Drift Gain Experiment - Grating Report
Do temporal modulations matter outside of the fovea?

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Contents

1 Introduction

In this study we wished to determine the role of temporal modulations for perception of high spatial frequencies outside of the foveola. First, do temporal modulations matter outside of the foveola where receptive fields are so large that motion resulting from ocular drift may go unnoticed? And second, would more motion improve vision outside of the foveola?

2 Prediction of Human Sensitivity

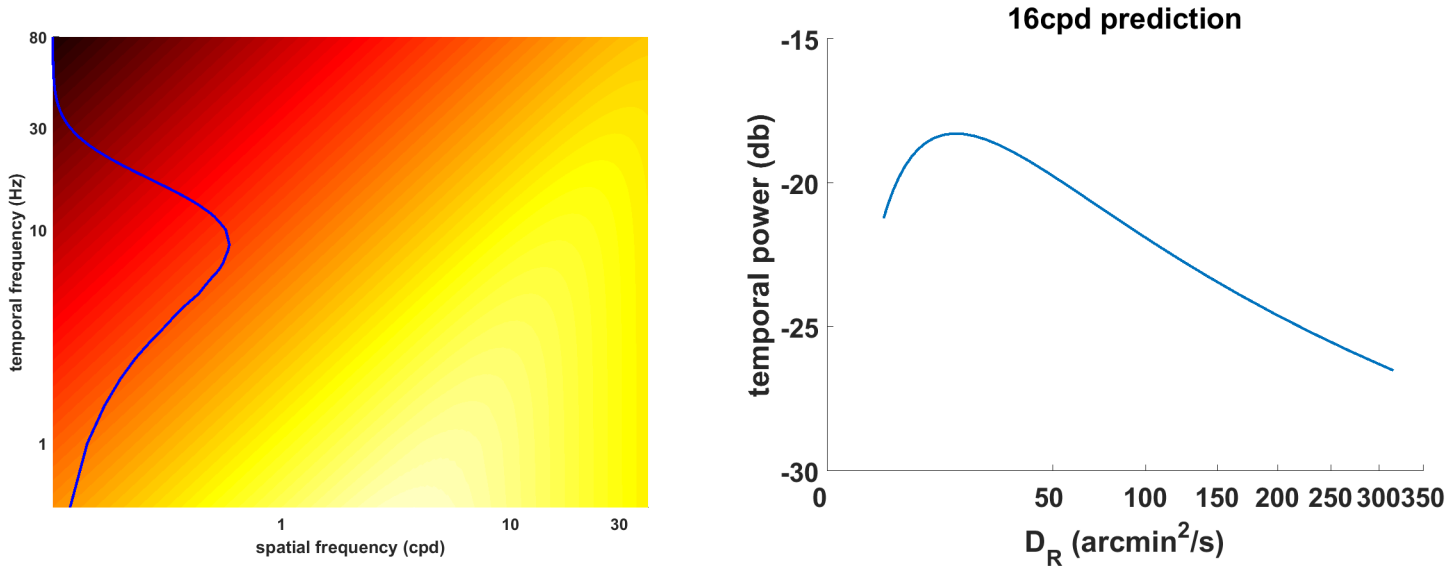


Figure 1: LEFT: Spatiotemporal power generated by a brownian motion drift with $D_E = 5$ arcmin^2/s. Integrating temporal power with a model of human temporal sensitivity (blue) results in predictions of human sensitivity at different amounts of retinal image motion (RIGHT).

2.1 Details

The Brownian motion model of drift is parameterized by a retinal diffusion coefficient D_R. The Fourier transform of the probability distribution of the displacement of the image on the retina over time $q(x, y, t; D_R)$ is the power that the motion provides to the retinal input $Q(\xi_x, \xi_y, f; D_R)$. The two spatial dimensions are combined for simplicity: $\xi^2 = \xi_x^2 + \xi_y^2$.

$$
\begin{aligned}
q(x, y, t; D_R) &= \frac{1}{4\pi D_R t} \exp\left(-\frac{x^2 + y^2}{4 D_R t}\right) \\
Q(\xi_x, \xi_y, f; D_R) &= \frac{2 D_R (\xi_x^2 + \xi_y^2)}{4\pi^2 D_R^2 (\xi_x^2 + \xi_y^2)^2 + f^2} \\
Q(\xi, f; D_R) &= \frac{2 D_R \xi^2}{4\pi^2 D_R^2 \xi^4 + f^2} \qquad (1)
\end{aligned}
$$

Equation (1) generated the Figure 1 (LEFT) and is implemented in
`https://gitlab.com/jintoy/DriftGainGrating/blob/master/Theoretical/Qfunction.m`

The temporal sensitivity function shown in Figure 1 was by Watson (1986) to psychophysical data (Roufs and Blommaert, 1981):

$$|H(f)| = |\alpha([2\pi\imath f\tau + 1)^{-n_1} + \beta(2\pi\imath f\kappa\tau + 1)^{-n_2}]|$$

$\kappa = 1.33, n_1 = 9, n_2 = 10, \tau = 4.94, \alpha = 200, \beta = 1$. This temporal filter is implemented in
`https://gitlab.com/aplabBU/Modeling/blob/master/filters/human_Temporal_Watson.m`

Other temporal sensitivity functions $|H(f)|$ used in this report are:

- mRGC as reported by Benardete and Kaplan (1999, Visual Neuroscience) implemented in `https://gitlab.com/aplabBU/Modeling/blob/master/filters/MacaqueRetinaM_Temporal_BK.m`
- pRGC as reported by Benardete and Kaplan (1999, Journal of Physiology) implemented in `https://gitlab.com/aplabBU/Modeling/blob/master/filters/MacaqueRetinaP_Temporal_BK.m`
- ideal bandpass with cutoffs 2Hz and 80Hz
- curve fit to Janis's psychophysical data for 16cpd gratings withOUT stabilization (similar to Robson (1966) data for 16cpd)
- curve fit to naive subject's psychophysical data for a 6cpd grating fully stabilized with scotoma. (labelled "Stabilized6" in the following figures')
- model of stabilized temporal contrast sensitivity function from Kelly (1979) implemented in `https://gitlab.com/aplabBU/Modeling/blob/master/filters/HumanStabilized_Temporal.m`
- Delta10: include only 10Hz frequency band.

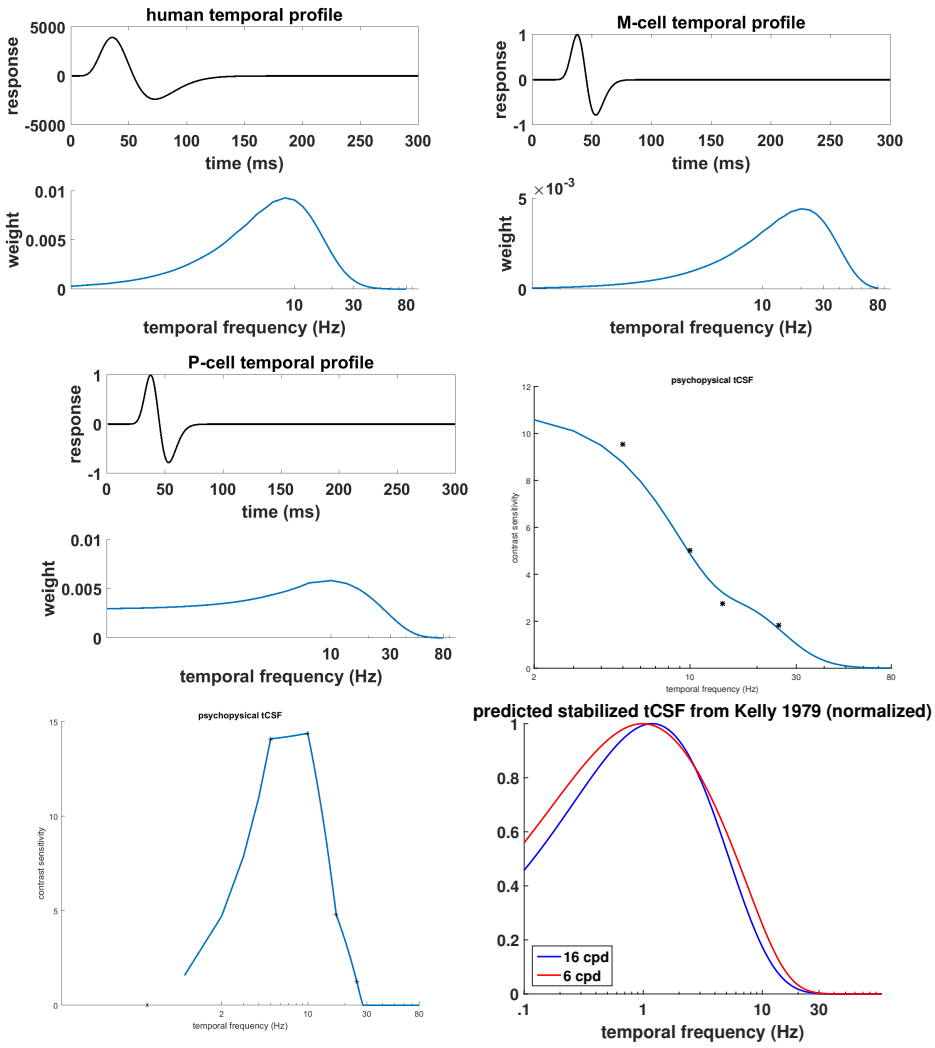


Figure 2: Temporal senstivitiy functions used in predictions. Two unlabelled panels are measured tCSF for Janis at 16cpd (normal) and naive subject at 6cpd (stabilized).

The prediction curves are generated by integrating the product:

$$T(\xi; D_R) = \int_0^\infty Q(\xi, f; D_R) \cdot |H(f)|, df \tag{2}$$

and is implemented in
`https://gitlab.com/jintoy/DriftGainGrating/blob/master/Theoretical/Q_theory2.m`
which also generates Figure 1 (RIGHT).

2.2 Specific Predictions

- Sensitivity is higher for normal amounts of retinal image motion (between D_R of 20-40 arcmin^2/s) than for stabilized amounts of retinal image motion (very small D_R).
- Sensitivity is optimal in a certain range of retinal image motion, and increasing motion beyond this amount impairs visual performance.

2.3 To Do (Aug 30)

This model does not distinguish between foveal and peripheral vision. We hoped to measure peripheral temporal senstivity at 16cpd but the task was too difficult for subjects to get a reliable CSF.

One way to do this is to incorporate the neural sampling of the retina into the model. This would essentially blur the retinal image as long as Nyquist is greater than 16cpd.

3 Experiment Design

To test these predictions, subjects completed a 2AFC task in a grating discrimination task where the central 1-degree of the stimulus was blocked by an artificial scotoma.

