Nitric oxide mediates differential effects in mouse retinal ganglion cells

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Neuromodulators have major influences on the regulation of neural circuit activity across the nervous system. Nitric oxide (NO) is a prominent neuromodulator in many circuits, and has been extensively studied in the retina across species. NO has been associated with the regulation of light adaptation, gain control, and gap junction coupling, but its effect on the retinal output, specifically on the different types of retinal ganglion cells (RGCs), is still poorly understood. Here, we used two-photon Ca^{2+} imaging to record RGC responses to visual stimuli to investigate the neuromodulatory effects of NO on the cell type-level in the *ex vivo* mouse retina. We found that about one third of the RGC types displayed highly reproducible and cell type-specific response changes during the course of an experiment, even in the absence of NO. Accounting for these adaptational changes allowed us to isolate NO effects on RGC responses. This revealed that NO affected only a few RGC types, which typically became more active due to a reduction of their response suppression. Notably, NO had no discernible effect on their spatial receptive field size and surround strength. Together, our data suggest that NO specifically modulates suppression of the temporal response in a distinct group of contrast-suppressed RGC types. Finally, our study demonstrates the need for recording paradigms that takes adaptational, non-drug-related response changes into account when analysing potentially subtle pharmacological effects.

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Introduction

The retina can be considered as a visual signal processor with a straightforward functional architecture (1–3). The photoreceptors convert the stream of photons from the environment into an electrical signal, which is relayed downstream by the bipolar cells (BCs) to the retinal ganglion cells (RGCs), the tissue's output neurons. Along this vertical pathway, the visual signal is shaped by two lateral, inhibitory cell classes: horizontal cells in the outer and amacrine cells (ACs) in the inner retina. The resulting intricate networks allow sophisticated computations, reflected in the >40 output channels that relay diverse visual feature representations as spike trains to higher visual brain regions (4–6).

Over the past decades, the retinal synaptic networks have been intensively studied, which greatly broadened our understanding of early visual signal processing (7–12). Specifically, the availability of connectome data for large parts of the retina helped in unprecedented ways, as can be seen from studies, for example, investigating direction-selective circuits and their precise wiring regarding starburst ACs and direction-selective RGCs (e.g., (13, 14)).

What is not well-captured by connectomic approaches are 'wireless' interactions mediated by neuromodulators, which comprise a broad variety of very different small molecules, including monoamines (e.g., dopamine (15, 16), histamine (17, 18), serotonin (19)), endocannabinoids (20–22), gasotransmitters such as nitric oxide (NO) (23, 24)), as well as a variety of neuropeptides (e.g., neuropeptide Y (25, 26)). Only few of the >20 neuromodulators (27) found in the retina are released from centrifugal fibers (e.g., histamine and serotonin (17–19, 28)), whereas most of them are released in addition to GABA or glycine by ACs (27, 29–32). Neuromodulators have long been implicated in adapting the retina to different contextual states necessary to robustly perform in a highly dynamic visual environment (e.g., (33–36)). For instance, dopamine (DA) is released by a distinct type of AC (37–40), and has been shown to regulate light adaptation (33, 41, 42) via several cellular mechanisms, such as modulation of gap-junction coupling (34, 43–45) and intrinsic conductances (46, 47). More recently, histamine was proposed to shape the retinal code in a top-down modulatory manner related to the animal's arousal state (17, 28). For several neuromodulators, the retinal release sites and receptors are known and their effects on cellular properties have been described, however, a comprehensive, function-oriented and cell-type view of these neuromodulators' functional implications and contributions to visual signal processing is only slowly emerging (e.g., (17, 48)).

One of the better-studied neuromodulators in the retina is NO. Neuronal nitric oxide synthesis (nNOS) is considered the dominant enzyme producing NO relevant for retinal signal processing, and – depending on species – was shown to be present in different retinal cell classes (49–57). In the mouse retina, nNOS was mainly found in specific ACs (36, 58–60). A few years ago, Jacoby et al. (36) demonstrated that one of those AC types (nNOS2-AC) controls the light-dependent release of NO in the inner retina. NO can function via two main pathways (61): (*i*) it can bind to the NO guanylate cyclase (NO-GC; also referred to as soluble guanylate cyclase (sGC)) receptor, triggering the production of the second messenger

cyclic guanosine monophosphate (cGMP), which binds to downstream targets (55, 62, 63), and (*ii*) via S-nitrosylation (cGMP-independent) by directly modifying certain receptor and channel proteins (64, 65).

