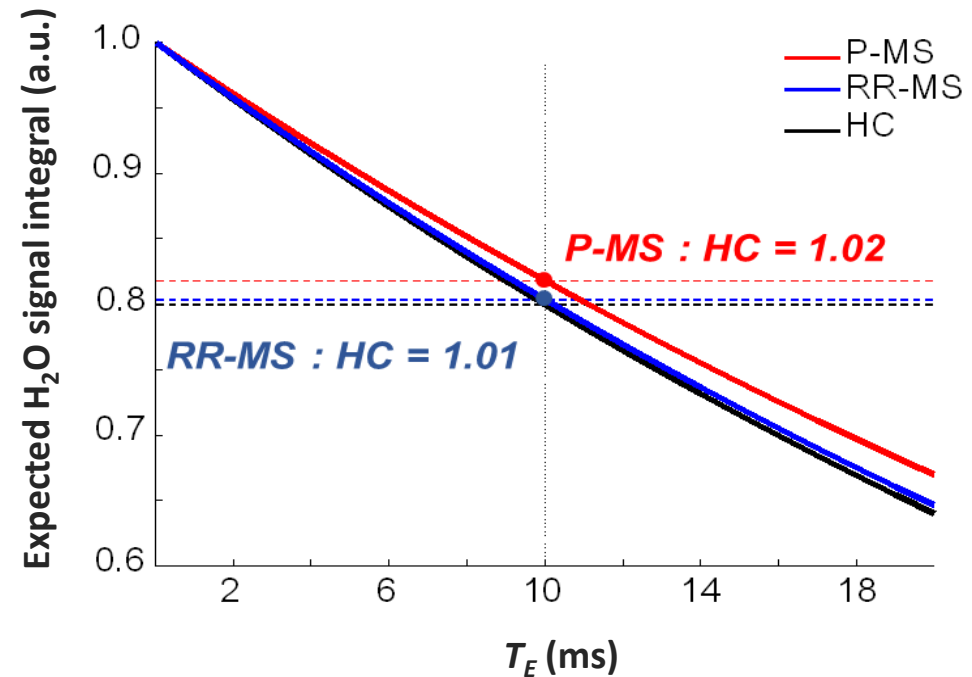
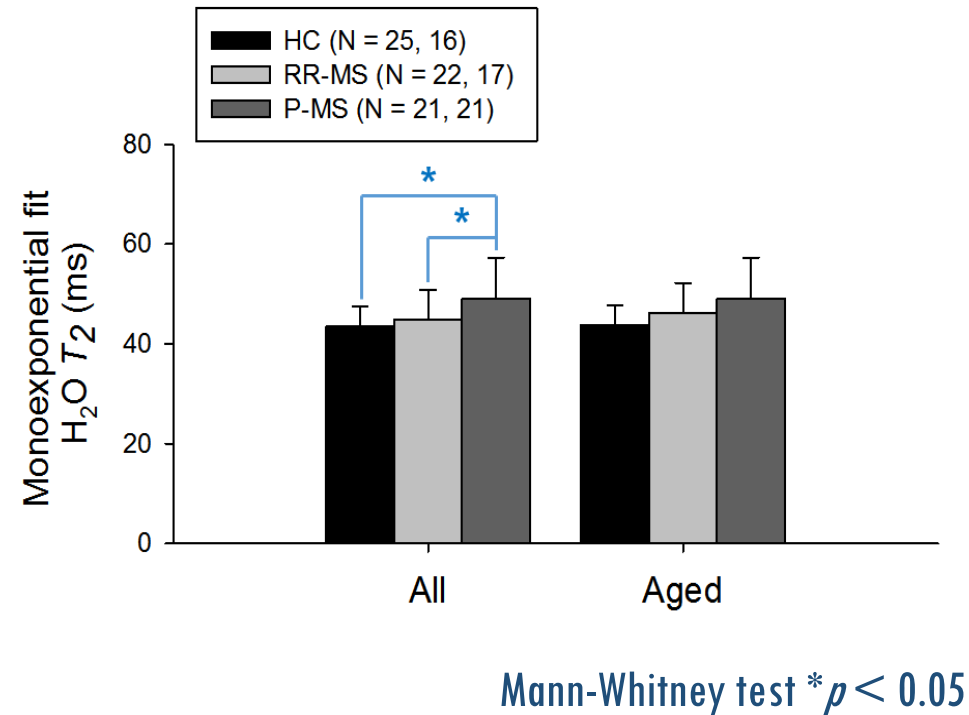
$$M_{TE} = M_0 \left(\chi_t e^{\frac{-T_E}{T_{2t}}} + \chi_f e^{\frac{-T_E}{T_{2f}}} \right)$$

$$\chi_t = \frac{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm}}{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm} + PV_{csf}[H_2O]_{csf}}$$

$$\chi_f = \frac{PV_{csf}[H_2O]_{csf}}{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm} + PV_{csf}[H_2O]_{csf}}$$

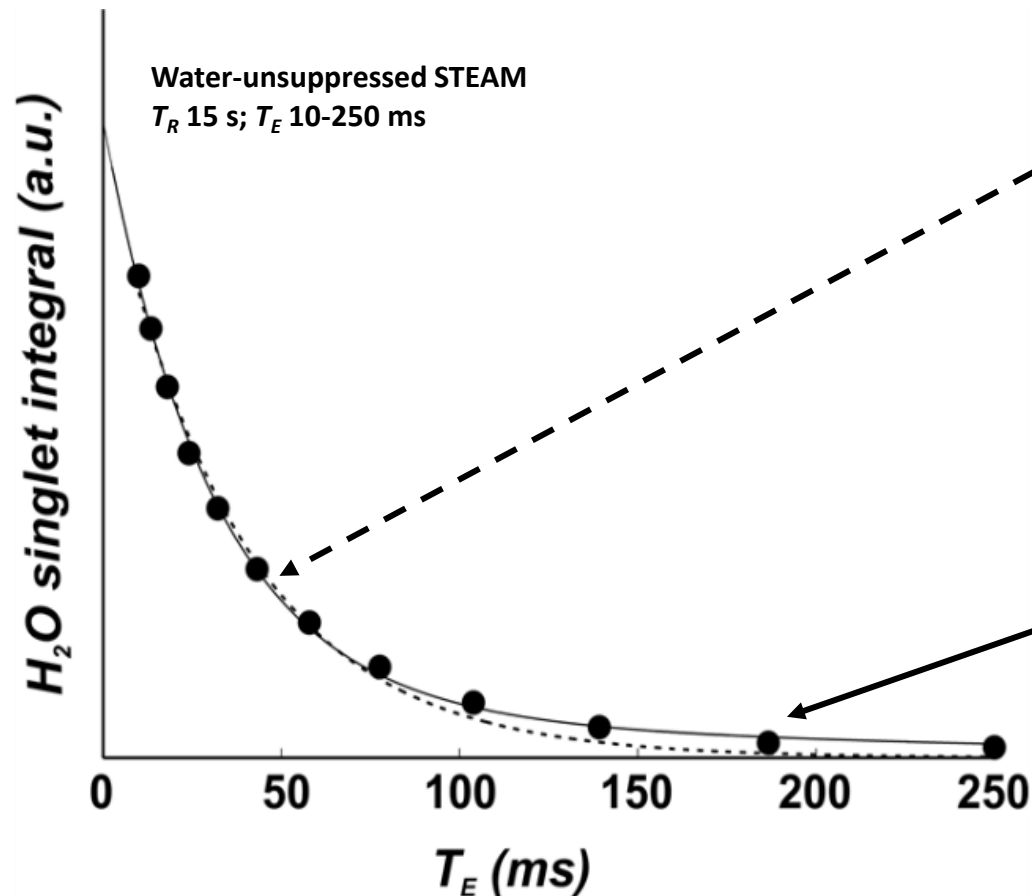
Swanberg, Prinsen, Kurada, Destefano, Bailey, Pitt, Fulbright, and Juchem. *Proc. Intl. Soc. Mag. Reson. Med.* (2018); 0161.We first assessed voxel water T_2 using monoexponential modeling.

CHAPTER 3: ABSOLUTE QUANTIFICATION



Swanberg, Prinsen, Kurada, Destefano, Bailey, Pitt, Fulbright, and Juchem. *Proc. Intl. Soc. Mag. Reson. Med.* (2018); 0161.

Monoexponentially modeled water T_2 was higher in the aged progressive MS group than the other two groups.



Monoexponential

$$M_{TE} = M_0 e^{\frac{-T_E}{T_2}}$$

Biexponential with fixed coefficients

$$M_{TE} = M_0 \left(\chi_t e^{\frac{-T_E}{T_{2t}}} + \chi_f e^{\frac{-T_E}{T_{2f}}} \right)$$

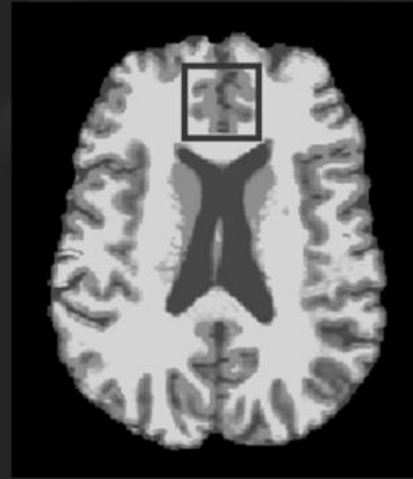
$$\chi_t = \frac{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm}}{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm} + PV_{csf}[H_2O]_{csf}}$$

$$\chi_f = \frac{PV_{csf}[H_2O]_{csf}}{PV_{gm}[H_2O]_{gm} + PV_{wm}[H_2O]_{wm} + PV_{csf}[H_2O]_{csf}}$$

Swanberg, Prinsen, Kurada, Destefano, Bailey, Pitt, Fulbright, and Juchem. *Proc. Intl. Soc. Mag. Reson. Med.* (2018); 0161.

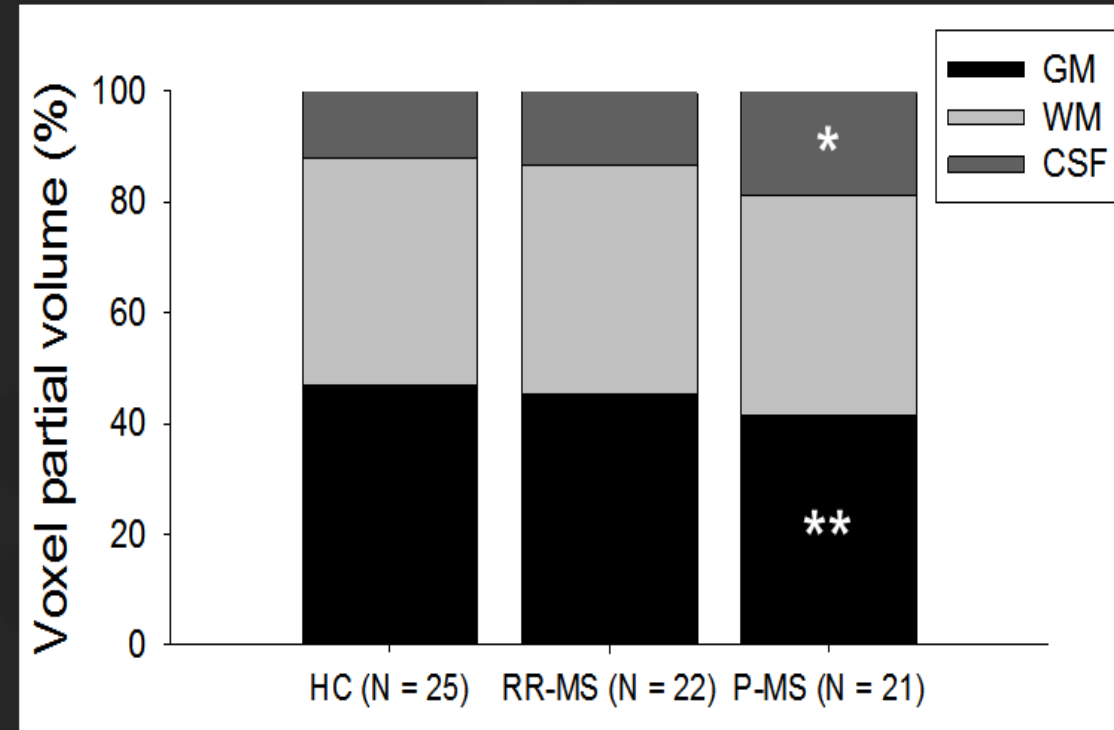
We then assessed voxel water T_2 using biexponential modeling.