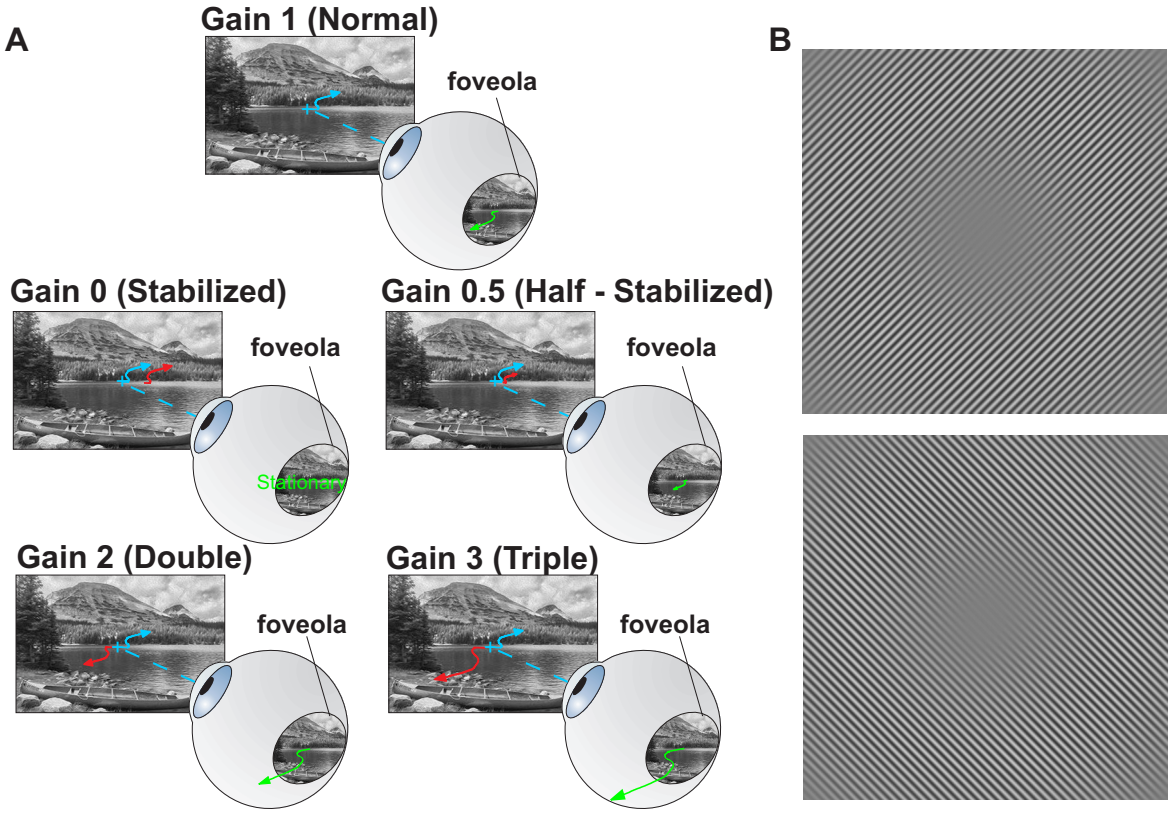


Figure 3: A: Experimental conditions. A gain is applied to drift to reduce (gain < 1) or amplify (gain > 1) retinal image motion. B: Stimulus examples with 1-degree scotoma. The stimulus contrast ramped in linearly over a period of 500ms then plateaued for a period of 800ms after which the subject responded with the orientation of the grating stimulus (left or right tilt).

The contrast of the stimulus varied from trial to trial following the PEST procedure (Hall, 1981).

4 Experiment Results

The analysis code that analyzes the data and makes the following graphs are in the folder
`https://gitlab.com/jintoy/DriftGainGrating/tree/master/DataAnalysis_Janis`
The original data (valid trials) are located on cas:
`//casfsb/APLAB/JanisData/CopyOfNorickData/Scotoma/data` and the most recent results and figures are located in:
`//casfsb/APLAB/JanisData/APLab/DriftGain/local_2017-08-30`

Trials in which track of the eye were lost and trials in which the subject blinked or made a saccade or microsaccade during stimulus presentation were eliminated from analysis. A summary of trial counts is presented in **Table 1**.

4.1 Stabilized vs. Unstabilized

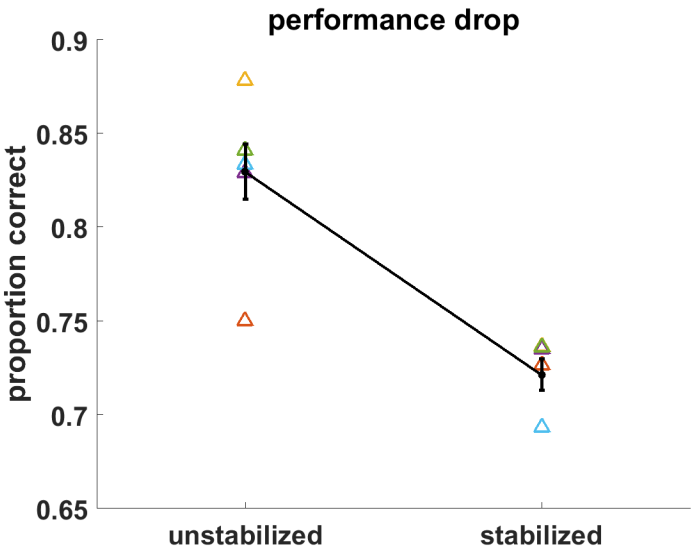


Figure 4: Performance at the same contrast level falls when the stimulus is stabilized.

4.2 Eye Movement Data

Diffusion coefficients are estimated using the routine in `https://gitlab.com/aplabBU/Modeling/blob/master/BrownianMotion/CalculateDiffusionCoef.m`. D_E is calculated using the raw eye movement traces.

D_R is calculated from the differences between the eye movement trace (x_E, y_E) and the movement of the image on the monitor (x_M, y_M):

$$x_R = (x_E - x_I) \cdot 1.46$$
$$y_R = (y_E - y_I) \cdot 1.46$$

where 1.46 is the amplification factor to convert external motion to motion on the retina. (MR has a note on this on the wiki page.)

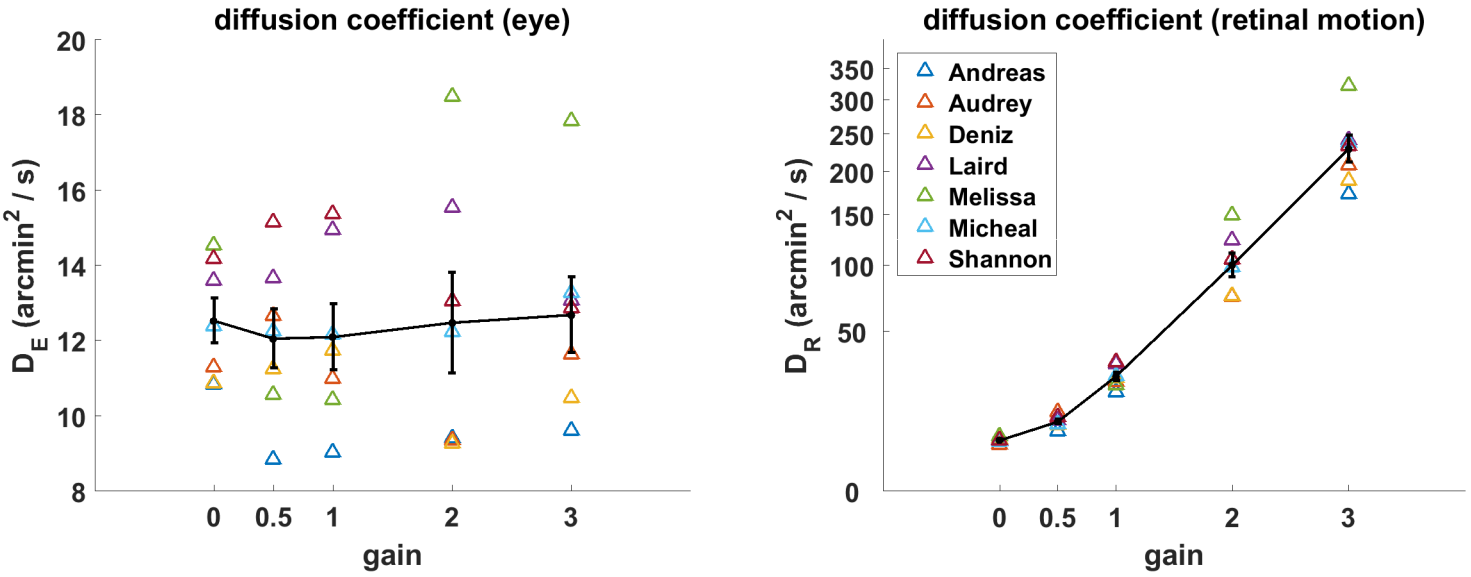


Figure 5: LEFT: Diffusion coefficient of the eye remained unchanged in the different gain conditions. RIGHT: Diffusion coefficient of the image on the retina increased with increasing gains. Since D_E remained relatively constant across gain conditions for each subject, applying the gain had the expected effect of decreasing or increasing retinal image motion.

4.3 Contrast sensitivities

Contrast sensitivities were estimated for each gain condition. Using drift only trials, 75% contrast thresholds were estimated by fitting a psychometric function to the performance data (Wichmann and Hill, 2001 procedure implemented in `https://gitlab.com/aplabBU/Utilities/tree/master/psyfun`.

Psychometric curves for individual subjects are shown in **Figures 14, 15, 16**. Thresholds are converted to Michelson contrast sensitivity.

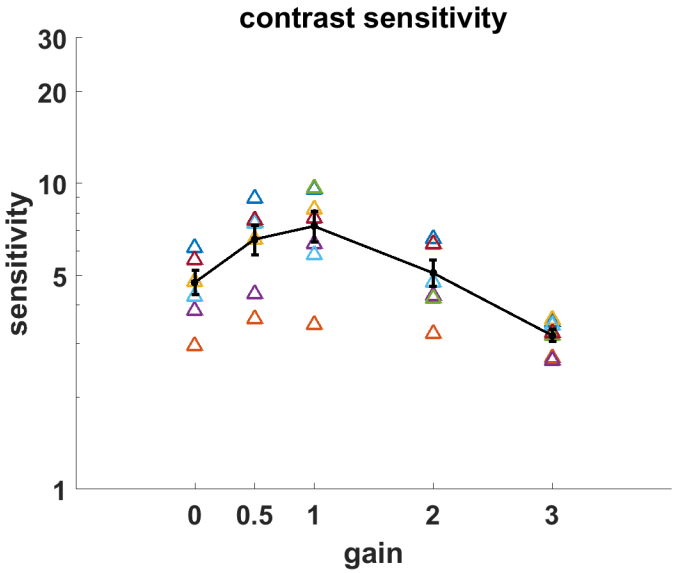


Figure 6: Contrast sensitivity at each gain condition.

5 Comparison of Data and predictions

To compare the experimental data with the predictions, the prediction curve $P(D_R)$ was scaled and translated to best match the contrast sensitivities $\log_{10}(C(D_R))$ by find the coefficients β_i that minimize $(\log_{10}(C(D_R)) - (\beta_1 P(D_R) + \beta_0))^2$. In this case data for all subjects were included in the regression. This procedure was also done for two types of data normalization (mean CS removed from each individual and normalization to each individual peak).

