Pharmacokinetic analysis of dynamic contrast-enhanced (DCE) MRI data allows estimation of quantitative imaging biomarkers such as $K_{\text{trans}}$ (rate constant for plasma/interstitium contrast reagent (CR) transfer) and $v_e$ (extravascular and extracellular volume fraction). However, the use of quantitative DCE-MRI in clinical practice is limited with uncertainty in arterial input function (AIF) determination being one of the primary reasons. In this multicenter study to assess the effects of AIF variations on pharmacokinetic parameter estimation, DCE-MRI data acquired at one center from 11 prostate cancer patients were shared among nine centers. Individual AIF from each data set was determined by each center and submitted to the managing center. These AIFs, along with a literature population averaged AIF, and their reference-tissue-adjusted variants were used by the managing center to perform pharmacokinetic data analysis using the Tofts model (TM). All other variables, including tumor region of interest (ROI) definition and pre-contrast T1, were kept constant to evaluate parameter variations caused solely by AIF discrepancies. Considerable parameter variations were observed with the within-subject coefficient of variation (wCV) of $K_{\text{trans}}$ obtained with unadjusted AIFs being as high as 0.74. AIF-caused variations were larger in $K_{\text{trans}}$ than $v_e$ and both were reduced when reference-tissue-adjusted AIFs were used. These variations were largely systematic, resulting in nearly unchanged parametric map patterns. The intravasation rate constant, $k_e$ ($= K_{\text{trans}}/v_e$), was less sensitive to AIF variation than $K_{\text{trans}}$ (wCV for unadjusted AIFs: 0.45 vs. 0.74), suggesting that it might be a more robust imaging biomarker of prostate microvasculature than $K_{\text{trans}}$. 

INTRODUCTION

Dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) is widely used in studies of cancer and other pathologies. Often included as one component of a prostate multiparametric MRI protocol (1), DCE-MRI is routinely used in clinical MRI examination of the prostate. Nevertheless, its use as a quantitative diagnostic imaging modality remains limited. In clinical practice, only qualitative estimations of contrast reagent (CR) wash-in and wash-out are generally used in interpreting prostate DCE-MRI data. Although pharmacokinetic modeling ap-
proaches have been under extensive investigation for more than a decade (2-10), pharmacokinetic analysis of prostate DCE time-course data is not currently recommended for routine use under the Prostate Imaging-Reporting and Data System (PI-RADS) version 2 guidelines (11, 12). Improved reproducibility and standardization in pharmacokinetic analysis of prostate DCE-MRI data is needed for the translation of this quantitative data analysis method into clinical settings.

Quantitative DCE-MRI data analysis using pharmacokinetic models allows extraction and mapping of quantitative parameters of tissue biology in vivo. The most commonly estimated parameters are usually variants of $K^{\text{trans}}$, a rate constant for passive CR molecule plasma/interstitium transfer, and $v_e$, the volume fraction of interstitial space (extravascular extracellular space, i.e., the putative CR distribution volume). The CR extravasation rate constant, $k_{\text{ep}}$, can be calculated as $K^{\text{trans}}/v_e$. Unlike qualitative or semiquantitative analysis, the parameters derived from pharmacokinetic modeling of DCE-MRI time-course data are, in principle, independent of the MRI scanner platform (vendor and field strength), data acquisition details (pulse sequence and parameters), CR dose and/or injection protocol, personnel skills, etc. This makes them promising imaging biomarkers in multicenter clinical trials as imaging endpoints for standardization and comparison of results. However, the accuracy and precision of these parameters can be affected by a plethora of factors contributing to the process of pharmacokinetic modeling, including errors in quantification of precontrast $T_1$ (13) and determination of arterial input function (AIF) (14-20), inadequate temporal resolution (21), selection of pharmacokinetic models to fit the data (22, 23), and differences in DCE-MRI acquisition time duration (24, 25).

As a requirement in quantitative estimation of DCE-MRI pharmacokinetic parameters, the time dependence of the plasma and tissue CR concentrations, $C_p(t)$ and $C_t(t)$, respectively, needs to be determined from the DCE-MRI images. The former is the AIF, and its direct quantification from an imaged blood vessel is not straightforward because of, for example, the partial volume effect (signal from a selected image voxel, ideally from 100% blood, is contaminated with signal from nonblood tissues) and in-flow effect (the measured blood signal is affected by signal from the “fresh” blood outside the imaging volume that flows into the imaging volume during data acquisition). Nonetheless, as the driving force that causes in vivo DCE-MRI signal changes in the tissue, accurate AIF determination is fundamental for accurate estimation of pharmacokinetic parameters, particularly for in vivo systems like the prostate where CR extravasation is substantial (9). Significant research effort has been devoted to the development of AIF quantification methods. The most commonly used method is to measure AIF directly from a feeding artery if it is clearly detected within the image field of view (FOV). Other methods include blinded AIF estimation (14, 15), reference tissue and double reference tissue approaches (16, 26), direct blood sampling, empirically derived population-averaged AIF (28), and automated vessel region identification (27). However, given these various methods for AIF quantification, there is a lack of studies investigating the impact of variations in AIF determination on pharmacokinetic analysis of DCE-MRI data, which may potentially lead to best-practice guidelines for analysis of DCE-MRI data acquired from different organs.