CHAPTER 3: ABSOLUTE QUANTIFICATION



**Skull-stripping (FMRIB Brain Extraction Tool; BET) +
segmentation (BrainSuite)**

Smith SM. *Human Brain Mapping* 2002; 17(3): 143-155
Shattuck D, Leahy RM. *Medical Image Analysis* 2002; 6(2): 129-142



Mann-Whitney test v. HC * $p < 0.05$, ** $p < 0.01$

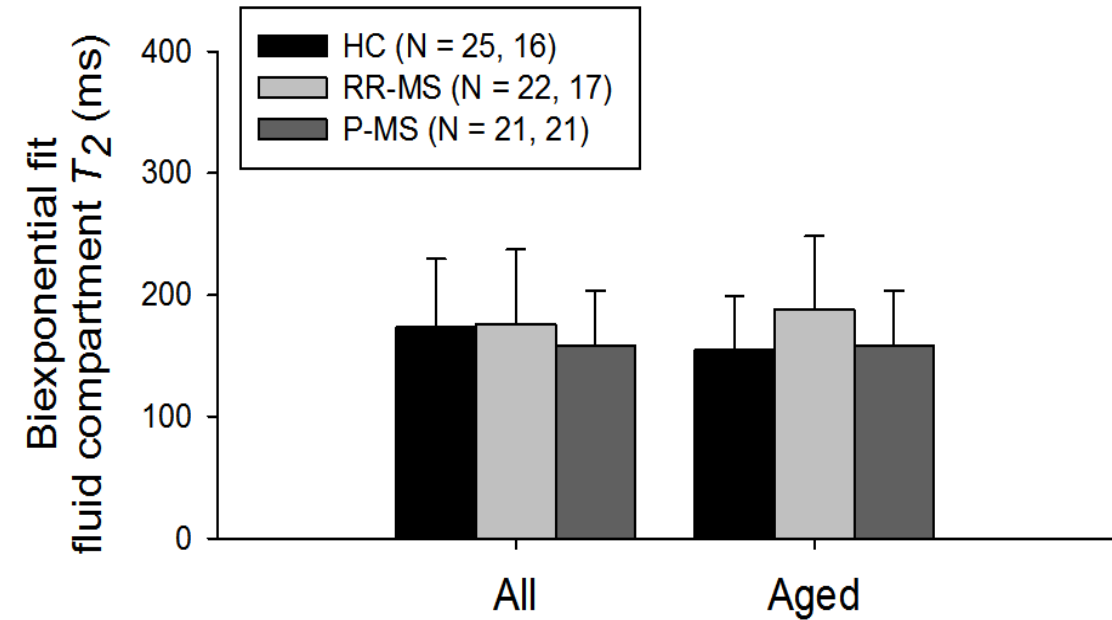
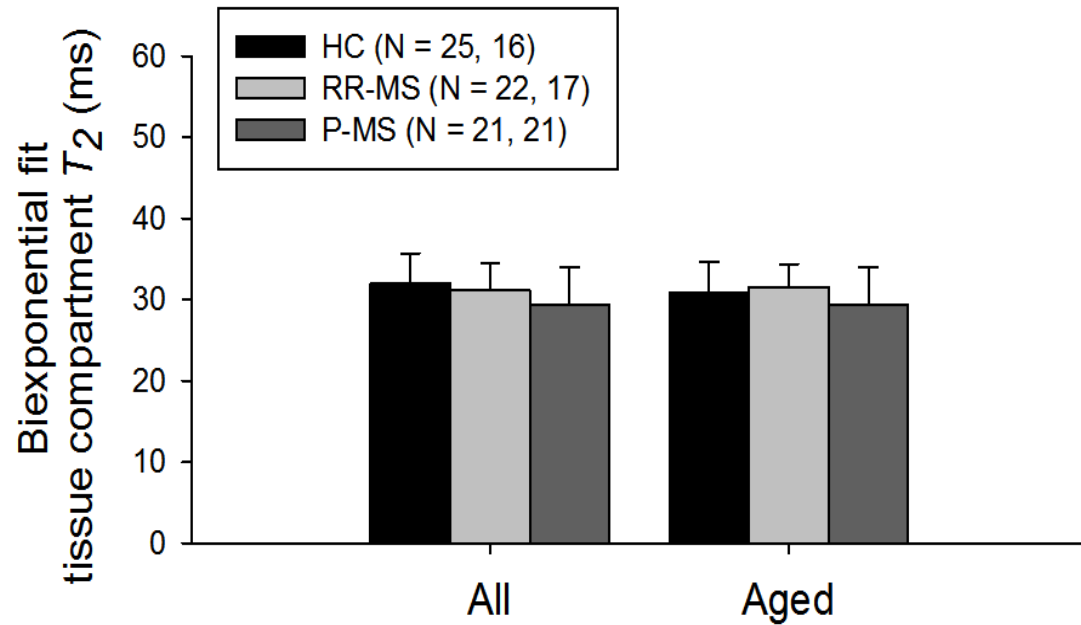
Swanberg, Prinsen, Kurada, Destefano, Bailey, Pitt, Fulbright, and Juchem. *Proc. Intl. Soc. Mag. Reson. Med.* (2018); 0161.

We controlled T_2 fits for voxel composition differences in relapsing-remitting, progressive, and no MS.



In collaboration
with Abhinav
Kurada, B.Sc.

CHAPTER 3: ABSOLUTE QUANTIFICATION



Swanberg, Prinsen, Kurada, Destefano, Bailey, Pitt, Fulbright, and Juchem. *Proc. Intl. Soc. Mag. Reson. Med.* (2018); 0161.

Biexponentially modeled water T_2 controlled for voxel composition displayed no between-group differences.

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

CHAPTER I

Spectral Quantification:

Data quality (FWHM and SNR) interacts with spectral baselines to affect metabolite fit accuracy.

Fit residual can be misleading when deciding whether a spectral baseline model supports accurate metabolite estimates.

Incorporating baseline terms to the Fisher information matrix improves utility of CRLB as a proxy for metabolite fit precision.

CHAPTER II

Absolute Quantification:

Water T_2 was shown to differ between individuals with and without progressive multiple sclerosis, emphasizing the utility of group-specific corrections for this variable when employed in cross-sectional ^1H MRS studies of disease.

CHAPTER III

Statistical Analysis:

Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of ^1H MRS data alone classify disease states (case application multiple sclerosis)?

CHAPTER IV

Generalization:

Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

CHAPTER V

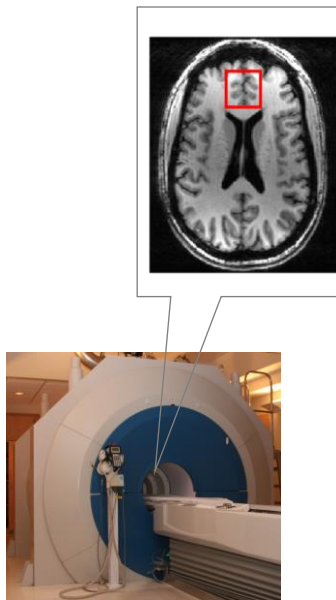
Back to the Big Picture:

General conclusions and outlook

CHAPTER VI

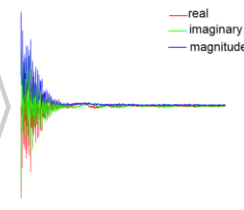
Chapter IV

Statistical Analysis: Can single- or multivariate analysis of metabolite concentrations derived from optimized quantification of 1H MRS data alone classify disease states (case application multiple sclerosis)?

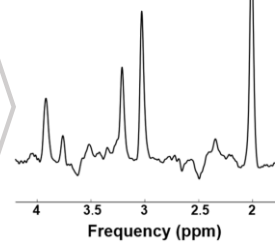


Analog preprocessing

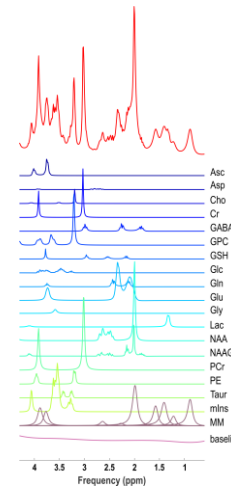
Digital preprocessing



FFT



Spectral quantification



Metabolite
signal
intensities
(a.u.)

Absolute quantification

Metabolite
concentrations
(mM)

Biological interpretation

Metabolite concentrations by tissue
Intracellular vs. extracellular metabolite concentration
Intracellular metabolite concentrations within cell types of interest
Biological functions of metabolite with respect to cell types of interest
...And more

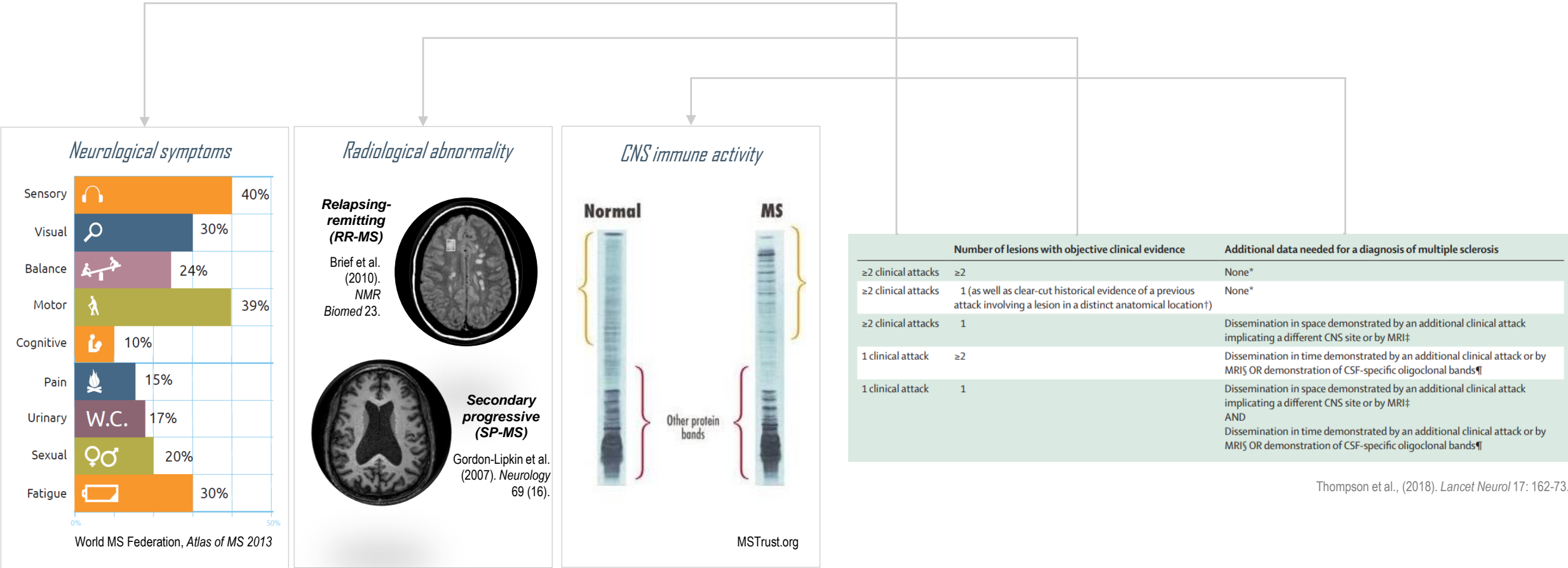
$$\hat{Y}(\nu_k) = e^{-i(\phi_0 + \nu\phi_1)} \left[\sum_{j=1}^{N_B} \beta_j B_j(\nu_k) + \sum_{l=1}^{N_M} C_l \sum_{n=-N_s}^{N_s} S_n M_l(\nu_{k-n}, \gamma_l, \epsilon_l) \right]$$

$\Phi_{0,1}$ = zero-, first-order phase
 N_M = number of metabolites
 C_l = Metabolite concentrations
 N_B = number of baseline splines
 B = baseline spline
 S_n = metabolite basis function lineshape coefficients
 ν = frequency domain value
 γ = line broadening parameter
 ϵ = frequency shift parameter

$$f_c = (1 - F_{CSF})^{-1} \left[\frac{2M_w \sum_{i=GM,WM,CSF} (F_i \beta_i)}{N_h S_w} \right] \frac{\sum_{i=GM,WM,CSF} \left[F_i \left(e^{\frac{-T_E}{T_{2wi}}} \right) \left(1 - e^{\frac{-T_R}{T_{1wi}}} \right) \right]}{e^{\frac{-T_E}{T_{2m}}} \left(1 - e^{\frac{-T_R}{T_{1m}}} \right)}$$

S_w = water signal scaling coefficient
 2 = number of protons in water molecule
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 M_w = molarity of pure water
 β_i = molarity of water as a fraction of pure water in either grey matter (GM), white matter (WM), or CSF
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 T_{2wi} = T_2 of water in grey matter (GM), white matter (WM), or CSF
 T_{1wi} = T_1 of water in grey matter (GM), white matter (WM), or CSF
 T_{2m} = T_2 of metabolite
 T_{1m} = T_1 of metabolite
 T_E = echo time of sequence
 T_R = repetition time of sequence

CHAPTER 4: STATISTICAL ANALYSIS



Multiple sclerosis is an autoimmune disease with multiple heterogeneous physical manifestations and diagnostic uncertainty.

CHAPTER 4: STATISTICAL ANALYSIS



In collaboration
with Hetty
Prinsen, Ph.D.