The next three subsections (5.1-5.3) show the fits of the Human and M-cell models to the data.

5.1 No CS normalization

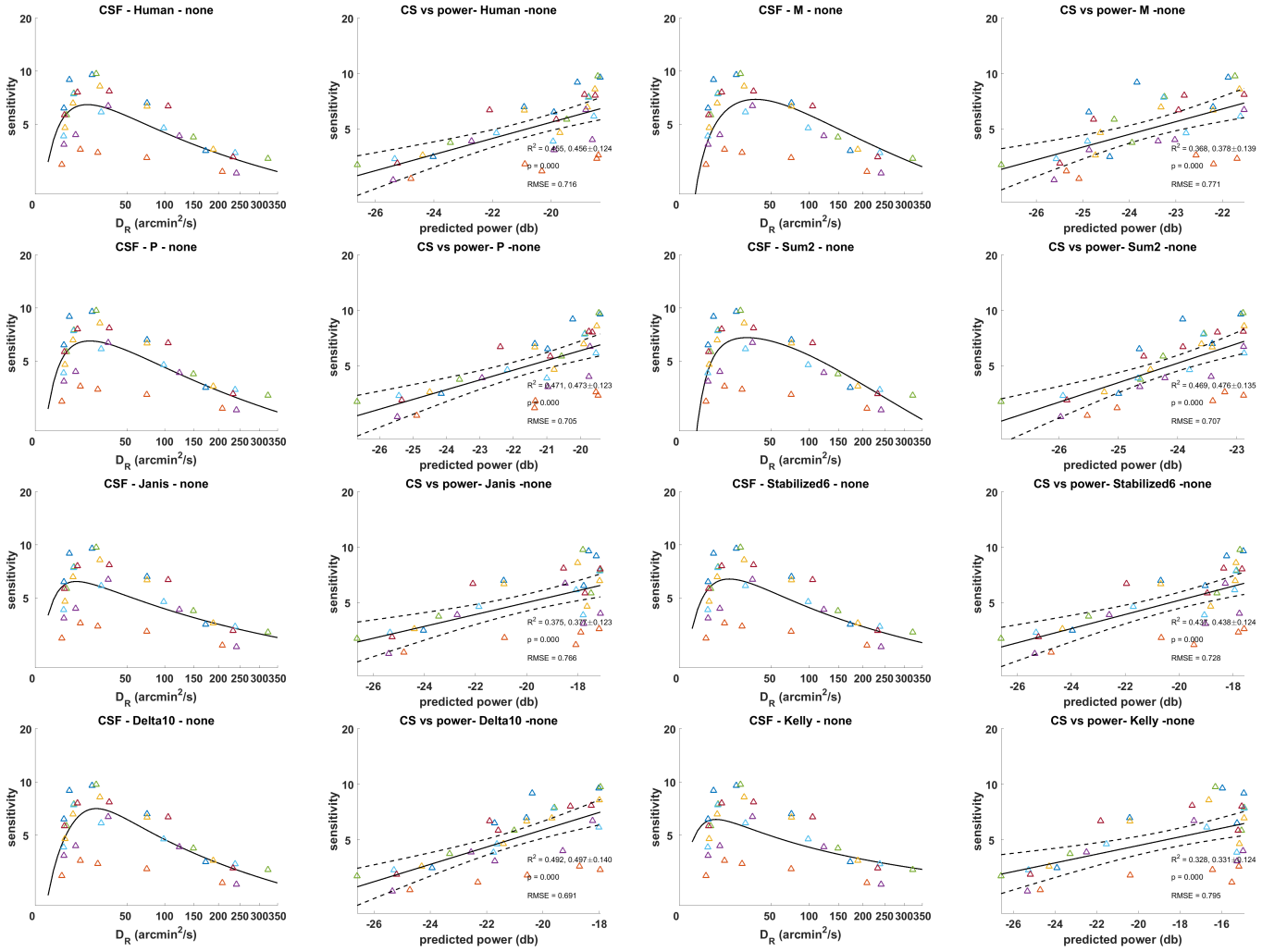


Figure 7: Same contrast sensitivity data as Figure 4 plotted now against the amount of image motion on the retina D_R.

5.2 mean-subtracted CS

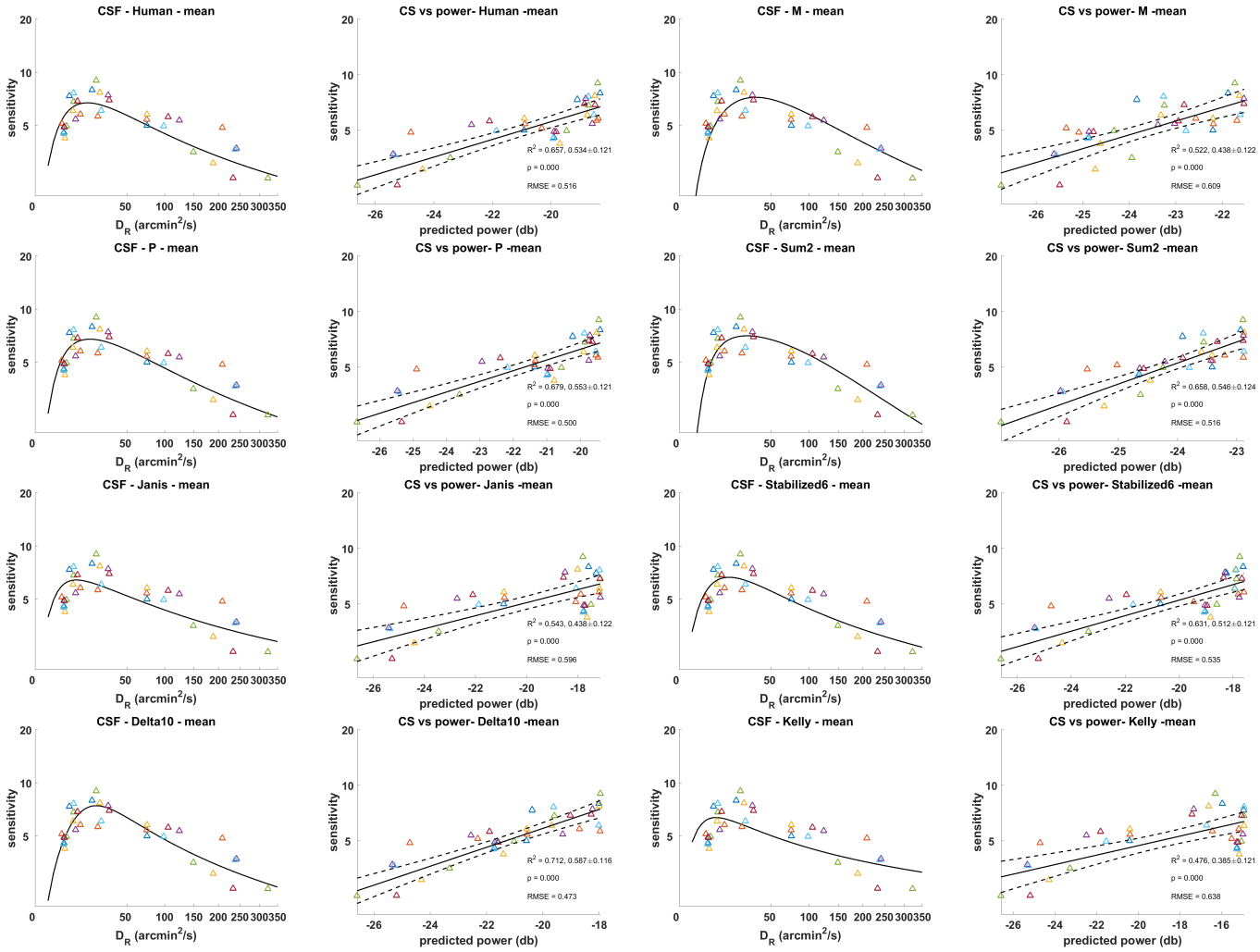


Figure 8: Mean CS for each subject subtracted. Global mean added back in for everyone.

5.3 normalized to max

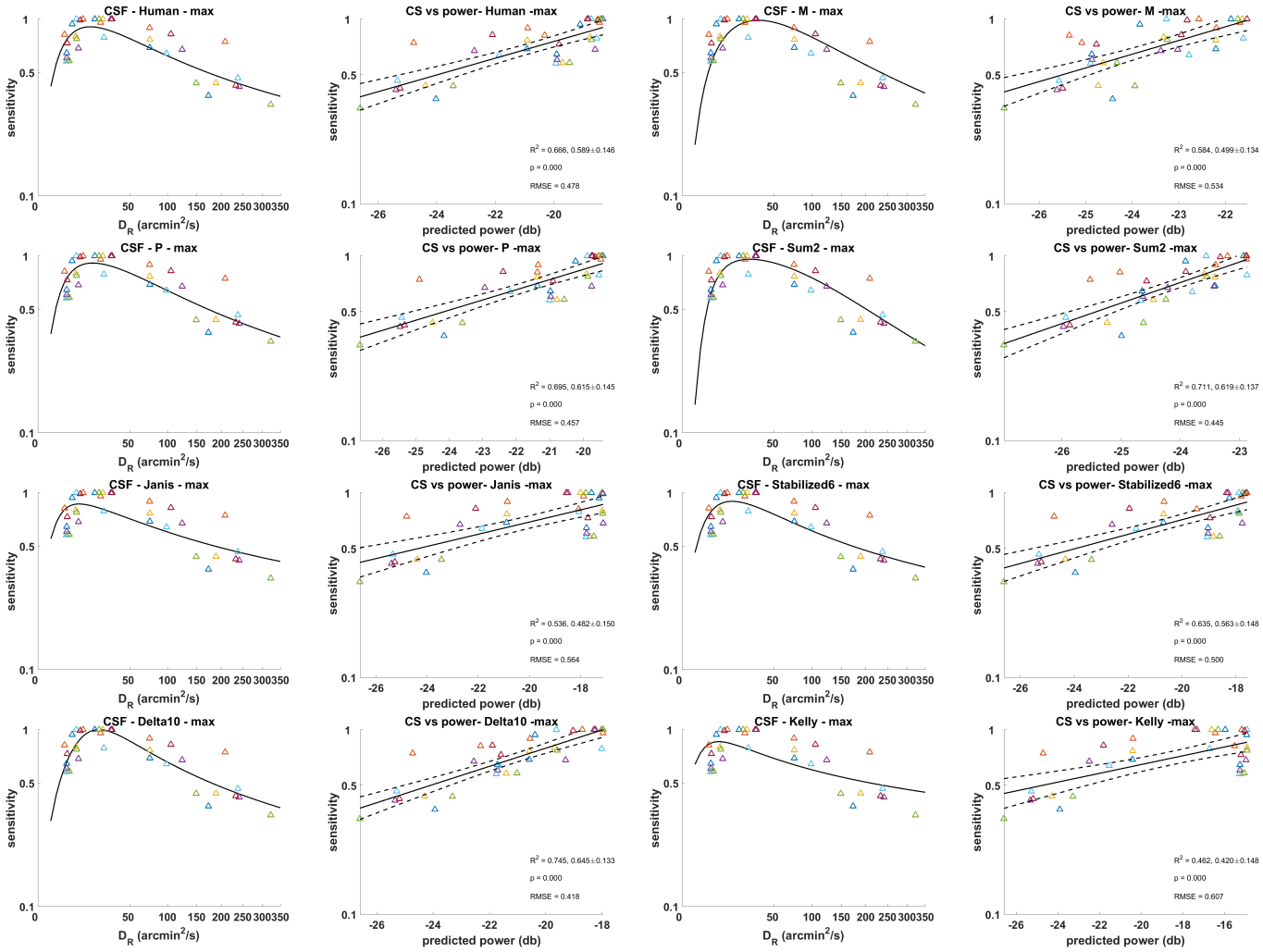


Figure 9: CS for each subject normalized to peak.

