Supplementary material for:
Towards a quality metric for dense light fields

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In the main paper, we presented our method and the procedure for collecting reliable subjective responses for various distortions that are applied to dense light fields. We also introduced a new light-field dataset that is used for the subjective quality assessment and evaluating the performance of existing 2D, stereo 3D, video, and multi-view quality metrics. Due to the space limitations, we only report a portion of our results in the main paper. In this supplementary material, we present a comprehensive analysis of metrics' behavior and scatter plots that provide further insights.

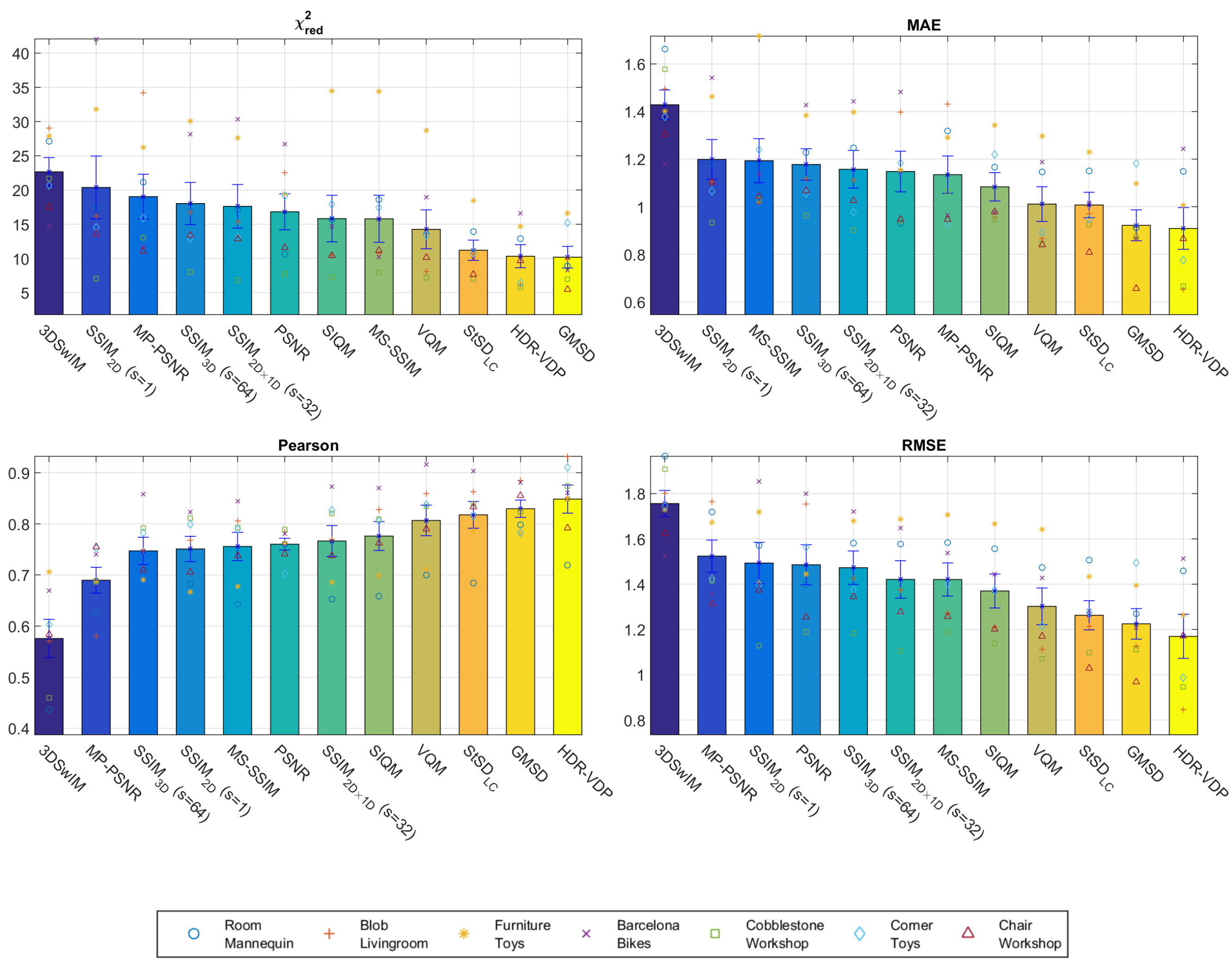
Our full light-field dataset is available online[1]. A preview of our light fields is included in the accompanying[2]. For the synthetic scenes, HDR images and ground truth depth information can be provided up on request. The dataset also includes distorted light fields and the corresponding subjective scaling data for various test conditions which can be used for testing and training new metrics. Due to the large variability in our light-field dataset (e.g., scenes, reflectance properties, etc.), we believe, that our dataset is also beneficial in other applications where light fields are required, e.g., depth estimation, view synthesis, etc.

Contents

[1]http://lightfields.mpi-inf.mpg.de/
[2]http://lightfields.mpi-inf.mpg.de/other/Video.mp4

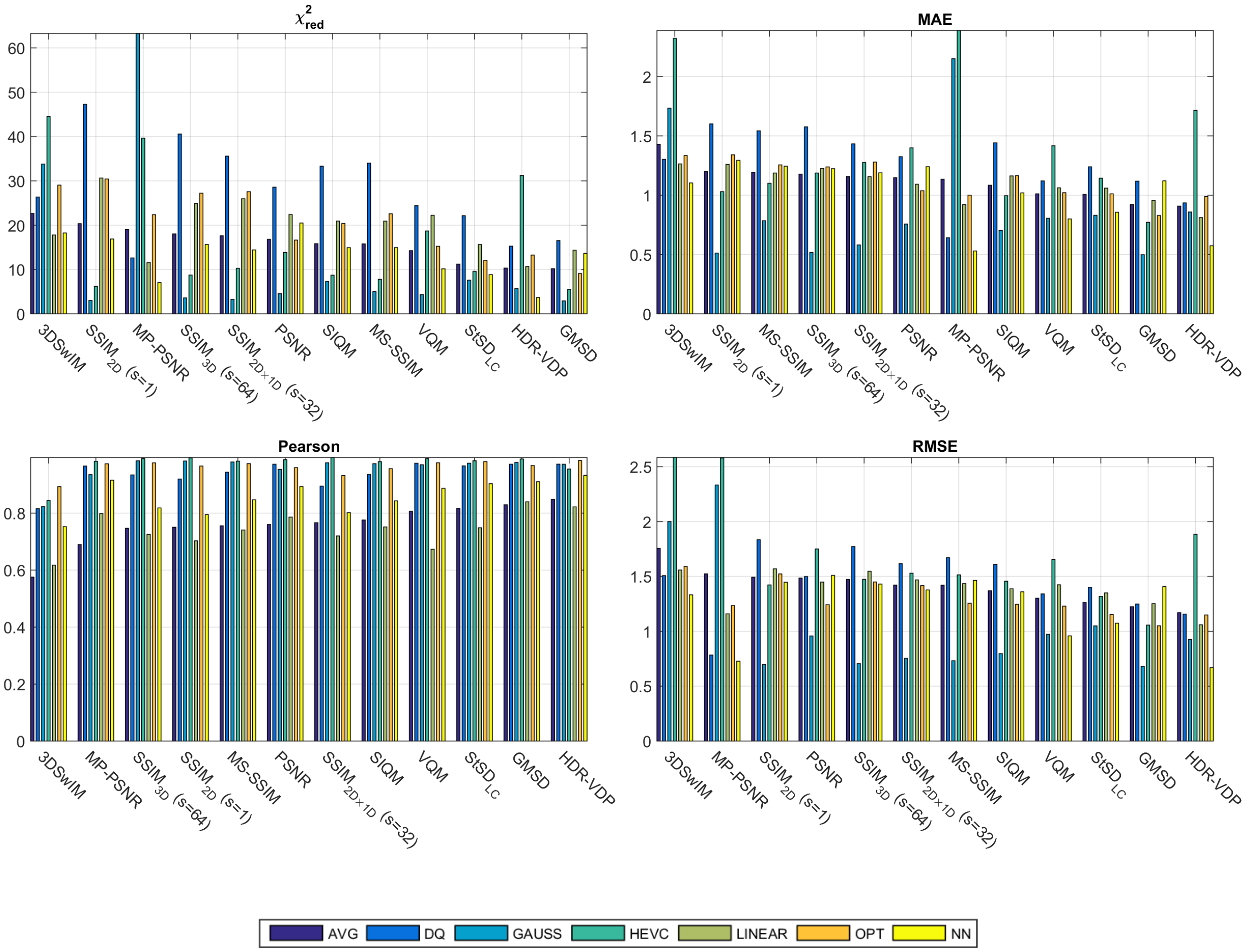
1. Goodness-of-fit measures for metrics across various cross validation folds

Here we show the goodness-of-fit scores for each metric after the logistic function fitting. As measures of the fits quality we use reduced chi-squared statistic (χ^2_{red}), Mean Absolute Error (MAE), Pearson Correlation Coefficient (Pearson), and Root Mean Squared Error (RMSE). For a fair comparison, we employed a seven-fold cross-validation where the whole dataset was divided according to the scenes. Each fold was constructed by taking data corresponding to two scenes as a testing set, and the rest was considered for training. The bars indicate the scores that are averaged after testing across different cross-validation folds. The scores obtained for each fold are indicated using different symbols such as a circle, plus, square, triangle, etc. The error bars represent standard error. The metrics are sorted in increasing order of fit quality for the given statistic.