12 ♀ 13 ♂
43 ± 15 y.*

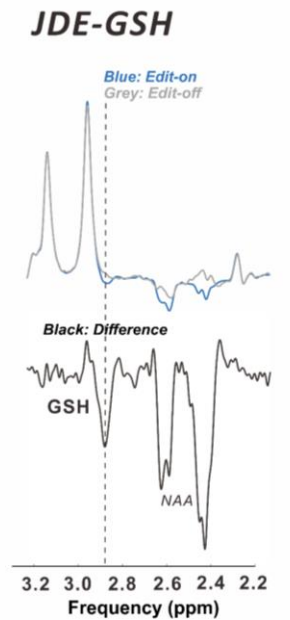
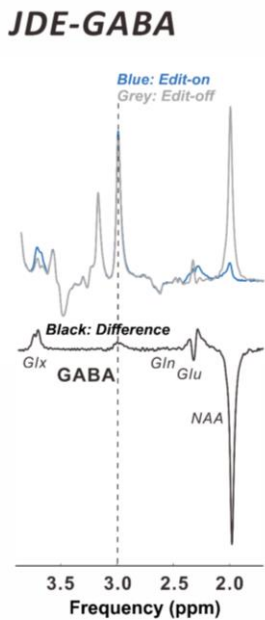
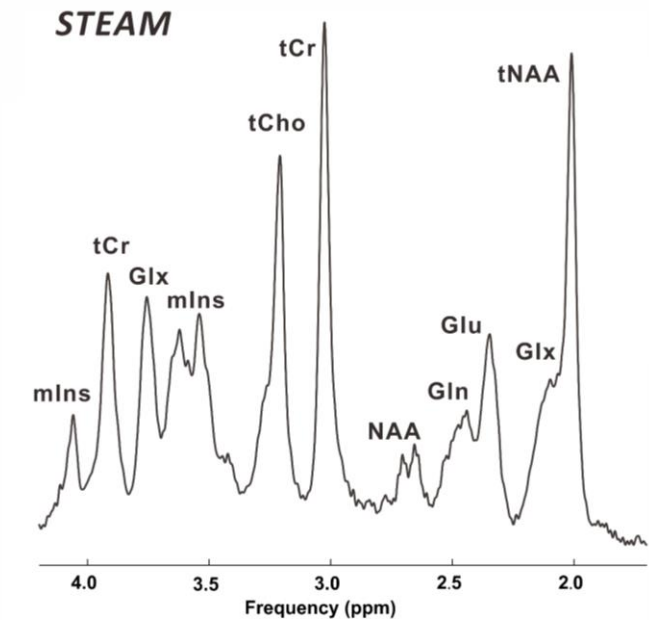
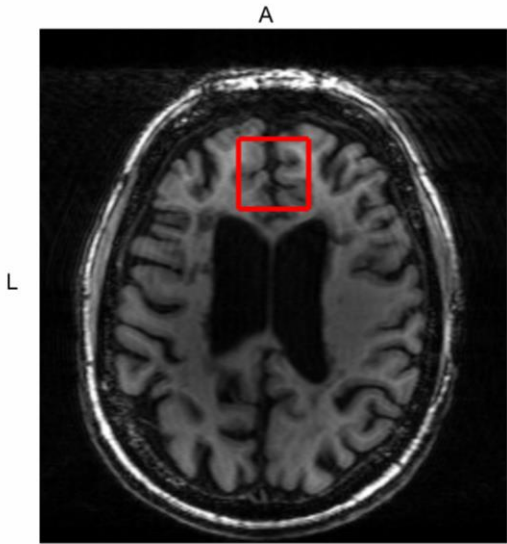
Non-MS
control

18 ♀ 8 ♂
44 ± 13 y.

Relapsing-
remitting MS

12 ♀ 9 ♂
55 ± 8 y.

Progressive
MS



*mean ± standard deviation

Swanberg, Prinsen, Kurada, Bailey, Destefano, Pitt, Fulbright, and Juchem, *NMR in Biomedicine* (2021); 34(11): e4590.

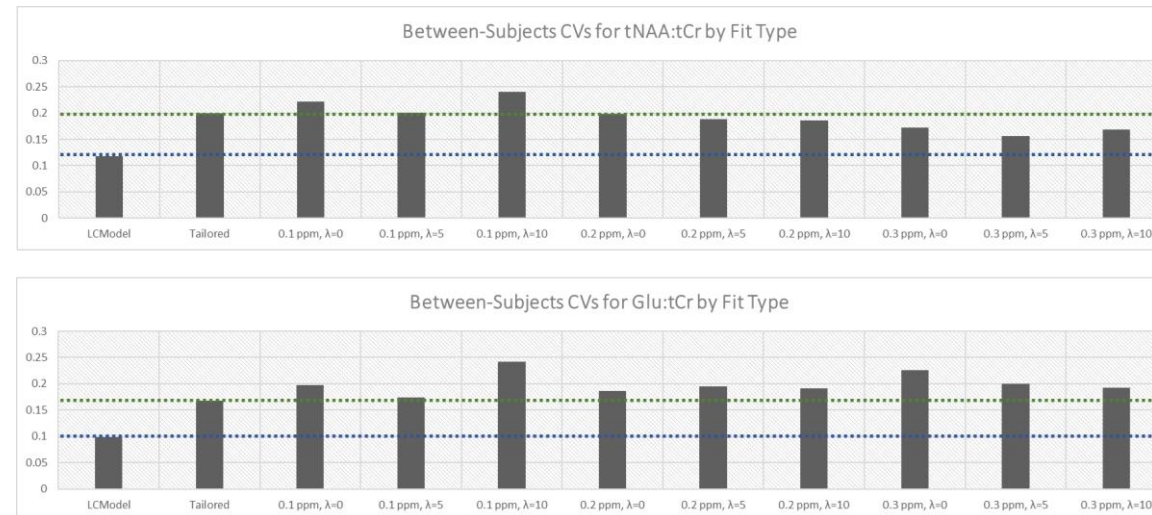
We used 7-Tesla ¹H MRS to characterize the prefrontal cortex metabolic signatures of two multiple sclerosis phenotypes.

CHAPTER 4: STATISTICAL ANALYSIS

Spectral Quantification:

Data quality (FWHM and SNR) can interact with spectral baselines to induce systematic effects on spectral fit accuracy. Fit residual is a misleading proxy for spectral baseline model's support of accurate metabolite estimates.

CHAPTER 2: SPECTRAL QUANTIFICATION

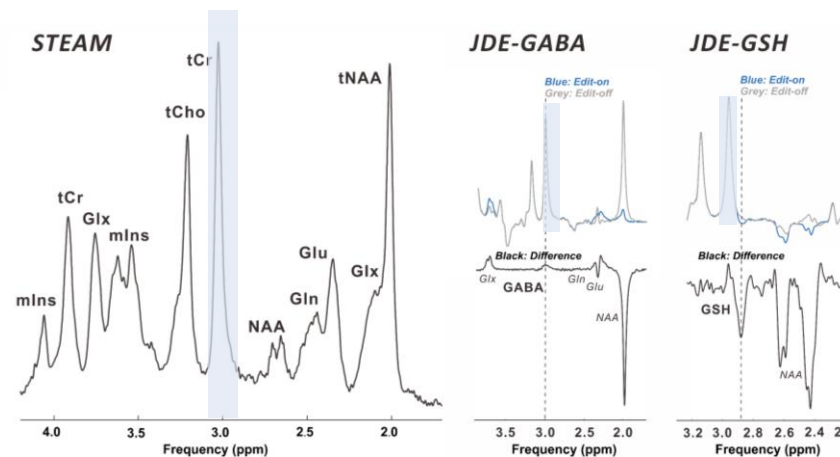


EMPIRICALLY SUPPORTED SPECTRAL
QUANTIFICATION METHOD

Absolute Quantification:

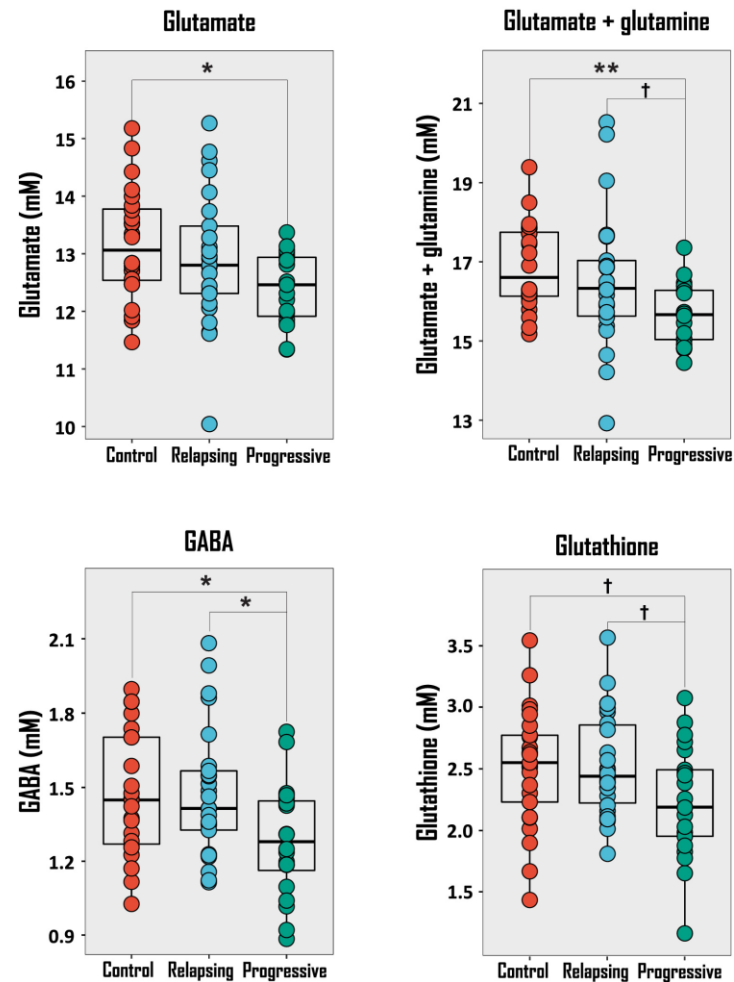
Water T_2 was shown to differ between individuals with and without progressive multiple sclerosis, emphasizing the utility of group-specific corrections for this variable when employed in cross-sectional ^1H MRS studies of disease.

CHAPTER 3: ABSOLUTE QUANTIFICATION

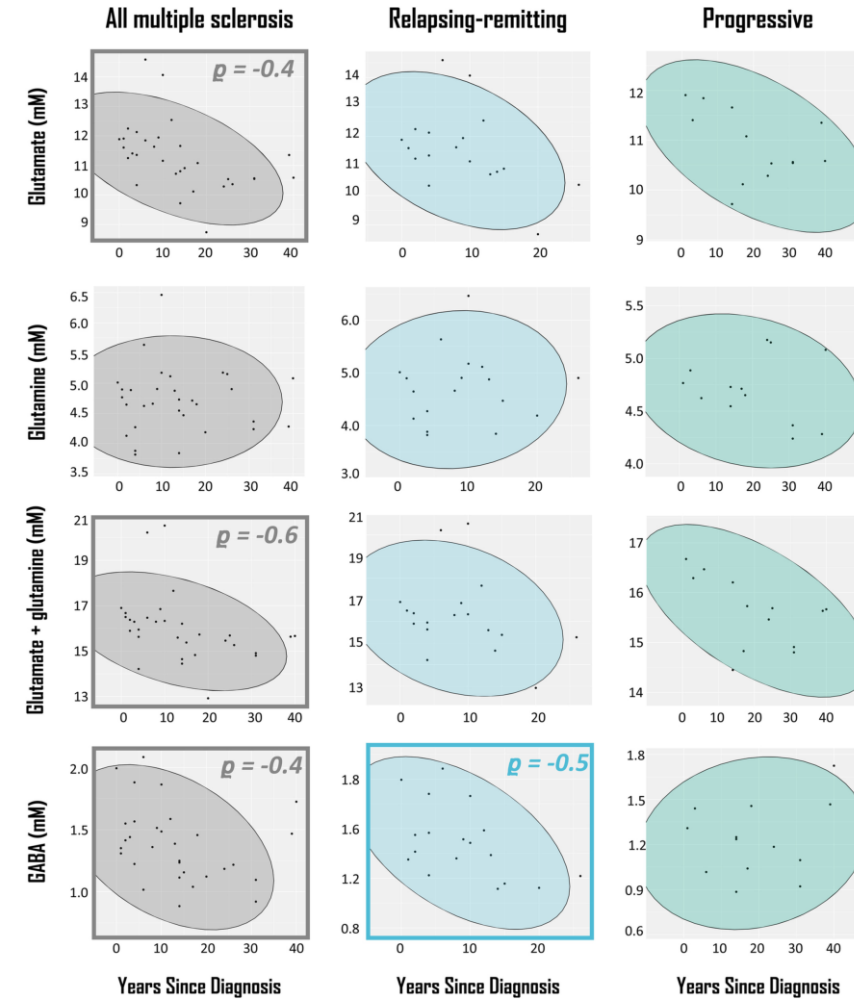


EMPIRICALLY SUPPORTED ABSOLUTE
QUANTIFICATION METHOD

CHAPTER 4: STATISTICAL ANALYSIS



Tukey's honest significant difference test post hoc to analysis of variance $*p \leq 0.05$, $**p < 0.01$, $\dagger p < 0.1$
 Metabolite concentrations corrected for age when regression coefficient significant in control



Boxes indicate Spearman's $\rho p < 0.05$

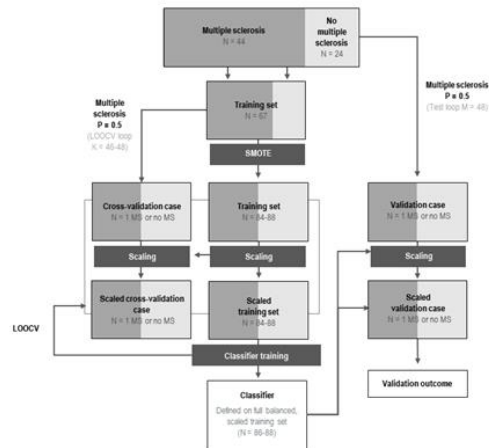
Swanberg, Prinsen, Kurada, Bailey, Destefano, Pitt, Fulbright, and Juchem, *NMR in Biomedicine* (2021); 34(11): e4590.

CHAPTER 4: STATISTICAL ANALYSIS

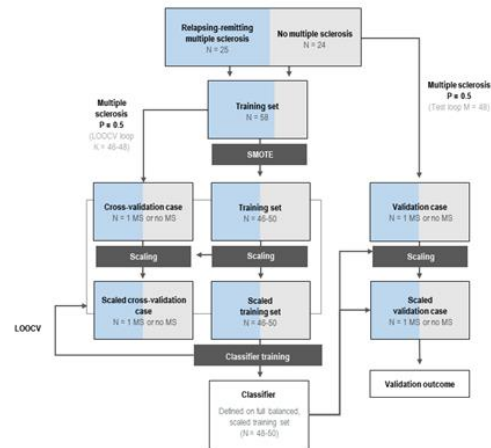


In collaboration
with Abhinav
Kurada, B.Sc.