5.4 normalized to prediction

Here we normalize each individual's data to the model. So, we do the regression between the CS data and prediction curve as above but now transform the CS data in the prediction space (instead of vice versa as we do above).

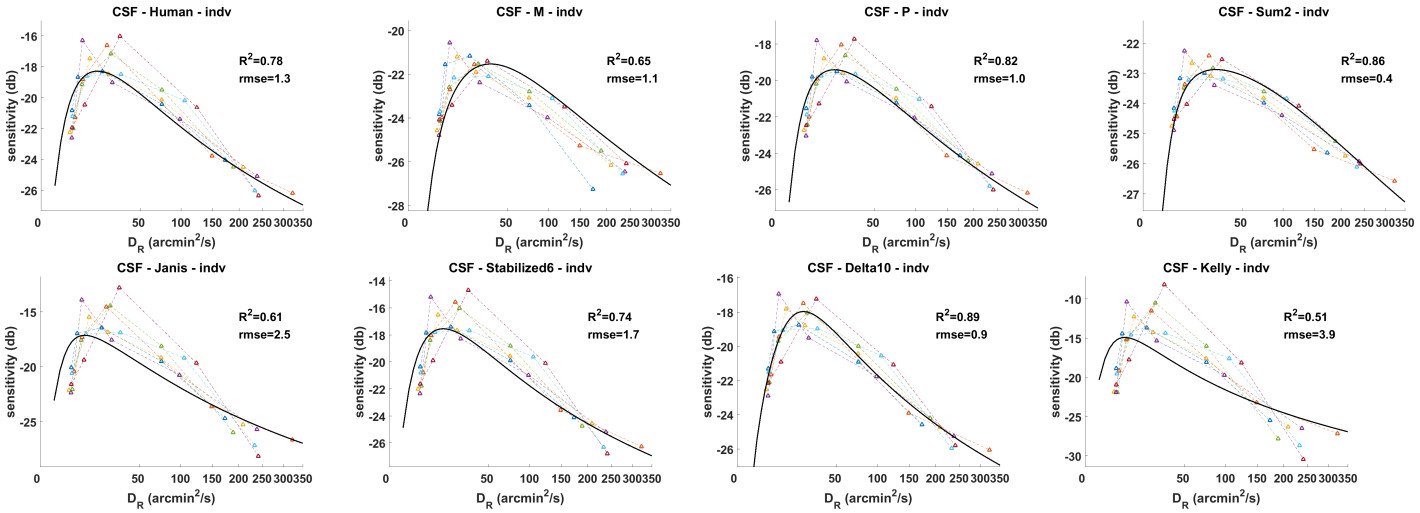


Figure 10: CS for each subject normalized to the prediction. In this case the regression of the cs data with the model is done for each individual, and the parameters from the linear regression are the parameters that normalize the cs data to the prediction.

5.5 Optimal tCSF

Here we attempt to determine the temporal sensitivity profile that would result in an optimal fit of the data to the resulting prediction.

I originally intended to fit these by simple linear regression (where X is the temporal power produced by the 5 different D_R and the dependent variable are the contrast sensitivity values). However, without contraints on the shape of the function the 'optimal' tCSF turned out to be nonsense. Instead, I optimized the parameters of a gamma distribution: k and θ.

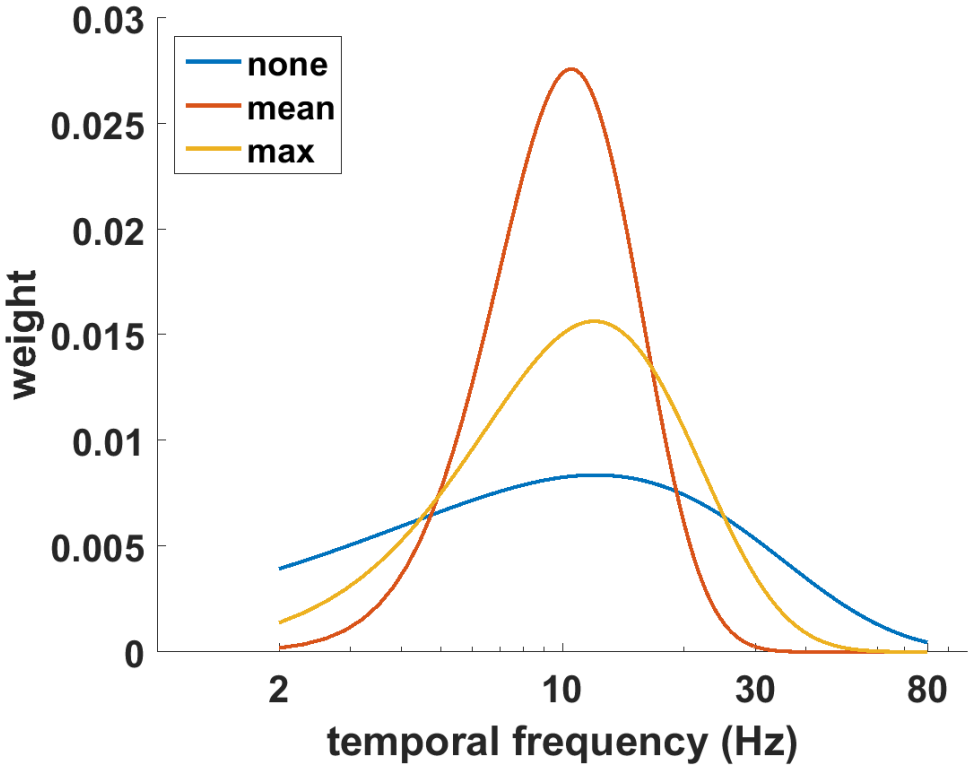


Figure 11: Optimal temporal contrast sensitivity curves for different normalization methods and including all subjects. These were fit by minimizing the MSE beween the data and the prediction over the k and θ parameters of a gamma distribution. It seems that a band around 10Hz is optimal across all subjects.

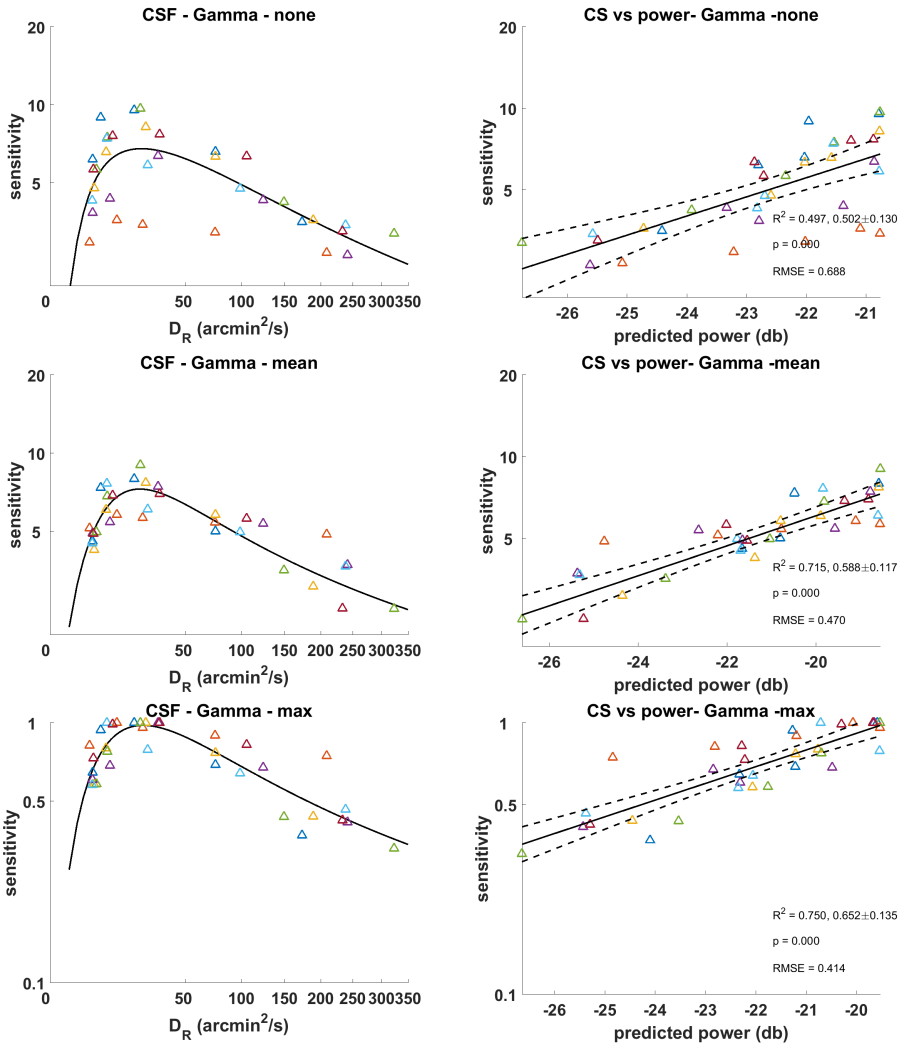


Figure 12: Fits of predictions to data using optimal temporal contrast sensitivity curves.

6 Supplemental

- Model details.
- M-cell prediction curves.
- Diffusion coefficients of motion orthogonal and parallel to grating stimuli (pretty much the same).