2. Overall prediction accuracy per distortion

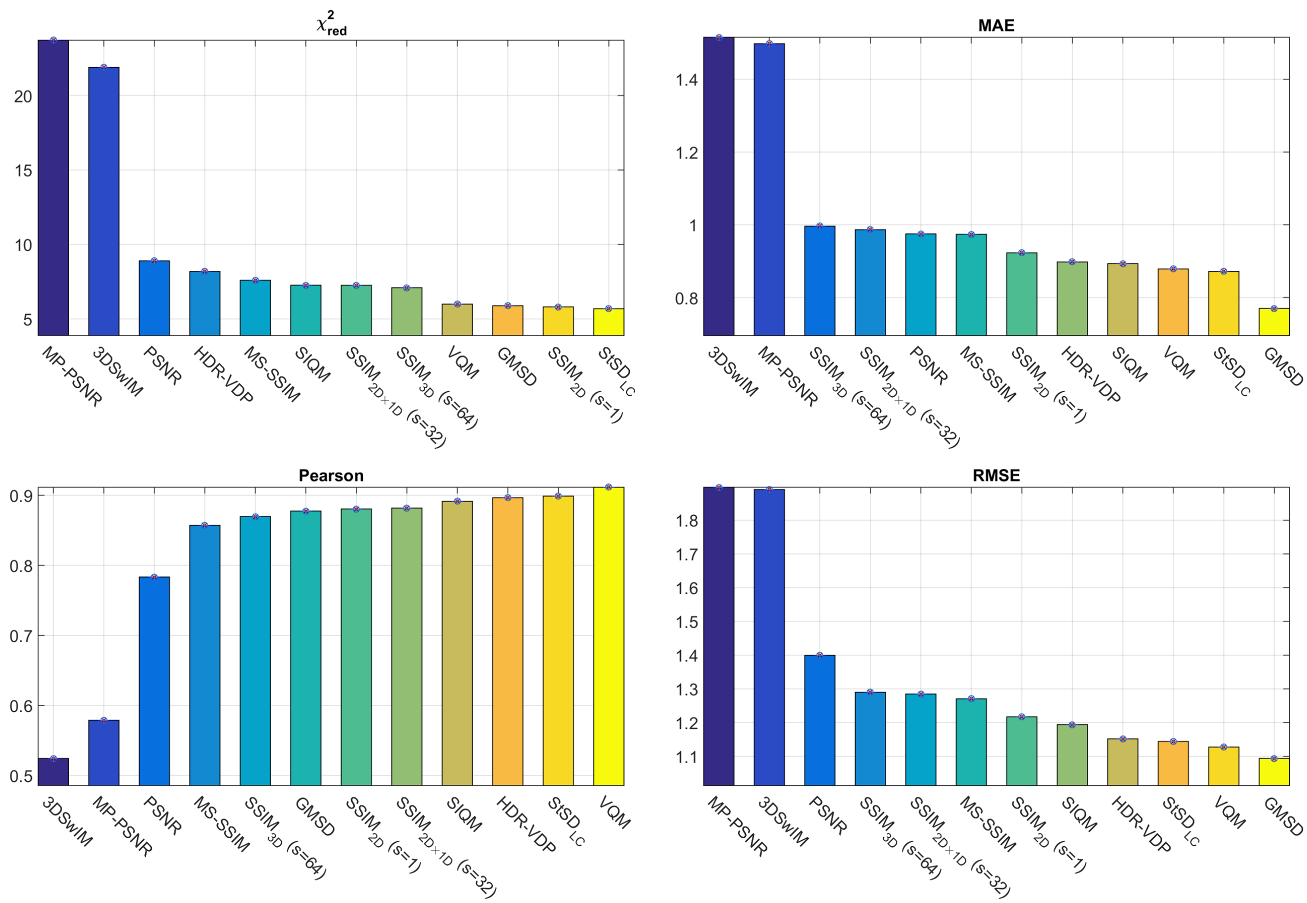
Here we present the summary of the results across all cross-validation folds for each distortion separately. Differently colored bars within each group represent specific distortions. The first bar within each group (dark blue) is the average metric score that corresponds to the bars shown in the previous section. The order of the metrics is the same as in the previous plots. It can be observed that the metrics GMSD and HDR-VDP coup up well with a variety of distortions.



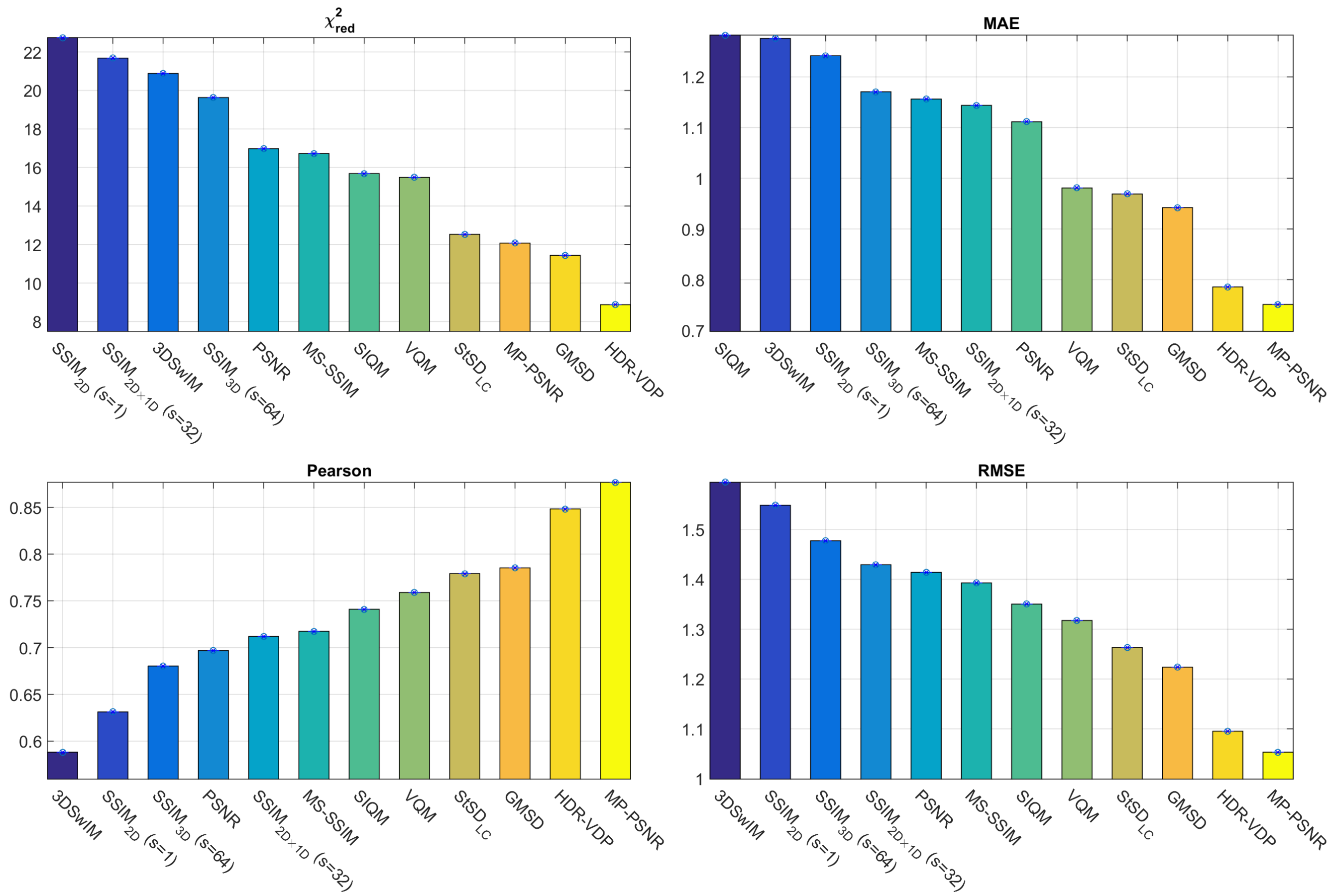
3. Prediction accuracy: real-world scenes vs synthetic scenes

Here we present the summary of the results obtained from testing on real-world scenes and synthetic scenes separately. The statistics reduced chi-squared statistic (χ^2_{red}), Mean Absolute Error (MAE), Pearson Correlation Coefficient (Pearson), and Root Mean Squared Error (RMSE) are reported. The logistic function trained over all the database is used to test explicitly on the subsets containing real-world and synthetic scenes. The metrics are sorted in increasing order of fit quality for the given statistic. In general, the metrics perform better on real-world images although the dataset contains more synthetic scenes. The exact reason for this behavior has to be further investigated in the future.