The National Cancer Institute has recently founded the Quantitative Imaging Network (QIN) for the development and validation of quantitative imaging methods for evaluation of cancer therapy response. The main mission of the QIN Image Analysis and Performance Metrics Working Group is to provide guidance and reach consensus on quantitative image analysis methods through comparison and validation of analysis algorithms. For quantitative DCE-MRI data analysis, it is important to understand the variations of DCE-MRI pharmacokinetic parameters caused by specific error-prone steps encountered during data analysis. A recent QIN multicenter study showed the effects of variations in pharmacokinetic models and software tools on assessment of breast cancer response to neoadjuvant chemotherapy (23). Here, we report the results and experience from a DCE-MRI AIF challenge project, in which 9 QIN centers independently performed AIF quantifications from the same prostate DCE-MRI data sets and submitted the AIFs to one managing center for central pharmacokinetic analysis of the shared data. The goal of this study is to assess variations in estimated prostate $K^{\text{trans}}$, $v_e$, and $k_{\text{ep}}$ parameters that are resulted from various AIF extraction approaches.

**MATERIALS AND METHODS**

**AIF Challenge Participating QIN Centers**

The QIN centers that participated in this DCE-MRI AIF challenge project were Oregon Health and Science University (OHSU) - managing center, Brigham and Women’s Hospital (BWH) in collaboration with General Electric Research and Development, Medical College of Wisconsin (MCW), Icahn School of Medicine at Mount Sinai (MS), University of Michigan center #1 (UM1), University of Michigan center #3 (UM3), University of Pittsburgh (UPitt), Vanderbilt University (VU), and University of Washington (UW). Hereafter, except for where it is explicitly indicated, these 9 institutions are denoted as, not necessarily in the order listed above, QIN1 to QIN9.

Although some centers may have used more than one method for AIF determination from the shared data, only one AIF method from each participating center was included in this study. In addition, we also included a population-averaged AIF published by Geoff Parker (GP) et al (28) for comparison. This AIF was selected because it is extensively cited. The analytical expression of the GP AIF was implemented at the managing center and temporally resampled to match the temporal features of the shared prostate DCE-MRI data.

**Human Prostate DCE-MRI Data Acquisition and Sharing**

As part of the institutional review board-approved BWH quantitative imaging studies, multiparametric magnetic resonance images were collected for the purposes of detection and/or staging of prostate cancer. The images were obtained with a GE Signa HDx 3.0 T system (GE Healthcare, Waukesha, Wisconsin) using a combination of 8-channel abdominal array and endorectal coil (Medrad, Pittsburgh, Pennsylvania). The MRI sequences included $T_1$- and $T_2$-weighted imaging, diffusion-weighted imaging, and DCE-MRI as described by Hegde JV et al (29). The axial DCE-MRI acquisition with full prostate gland...
coverage used a 3-dimensional SPoiled Gradient Recalled (SPGR) sequence with repetition time (TR)/echo time (TE)/Flip Angle (α) = 3.6 ms/1.3 ms/15°, FOV = (26 cm)², slice thickness = 6 mm, and reconstructed image voxel size = 1 × 1 × 6 mm. DCE-MRI frames were acquired at approximately 5-second intervals (the number of slices per frame varied between 12 and 16, resulting in time resolution between 4.4 and 5.3 seconds) to achieve a clinically appropriate compromise between spatial and temporal resolutions. Gadopentetate dimeglumine (Magnevist; Berlex Laboratories, Wayne, New Jersey) was injected intravenously (0.15 mmol/kg) using a syringe pump at a rate of 3 mL/s followed by 20 mL of saline flush at the same rate. The DCE protocol included approximately 5 baseline frames before contrast injection.

A subset of the imaging data from the BWH prostate DCE-MRI database was uploaded to The Cancer Imaging Archive (TCIA) server for data sharing (10). From these, 11 data sets from 11 patients with known prostate cancer diagnosis, tumor region of interest (ROI) and relatively consistent acquisition time length (4.5–6 minutes) were downloaded by participating QIN centers of interest (ROI) and relatively consistent acquisition time length (4.5–6 minutes) were downloaded by participating QIN centers for further analysis. The QIN centers were required to extract an AIF for each DCE data set. For example, when measuring AIF directly from a femoral artery within the image FOV, the actual number of voxels used to derive the final AIF time course varied substantially among all centers. In general, the following results were saved and submitted to the managing center: (1) extracted AIF signal intensity-time course saved as a single column text (".txt" file); (2) converted blood plasma CR concentration time-course (see Equation 1); and (3) screen-captured images showing the ROI/voxel locations for AIF measurement.