6.1 Drift characteristics were consistent in different gain conditions.

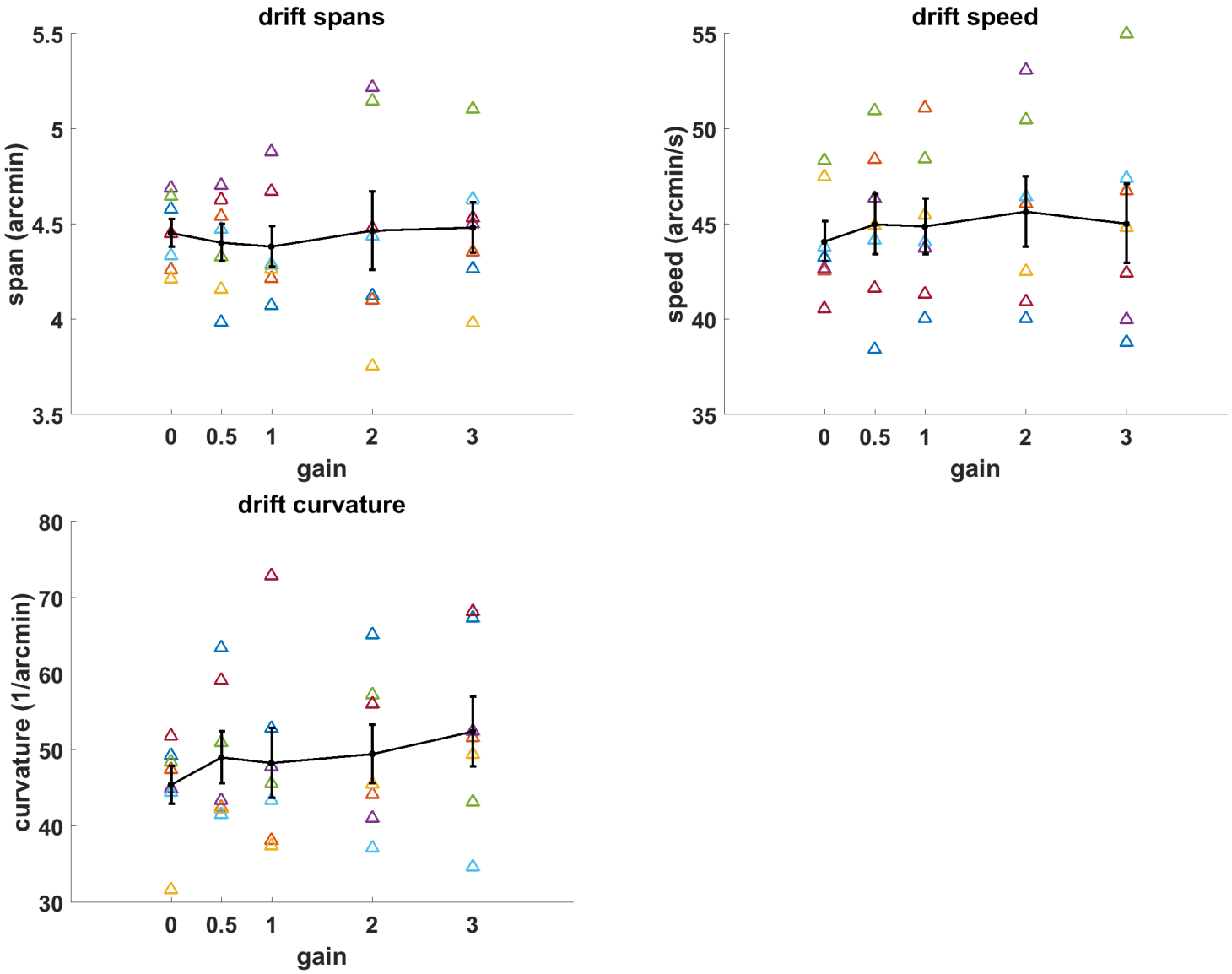


Figure 13: On average, drift characteristics did not change across gain conditions.

7 Individual Results

(Second row for each subject is the number of near-threshold trials.)

7.1 Trial Counts

		Valid Trials					Invalid Trials		
Subject	Total	Gain = 0	Gain = 0.5	Gain = 1	Gain = 2	Gain = 3	ND/NT/B	S	MS
Andreas	1481	127	170	123	145	278	205	226	207
		90	118	81	84	157			
Audrey	1360	170	205	189	181	182	271	76	86
		84	125	88	75	83			
Deniz	1840	147	167	141	107	125	596	325	232
		91	74	83	72	74			
Laird	1600	227	251	194	245	241	13	185	244
		132	146	126	141	107			
Melissa	1479	203	194	143	155	165	202	97	320
		106	107	90	91	115			
Micheal	1440	100	127	137	115	207	283	83	388
		54	94	104	92	116			
Shannon	1320	175	191	125	156	177	330	140	26
		75	131	78	93	101			

Table 1: Trial counts by subject. ND = no data. NT = no track. B = blink. S = saccade. MS = microsaccade.

7.2 Trial Counts Near Gain = 0 Threshold

Subject	**Gain = 0**	Gain = 0.5	**Gain = 1**	Gain = 2	Gain = 3
Andreas	90	102	68	97	46
Audrey	84	93	88	89	55
Deniz	91	104	74	84	77
Laird	132	117	76	109	104
Melissa	106	90	44	79	24
Micheal	54	36	19	72	108
Shannon	75	115	54	92	9

Table 2: Trial counts near gain = 0 threshold. Subject Micheal is eliminated from this analysis for too few data.

7.3 Contrast Threshold Estimations

Matlab figures for the psyfit functions that have the fit values are located in `//casfsb/APLAB/JanisData/APLab/DriftGain/local_2017-06-02/Figures`