3.1. Metric performances on real-world scenes



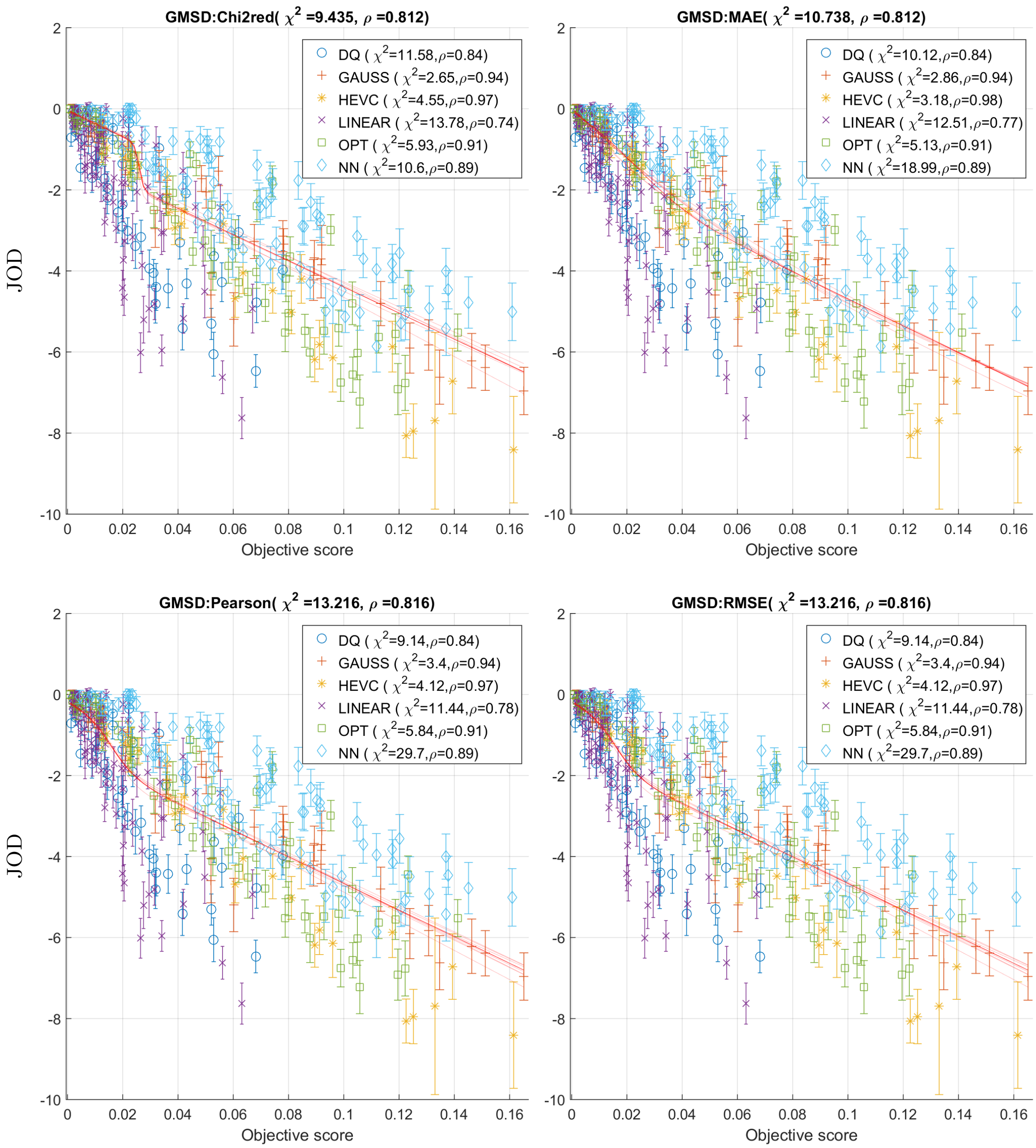
3.2. Metric performances on synthetic scenes



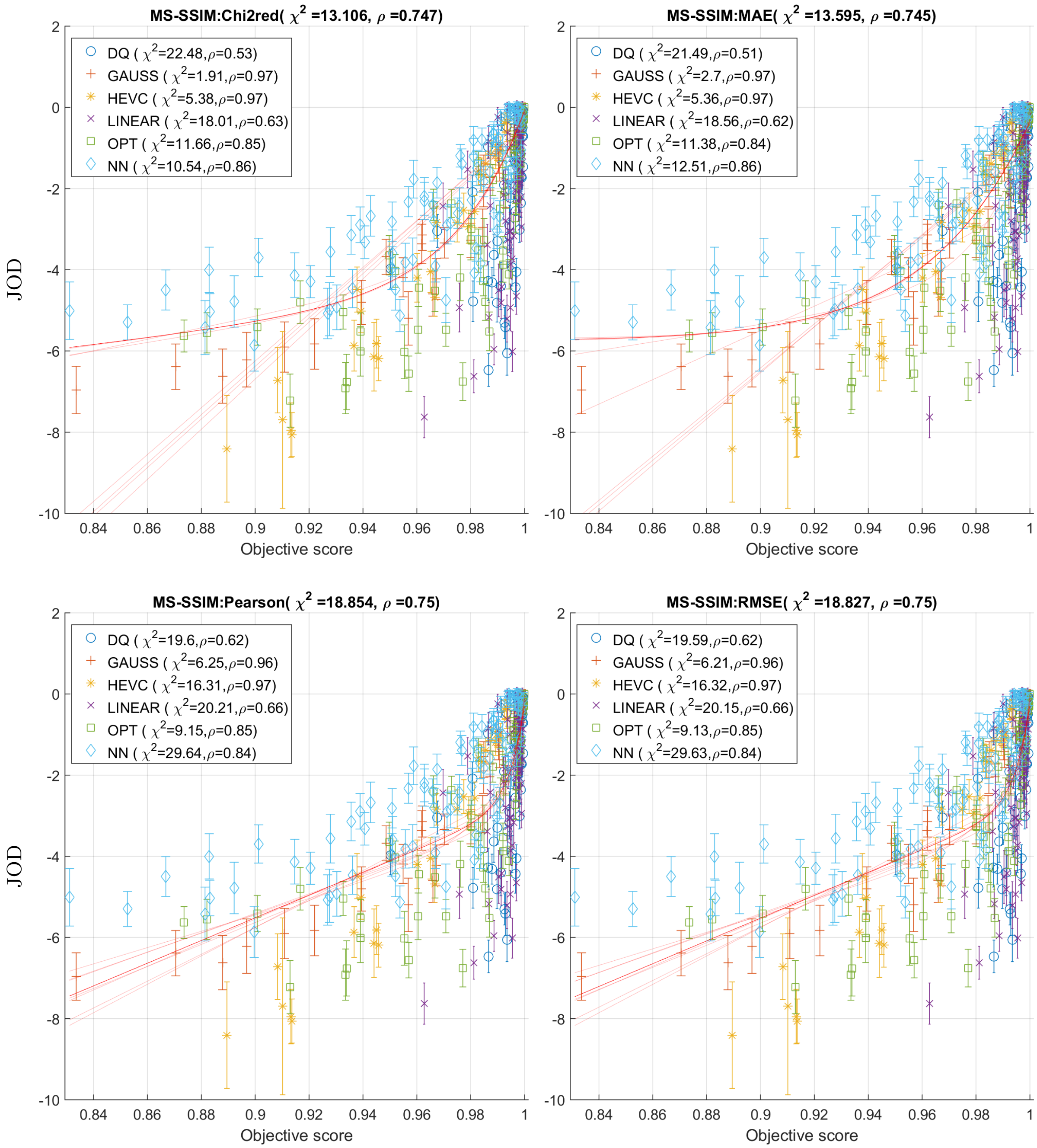
4. Scatter plots with logistic fits

In this section, we show scatter plots of all our subjective data with logistic functions for various metrics. For each metric, we optimized the logistic function separately for each statistic by minimizing the prediction error according to the statistics. This results in four plots for each considered metric. Each data point in the plots is a result of comparing a distorted light field to a dense reference. The logistic functions computed using all pairs are shown in dark red, and the logistic functions calculated in individual cross-validation folds are shown in light red. The scatter plot points that belong to the same distortion are marked with the same color. We make two main observations. First, the points corresponding to only one distortion follow different characteristic than the logistic functions. This suggests that one can improve the performance of current metrics if the distortion type is known in advance. The second observation is that the logistic functions from individual folds, in most cases, are very similar. This proves the reliability of the logistic functions.