### AIF Determination by QIN Centers

Although the AIF challenge participants were informed of the single-image slice in each data set where the tumor ROI was drawn and for which the ROI time-course data will be subjected to pharmacokinetic analysis by the managing center, there was no restriction on which image slice(s) to be used for the AIF quantification. Participating centers were required to extract an AIF time course using their own methodology for each DCE data set. For example, when measuring AIF directly from a femoral artery within the image FOV, the actual number of voxels used to derive the final AIF time course varied substantially among all centers. In general, the following results were saved and submitted to the managing center: (1) extracted AIF signal intensity-time-courc saved as a single column text (".txt" file); (2) converted blood plasma CR concentration time-course (see Equation 1); and (3) screen-captured images showing the ROI/voxel locations for AIF measurement.

| Center  | Method                                                                 |
|---------|------------------------------------------------------------------------|
| OHSU    | A single, fixed-size region of interest (ROI) was manually placed inside the femoral artery within the field of view (FOV). Averaged blood intensity time-course was extracted from the ROI, which is further converted to C_p(t) using the parameter values provided in the Materials and Methods section. |
| BWH     | GE’s OncoQuant prototype tool was used, which includes the following: (1) AIF Search Region Slice Localization; (2) AIF Search Mask Localization; (3) AIF Detection Using Shape-Based Statistics; and (4) AIF Signal-to-Concentration Conversion. See (27) for more details. |
| MCW     | Motion-corrected dynamic contrast-enhanced (DCE) series were processed using probabilistic-independent component analysis implemented in the FSL (FMRIB’s Software Library, www.fmrib.ox.ac.uk/fsl). These were further whitened and projected into a 20-dimensional subspace using principal component analysis. The AIFs were manually chosen from the results (4, 36-38). |
| MS      | ROIs were manually placed inside the iliac arteries within the field of view (FOV) using Osirix (v5.8; Pixmeo, Switzerland). For each AIF determination, 1 ROI was drawn on 1 DCE frame, and its position was adjusted when necessary to account for interframe subject motion. Blood intensity time-courses were extracted from the ROIs. |
| UM1     | ROIs of 5 × 5 voxels were manually placed in 2 to 4 slices showing the highest artery conspicuity on maximum intensity projection displays of the baseline-subtracted DCE images. Voxel time-courses within the ROI were individually displayed on a 5 × 5 panel. Voxel times-courses showing an AIF curve shape were then individually selected, and their locations and time-courses were automatically saved. |
| UM3     | ROIs were manually drawn on both left and right femoral arteries on the central 4 slices. To minimize the in-flow effect, the inferior and superior slices were excluded. Further, 20 voxels within the ROIs with the highest signal increases were determined by thresholding the histogram of intensity changes. The average signal intensity time course of the 20 voxels yielded the final AIF signal intensity time-course. |
| UPitt   | Images were loaded into PMOD 3.505 (PMOD Technologies Ltd.), a commercial software package. Images were examined to search for an artery near the lesion. A region including the identified artery was surveyed using the voxel browser of PMOD to identify an area with high signal intensity change, followed by AIF ROI delineation. |
| UW      | An adapted version of a positron emission tomography (PET) AIF extraction scheme (39), which does not require user-specified AIF ROI, was used. The approach was implemented in R (open-source). The extracted input function was then scaled so that the apparent extraction of gadolinium contrast reagent (CR) based on the analysis of the entire tissue volume signal is 2.5%. |
| VU      | A seed point was placed manually inside an artery and then a region-growing method was applied to automatically select the AIF voxels. The intensity range for the region-growing method was set as 80% to 120% of that of the seed point, and the voxel distance from the seed was <10 voxels. Mean signal intensity-time-courc of the selected voxels was obtained. |

Table 1. Arterial Input Function (AIF) Quantification Methods by Participating Quantitative Imaging Network (QIN) Centers
converted to plasma CR concentration time course, \( C_p(t) \), using the following equation:

\[
R_{1,b}(t) = r_1 \cdot h \cdot C_p(t) / H_{1101} \cdot 0.61 \left( \frac{1}{1 + \frac{t}{h}} \right)
\]

where \( r_1 \) is the CR relaxivity at 3T, set at 3.8 mM/s; and \( h \) is the hematocrit, set at 0.45.