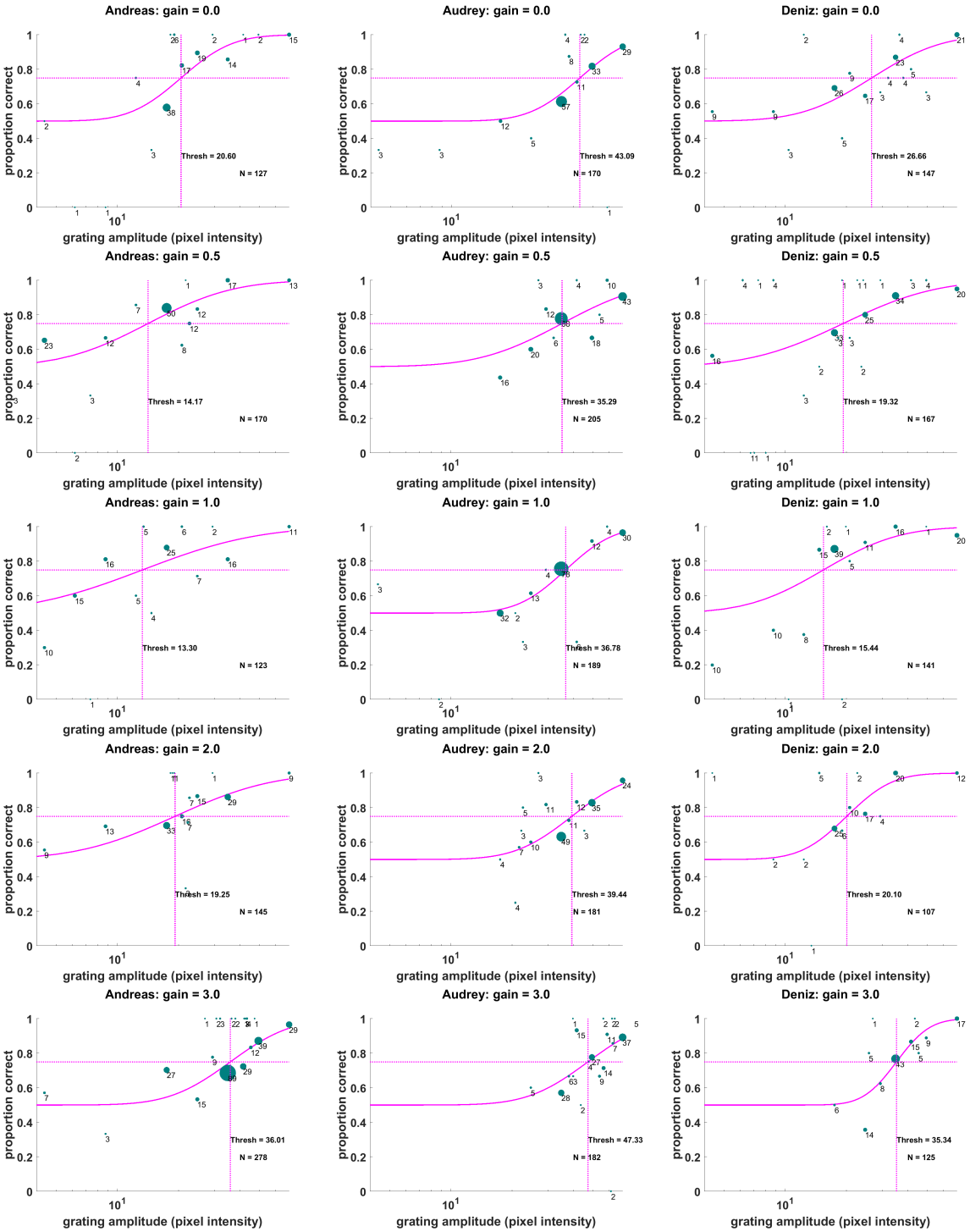


Figure 14: Andreas, Audrey, Deniz

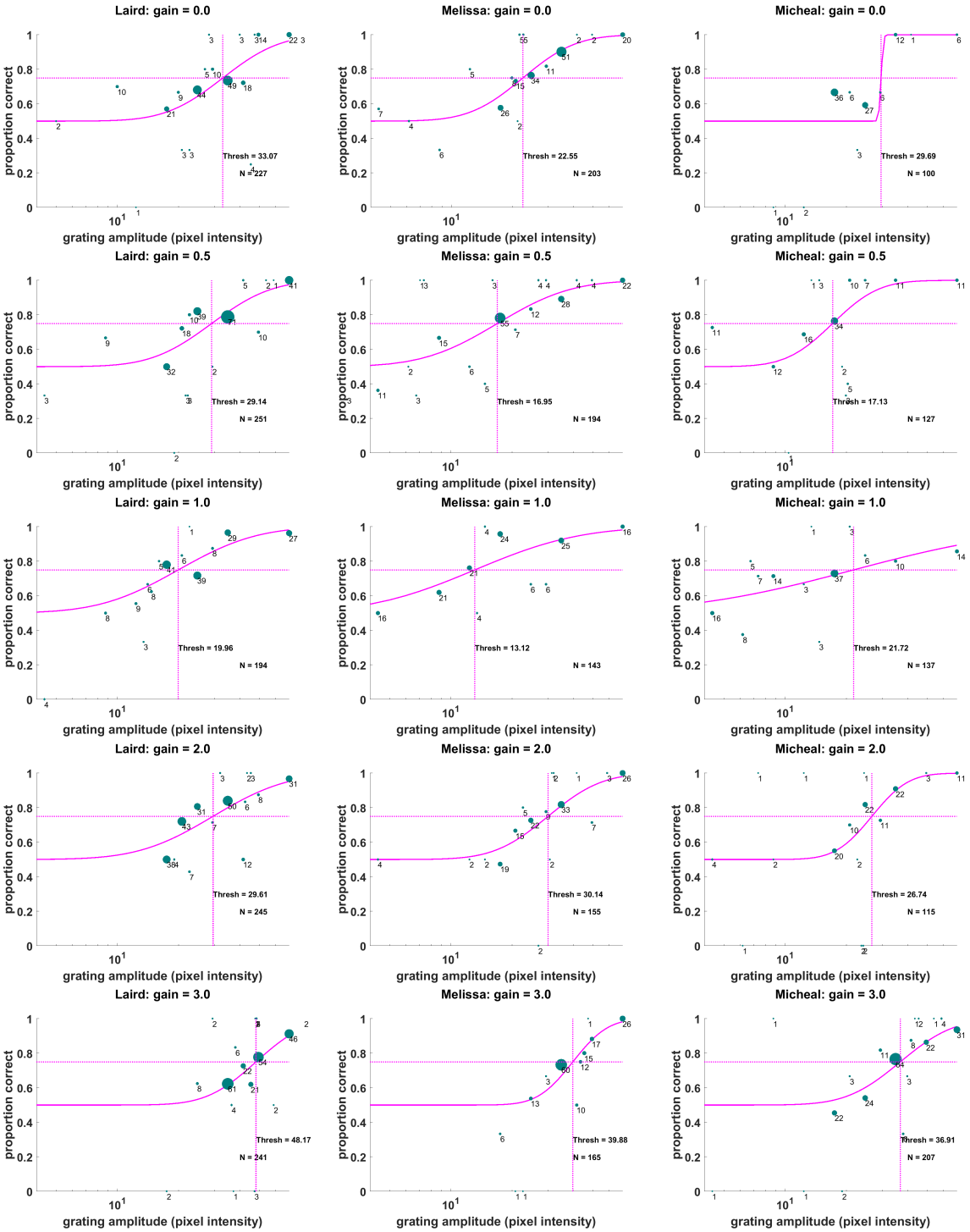


Figure 15: Laird, Melissa, Micheal

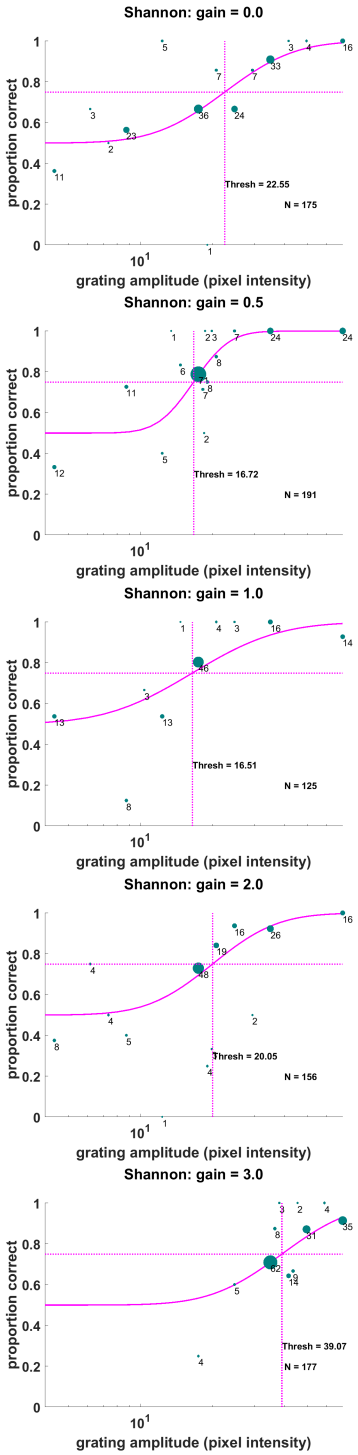
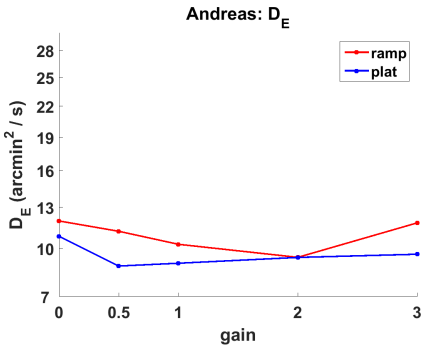
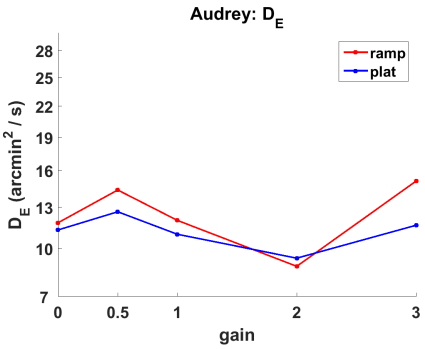
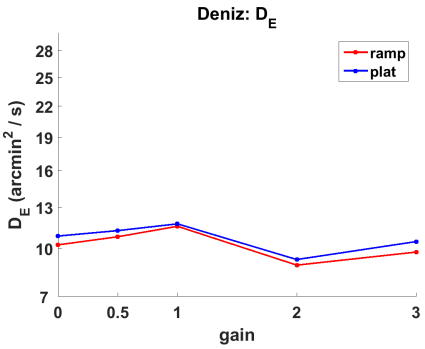