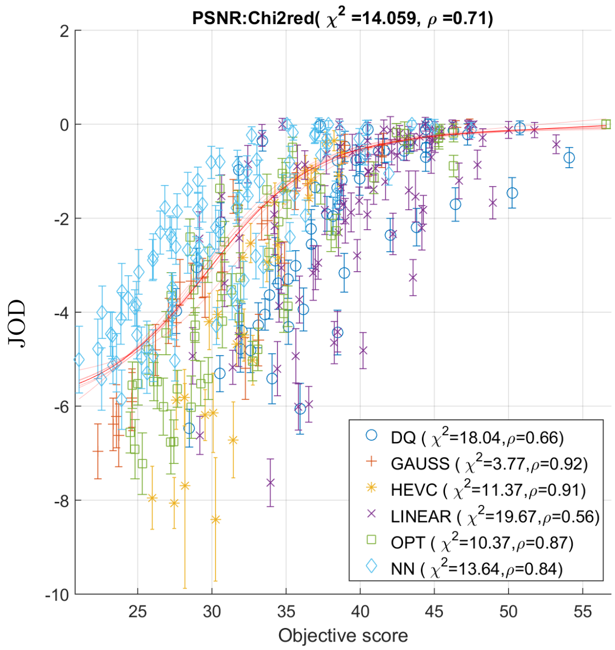
4.1. GMSD

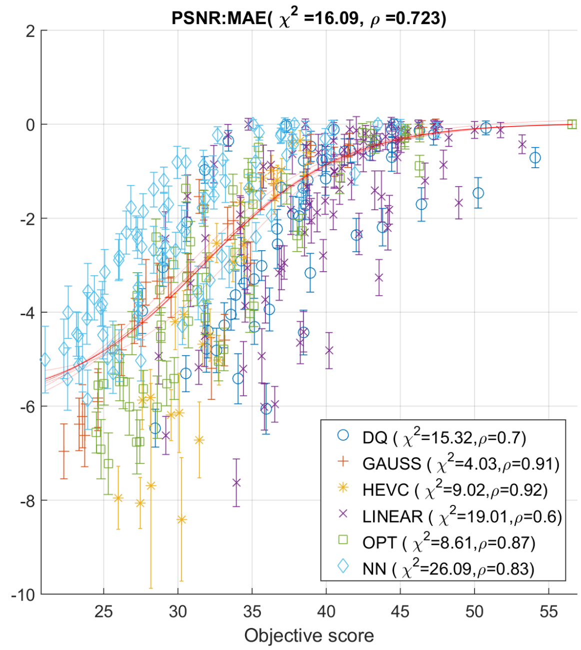


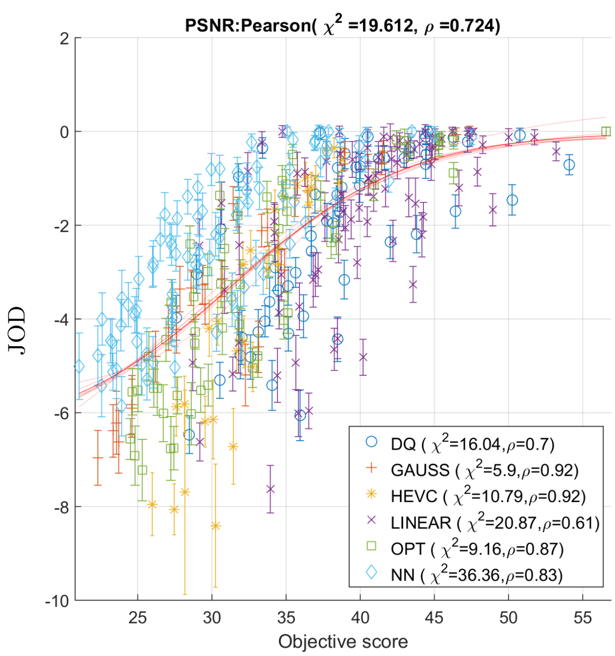
4.2. MS-SSIM

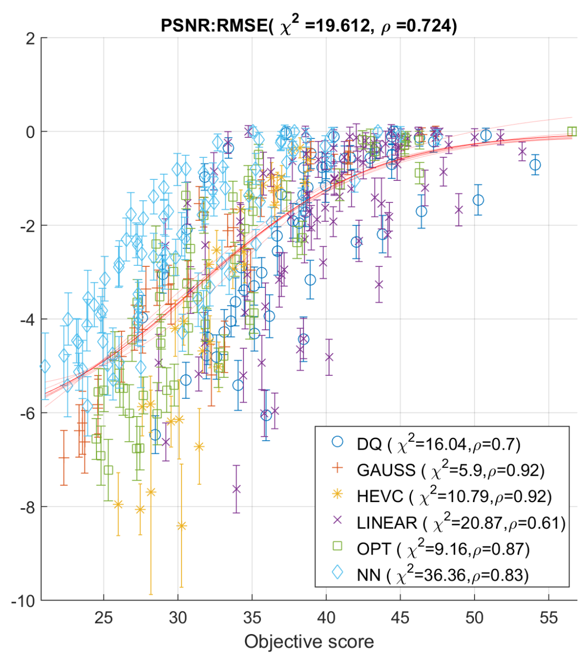

MS-SSIM:Chi2red(χ^2 =13.106, ρ =0.747)
DQ (χ^2=22.48,ρ=0.53)
GAUSS (χ^2=1.91,ρ=0.97)
HEVC (χ^2=5.38,ρ=0.97)
LINEAR (χ^2=18.01,ρ=0.63)
OPT (χ^2=11.66,ρ=0.85)
NN (χ^2=10.54,ρ=0.86)
MS-SSIM:MAE(χ^2 =13.595, ρ =0.745)
DQ (χ^2=21.49,ρ=0.51)
GAUSS (χ^2=2.7,ρ=0.97)
HEVC (χ^2=5.36,ρ=0.97)
LINEAR (χ^2=18.56,ρ=0.62)
OPT (χ^2=11.38,ρ=0.84)
NN (χ^2=12.51,ρ=0.86)
MS-SSIM:Pearson(χ^2 =18.854, ρ =0.75)
DQ (χ^2=19.6,ρ=0.62)
GAUSS (χ^2=6.25,ρ=0.96)
HEVC (χ^2=16.31,ρ=0.97)
LINEAR (χ^2=20.21,ρ=0.66)
OPT (χ^2=9.15,ρ=0.85)
NN (χ^2=29.64,ρ=0.84)
MS-SSIM:RMSE(χ^2 =18.827, ρ =0.75)
DQ (χ^2=19.59,ρ=0.62)
GAUSS (χ^2=6.21,ρ=0.96)
HEVC (χ^2=16.32,ρ=0.97)
LINEAR (χ^2=20.15,ρ=0.66)
OPT (χ^2=9.13,ρ=0.85)
NN (χ^2=29.63,ρ=0.84)
JOD
Objective score
2
0
-2
-4
-6
-8
-10
0.84
0.86
0.88
0.9
0.92
0.94
0.96
0.98
1

4.3. PSNR

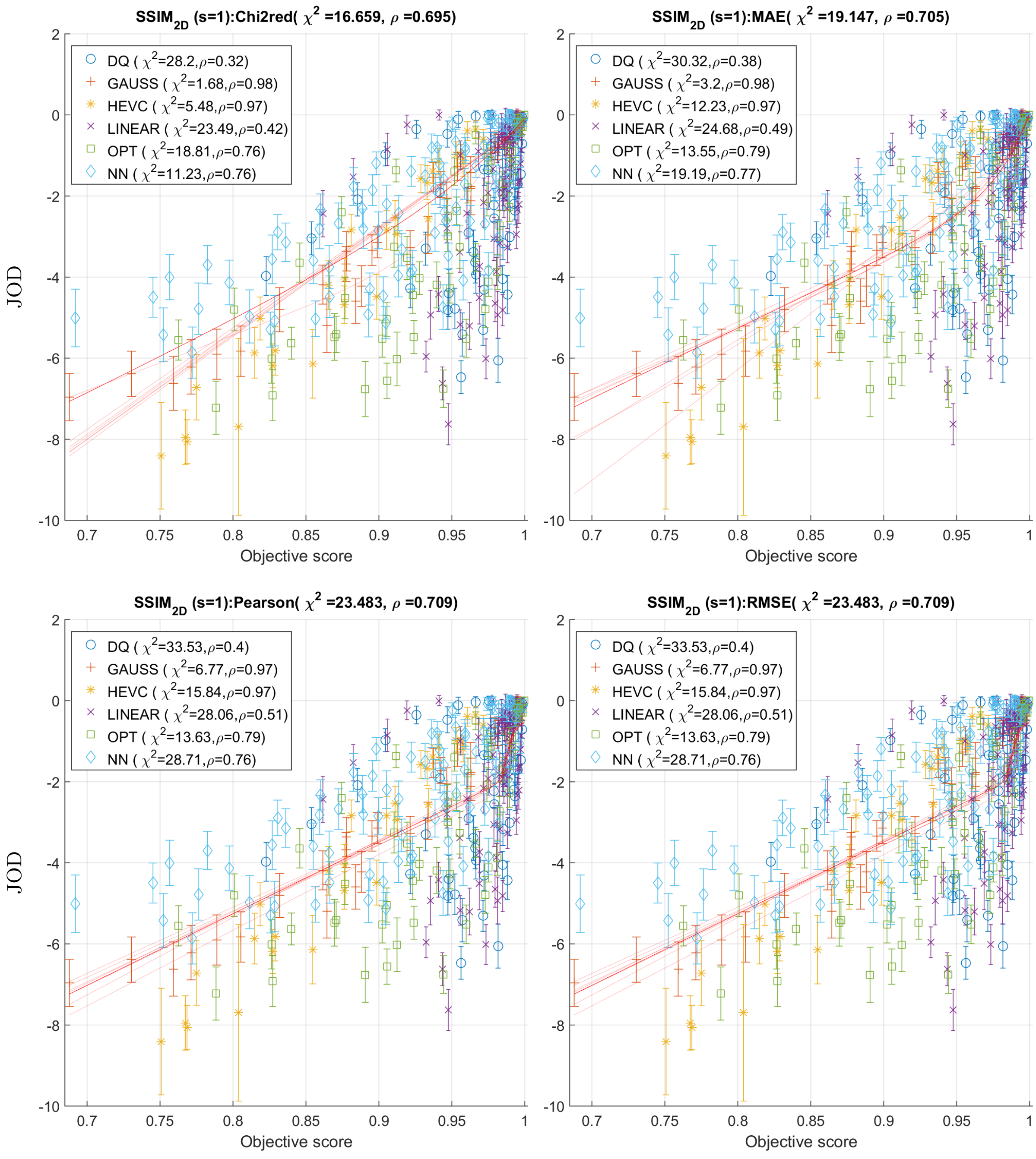

PSNR:Chi2red(χ2 =14.059, ρ =0.71)
JOD
Objective score
DQ (χ2=18.04,ρ=0.66)
GAUSS (χ2=3.77,ρ=0.92)
HEVC (χ2=11.37,ρ=0.91)
LINEAR (χ2=19.67,ρ=0.56)
OPT (χ2=10.37,ρ=0.87)
NN (χ2=13.64,ρ=0.84)