**Pharmacokinetic Analysis of Human Prostate DCE-MRI Data**

Using a single in-house Matlab-based software package, the managing center performed pharmacokinetic analysis of the shared 11 sets of prostate DCE-MRI data using the AIFs determined by the 9 QIN centers and the literature-based GP AIF. All AIF arrival times were manually aligned with the uptake phase of the tissue response curves. The most commonly used pharmacokinetic model, the Tofts model (TM) (32), was applied to data analysis, and its basic formulation is shown in Equation (2) as follows:

\[
C_t(t) = K_{\text{trans}} \int_0^t C_p(t') \exp(-K_{\text{trans}} v_e^{-1})(t - t') \, dt' \tag{2}
\]

where \( C_t(t) \) represents the tissue CR concentration at time \( t \); \( C_p(t') \) is the AIF obtained from Equation (1). The fast exchange limit condition intrinsic to the TM (23) implies a linear relationship between \( R_1(t) \) and \( C_t(t) \):

\[
R_1(t) = r_1 C_t(t) + R_{10} \tag{3}
\]

where \( R_1(t) \) is tissue \( R_1 \) measured at time \( t \), and \( R_{10} \) is the precontrast tissue \( R_1 \) (assumed to be 0.63 s\(^{-1}\)) (10).

For each DCE-MRI data set, the voxel intensity time-courses within the predefined prostate tumor ROI on a single image slice, drawn by the center (BWH) that acquired the data, were subjected to the TM pharmacokinetic analysis. The mean values of the tumor ROI pharmacokinetic parameters \( (K_{\text{trans}}, v_e, \text{and } k_{\text{ep}}) \) were obtained by averaging the corresponding voxel parameter values.

Because of different approaches (Table 1) used by participating centers in direct measurement of the AIF, large variations in the AIF amplitude were observed as a result of differences in measurement locations, number of voxels used, inflow effects, etc. As an alternative approach for pharmacokinetic analysis, an ROI (Figure 1, inset) in the adjacent obturator muscle area on the same image slice as that of the tumor ROI was used as a reference tissue for AIF amplitude adjustment (9, 33). The AIF (including the literature-based GP AIF) amplitude was adjusted until the TM fitting of the muscle ROI DCE-MRI data returned a \( v_e \) value of 0.1, which is within the range of literature-reported values (34). Therefore, in total, 20 AIFs representing unadjusted and reference tissue-adjusted AIFs from the 9 centers and the GP AIFs were applied for the pharmacokinetic modeling of each prostate DCE-MRI data set using the TM, resulting in 20 sets of \( K_{\text{trans}}, v_e, \text{and } k_{\text{ep}} \) parameters that were then separated into two groups of results obtained with adjusted and unadjusted AIFs.

All voxel-fitting results were included in calculating the mean tumor ROI pharmacokinetic parameter values, as it was difficult to set optimal criteria for excluding voxel fittings obtained with AIFs determined by a diverse array of methods. Using the prior knowledge that a physically meaningful \( v_e \) is

![Figure 1.](image-url)
RESULTS
Pharmacokinetic Parameter Variations Due to AIF Differences
Figure 1A plots the AIFs extracted from the DCE-MRI data of one subject by the 9 participating QIN centers. The inset shows a post-CR DCE image slice zoomed to the prostate area. The smaller circular ROI indicates a common location—the femoral artery—where blood signals were measured for AIF determination, whereas the larger elliptical ROI indicates the general location of the reference tissue ROI in the obturator muscle. Noticeable variations are evident in both the shape and the amplitude among the Cp time-courses, converted from the measured signal intensity time-courses using Equation (1). Figure 1B shows the reference tissue-adjusted AIFs of those shown in Figure 1A. The agreement among the individually measured AIFs is clearly improved following the adjustment. The standard deviation of the 9 measured AIFs over the DCE time-course is significantly smaller for the reference tissue-adjusted AIFs than for the unadjusted ones (Wilcoxon signed-rank test, \( P < .0001 \)). Similar findings are observed for AIFs from the other 10 subjects.

At the center of Figure 2, a zoomed post-CR image slice of the prostate of another subject is shown. The cyan ROI demarks the lesion area used for subsequent TM modeling and parameter comparisons. K\text{\scriptsize trans} color maps generated by TM analysis of the DCE-MRI data using unadjusted (unadj.) AIFs from the 9 centers are shown on the left panels and those with reference tissue-adjusted (adj.) AIFs are shown on the right. All 18 panels used the same color scale.
between the unadjusted and adjusted AIFs is better for \( k_{ep} \) than for \( K^{trans} \). In fact, \( k_{ep} \) dispersion is hardly affected by the difference in AIF scaling.