The effects of NO have been primarily linked with light adaptation and the transition between scotopic and photopic signaling pathways via a number of mechanisms, including uncoupling the gap junctions between AII ACs and On-cone BCs (66), increasing the gain of On-cone BCs in response to dim light (67, 68), and modulating the gain of Off-cone BCs (69, 70). At the retina's output level, increasing NO was found to decrease On- and Off-responses in RGCs (71). Notably, genetically knocking-out nNOS also led to a reduced light sensitivity in RGCs (72). Additionally, NO has been shown to modulate RGC responses via cGMP by altering their cGMP-gated conductances (73, 74). Taken together, NO can act on different levels and via different pathways in the retina. However, the function of NO at the cell-type level and its role in early visual processing are far from understood.

Here, we systematically studied the functional role of NO and its effects on the different retinal output channels in *ex vivo* mouse retina. Surprisingly, we observed highly reproducible, cell type-specific changes in the light responses of some RGCs already in the absence of pharmacological manipulation. To account for these adaptational response changes, we developed a recording paradigm to measure 'paired' RGC responses under control and drug conditions. We found that NO had a highly selective effect on a distinct set of three suppressed-by-contrast RGCs, where NO strongly and differentially reduced the suppression in their temporal responses. Yet, NO had no discernible effects on their spatial receptive field properties. Together, our data suggest that NO modulates the visual feature representation of the retinal output in a highly selective and type-specific manner.

Results

To investigate NO effects systematically on the retinal output, we performed population imaging from somata in the ganglion cell layer (GCL) of *ex vivo* mouse retina electroporated with the synthetic Ca^{2+} indicator Oregon Green BAPTA-1 (Fig. 1a-c; Methods). To identify the different types of RGCs and detect potential NO-induced response changes, we presented a set of visual stimuli, including full-field chirps, moving bars (Fig. 1d), and binary dense noise (5).

A protocol for 'paired' control/drug recordings. Previous studies have shown that retinal responses recorded with two-photon Ca^{2+} imaging can be systematically affected by experimental factors, such as excitation laser-induced activity, photoreceptor bleaching, and temporal filtering due to Ca^{2+} buffering by the fluorescent indicator (75–77). These changes can be summarized by the umbrella term 'batch effects' (a term coined in the molecular genetics field), which can confound the biological signal and potentially cause erroneous interpretations of the data (77, 78). Such batch effects may play a role when, as in our study, data are recorded in a sequential manner to infer possible drug effects.

Because we wanted to detect potentially subtle NO effects, we devised a protocol to make experiments as comparable as possible (Fig. 1e). After placing the tissue into the recording chamber, it was allowed to recover from the electroporation for 15 min, before we light-adapted the retina for 10 min by presenting the dense noise stimulus. We then selected retinal recording fields, each of which was recorded twice for the complete stimulus set in an interlaced manner (Fig. 1e). The first field was recorded twice without perturbation (*control-control pair*). For the next field, we added the drug to the perfusion medium and incubated the tissue for approx. 15 min, before recording the field for the second time (*control-drug pair*).

Using this protocol, we recorded the following paired datasets: (*i*) a control dataset to test response stability, i.e., Ctrl 1 and Ctrl 2, (*ii*) a strychnine dataset to test the protocol for a drug with well-described effects, i.e., Ctrl 1 and Strychnine (1 µM), and *(iii)* a NO dataset to infer NO-induced response changes, i.e., Ctrl 1 and NO (DETA/NO; 100 µM). The control dataset was leveraged to reveal NO-induced effects on the background of potential nonspecific response changes over the course of the experiment.

For the following analyses, we used 3,864 paired RGCs (n_{Ctrl}=1,590; n_{NO}=1,838, $n_{strychnine}$=436) that fulfilled our response quality filtering (see Methods).

Identifying functional RGC types using a classifier. The mouse retina contains more than 40 RGC types (5, 6). As we wanted to investigate if the tested drugs differentially affect the different retinal output channels, we applied an RGC classifier (Fig. 2a) (79), which had been trained and validated on a previously published RGC Ca^{2+} imaging dataset (5). The classifier predicts an GCL cell's functional type based on soma size and the responses to chirp and moving bar stimuli (Methods). While the classifier also identifies displaced ACs, we focused our analysis on RGCs. To match the conditions under which the classifier's training data was acquired as closely as possible, we predicted types based on the responses from the first control recording (Ctrl 1). To minimize classification uncertainty, we additionally discarded cells with low confidence scores (< 0.25, see Methods for details).

We found that the distributions of the predicted RGC types in our datasets matched that of the earlier dataset quite well (Fig. 2b-d). Also the predicted mean traces for the individual RGC types were very similar to those in Baden et al. (5) (Fig. 2e), as indicated by the high correlations of their chirp and moving bar responses (Fig. 2f left and right, respectively). That the moving bar responses were more strongly correlated than the chirp responses is likely due to the lower complexity and shorter duration of the former stimulus. Nonetheless, we found the RGC classification overall to be robust.