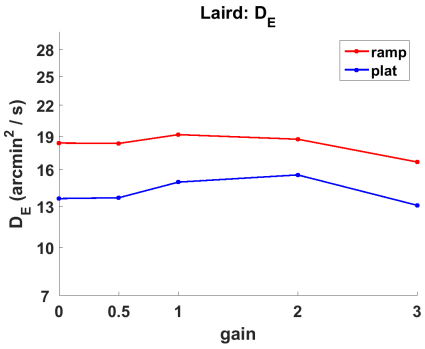
Figure 16: Shannon

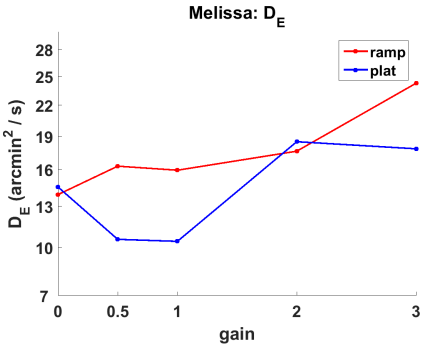
7.4 Diffusion Coefficient of the Eye

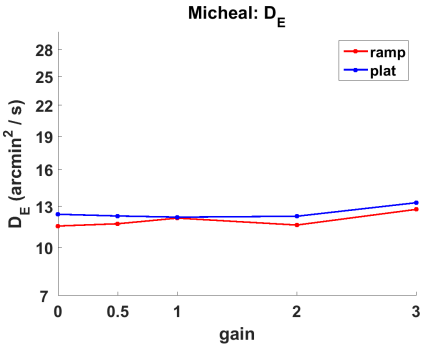


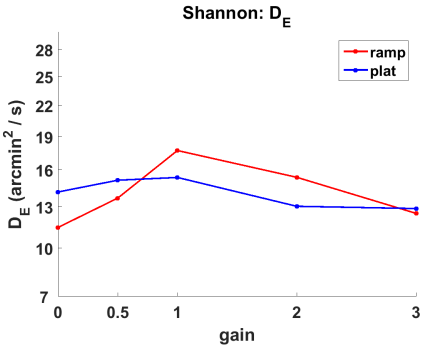




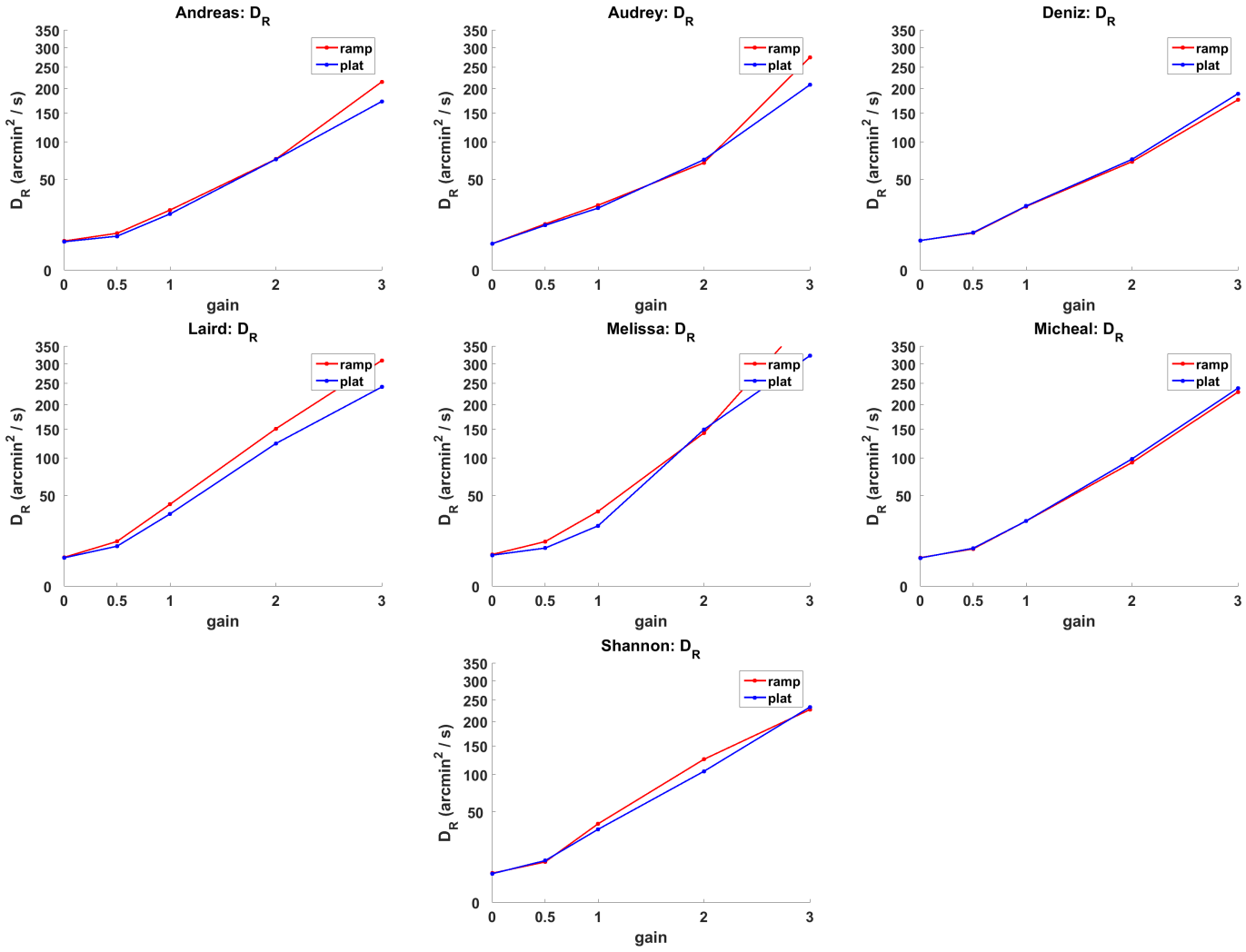




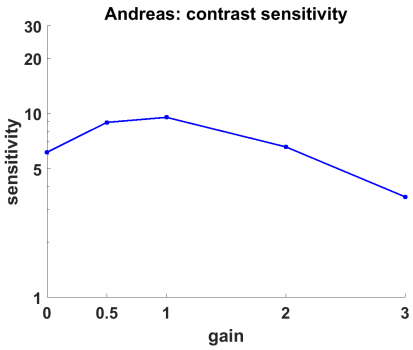


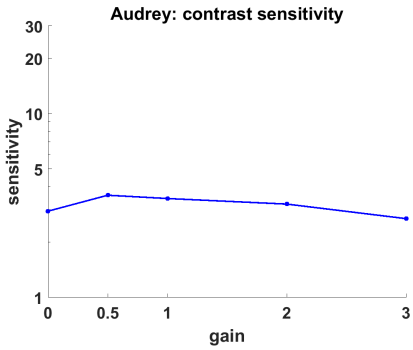


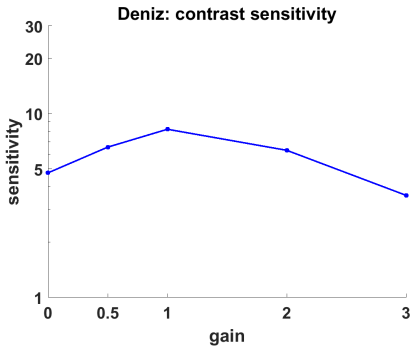
7.5 Diffusion Coefficient on the Retina

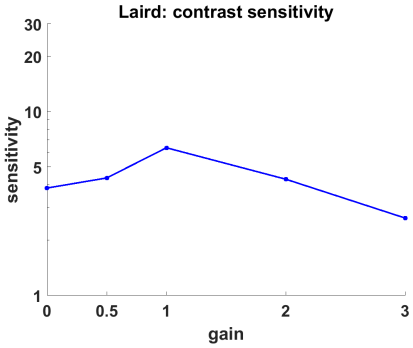


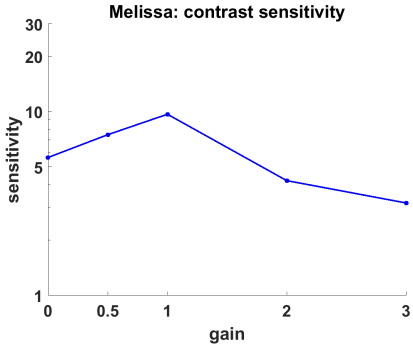
7.6 Contrast sensitivities

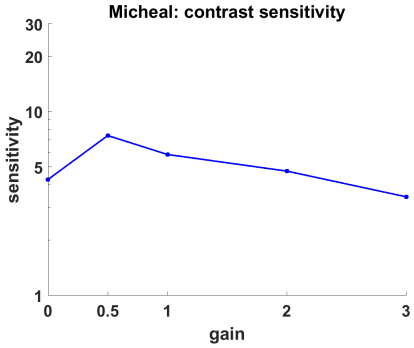


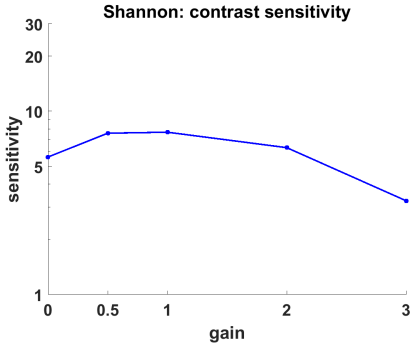






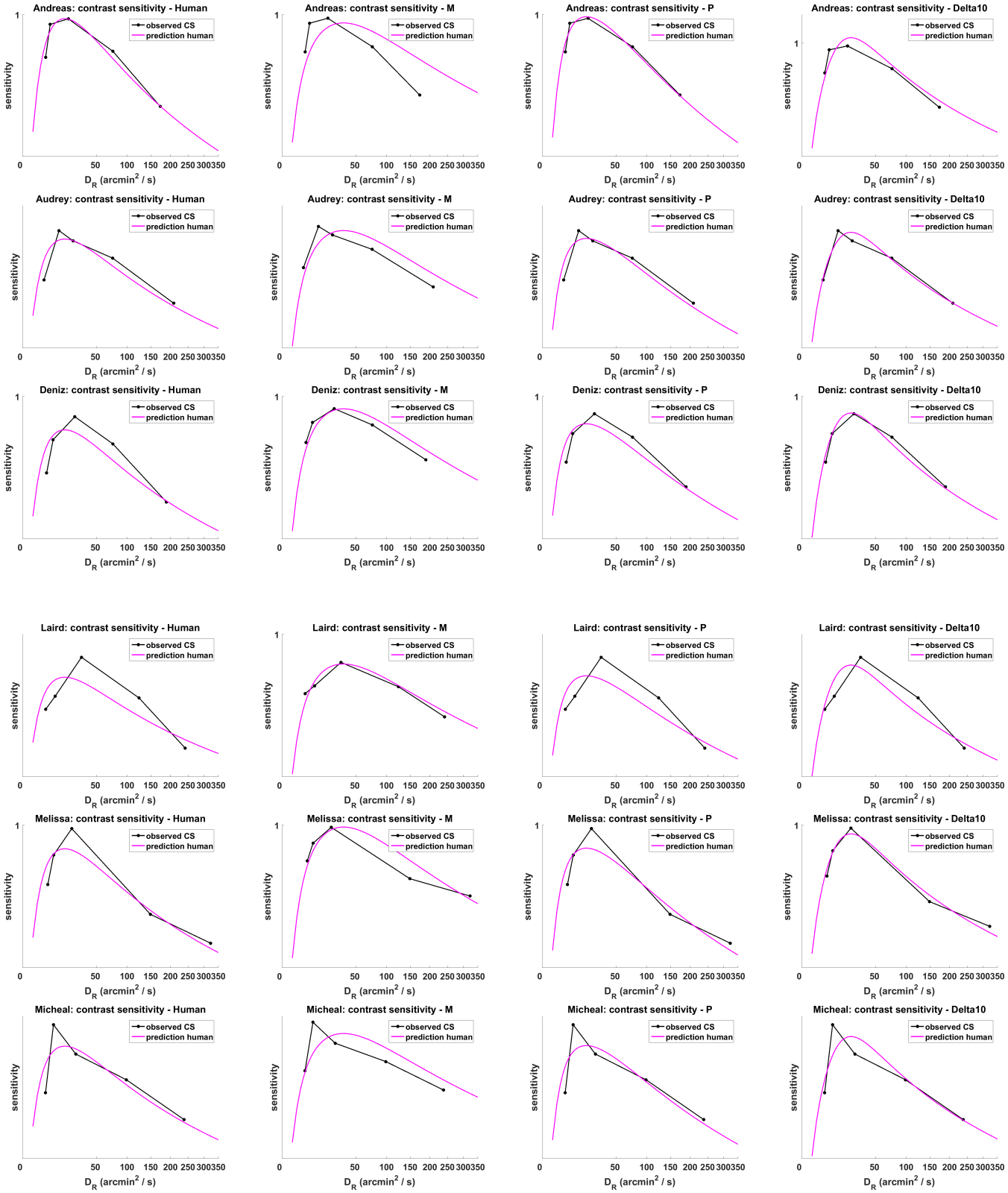


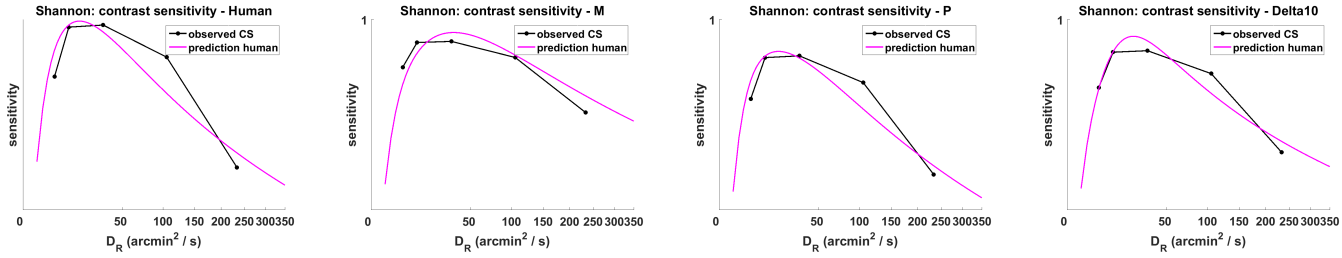




7.7 Contrast sensitivities with prediction curves

Here the prediction curves were scaled and translated to each individual's data.