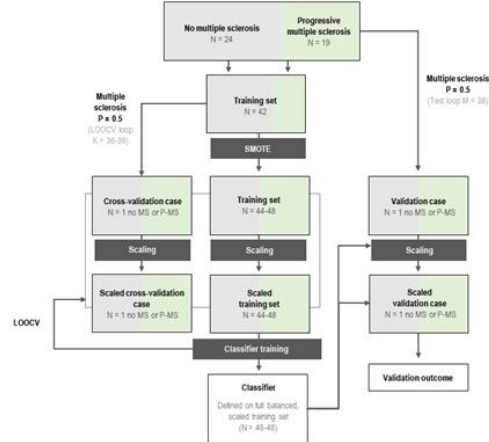
All MS vs. no MS



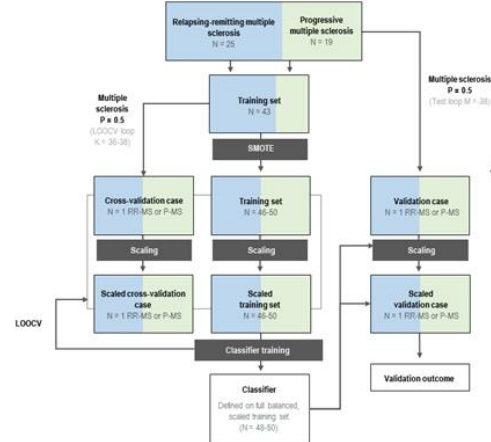
RR-MS vs. no MS



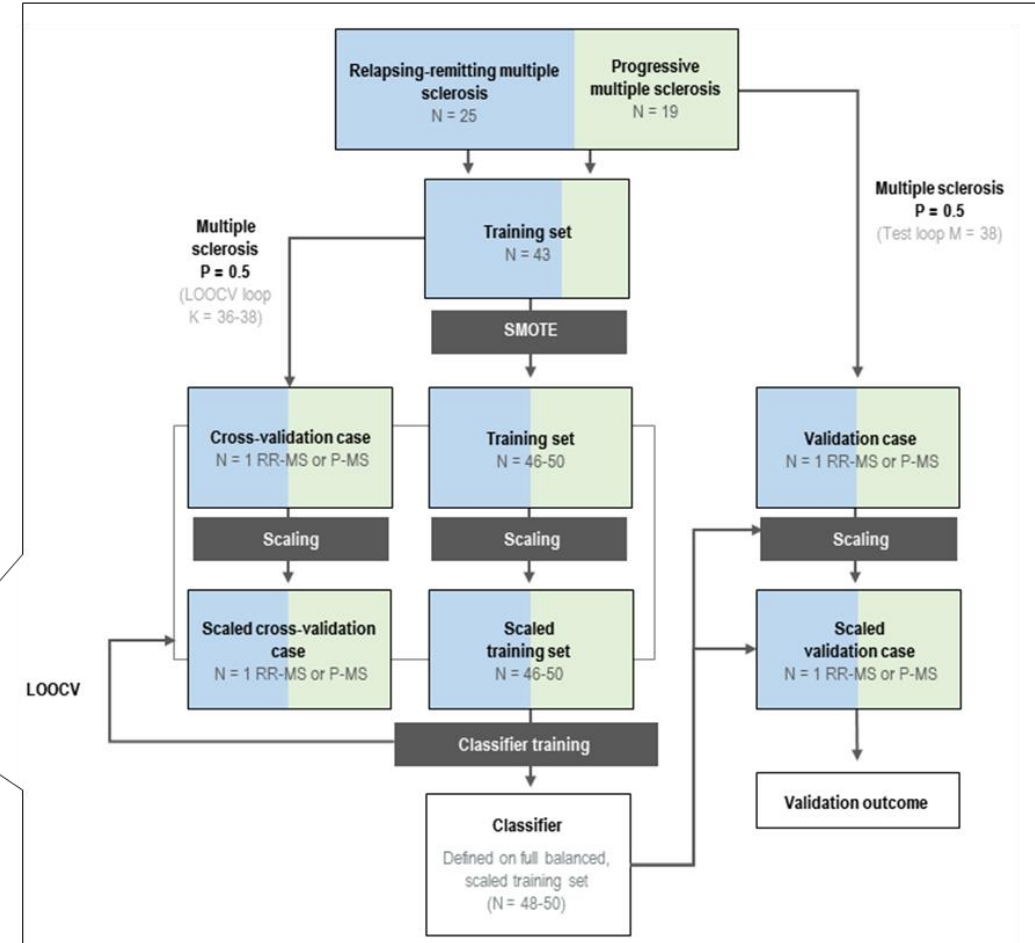
P-MS vs. no MS



P-MS vs. RR-MS



Relapsing-remitting (RR-MS) vs. progressive (P-MS)



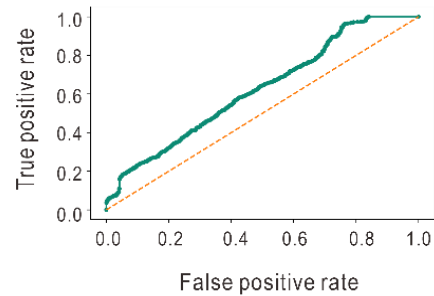
Swanberg, Kurada, Prinsen, and Juchem. Manuscript in review.

We applied supervised learning to non-reduced feature sets of seven metabolites to perform one of four classifications.

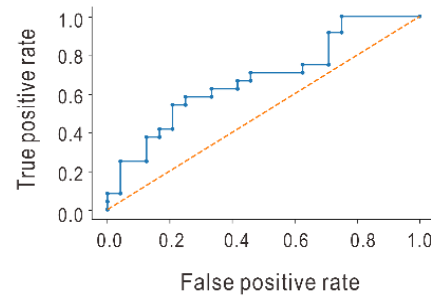
CHAPTER 4: STATISTICAL ANALYSIS

Control versus all multiple sclerosis

LOOCV



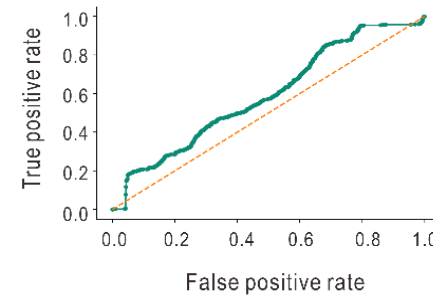
Validation



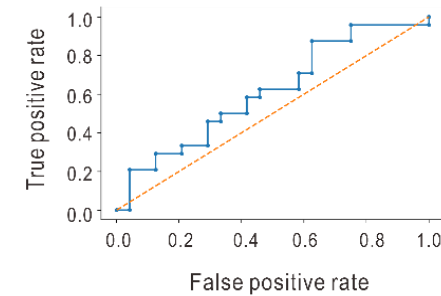
QDA

Control versus relapsing-remitting multiple sclerosis

LOOCV



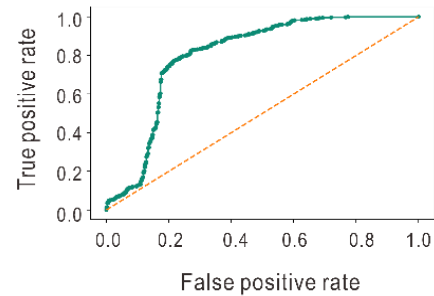
Validation



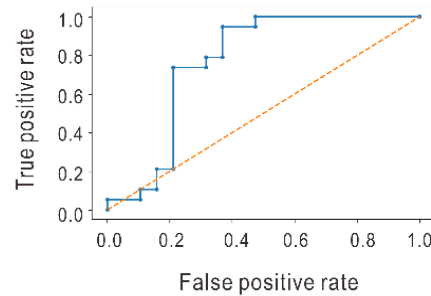
QDA

Control versus progressive multiple sclerosis

LOOCV



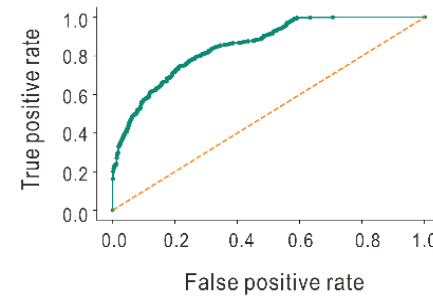
Validation



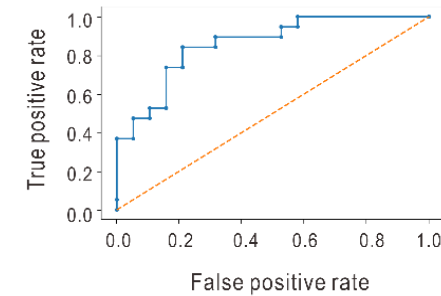
QDA

Relapsing-remitting versus progressive multiple sclerosis

LOOCV



Validation



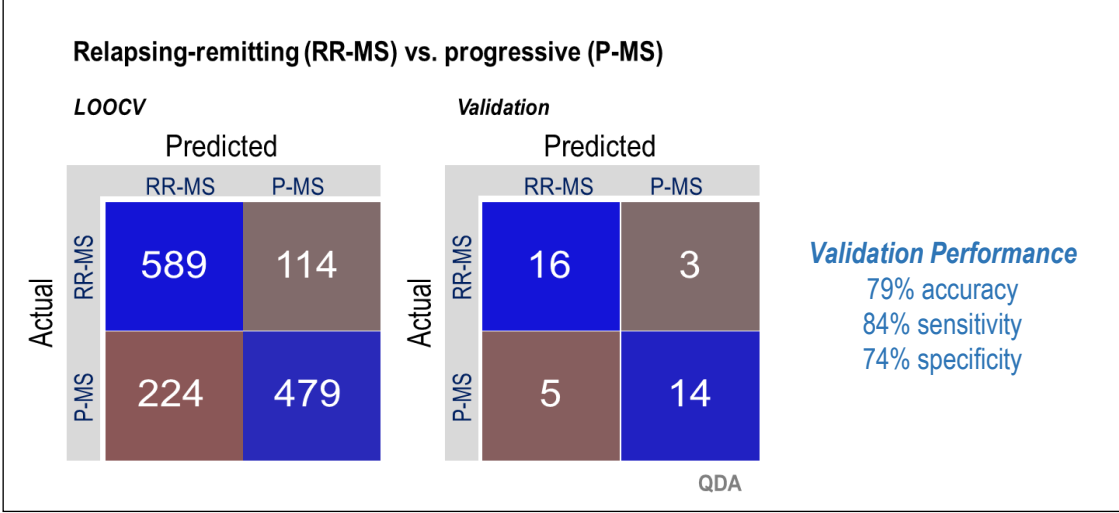
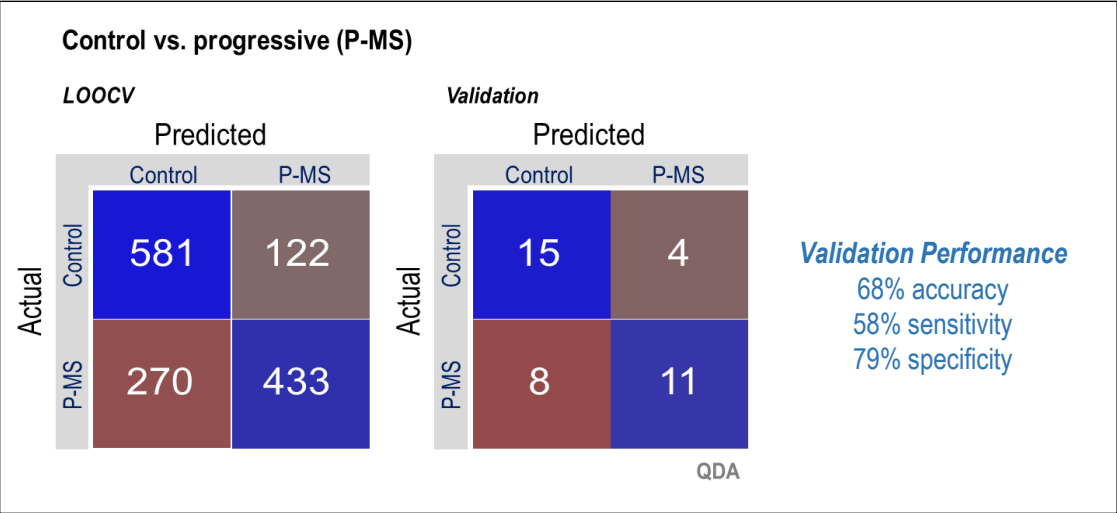
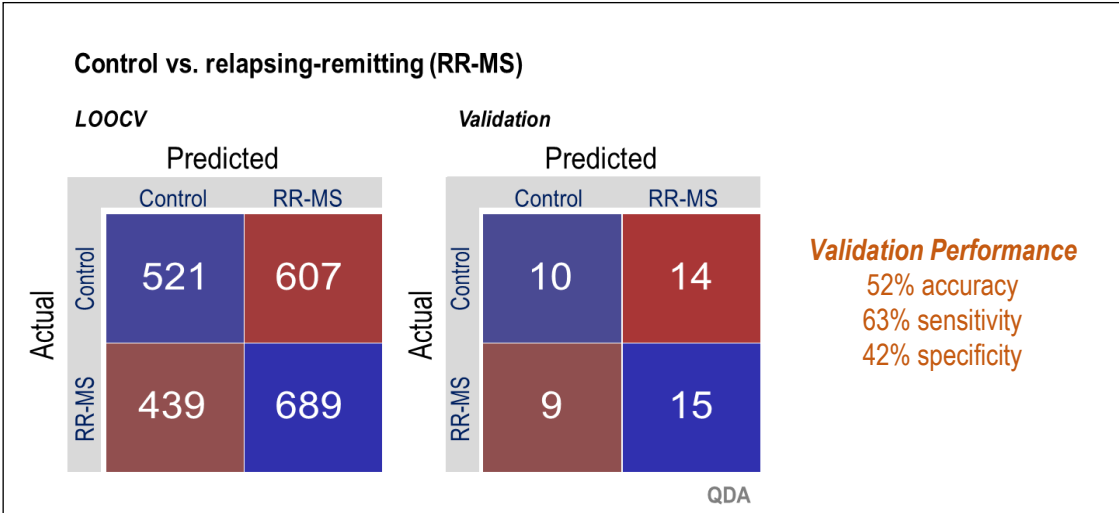
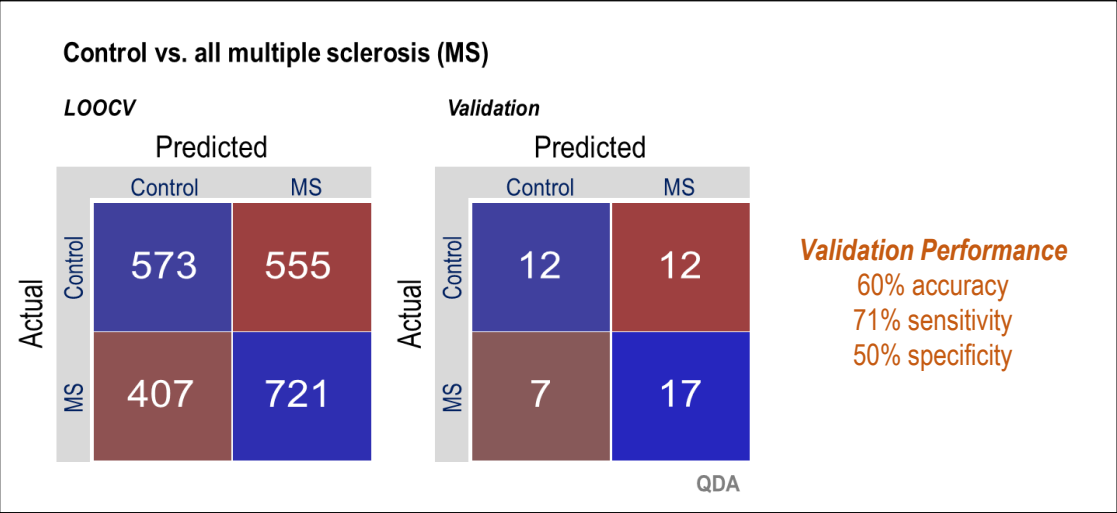
QDA