PSNR:MAE(χ2 =16.09, ρ =0.723)
Objective score
DQ (χ2=15.32,ρ=0.7)
GAUSS (χ2=4.03,ρ=0.91)
HEVC (χ2=9.02,ρ=0.92)
LINEAR (χ2=19.01,ρ=0.6)
OPT (χ2=8.61,ρ=0.87)
NN (χ2=26.09,ρ=0.83)

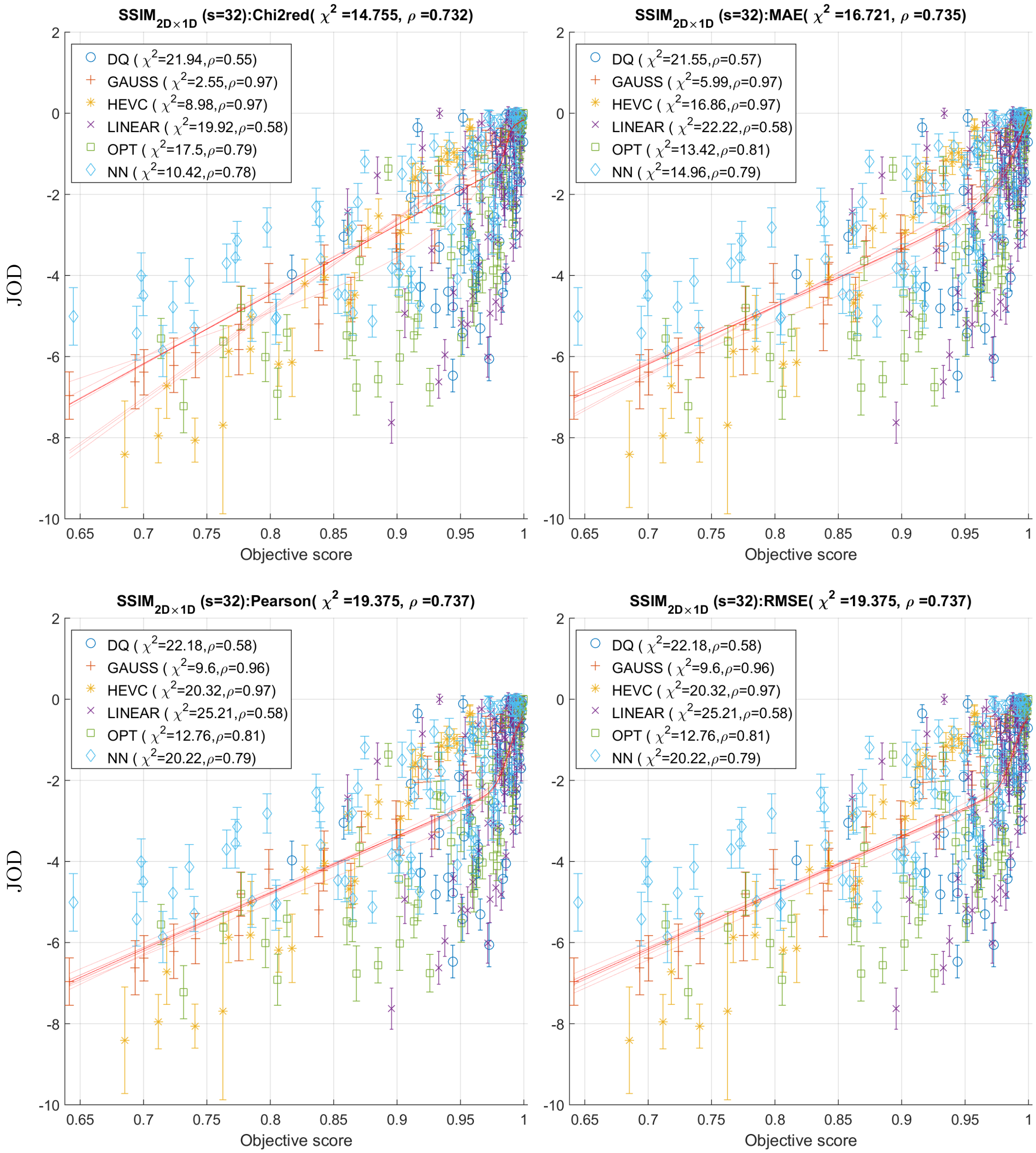

PSNR:Pearson(χ2 =19.612, ρ =0.724)
JOD
Objective score
DQ (χ2=16.04,ρ=0.7)
GAUSS (χ2=5.9,ρ=0.92)
HEVC (χ2=10.79,ρ=0.92)
LINEAR (χ2=20.87,ρ=0.61)
OPT (χ2=9.16,ρ=0.87)
NN (χ2=36.36,ρ=0.83)


PSNR:RMSE(χ2 =19.612, ρ =0.724)
Objective score
DQ (χ2=16.04,ρ=0.7)
GAUSS (χ2=5.9,ρ=0.92)
HEVC (χ2=10.79,ρ=0.92)
LINEAR (χ2=20.87,ρ=0.61)
OPT (χ2=9.16,ρ=0.87)
NN (χ2=36.36,ρ=0.83)