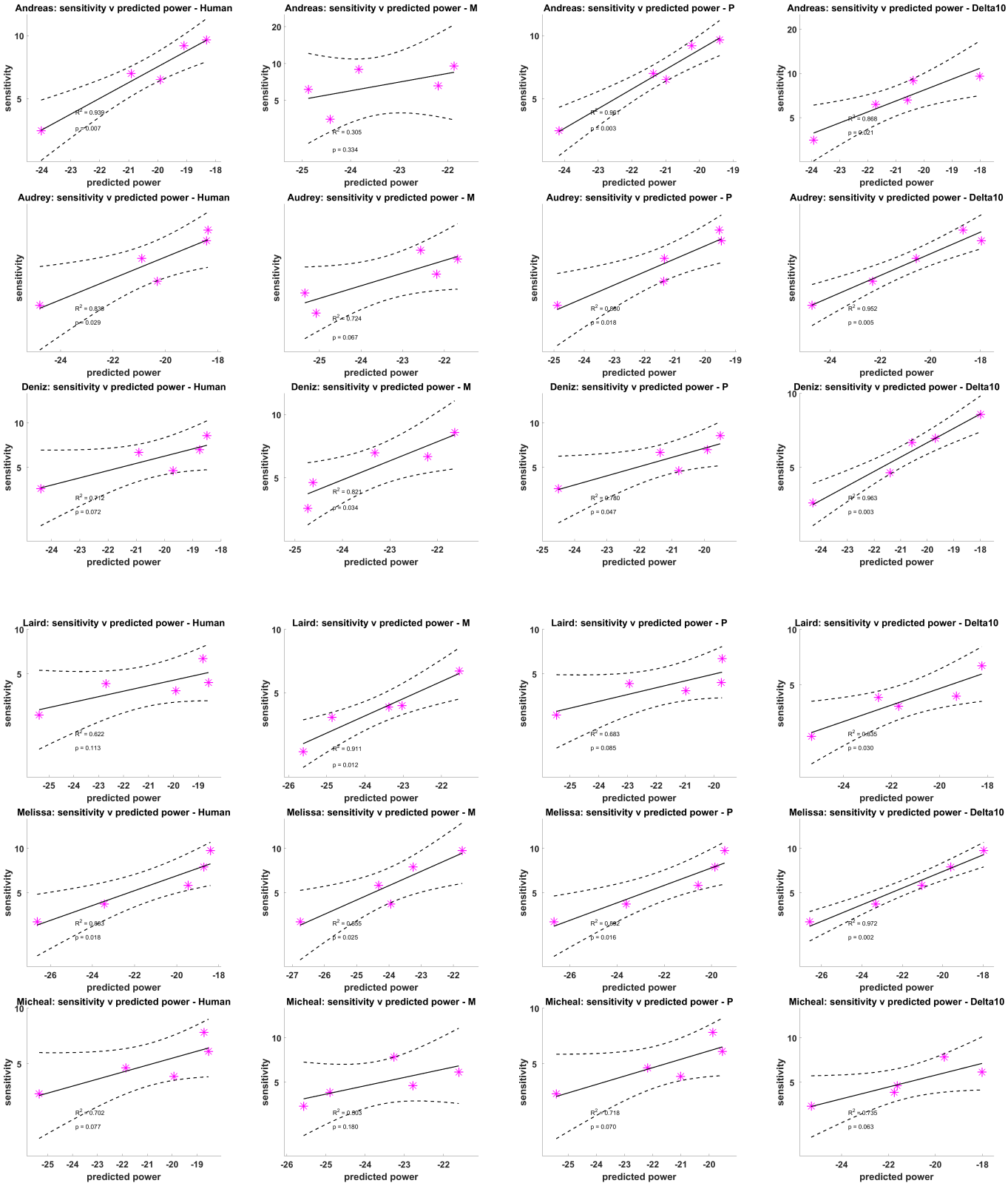


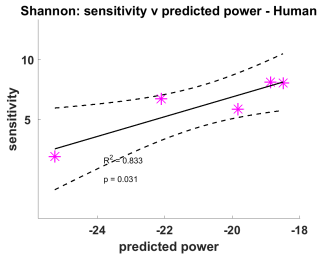
	Human		M cell		P cell		10Hz
	> 2Hz	> 0Hz	> 2Hz	> 0Hz	> 2Hz	> 0Hz	
1	**.939**		.305		**.961**		**.868**
2	**.838**		.724		**.860**		**.952**
3	.712		**.821**		**.780**		**.963**
4	.622		**.911**		.683		**.835**
5	**.883**		**.855**		**.892**		**.972**
6	.702		.503		.718		.735
7	**.833**		.772		**.868**		**.912**

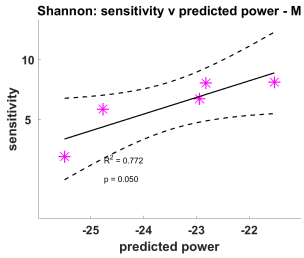
Table 3: R^2 values by subject and model. Values in bold have $p < 0.05$

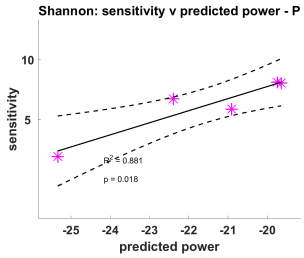
7.8 Contrast sensitivities versus prediction curve

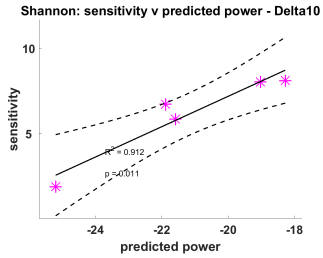
Here the prediction curves were scaled and translated to each individual's data.




Shannon: sensitivity v predicted power - Human
sensitivity
predicted power
R² = 0.833
p = 0.031


Shannon: sensitivity v predicted power - M
sensitivity
predicted power
R² = 0.772
p = 0.050


Shannon: sensitivity v predicted power - P
sensitivity
predicted power
R² = 0.881
p = 0.018


Shannon: sensitivity v predicted power - Delta10
sensitivity
predicted power
R² = 0.912
p = 0.011

7.9 Optimal tCSF

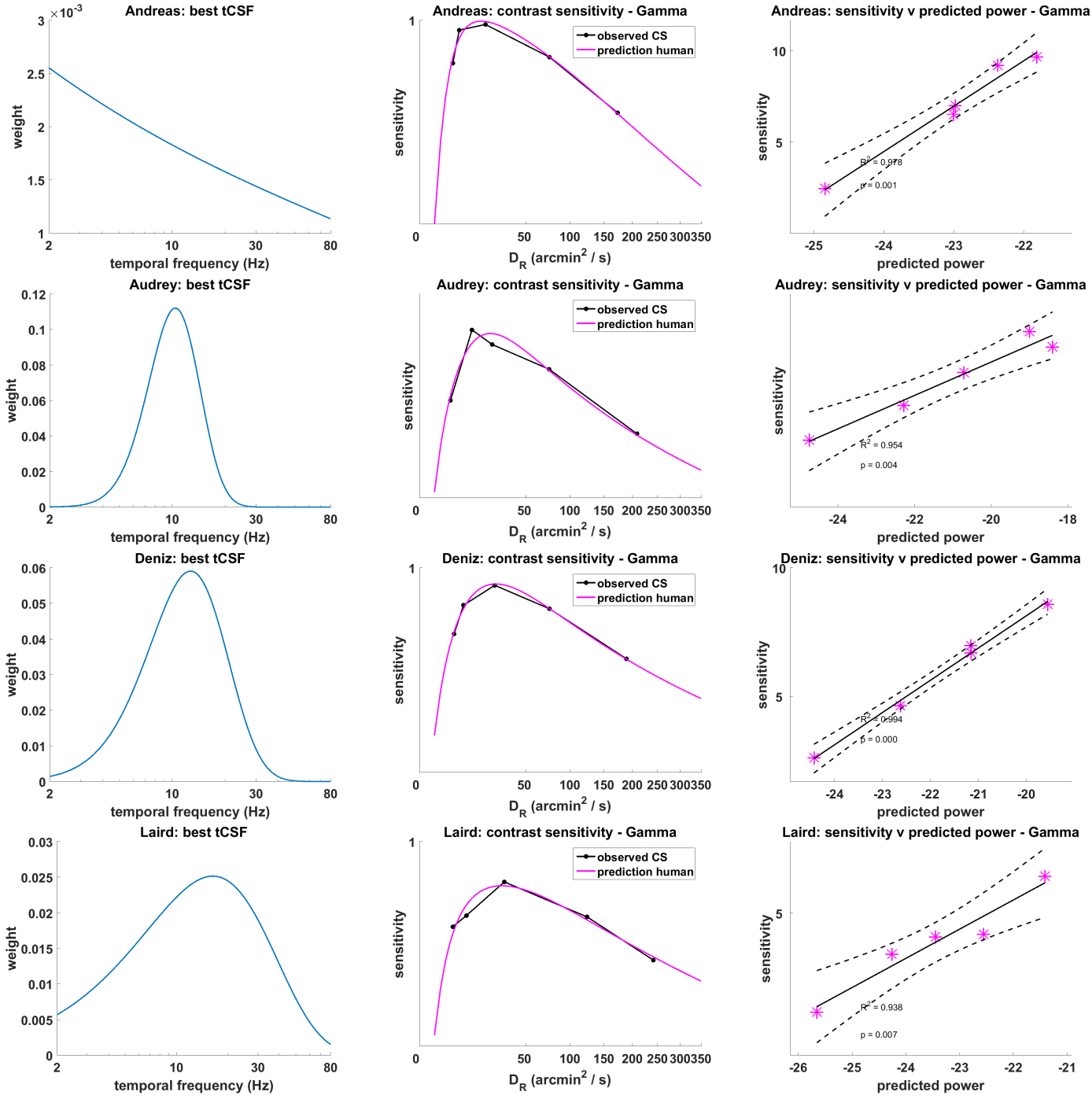


Figure 17: Individual predictions using optimal temporal senstivity functions.

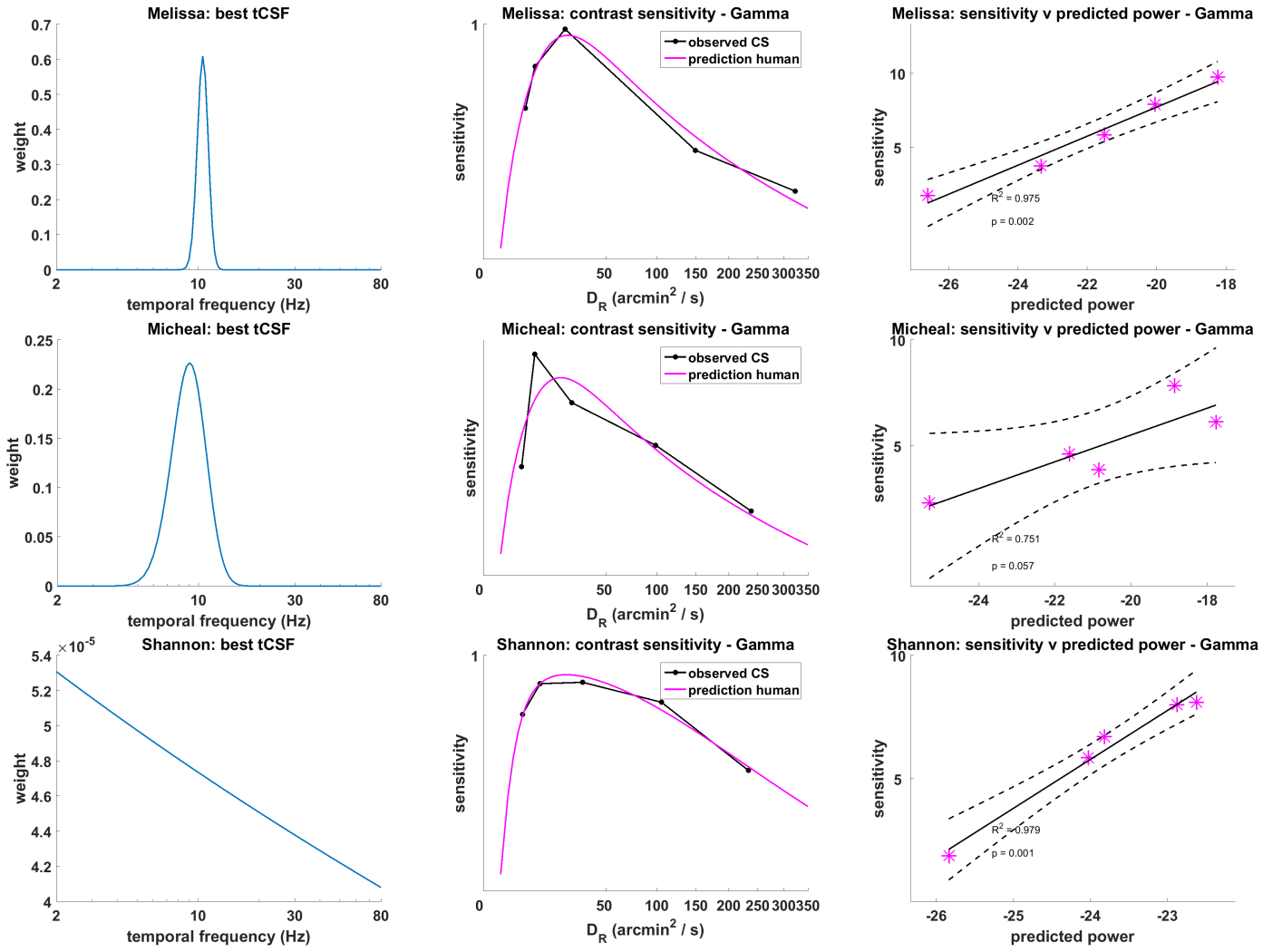


Figure 18: Individual predictions using optimal temporal senstivity functions.