Figure 4 shows the column graphs of wCV for \( K^{trans}, v_e, \) and \( k_{ep} \) obtained with the unadjusted (shaded light gray) and adjusted (dark gray) AIFs. The error bars are the 95% CIs. A smaller wCV value indicates less variation in measurements on the same subject by different approaches. In this study, the wCV values range from 0.15 for \( v_e \) with adjusted AIFs to 0.74 for \( K^{trans} \) with unadjusted AIFs. The wCV of \( v_e \) is the smallest, whereas that of \( K^{trans} \) is the largest among the three pharmacokinetic parameters with either unadjusted or adjusted AIFs. From unadjusted to adjusted AIFs, the parameter variations decrease for \( K^{trans} \) and \( v_e \) (wCV values decrease from 0.74 to 0.60 and from 0.33 to 0.15, respectively). On the other hand, it increases slightly for \( k_{ep} \) (wCV value increases from 0.45 to 0.54).

Figure 5 shows the column graphs of ICC values for \( K^{trans}, v_e, \) and \( k_{ep} \) obtained with unadjusted (shaded light gray) and adjusted (dark gray) AIFs. The respective 95% CIs are shown as error bars. Consistent with the results shown in Figure 4, \( K^{trans} \) has the smallest ICC value compared with \( k_{ep} \) and \( v_e \) with either unadjusted or adjusted AIF, indicating its high dependence on AIF quantification for prostate DCE-MRI. From unadjusted to adjusted AIFs, the ICC value increases from 0.30 to 0.38 and
Table 2A. CCC values for the unadjusted AIFs are listed above the dashed diagonal line, and those for the adjusted AIFs are listed below the diagonal line. Tables 2, B and C show the corresponding equivalents for the $v_e$ and $k_{ep}$ parameters, respectively. The CCC ranges obtained with unadjusted AIFs are 0.031–0.944, 0.334–0.986, and 0.145–0.957 for $K_{trans}$, $v_e$, and $k_{ep}$, respectively; and those obtained with adjusted AIFs are 0.082–0.965, 0.554–0.993, and 0.129–0.965 for $K_{trans}$, $v_e$, and $k_{ep}$, respectively. In general, the CCC values increase from unadjusted to adjusted AIFs for the $K_{trans}$ and $v_e$ parameters, although few changes are observed for the $k_{ep}$ parameter. In addition, the CCC value that resulted from pairing of the GP AIF with any other AIF (unadjusted or adjusted) is usually among the smallest in the CCC ranges described above.

The Bland–Altman plots depicted in Figure 6 show examples of the agreement in $K_{trans}$ for AIF pairs with the largest (Figure 6, A and B) and smallest (Figure 6, C and D) CCC values within the unadjusted (Figure 6, A and C) and adjusted (Figure 6, B and D) AIF groups. Although the differences between measurements are mostly within the 95% CIs for all plots, it is rather visually clear (with all 4 plots having the same vertical-axis scale) that the width of confidence bands substantially differs between AIF pairs with greater CCC values (Figure 6, A and B) and those with smaller CCC values (Figure 6, C and D): narrower for the former, wider for the latter. For the AIF pairs with the largest CCCs (Figure 6, A and B), or the best agreements in the estimated $K_{trans}$ values, the means of $K_{trans}$ differences between the two AIFs represented by the dotted lines are close to 0 at 0.076 and 0.009 min$^{-1}$, respectively, for unadjusted and adjusted AIFs. For the AIF pairs with the smallest CCCs (Figure 6, C and D), or the worst agreements in the estimated $K_{trans}$ values, the means of $K_{trans}$ differences are 0.529 and –1.085 min$^{-1}$, respectively.
Table 2A. CCC Values of the $K_{trans}$ Parameter Obtained With Unadjusted and Adjusted AIFs

| QIN1 | QIN2 | QIN3 | QIN4 | QIN5 | QIN6 | QIN7 | QIN8 | QIN9 | GP  |
|------|------|------|------|------|------|------|------|------|------|
| QIN1 | 0.185 | 0.759 | 0.825 | 0.501 | 0.755 | 0.747 | 0.412 | 0.941 | 0.049 |
| QIN2 | 0.228 | 0.395 | 0.186 | 0.082 | 0.241 | 0.297 | 0.159 | 0.189 | 0.047 |
| QIN3 | 0.726 | 0.507 | 0.645 | 0.336 | 0.836 | 0.889 | 0.301 | 0.732 | 0.083 |
| QIN4 | 0.835 | 0.267 | 0.637 | 0.591 | 0.769 | 0.645 | 0.515 | 0.750 | 0.084 |
| QIN5 | 0.776 | 0.179 | 0.531 | 0.880 | 0.472 | 0.367 | 0.307 | 0.445 | 0.223 |
| QIN6 | 0.780 | 0.370 | 0.896 | 0.744 | 0.612 | 0.944 | 0.209 | 0.639 | 0.115 |
| QIN7 | 0.755 | 0.376 | 0.887 | 0.662 | 0.965 | 0.548 | 0.262 | 0.612 | 0.105 |
| QIN8 | 0.825 | 0.250 | 0.621 | 0.882 | 0.739 | 0.666 | 0.353 | 0.107 |
| QIN9 | 0.897 | 0.130 | 0.610 | 0.720 | 0.747 | 0.507 | 0.655 | 0.031 |
| GP  | 0.210 | 0.082 | 0.212 | 0.287 | 0.297 | 0.393 | 0.300 | 0.253 | 0.104 |