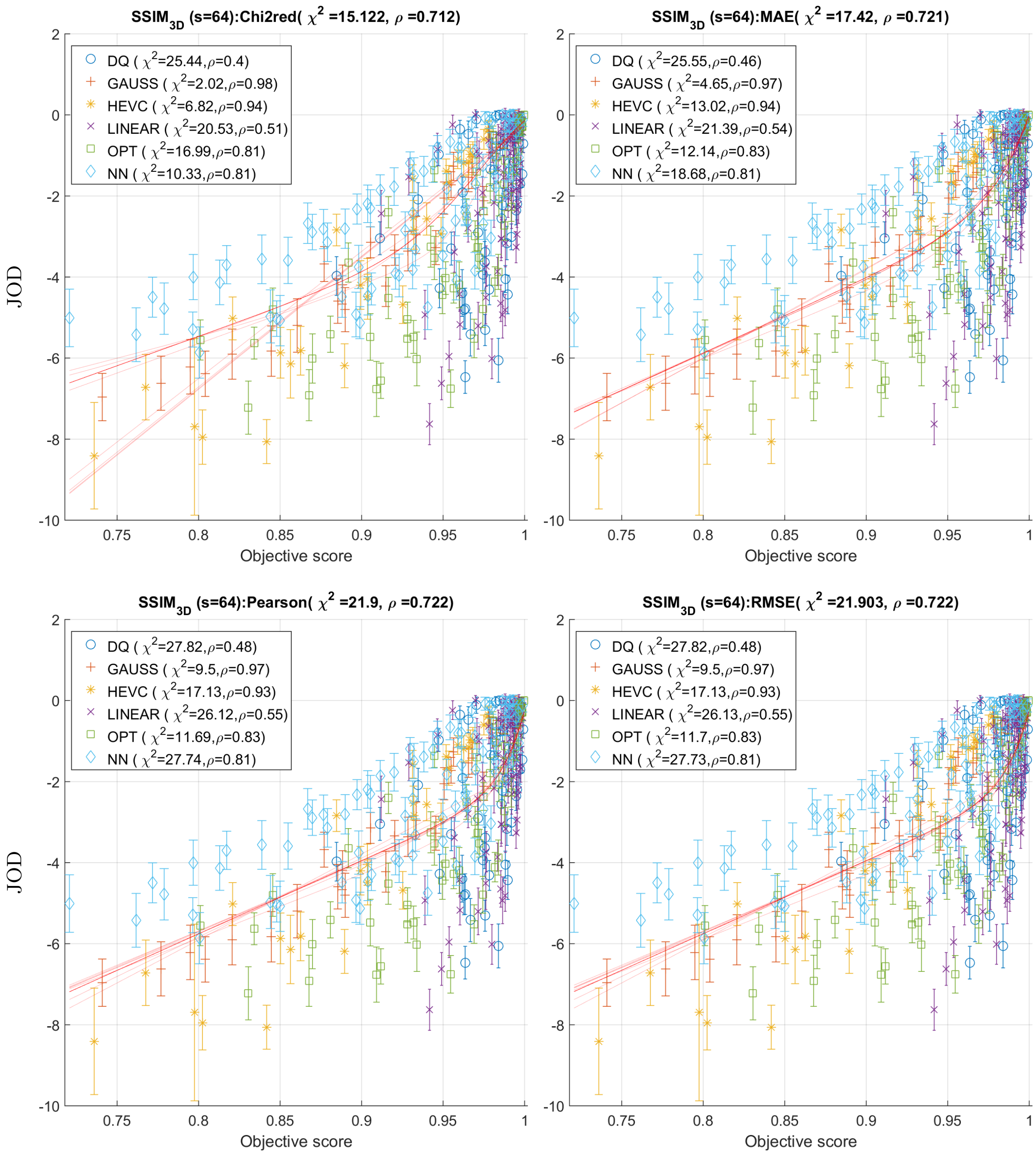
4.4. SSIM_{2D}



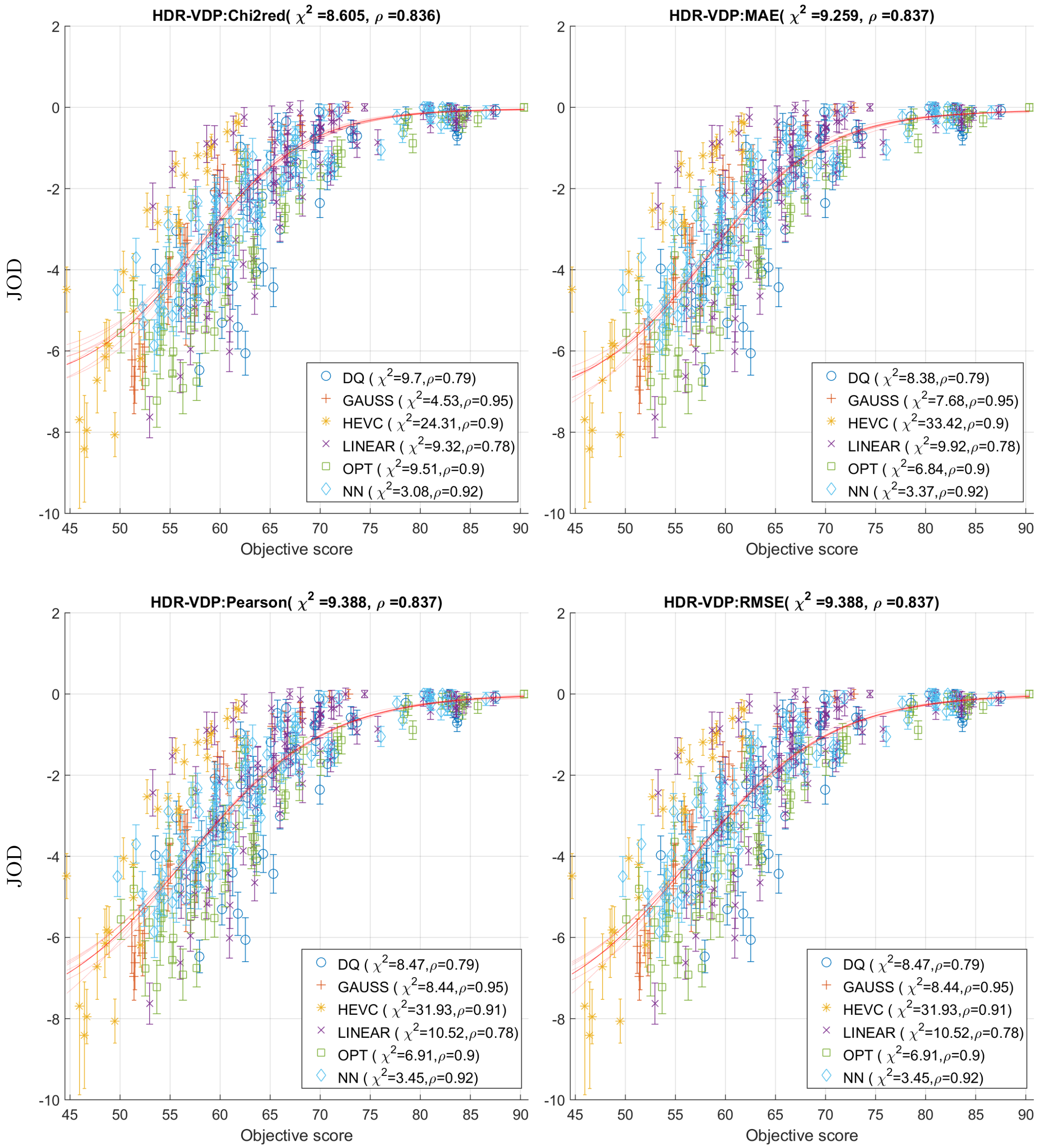
4.5. $\mathrm{SSIM}_{\mathrm{2Dx1D}}$



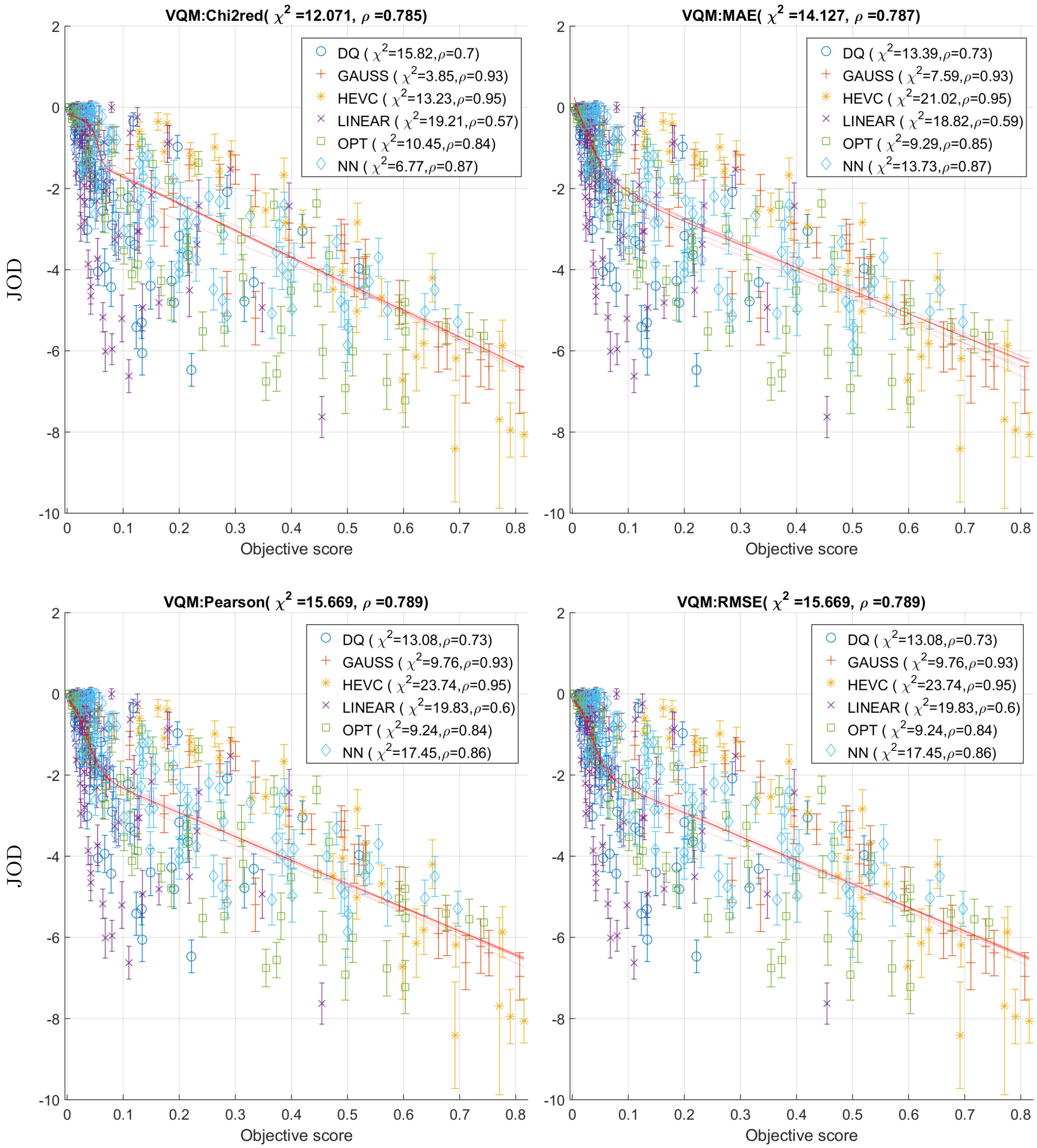
4.6. SSIM_{3D}



4.7. HDR-VDP

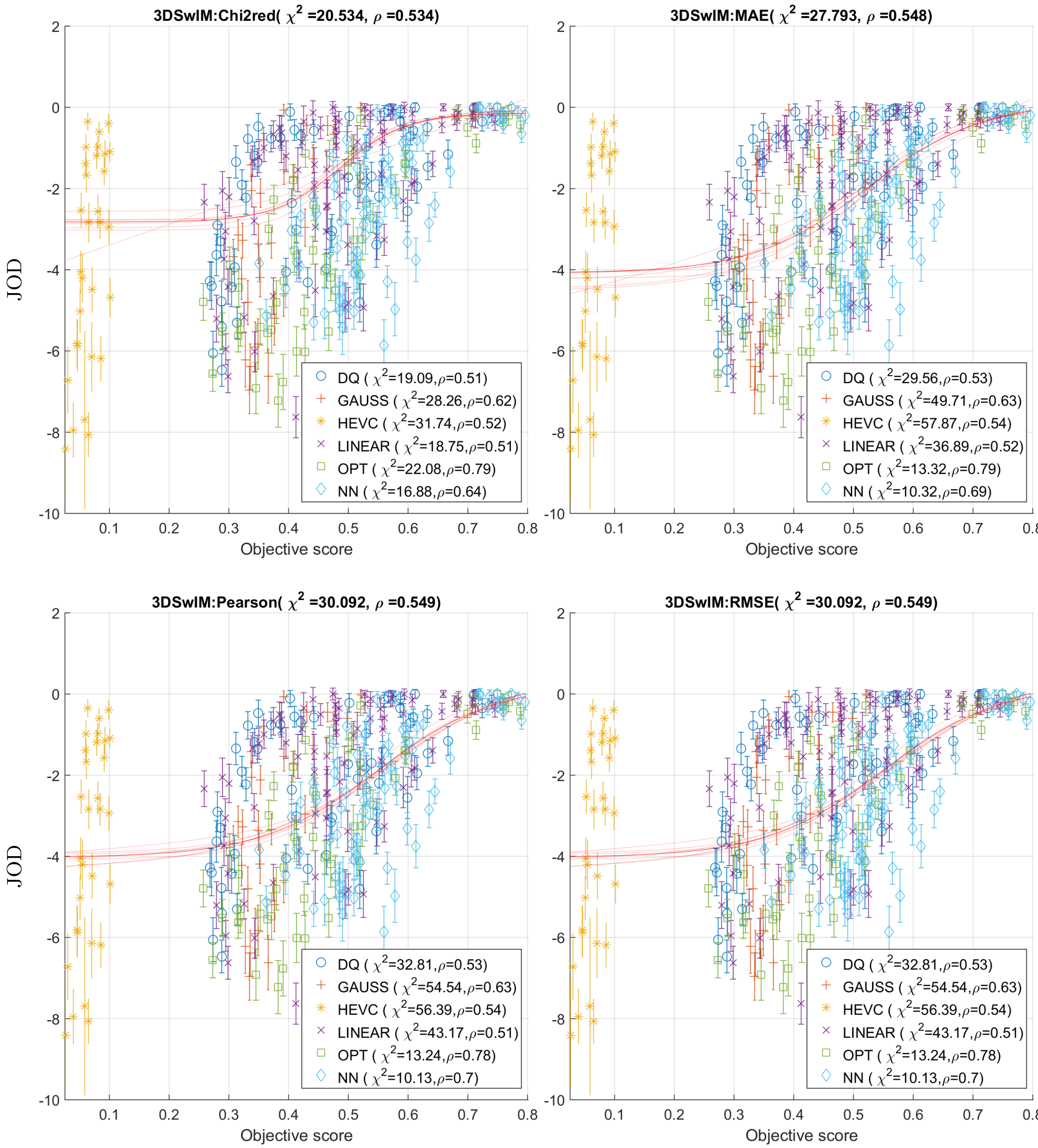

HDR-VDP:Chi2red(χ^2 =8.605, ρ =0.836)
DQ (χ^2=9.7,ρ=0.79)
GAUSS (χ^2=4.53,ρ=0.95)
HEVC (χ^2=24.31,ρ=0.9)
LINEAR (χ^2=9.32,ρ=0.78)
OPT (χ^2=9.51,ρ=0.9)
NN (χ^2=3.08,ρ=0.92)
HDR-VDP:MAE(χ^2 =9.259, ρ =0.837)
DQ (χ^2=8.38,ρ=0.79)
GAUSS (χ^2=7.68,ρ=0.95)
HEVC (χ^2=33.42,ρ=0.9)
LINEAR (χ^2=9.92,ρ=0.78)
OPT (χ^2=6.84,ρ=0.9)
NN (χ^2=3.37,ρ=0.92)
HDR-VDP:Pearson(χ^2 =9.388, ρ =0.837)
DQ (χ^2=8.47,ρ=0.79)
GAUSS (χ^2=8.44,ρ=0.95)
HEVC (χ^2=31.93,ρ=0.91)
LINEAR (χ^2=10.52,ρ=0.78)
OPT (χ^2=6.91,ρ=0.9)
NN (χ^2=3.45,ρ=0.92)
HDR-VDP:RMSE(χ^2 =9.388, ρ =0.837)
DQ (χ^2=8.47,ρ=0.79)
GAUSS (χ^2=8.44,ρ=0.95)
HEVC (χ^2=31.93,ρ=0.91)