— Validation performance
— Cross-validation performance
— Baseline

Swanberg, Kurada, Prinsen, and Juchem. Manuscript in review.

Models identifying progressive MS vs. control or relapsing-remitting MS outperformed those classifying only relapsing-remitting or all MS vs. control.

CHAPTER 4: STATISTICAL ANALYSIS



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Models identifying progressive MS vs. control or relapsing-remitting MS outperformed those classifying only relapsing-remitting or all MS vs. control.

CHAPTER 4: STATISTICAL ANALYSIS

Control vs. all multiple sclerosis (MS)

LOOCV

		Predicted	
		Control	MS
Actual	Control	573	555
	MS	407	721

Validation

		Predicted	
		Control	MS
Actual	Control	12	12
	MS	7	17

QDA

Top 3 features
Myoinositol (3/3)
Glutamate (3/3)
GABA (2/3)

Control vs. relapsing-remitting (RR-MS)

LOOCV

		Predicted	
		Control	RR-MS
Actual	Control	521	607
	RR-MS	439	689

Validation

		Predicted	
		Control	RR-MS
Actual	Control	10	14
	RR-MS	9	15

QDA

Top 3 features
Myoinositol (3/3)
Glutamate (3/3)
N-acetyl aspartate (2/3)

Control vs. progressive (P-MS)

LOOCV

		Predicted	
		Control	P-MS
Actual	Control	581	122
	P-MS	270	433

Validation

		Predicted	
		Control	P-MS
Actual	Control	15	4
	P-MS	8	11

QDA

Top 3 features
Myoinositol (2/3)
Glutamate (3/3)
GABA (2/3)

Relapsing-remitting (RR-MS) vs. progressive (P-MS)

LOOCV

		Predicted	
		RR-MS	P-MS
Actual	RR-MS	589	114
	P-MS	224	479

Validation

		Predicted	
		RR-MS	P-MS
Actual	RR-MS	16	3
	P-MS	5	14

QDA

Top 3 features
Total choline (3/3)
Glutamine (2/3)
Glutathione (2/3)

Swanberg, Kurada, Prinsen, and Juchem. Manuscript in review.

Myoinositol, glutamate, and GABA were consistently important for identifying MS, while total choline, glutamine, and glutathione were consistently informative for differentiating MS phenotypes.

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

CHAPTER I

Spectral Quantification:

Data quality (FWHM and SNR) interacts with spectral baselines to affect metabolite fit accuracy.

Fit residual can be misleading when deciding whether a spectral baseline model supports accurate metabolite estimates.

Incorporating baseline terms to the Fisher information matrix improves utility of CRLB as a proxy for metabolite fit precision.

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Metabolite concentrations derived from ^1H MRS were a viable means of characterizing progressive multiple sclerosis disease status relative to either relapsing-remitting or control.

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Can a quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations be generalized to identification of PTSD and MDD?

CHAPTER V

Back to the Big Picture:

General conclusions and outlook

CHAPTER VI

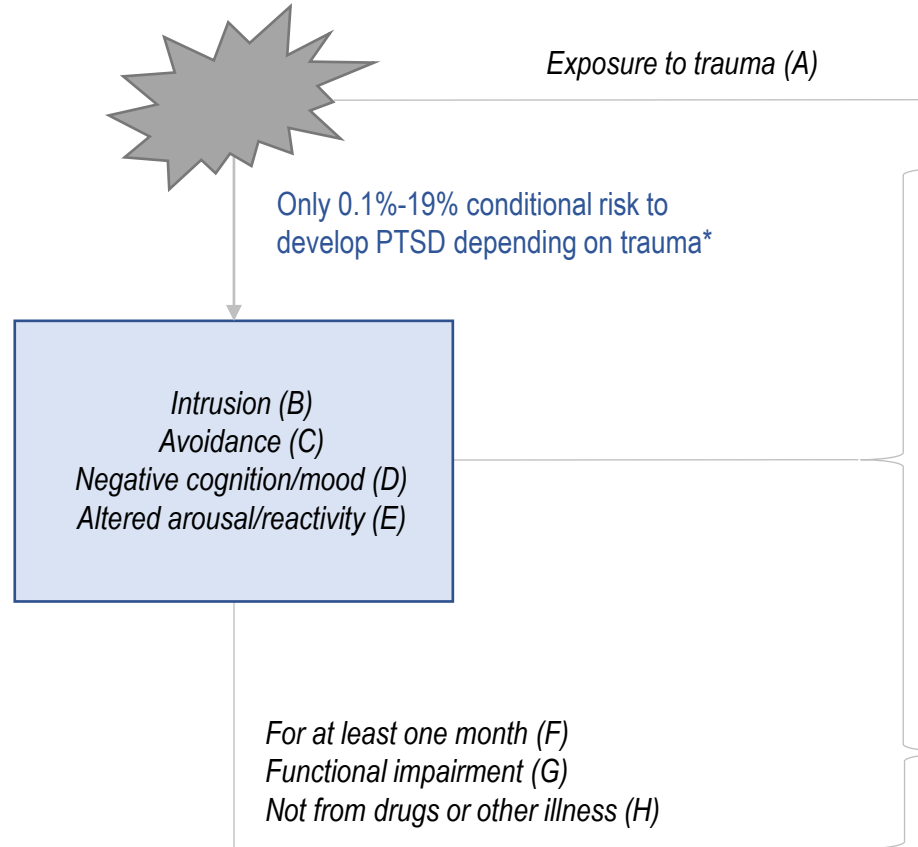


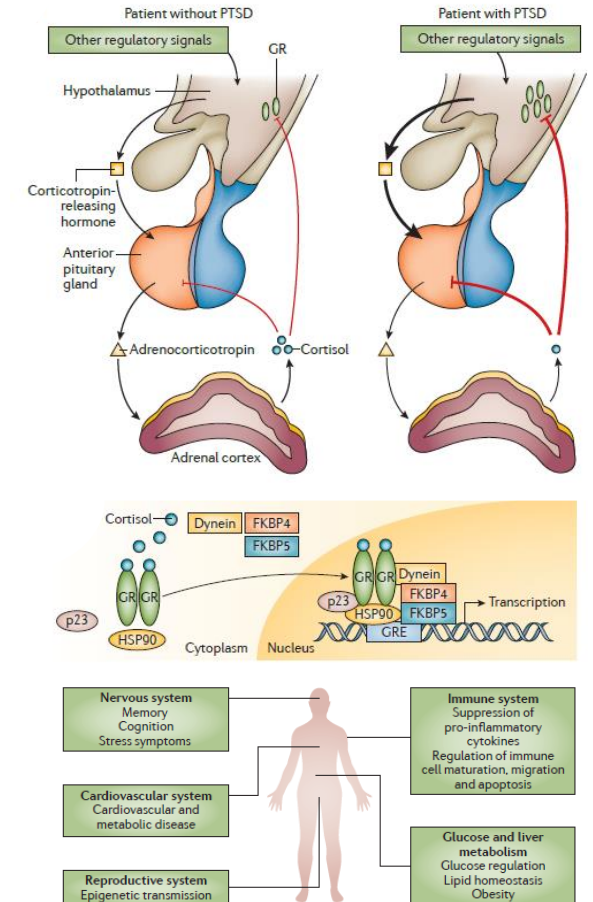
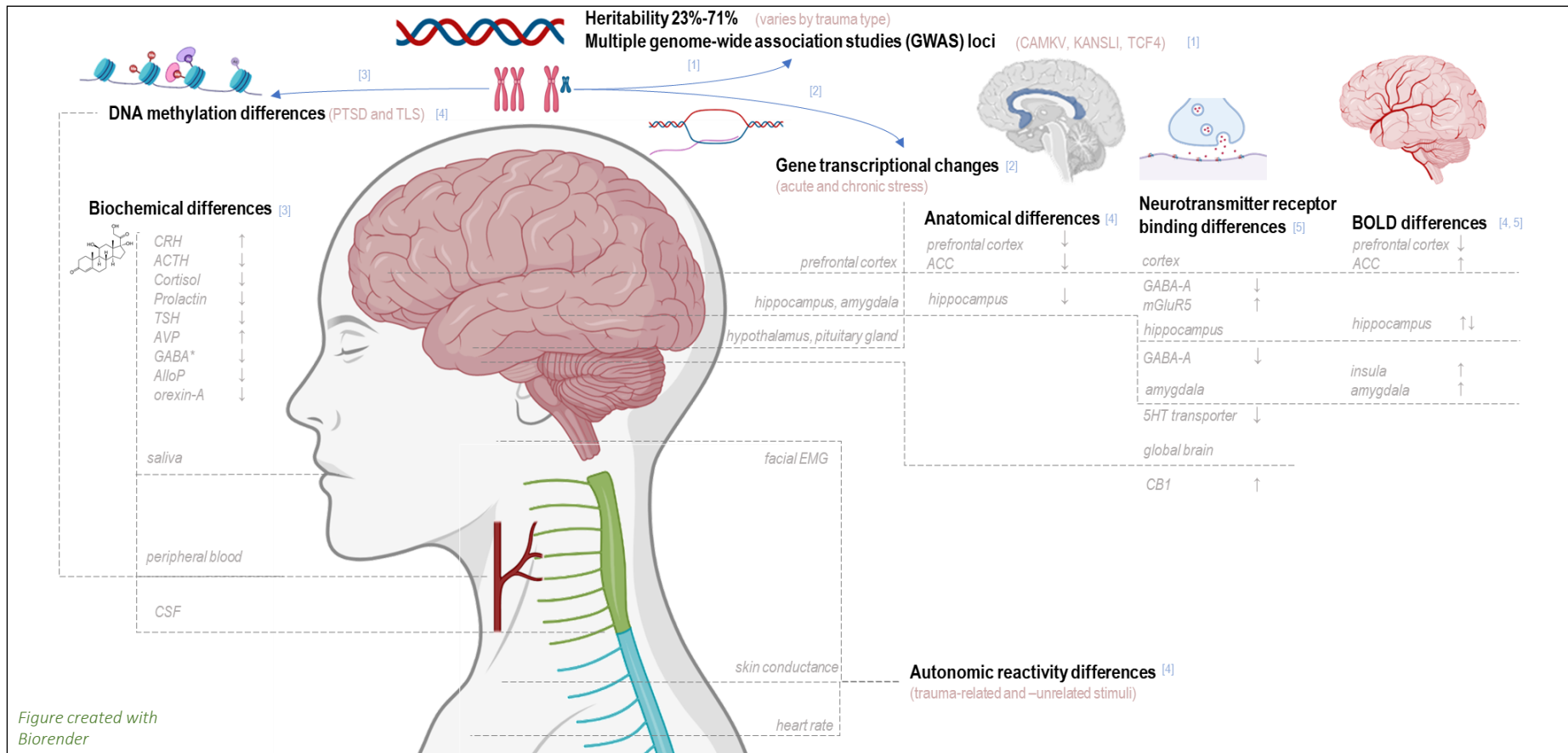
Table 1 | DSM-5 criteria for PTSD