CCC: concordance correlation coefficient; values from unadjusted AIFs are presented in the top right triangle and those from reference-tissue-adjusted AIFs are presented in bottom left triangle; $K_{trans}$: rate constant for plasma/interstitium contrast reagent (CR) transfer.

Table 2B. CCC Values of the $v_e$ Parameter Obtained With Unadjusted and Adjusted AIFs

| QIN1 | QIN2 | QIN3 | QIN4 | QIN5 | QIN6 | QIN7 | QIN8 | QIN9 | GP  |
|------|------|------|------|------|------|------|------|------|------|
| QIN1 | 0.458 | 0.873 | 0.696 | 0.822 | 0.911 | 0.890 | 0.713 | 0.913 | 0.732 |
| QIN2 | 0.942 | 0.473 | 0.369 | 0.347 | 0.421 | 0.453 | 0.538 | 0.535 | 0.334 |
| QIN3 | 0.981 | 0.969 | 0.666 | 0.587 | 0.868 | 0.886 | 0.676 | 0.745 | 0.510 |
| QIN4 | 0.973 | 0.965 | 0.971 | 0.545 | 0.737 | 0.782 | 0.767 | 0.538 | 0.530 |
| QIN5 | 0.726 | 0.668 | 0.693 | 0.803 | 0.787 | 0.719 | 0.591 | 0.733 | 0.936 |
| QIN6 | 0.982 | 0.955 | 0.980 | 0.951 | 0.622 | 0.986 | 0.797 | 0.713 | 0.737 |
| QIN7 | 0.993 | 0.965 | 0.992 | 0.982 | 0.984 | 0.732 | 0.838 | 0.696 | 0.688 |
| QIN8 | 0.979 | 0.951 | 0.965 | 0.954 | 0.973 | 0.690 | 0.985 | 0.534 | 0.619 |
| QIN9 | 0.952 | 0.820 | 0.913 | 0.887 | 0.924 | 0.703 | 0.929 | 0.900 | 0.621 |
| GP  | 0.929 | 0.879 | 0.949 | 0.873 | 0.933 | 0.554 | 0.931 | 0.924 | 0.880 |

CCC: concordance correlation coefficient; values from unadjusted AIFs are presented in the top right triangle and those from reference-tissue-adjusted AIFs are presented in bottom left triangle; $v_e$: extravascular and extracellular volume fraction.

Table 2C. CCC Values of the $k_{ep}$ Parameter Obtained With Unadjusted and Adjusted AIFs

| QIN1 | QIN2 | QIN3 | QIN4 | QIN5 | QIN6 | QIN7 | QIN8 | QIN9 | GP  |
|------|------|------|------|------|------|------|------|------|------|
| QIN1 | 0.400 | 0.649 | 0.881 | 0.894 | 0.792 | 0.745 | 0.872 | 0.891 | 0.319 |
| QIN2 | 0.303 | 0.620 | 0.339 | 0.327 | 0.553 | 0.645 | 0.407 | 0.335 | 0.145 |
| QIN3 | 0.752 | 0.605 | 0.591 | 0.591 | 0.934 | 0.942 | 0.690 | 0.465 | 0.356 |
| QIN4 | 0.872 | 0.282 | 0.586 | 0.932 | 0.684 | 0.595 | 0.866 | 0.788 | 0.352 |
| QIN5 | 0.883 | 0.247 | 0.569 | 0.965 | 0.680 | 0.615 | 0.856 | 0.811 | 0.442 |
| QIN6 | 0.775 | 0.427 | 0.856 | 0.677 | 0.656 | 0.957 | 0.705 | 0.579 | 0.385 |
| QIN7 | 0.748 | 0.525 | 0.910 | 0.614 | 0.938 | 0.616 | 0.936 | 0.519 | 0.344 |
| QIN8 | 0.867 | 0.308 | 0.656 | 0.873 | 0.683 | 0.856 | 0.697 | 0.722 | 0.346 |
| QIN9 | 0.925 | 0.231 | 0.642 | 0.783 | 0.542 | 0.812 | 0.547 | 0.738 | 0.182 |
| GP  | 0.318 | 0.129 | 0.248 | 0.390 | 0.391 | 0.438 | 0.348 | 0.350 | 0.171 |