LINEAR (χ^2=10.52,ρ=0.78)
OPT (χ^2=6.91,ρ=0.9)
NN (χ^2=3.45,ρ=0.92)
JOD
Objective score

4.8. VQM



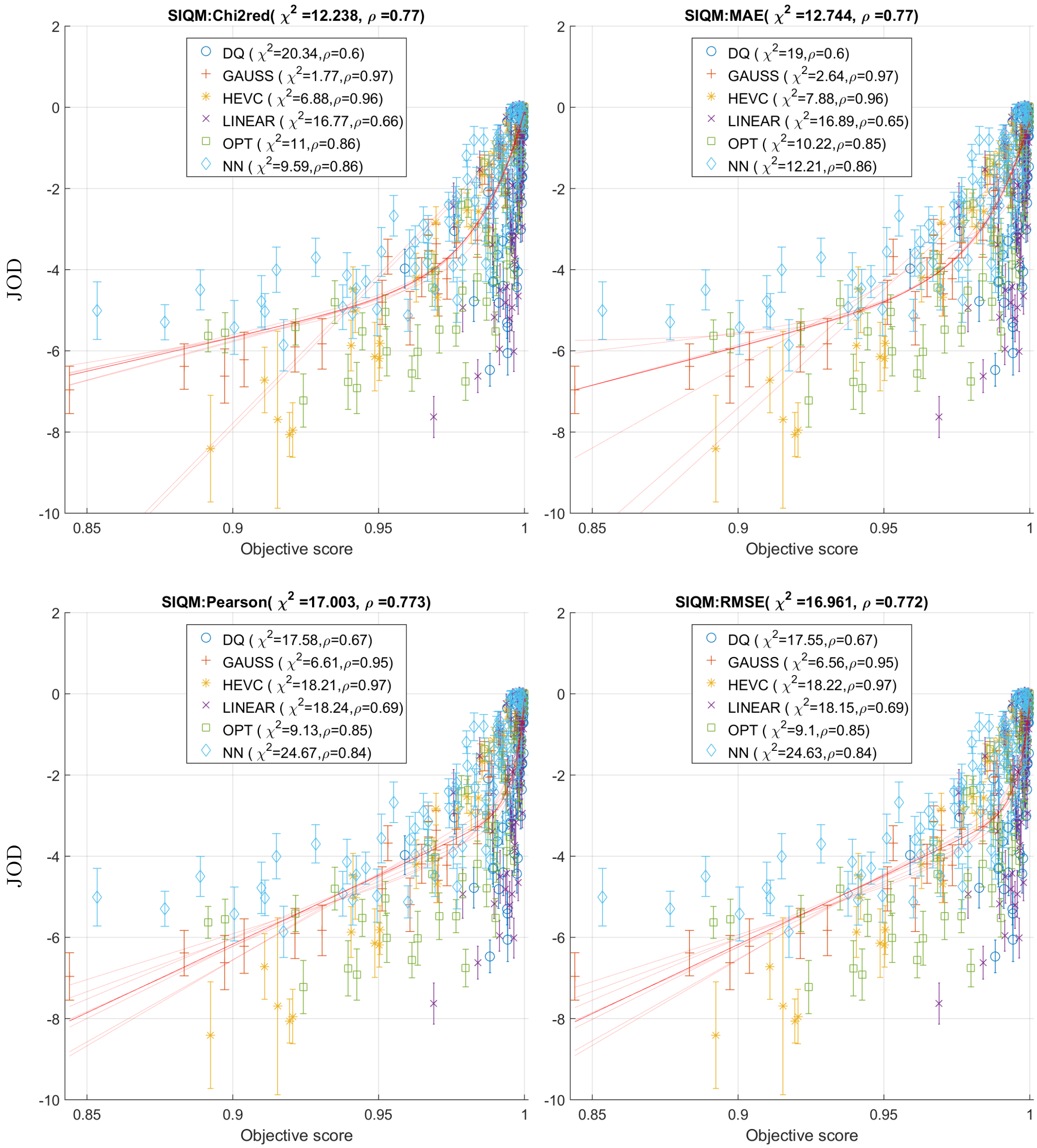
VQM:Chi2red(χ^2 =12.071, ρ =0.785)
DQ (χ^2=15.82,ρ=0.7)
GAUSS (χ^2=3.85,ρ=0.93)
HEVC (χ^2=13.23,ρ=0.95)
LINEAR (χ^2=19.21,ρ=0.57)
OPT (χ^2=10.45,ρ=0.84)
NN (χ^2=6.77,ρ=0.87)
VQM:MAE(χ^2 =14.127, ρ =0.787)
DQ (χ^2=13.39,ρ=0.73)
GAUSS (χ^2=7.59,ρ=0.93)
HEVC (χ^2=21.02,ρ=0.95)
LINEAR (χ^2=18.82,ρ=0.59)
OPT (χ^2=9.29,ρ=0.85)
NN (χ^2=13.73,ρ=0.87)
VQM:Pearson(χ^2 =15.669, ρ =0.789)
DQ (χ^2=13.08,ρ=0.73)
GAUSS (χ^2=9.76,ρ=0.93)
HEVC (χ^2=23.74,ρ=0.95)
LINEAR (χ^2=19.83,ρ=0.6)
OPT (χ^2=9.24,ρ=0.84)
NN (χ^2=17.45,ρ=0.86)
VQM:RMSE(χ^2 =15.669, ρ =0.789)
DQ (χ^2=13.08,ρ=0.73)
GAUSS (χ^2=9.76,ρ=0.93)
HEVC (χ^2=23.74,ρ=0.95)
LINEAR (χ^2=19.83,ρ=0.6)
OPT (χ^2=9.24,ρ=0.84)
NN (χ^2=17.45,ρ=0.86)
JOD
Objective score