Criterion*	Description	Specific examples	Requirements	Compared with DSM-IV
Criterion A	Exposure to stressor	<ul style="list-style-type: none"> • Direct exposure • Witnessing trauma • Learning of a trauma • Repeat or extreme indirect exposure to aversive details 	DSM-5 recognizes that exposure to trauma can occur either by direct or indirect confrontation with extreme trauma	Specific definition of details of the stressor needed, including repeated experience or extreme exposure to details of events
Criterion B	Intrusion symptoms	<ul style="list-style-type: none"> • Recurrent memories • Traumatic nightmares • Dissociative reactions (flashbacks) • Psychological distress at traumatic reminders • Marked physiological reactivity to reminders 	At least one of these five examples is required	No change, but further clarification of the dissociative quality of flashbacks needed
Criterion C	Persistent avoidance	<ul style="list-style-type: none"> • Trauma-related thoughts or feelings • Trauma-related external reminders such as people, places or activities 	At least one of these two examples is required	DSM-IV did not separate the avoidance criterion
Criterion D	Negative alterations in cognitions and mood	<ul style="list-style-type: none"> • Dissociative amnesia • Persistent negative beliefs and expectations • Persistent distorted blame of self or others for causing trauma • Negative trauma-related emotions: fear, horror, guilt, shame and anger • Diminished interest in activities • Detachment or estrangement from others • Inability to experience positive emotions 	At least two of these seven examples are required	DSM-IV noted social estrangement and restricted the range of affect; numbing redefined to positive rather than all affects
Criterion E	Alterations in arousal and reactivity	<ul style="list-style-type: none"> • Irritable and aggressive behaviour • Self-destructive and reckless behaviour • Hypervigilance • Exaggerated startle • Problems concentrating • Sleep disturbance 	At least two of these six examples are required	Self-destructive and risk-taking behaviours were not defined in DSM-IV
Criterion F	Duration	Must experience criteria B, C, D and E for >1 month	Acute stress disorder is diagnosed for symptoms occurring for <1 month post trauma	No change
Criterion G	Functional significance	Impairment in social, occupational or other domains	Disability in at least one of these domains is required	No change
Criterion H	Exclusion	Not attributable to medication, substance use or other illness	Symptoms must not be secondary to other causes	Not stated in DSM-IV
Subtypes	<ul style="list-style-type: none"> • Dissociative subtype: used when depersonalization and derealization occur in tandem with other symptoms described above. • Delayed subtype: used to describe the emergence of symptoms following a period post trauma in which symptoms were not present or were present at a subthreshold level. 			

DSM, Diagnostic and Statistical Manual of Mental Disorders; PTSD, post-traumatic stress disorder. *Criteria according to DSM-5 (REF. 1).

* Kessler et al. *Eur J Psychotraumatol* 8(S5): 1353383. (2017)

Yehuda et al. *Nat Rev*: 1. (2015).

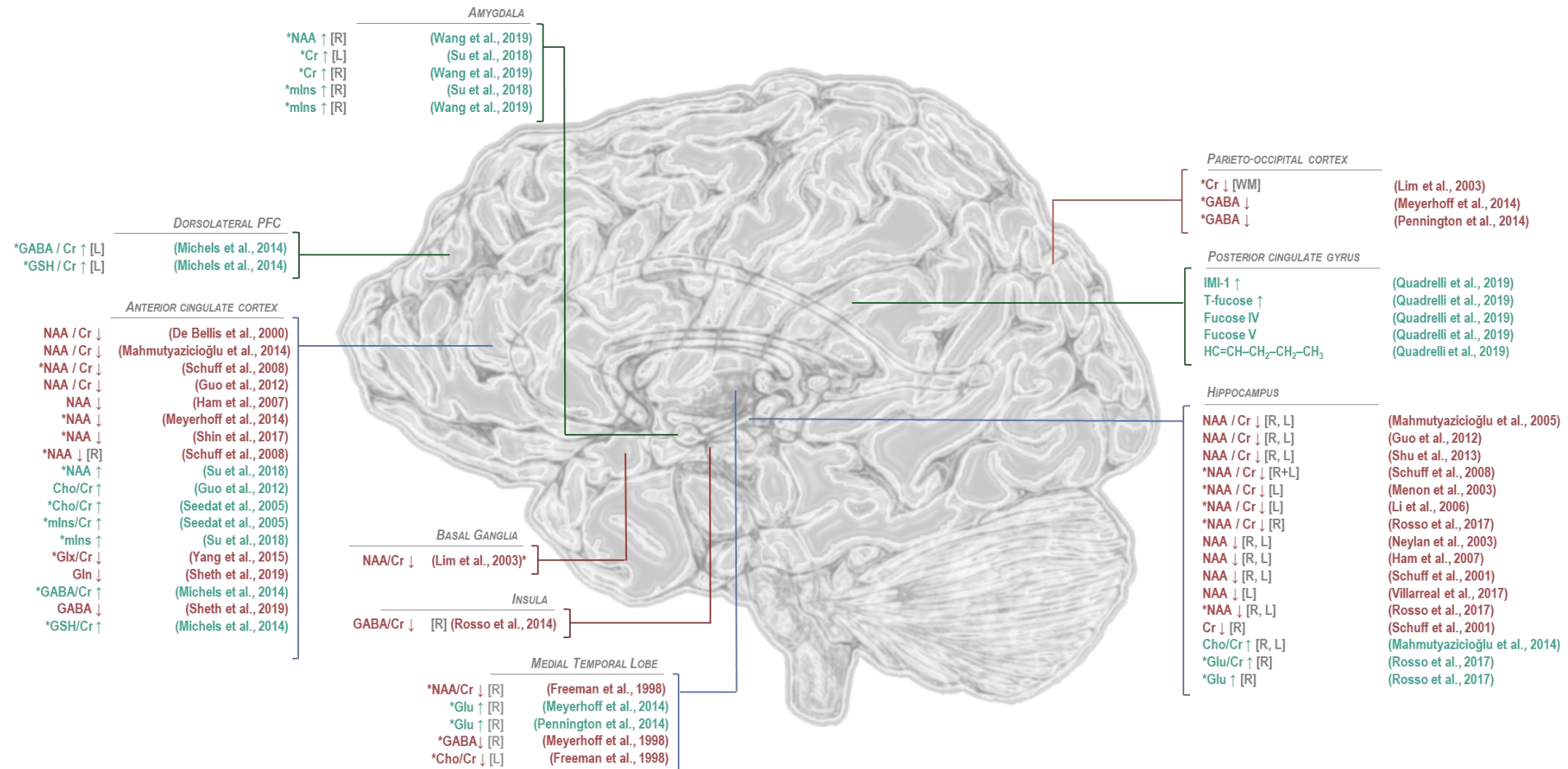


[1] Duncan et al. *Curr Psychiatry Rep* 20:115 (2018). [2] Brivio et al. *Genes Brain Behav* 19: e12643. (2020). [3] Malikowska-Racia et al. *Pharmacol Res* 142: 30-49. (2019). [4] Pitman et al. *Nat Rev* 13: 769. (2012). [5] Yehuda et al. *Nat Rev* 1: 1. (2015).

Swanberg, Campos, Abdallah, and Juchem. Manuscript in preparation.

Yehuda et al. *Nat Rev* 1: 1. (2015).

PTSD has been associated with a broad range of measurable signatures across the body.



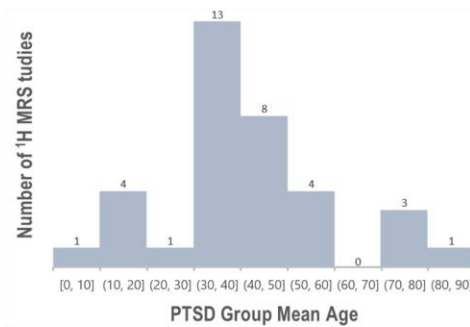
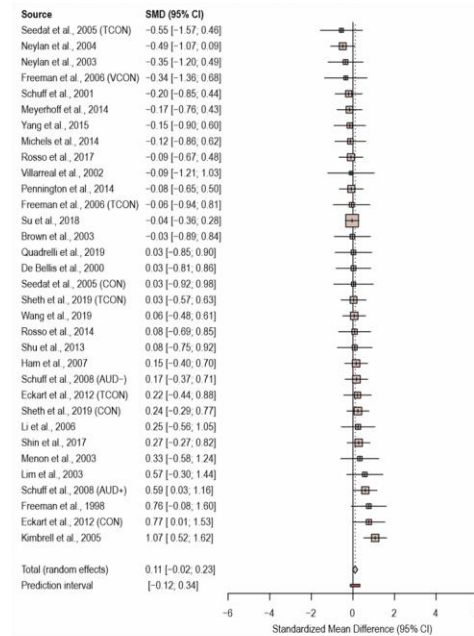
*PTSD vs. control groups that included trauma-exposed and/or military veteran individuals

PTSD: Post-Traumatic Stress Disorder; NAA: N-acetyl aspartate, Cr: total creatine; mlns: myoinositol; GABA: γ-aminobutyric acid; GSH: glutathione; Cho: total choline; Glx: glutamate + glutamine; Gln: glutamine; IMI-1: Imidazole from histamine, histidine, and homocarnosine; Glu: glutamate

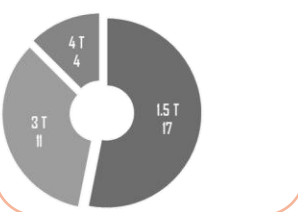
Swanberg, Campos, Abdallah, and Juchem. Manuscript in preparation.

So far the ¹H-MRS-visible manifestation of PTSD appears unremarkable at first glance.

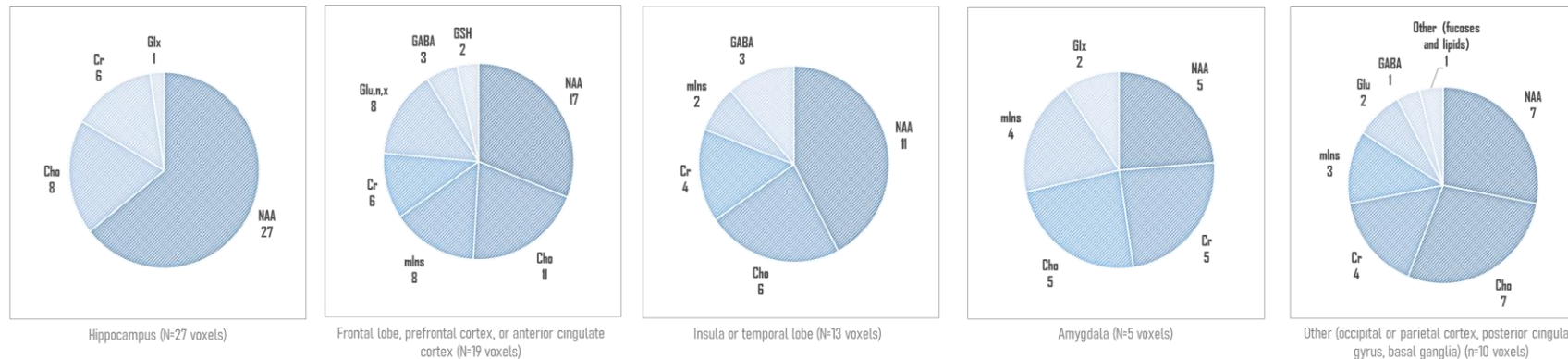
A

 ^1H MRS Studies of PTSD by Patient Group Mean AgeBetween-Group Age Differences in ^1H MRS Studies of PTSD

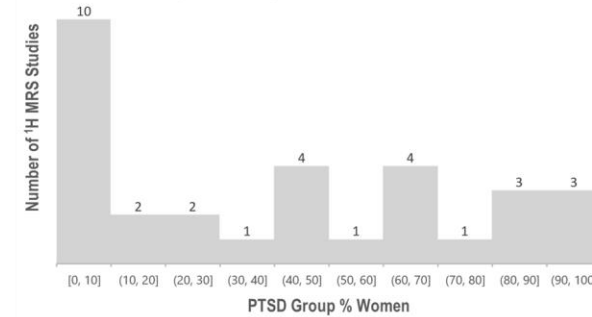
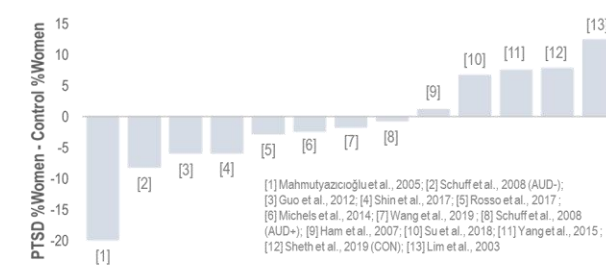
C

 ^1H MRS Studies of PTSD by Field Strength

D

Metabolite Concentrations Reported by Unique ^1H MRS Study Voxel

B

 ^1H MRS Studies of PTSD by Patient Group % WomenBetween-Group Sex-Matching in Sex-Unmatched ^1H MRS Studies of PTSD

Swanberg, Campos, Abdallah and Juchem. Manuscript in preparation.

PTSD- MDD- 5 F, 13 M; 34 ± 8 y.o.
 PTSD- MDD+ 2 F, 7 M; 35 ± 15 y.o.
 PTSD+ MDD- 2 F, 3 M; 37 ± 16 y.o.
 PTSD+ MDD+ 1 F, 5 M; 39 ± 8 y.o.

Scan Participants

FOV x20 y22 z7.8 cm **T_R** 3s
Matrix x256 y256 z39 **T_E** 6 ms
Resolution x0.78 y0.86 z2 mm **T_{ACQ}** 5 min
 T_{INV} 1 s

Voxel Placement: IR-prepared T_1 w MRI

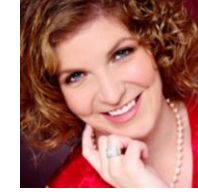
In collaboration with:



Hetty Prinsen,
Ph.D.