CCC: concordance correlation coefficient; values from unadjusted AIFs are presented in the top right triangle and those from reference-tissue-adjusted AIFs are presented in bottom left triangle; $k_{ep}$ (= $K_{trans}/v_e$): CR intravasation rate constant.
respectively, for unadjusted and adjusted AIFs, considerably different from 0. In addition, in cases of poor $K_{\text{trans}}$ agreement (Figure 6, C and D), there seems to be a pattern of correlation between the difference in $K_{\text{trans}}$ and the mean of $K_{\text{trans}}$, with larger differences corresponding to larger mean values.

**DISCUSSION**

The main goal of this multicenter AIF data analysis challenge was to evaluate variations of estimated pharmacokinetic parameters in prostate cancer due to differences in AIF determination. Individually measured AIFs were obtained for each DCE-MRI data set with different QIN center-specific methods, which include manual AIF–voxel selection, semiautomatic AIF–voxel identification, automated AIF region identification, and AIF determination using commercial software packages. Quality control measures such as fixed tumor ROI definition, fixed tumor $T_1$, and central data analysis with a commonly used pharmacokinetic model were adopted to ensure that DCE-MRI parameter variations are mainly due to AIF differences only. Although the software package used by the managing center for central pharmacokinetic data analysis was an in-house-developed version of the TM (32), its mathematical formulation was validated using digital reference object phantom data in a previous DCE-MRI data analysis challenge (23).

The results from this multicenter study clearly show that variations in AIF quantification result in variations in the estimated pharmacokinetic parameter values for prostate DCE-MRI data. Among the $K_{\text{trans}}$, $k_{\text{ep}}$, and $v_e$ parameters, $K_{\text{trans}}$ has the largest whereas $v_e$ has the smallest AIF uncertainty-caused variations. The wCV values ranged from as low as 0.33 for $v_e$ to as high as 0.74 for $K_{\text{trans}}$ with unadjusted AIFs, whereas the ICC ranged from 0.30 for $K_{\text{trans}}$ to 0.62 for $v_e$. Similar results of $v_e$ being the most “robust” parameter to AIF variation have been reported in a simulation study (35) previously, and its “robustness” may be the direct consequence that $v_e$ is the most influential parameter within the $K_{\text{trans}}$ range (33) seen in prostate cancer. This is, when comparing the effects of the same percentage change in a single parameter on the DCE-MRI time-course, $v_e$ change causes the most noticeable DCE-MRI time-course deviation than the other parameters (33), suggesting that the $v_e$ parameter is shaped more by the tissue DCE time-course during model fitting. Another probable reason that $K_{\text{trans}}$ is more susceptible to AIF variation than $v_e$ is that quantification of $K_{\text{trans}}$ strongly depends on the initial AIF spike, whereas $v_e$ quantification relies more on the entire AIF time-course. This work complements a recent study comparing AIF determinations with commercial software packages. Quality control measures such as fixed tumor ROI definition, fixed tumor $T_1$, and central data analysis with a commonly used pharmacokinetic model were adopted to ensure that DCE-MRI parameter variations are mainly due to AIF differences only.

It is important to point out that the AIF influence on $K_{\text{trans}}$ estimation is dependent on CR extravasation ($K_{\text{trans}}$ magnitude) (33), underscoring the importance of accurate AIF measurement in $K_{\text{trans}}$ modeling when CR extravasation is extensive. This CR extravasation-dependent characteristic is more clearly illustrated in extreme cases such as normal brain tissue where gadolinium-based CR acts as an intravascular agent during the short period after CR injection. Under this condition of no CR extravasation, the AIF has no effect on $K_{\text{trans}}$ (which is undetectable). For organs with extensive CR extravasation, like the prostate (10), the initial AIF curve shape strongly influences the estimation of $K_{\text{trans}}$. This is possibly the reason that the $K_{\text{trans}}$ values obtained with a fixed, population-based GP AIF show the least agreement (lowest CCC values) with those obtained with individually measured AIFs. The individually measured AIFs (mostly from the femoral artery voxels) from the actual DCE-MRI data generally captured similar initial AIF curve shapes despite the use of different quantification methods and potential errors from partial volume and inflow effects. The data acquisition-specific details may not be well characterized by the GP AIF, which is modeled on the basis of data from either the aorta or iliac arteries, acquired with different pulse sequence parameters and generated at different field strength. Thus, in cases of substantial CR extravasation, pharmacokinetic parameters should be estimated with individually determined AIFs whenever possible instead of a generic population-averaged AIF unrelated to a specific acquisition protocol.

