**Poors: Low-field MRI systems are generally less expensive, and in some settings can provide equivalent diagnostic performance [1]. Our goal is to provide a simulation tool for determining the minimum field strength requirements for MRI methods, including novel data sampling and reconstruction techniques. Developers can test the potential applicability of their techniques at lower B₀ field strengths when higher-field experiments have been performed.**

**SOFTWARE DESCRIPTION:** To simulate low-field raw data from data acquired at higher field, we make five modeling assumptions: (1) **Body noise dominance.** This can be achieved at 4 MHz or above in system sizes compatible with human extremities [2,3], suggesting the feasibility of most human MRI scans with body noise dominance at 0.1T or above. (2) **Consistent B₀/B₂ field.** RF transmit homogeneity is expected to improve at lower field strength, therefore this represents a worst case scenario. Receiver coils are assumed to have the same geometry and relative noise covariance at different field strengths. (3) **Consistent B₀ homogeneity.** We assume the same ppm off-resonance at different field strengths. (4) **Proton density weighting or single species dominance.** We use a single global relaxation correction function to account for the signal change at different B₀. (5) **Steady state acquisition.**

The process for simulating low-field data is illustrated in **Fig. 1.** The acquired high-field k-space data is: 

\[ y_h = s_h + n_h \]

where \( s_h \) and \( n_h \) are pure signal and noise respectively. \( n_h \) is bivariate and normally distributed: 

\[ \text{Re}(n_h) \sim N(0, \Sigma), \quad \text{Im}(n_h) \sim N(0, \Sigma) \]

where \( \Sigma \) is the noise covariance matrix for a k-channel receiver coil and is measured by data acquisition with RF turned off. Thermal noise variance is proportional to \( B_0^2 \) and readout bandwidth BW. Therefore, the simulated noise \( \tilde{n}_l \) at low field is: 

\[ \text{Re}(\tilde{n}_l) \sim N(0, a^2b^2 \Sigma), \quad \text{Im}(\tilde{n}_l) \sim N(0, a^2b^2 \Sigma) \]

where \( a = B_0/B_0, \quad b = BW/BW_h \). The k-space signal at low field is modeled as: 

\[ 
\tilde{s}_l = a^2f_s h 
\]

where \( f \) represents the signal change due to different relaxation as a function of \( B_0 \). This is computed based on the pulse sequence parameters and the dominant species’ relaxation times. Given \( f \), the simulated low field k-space data is: 

\[ \tilde{y}_l = \tilde{s}_l + \tilde{n}_l = a^2f_s h + \tilde{n}_l = a^2f y_h + \tilde{n}_{add} \]

where \( \text{Re}(\tilde{n}_{add}) \) & \( \text{Im}(\tilde{n}_{add}) \sim N(0, (a^2b - a^2f)^2 \Sigma) \).

Phantom studies were performed to validate the model above by comparing SNR at 1.5T/3T between the actual measurements and predictions from a 7T acquisitions. Modeling error was less than 8%. MATLAB source code is available: http://mrel.usc.edu/share.html.

**EXAMPLE APPLICATION:** Consider liver proton density fat fraction (PDFF) measurement using IDEAL SPGR (Acquisition: B0=3T, TE 2.2/3.1/4.0ms, TR 9ms, flip angle 3°, BW 62.5KHz). \( f = \frac{[1 - e^{-(TR/T1,h)}]}{[1 - e^{-(TR/T1,h)} + e^{-(TE/T1,h)}]} \text{Re}^{-(TE/T1,h)/T2_e} - e^{-y_{PDFF}(B_0/T1-h)/T2_e} \text{Im}(y_{PDFF}(B_0/T1-h)/T2_e)} \)

where \( E_1 = \text{exp}(-TR/T1), \) \( c \) is a constant and \( \Delta B_{ppm} \) is the ppm field inhomogeneity. To achieve the same phase shift between fat and water, the product of \( B_0 \) and TE needs to remain the same. Therefore simulated TE’s were set to be \( (B_0/B_0) \) times longer when simulated at low fields. Bandwidths were also set to \( (B_0/B_0) \) times shorter, enabled by longer TE’s. Given the small flip angle, (1) is reduced to \( f \approx \text{exp}[(TE_0 - TE)/T2] \), with liver T2 being 42ms [4]. **Fig. 2** compares fat-water separated images and fat fractions for a single axial slice at different simulated field strengths. Images were reconstructed using the ISMRM fat-water toolbox [5,6]. PDFF for a manually defined region of interest (ROI) was computed from fifty independent simulations at each \( B_0 \). PDFF precision (standard deviation) is worse as \( B_0 \) goes down. PDFF accuracy (mean) deviates from truth significantly at 0.1T, a result of dominant noise biasing estimated PDFF towards 50%. Although the accuracy and precision needed for a clinical liver fat biomarker is unknown [7], once determined, this analysis would facilitate determination of the required minimum \( B_0 \). For example, if the accuracy and precision needed are both less than 2%, it suggests \( B_0 = 0.3 \) T would be sufficient.

**DISCUSSION:** Many new MR data sampling and reconstruction methods are developed and validated on state-of-the-art high-field instruments. It is informative to determine the potential to apply these techniques on more affordable low-field systems. Besides cost-efficiency, low-field MRI also has other attractive properties including reduced acoustic noise and SAR, safer for metal implants, more uniform RF transmission, and less off-resonance. With the help of advanced sampling and reconstruction techniques, many applications that were previously prohibited at low fields may become feasible now. More details can be found in [8].