Chadi Abdallah,
M.D.

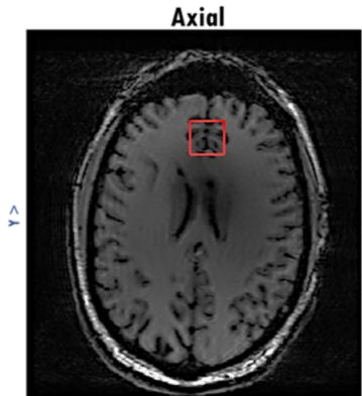


Lynette Averill,
Ph.D.

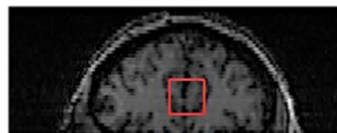


Christopher Averill,
B.Sc.

STEAM (8 cm³)



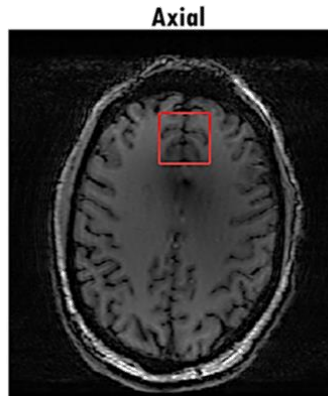
Coronal



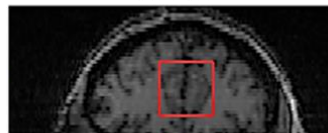
Sagittal



JDE-GABA; JDE-GSH (27 cm³)



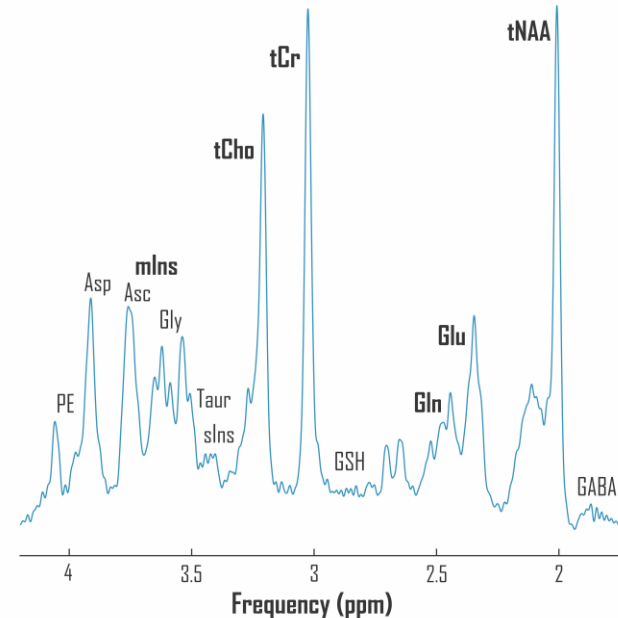
Coronal



Sagittal

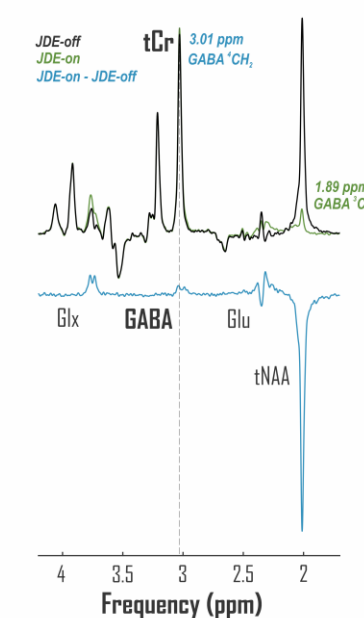


STEAM

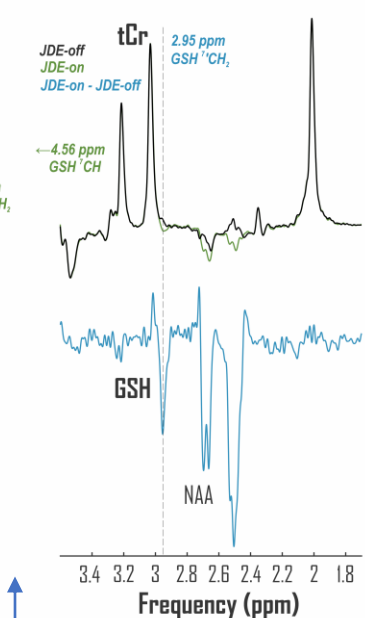


Asc: ascorbate, Asp: aspartate, GABA: γ amino-butyric acid, Gly: glycine, GSH: glutathione, PE: phosphorylethanolamine, sIns: scylloinositol, Taur: taurine, tCho: choline + phosphocholine + glycerophosphocholine, tCr: creatine + phosphocreatine, tNAA: N-acetyl aspartate + N-acetyl aspartylglutamate

MEGA-sLASER GABA



MEGA-sLASER GSH



^1H MRS Acquisitions

Swanberg, Prinsen, Averill C, Campos, Kurada, Krystal, Petrakis, Averill LA, Abdallah, and Juchem. Submitted to *Proc Intl Soc Mag Reson Med.* (2022).

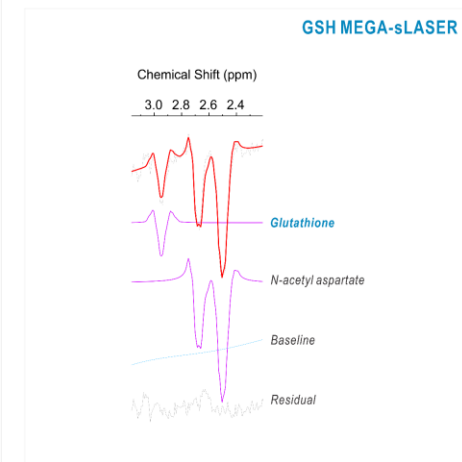
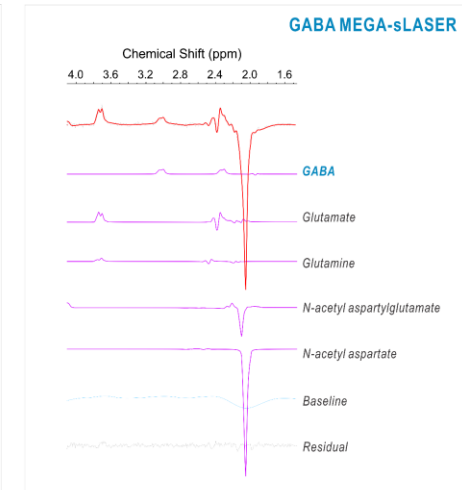
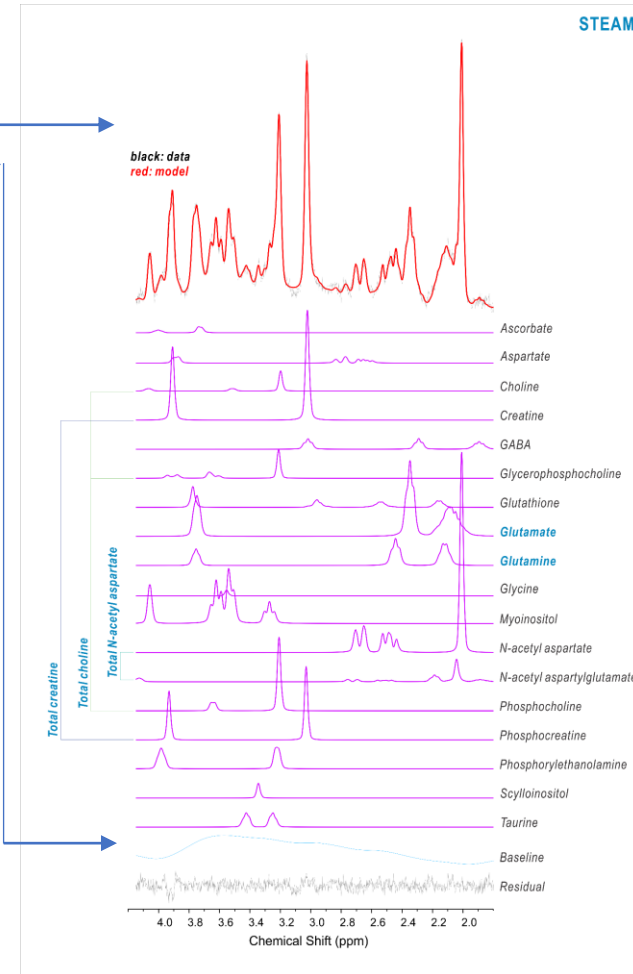
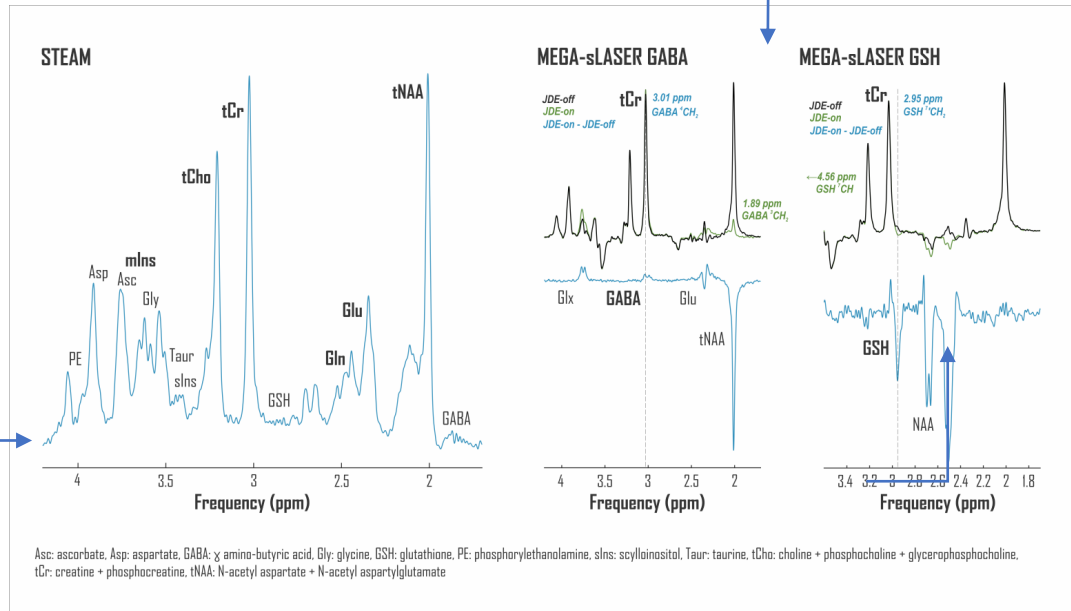
Manually zero-order phase-corrected and frequency shift-calibrated

JDE edit-off and -on aligned with cut, ZF, zero-order phase, frequency shift (x), offset (y)