As shown in this study, there are, however, steps one can take to lessen the effects of AIF variations on estimation of pharmacokinetic parameters. The agreement in the $K_{\text{trans}}$ and $v_e$ parameters obtained with reference tissue-adjusted AIFs is improved when compared with that obtained with unadjusted AIFs. This is a direct result of better agreement in AIF amplitude among the individually measured AIFs following the muscle reference tissue adjustment. However, the reference tissue approach is far from a perfect solution to AIF uncertainty-caused parameter variations. High wCV, low ICC, and low CCC values are still prevalent after the reference tissue method was used, particularly for $K_{\text{trans}}$, of which the estimated value is strongly influenced by both the magnitude and the initial curve shape of the AIF.

The results from this multicenter challenge project are supported by findings from a recent simulation study (unpublished results), which aims to identify pharmacokinetic parameters that are relatively insensitive to AIF variations. In fact, the simulations show complete $k_{\text{ep}}$ insensitivity to AIF magnitude errors (unpublished results). The current study shows that for TM analysis, $k_{\text{ep}}$ is less sensitive to AIF uncertainty when compared with $K_{\text{trans}}$. Defined as the CR intravasation rate constant, $k_{\text{ep}}$ is predominantly characterized by the washout phase of the DCE time-course. Because $k_{\text{ep}}$ is often calculated as $K_{\text{trans}}/v_e$ and not as an independent variable in model fitting of the DCE time-course data, it is sometimes underused in clinical DCE-MRI studies. Results from this work, however, suggest that, considering the uncertainties in AIF determination, $k_{\text{ep}}$ may be a more reproducible DCE-MRI parameter than the $K_{\text{trans}}$ parameter and thus a more robust imaging biomarker of perfusion and permeability. For prostate DCE-MRI, $k_{\text{ep}}$ can offer a different perspective of prostate microvasculature, particularly when the $K_{\text{trans}}$ ranges of benign and cancerous tissue overlap (5).

It is important to note that DCE-MRI parameter variations caused by AIF variations are mostly systematic. As an example shown in Figure 2, the differences among the prostate tumor $K_{\text{trans}}$ maps obtained with different AIFs are mostly in voxel $K_{\text{trans}}$ values. The pattern of voxel $K_{\text{trans}}$ distribution largely remains similar for all the maps. This suggests that assessment of
tumor heterogeneity through texture analysis of DCE-MRI parametric maps may not be affected greatly by variations in AIF determination. In addition, for longitudinal DCE-MRI studies to assess cancer therapy response, the systematic errors caused by AIF quantification variations may be largely cancelled in the calculation of percent changes of DCE-MRI parameters before and after therapy. In a multicenter breast DCE-MRI data analysis challenge study (23), we showed that the DCE-MRI parameter percent changes before and after the first cycle of neoadjuvant chemotherapy were substantially less sensitive to variations in the pharmacokinetic model and the software package used for data analysis when compared with the absolute parameter values.

Because of its unique temporal signatures and often superior image contrast, DCE-MRI is widely used in prostate imaging as part of a multiparametric prostate MRI protocol. DCE-MRI data analysis with qualitative and/or semiquantitative assessment is favored in current clinical practice largely because of their relative simplicity. However, the rich information embedded in the DCE-MRI data is likely underutilized. Pharmacokinetic data analysis for estimation of tissue biology-specific parameters has the potential to provide more consistent results for broad cross-vendor and cross-scanner platform applications. Robust and reliable AIF determination remains a real challenge for adoption of pharmacokinetic modeling of prostate DCE-MRI data in clinical settings. The results from this study provide useful information on how to minimize errors in the calculation of percent changes of pharmacokinetic parameter values were observed because of variations in AIF determination. The AIF-caused parameter variations are higher in $K^{\text{trans}}$ than in $v_e$. As a solution to reduce parameter variation, AIF amplitude can be adjusted after its measurement by using the reference tissue method. Compared with $K^{\text{trans}}$, $k_{ep}$ is less sensitive to AIF uncertainty, suggesting that $k_p$ may be a more robust pharmacokinetic parameter for characterization of prostate microvasculature. The variations in parameter estimates caused by differences in AIF are systematic, and thus, the patterns of voxel-based DCE-MRI parametric maps were largely unaffected. In multicenter clinical trials involving quantitative DCE-MRI, central data analysis with a fixed AIF determination method should be adopted for a single time-point study to minimize the undesirable effects due to uncertainty in AIF determination. This approach may introduce systematic errors in estimated pharmacokinetic parameters, but it avoids random errors resulted from data analysis by individual centers with different AIF determination methods, which could be detrimental in addressing biological questions. In a longitudinal multicenter study, percent changes of pharmacokinetic parameters, instead of their absolute values, should be used as imaging endpoints to more accurately evaluate biological changes.

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