4.9. 3DSwIM



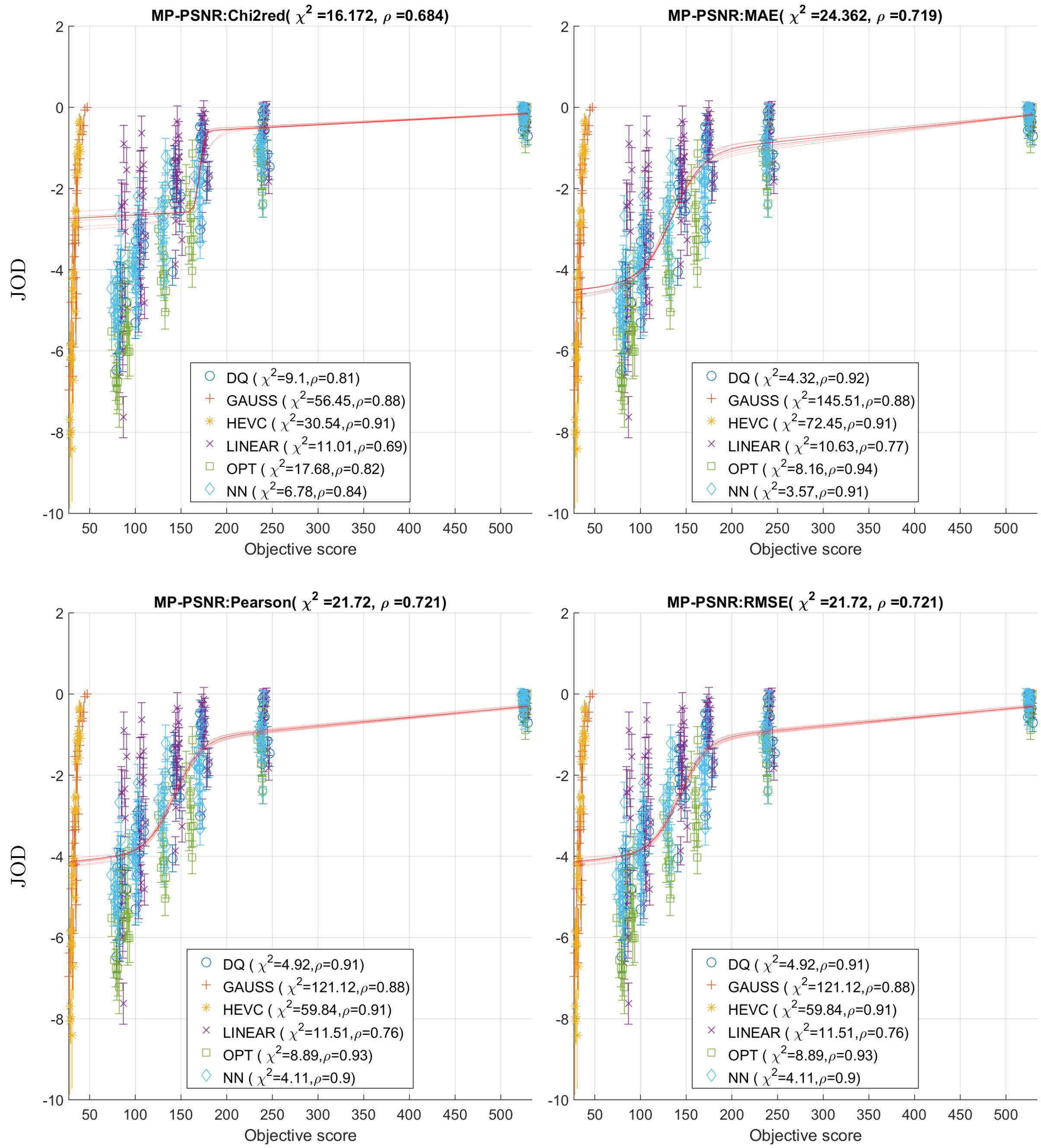
3DSwIM:Chi2red(χ² =20.534, ρ =0.534)
DQ (χ²=19.09,ρ=0.51)
GAUSS (χ²=28.26,ρ=0.62)
HEVC (χ²=31.74,ρ=0.52)
LINEAR (χ²=18.75,ρ=0.51)
OPT (χ²=22.08,ρ=0.79)
NN (χ²=16.88,ρ=0.64)
3DSwIM:MAE(χ² =27.793, ρ =0.548)
DQ (χ²=29.56,ρ=0.53)
GAUSS (χ²=49.71,ρ=0.63)
HEVC (χ²=57.87,ρ=0.54)
LINEAR (χ²=36.89,ρ=0.52)
OPT (χ²=13.32,ρ=0.79)
NN (χ²=10.32,ρ=0.69)
3DSwIM:Pearson(χ² =30.092, ρ =0.549)
DQ (χ²=32.81,ρ=0.53)
GAUSS (χ²=54.54,ρ=0.63)
HEVC (χ²=56.39,ρ=0.54)
LINEAR (χ²=43.17,ρ=0.51)
OPT (χ²=13.24,ρ=0.78)
NN (χ²=10.13,ρ=0.7)
3DSwIM:RMSE(χ² =30.092, ρ =0.549)
DQ (χ²=32.81,ρ=0.53)
GAUSS (χ²=54.54,ρ=0.63)
HEVC (χ²=56.39,ρ=0.54)
LINEAR (χ²=43.17,ρ=0.51)
OPT (χ²=13.24,ρ=0.78)
NN (χ²=10.13,ρ=0.7)
JOD
Objective score

4.10. SIQM



SIQM:Chi2red(χ^2 =12.238, ρ =0.77)
DQ (χ^2=20.34,ρ=0.6)
GAUSS (χ^2=1.77,ρ=0.97)
HEVC (χ^2=6.88,ρ=0.96)
LINEAR (χ^2=16.77,ρ=0.66)
OPT (χ^2=11,ρ=0.86)
NN (χ^2=9.59,ρ=0.86)
SIQM:MAE(χ^2 =12.744, ρ =0.77)
DQ (χ^2=19,ρ=0.6)
GAUSS (χ^2=2.64,ρ=0.97)
HEVC (χ^2=7.88,ρ=0.96)
LINEAR (χ^2=16.89,ρ=0.65)
OPT (χ^2=10.22,ρ=0.85)
NN (χ^2=12.21,ρ=0.86)
SIQM:Pearson(χ^2 =17.003, ρ =0.773)
DQ (χ^2=17.58,ρ=0.67)
GAUSS (χ^2=6.61,ρ=0.95)
HEVC (χ^2=18.21,ρ=0.97)
LINEAR (χ^2=18.24,ρ=0.69)
OPT (χ^2=9.13,ρ=0.85)
NN (χ^2=24.67,ρ=0.84)
SIQM:RMSE(χ^2 =16.961, ρ =0.772)
DQ (χ^2=17.55,ρ=0.67)
GAUSS (χ^2=6.56,ρ=0.95)
HEVC (χ^2=18.22,ρ=0.97)
LINEAR (χ^2=18.15,ρ=0.69)
OPT (χ^2=9.1,ρ=0.85)
NN (χ^2=24.63,ρ=0.84)
JOD
Objective score
2
0
-2
-4
-6
-8
-10
0.85
0.9
0.95
1

4.11. MP-PSNR


MP-PSNR:Chi2red(χ2 =16.172, ρ =0.684)
DQ (χ2=9.1,ρ=0.81)
GAUSS (χ2=56.45,ρ=0.88)
HEVC (χ2=30.54,ρ=0.91)
LINEAR (χ2=11.01,ρ=0.69)
OPT (χ2=17.68,ρ=0.82)
NN (χ2=6.78,ρ=0.84)
MP-PSNR:MAE(χ2 =24.362, ρ =0.719)
DQ (χ2=4.32,ρ=0.92)
GAUSS (χ2=145.51,ρ=0.88)
HEVC (χ2=72.45,ρ=0.91)
LINEAR (χ2=10.63,ρ=0.77)
OPT (χ2=8.16,ρ=0.94)
NN (χ2=3.57,ρ=0.91)
MP-PSNR:Pearson(χ2 =21.72, ρ =0.721)
DQ (χ2=4.92,ρ=0.91)
GAUSS (χ2=121.12,ρ=0.88)
HEVC (χ2=59.84,ρ=0.91)
LINEAR (χ2=11.51,ρ=0.76)
OPT (χ2=8.89,ρ=0.93)
NN (χ2=4.11,ρ=0.9)
MP-PSNR:RMSE(χ2 =21.72, ρ =0.721)
DQ (χ2=4.92,ρ=0.91)
GAUSS (χ2=121.12,ρ=0.88)
HEVC (χ2=59.84,ρ=0.91)
LINEAR (χ2=11.51,ρ=0.76)
OPT (χ2=8.89,ρ=0.93)
NN (χ2=4.11,ρ=0.9)
JOD
Objective score

4.12. $\mathrm{StSD_{LC}}$