No ZF; 4096-pt spectra cut to 1024, 2048, or 4096 pts

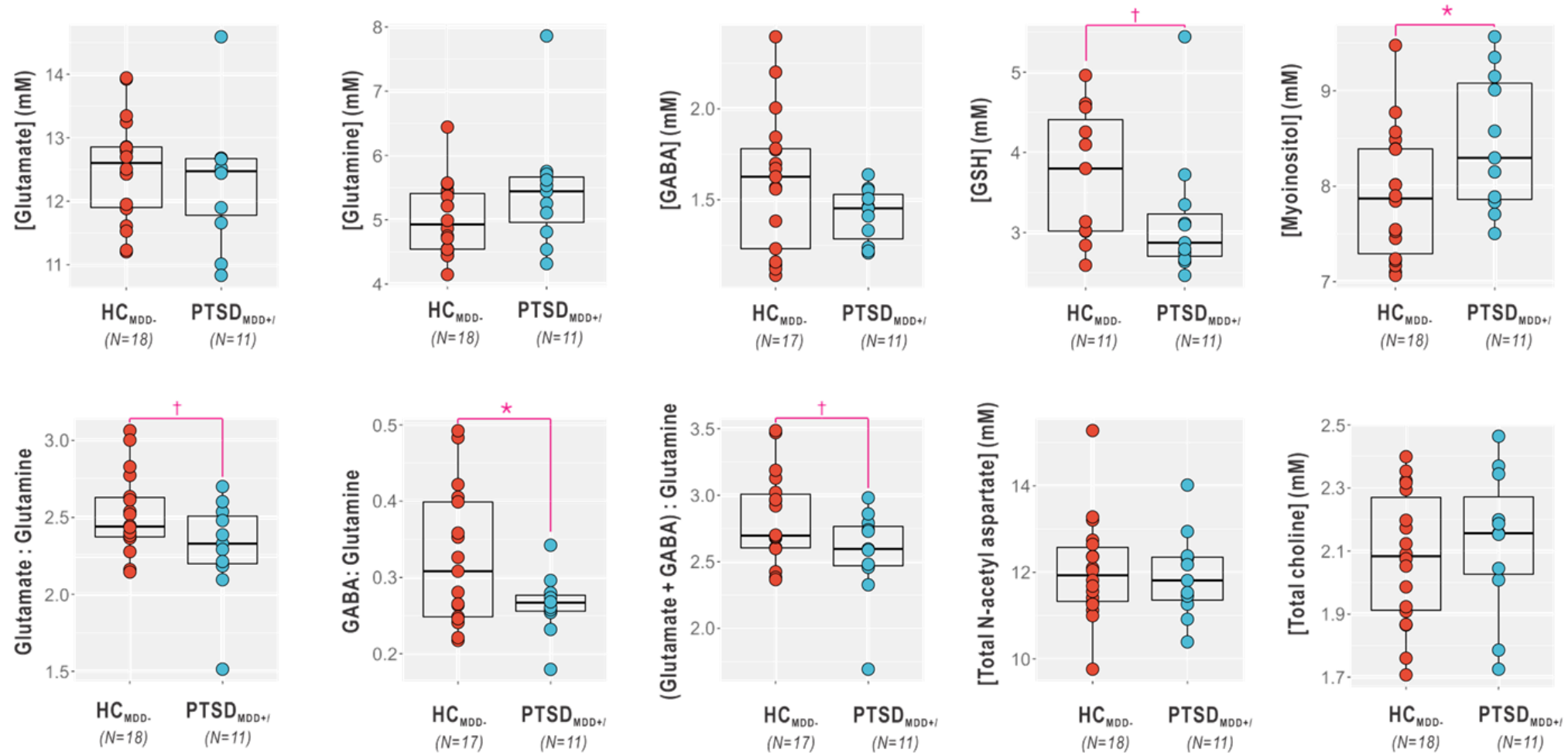
Cubic spline fit baseline

Referenced to total creatine in T_1 , T_2 -uncorrected fashion



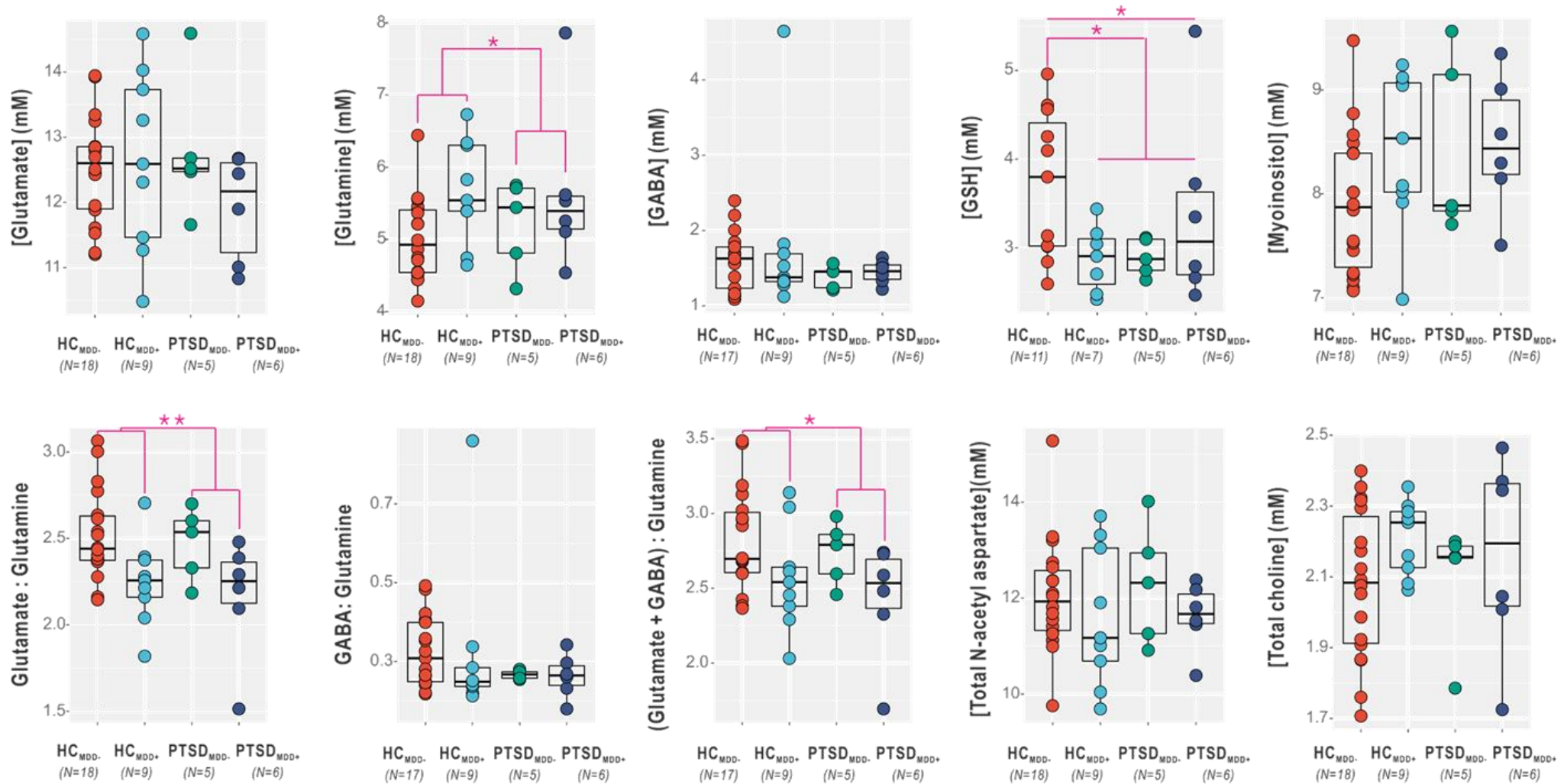
In collaboration with
Leonardo Campos
(B.Sc. '23)

Swanberg, Prinsen, Averill C, Campos, Kurada, Krystal, Petrakis, Averill LA, Abdallah, and Juchem. Submitted to *Proc Intl Soc Mag Reson Med.* (2022).



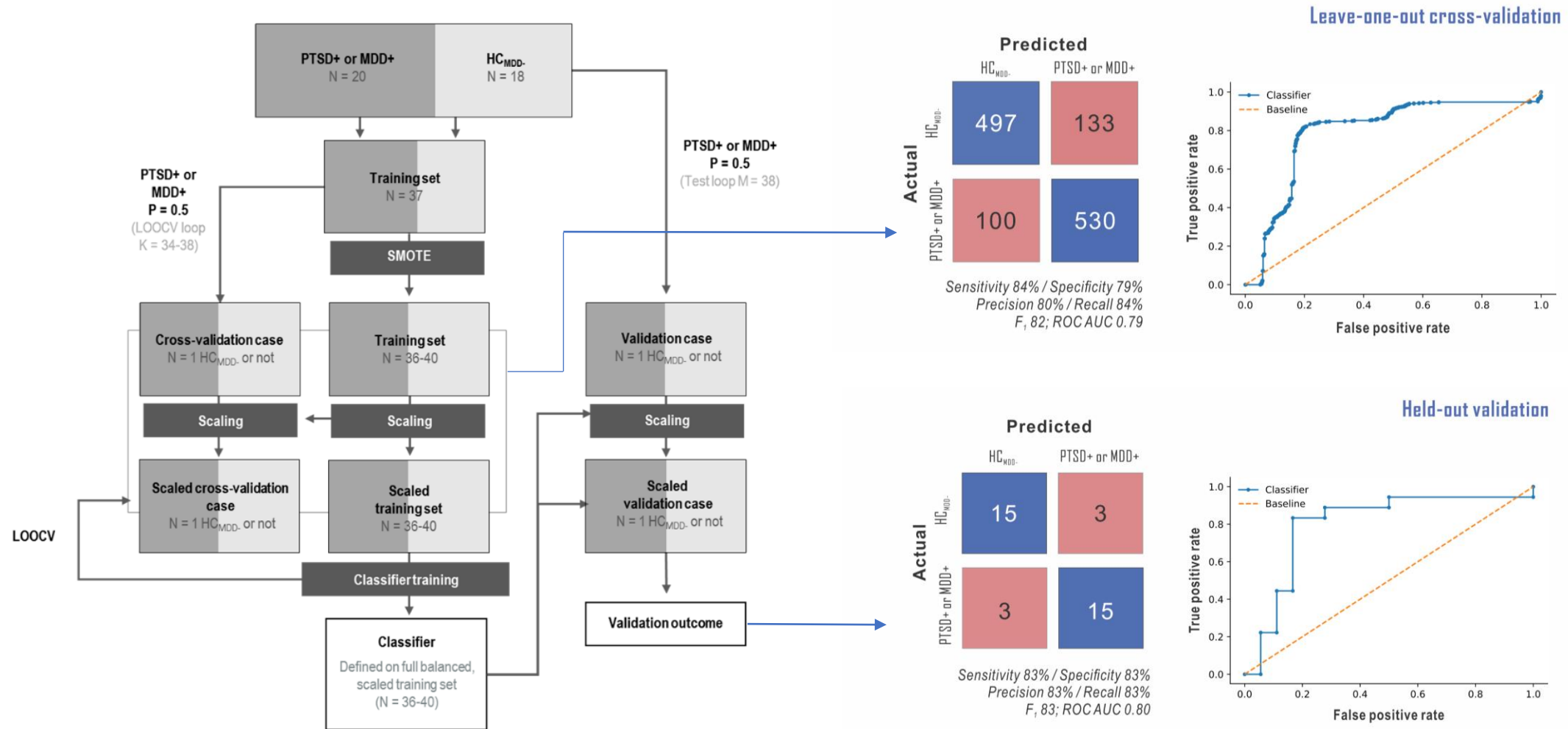
One-way ANOVA effect of fixed factor PTSD * $p < 0.05$ † $p < 0.1$

Swanberg, Prinsen, Averill C, Campos, Kurada, Krystal, Petrakis, Averill LA, Abdallah, and Juchem. Submitted to *Proc Intl Soc Mag Reson Med*. (2022).



Two-way ANOVA effect of fixed factor MDD * $p < 0.05$ ** $p < 0.01$, except GSH PTSD x MDD or W * $p < 0.05$

Swanberg, Prinsen, Averill C, Campos, Kurada, Krystal, Petrakis, Averill LA, Abdallah, and Juchem. Submitted to *Proc Intl Soc Mag Reson Med*. (2022).



Swanberg, Prinsen, Averill C, Campos, Kurada, Krystal, Petrakis, Averill LA, Abdallah, and Juchem. Submitted to *Proc Intl Soc Mag Reson Med*. (2022).

The Big Picture:

^1H MRS is a potential but currently untapped source of clinical diagnostic biomarkers.

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Data quality (FWHM and SNR) interacts with spectral baselines to affect metabolite fit accuracy.

Fit residual can be misleading when deciding whether a spectral baseline model supports accurate metabolite estimates.

Incorporating baseline terms to the Fisher information matrix improves utility of CRLB as a proxy for metabolite fit precision.

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Water T_2 was shown to differ between individuals with and without progressive multiple sclerosis, emphasizing the utility of group-specific corrections for this variable when employed in cross-sectional ^1H MRS studies of disease.

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Metabolite concentrations derived from ^1H MRS were a viable means of characterizing progressive multiple sclerosis disease status relative to either relapsing-remitting or control.

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A quantification and statistics pipeline optimized for classification of multiple sclerosis via ^1H MRS-derived metabolite concentrations can be generalized to comparably accurate identification of PTSD and MDD.

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General conclusions and outlook

CHAPTER VI

¹H MRS processing pipelines involve many opportunities for confound by **poorly defined or incorrect assumptions**.

The relative effects of confounds like **spectral quality** and **spectral baseline model** on **metabolite concentration estimates** can be explicitly quantified using **simulated ground truth standards**. The **variance** of these effects can be indirectly estimated using **Cramer-Rao Lower Bound calculation considering baseline shapes**. These results can be used to inform decision-making about **how to process ¹H MRS data** lacking a known ground truth.

Conditions like **age** or **progressive multiple sclerosis** may influence water-referenced absolute metabolite estimates by **affecting signal relaxation via processes like T_2 decay**. These effects can be counteracted by **measured T_2** or **voxel composition** or **using another concentration reference**.

Current understanding of both **MS** and **PTSD** implicates **multiple ¹H-MR-visible metabolites**, but **no single metabolite finding in the brain** currently supports **sensitive** or **specific** identification of either condition.

When processed and quantified according to **evidence from simulated validation of spectral quantification method** and **explicit measurement of reference T_2 behavior**, as well as **considered together by multivariate supervised classification model-building**, **¹H-MRS metabolites** measured in prefrontal cortex support **independent classification** of multiple **brain disorders** at **sensitivity and specificity near 80%**.

Despite its limitations, **¹H MRS data** can still support identification of **clinically relevant biological phenotypes** and therefore potential utility as an auxiliary or mainstay of **clinical diagnostics** for **neurological** or **psychiatric disease**.



Christoph Juchem, Ph.D.
Principal investigator



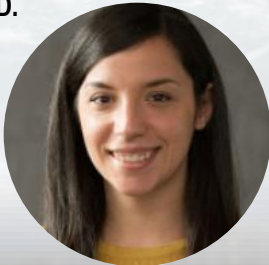
Sebastian Theilenberg, Ph.D.
Associate research scientist



Karl Landheer, Ph.D.
Postdoctoral alumnus



Martin Gajdošik, Ph.D.
Postdoctoral alumnus



Carlotta Ianniello, Ph.D.
Postdoctoral research scientist



Yun Shang, M.Sc.
Ph.D. student, BME



Ronald Instrella, M.Sc.
Ph.D. student, BME



Kay Igwe, M.Sc.
Ph.D. student, BME



Abhinav Kurada, B.Sc.
Undergraduate alumnus, BME



Michael Treacy, B.A.
Undergraduate alumnus, physics



Leonardo Campos
Undergraduate, BME



Ian Dorian Macleod
Undergraduate, computer science



Catherine Medeiros
Undergraduate, BME

In collaboration with:



Hetty Prinsen, Ph.D.
Yale School of Medicine



Lynette A. Averill, Ph.D.
Yale School of Medicine



Chris Averill, B.Sc.
Yale School of Medicine



Chadi Abdallah, M.D.
Yale School of Medicine

A very special thank you to the 120+ human volunteers who dedicated their sometimes quite limited time and energy to participating in many of the studies presented today.

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