Testing and evaluating the recording protocol. To test our recording protocol, we used the glycine receptor antag-

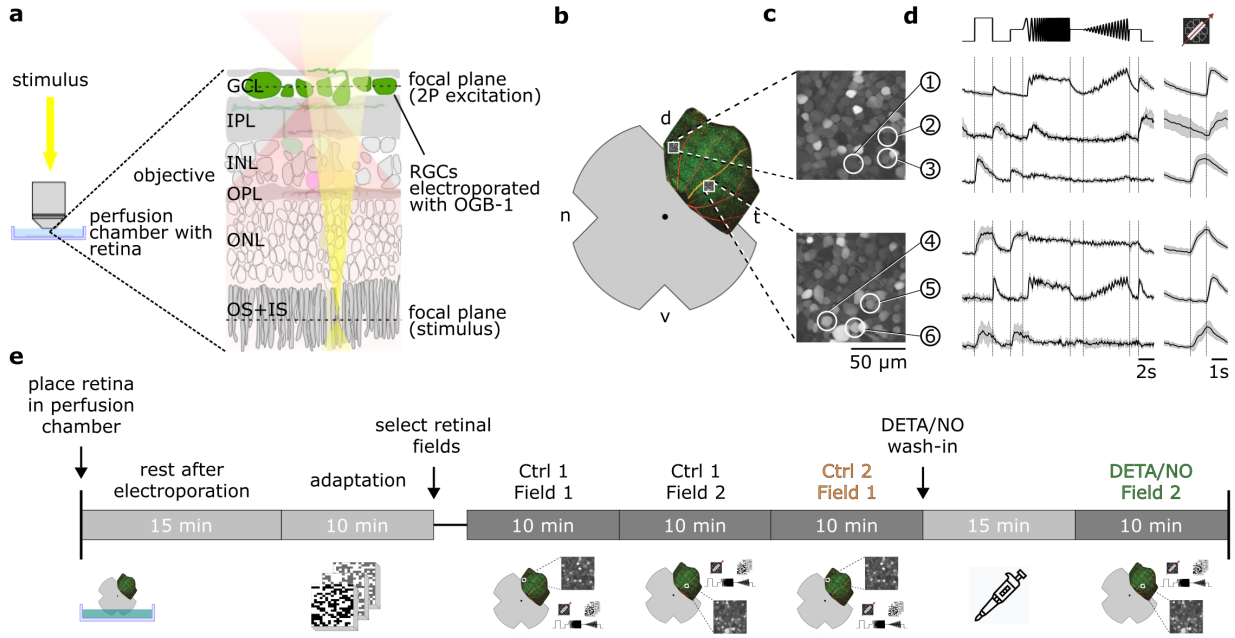

Fig. 1. Overview of experimental setup and recording procedure. (**a**) Two-photon imaging of ganglion cell layer (GCL) somata in the whole-mounted mouse retina. (**b**) Schematic *ex vivo* whole-mounted retina with two representative recording fields (white boxes; dot marks optic disc; d, dorsal; t, temporal; v, ventral; n, nasal). (**c**) Recording fields from (b) showing GCL somata loaded with Ca^{2+} indicator OGB-1 (Methods). (**d**) Representative GCL cell Ca^{2+} activity (white circles in (c)) in response to chirp (left) and moving bar stimulus (right) (black, mean; gray, s.d.). (**e**) Timeline of experimental procedure; for details, see text. IPL, inner plexiform layer; INL, inner nuclear layer; OPL, outer plexiform layer; ONL, outer nuclear layer; OS+IS, outer and inner segments; DETA/NO, nitric oxide (NO) donor.

onist strychnine (Fig. S1). In the mouse retina, glycine is released by small-field ACs and relays inhibition vertically across the inner plexiform layer (IPL; (32, 80)). For instance, such cross-over inhibition mediated by AII ACs relays the signals from rod BCs to Off-cone BCs, which is why strychnine eliminates Off RGC responses in dark-adapted retina (81). In the light-adapted retina, On-cone BCs boost light-Off responses in Off-cone BCs through cross-over inhibition (82, 83) and hence, strychnine affects Off-response components in RGCs – in line with our observations (Fig. S1): Strychnine application revealed additional On-responses in Off (e.g., G_1, G_2) and On-Off RGCs (e.g., G_{12}), as can be seen, for instance, in their leading-edge response to the moving bar (Fig. S1; left panel, middle column). In On RGCs, we did not detect substantial response changes with strychnine (Fig. S1; e.g., G_{17}).

Together, the strychnine dataset showcases that we can resolve drug-related effects on light responses at cell-type level.

Certain RGC types display adaptational response changes. To test if our recording conditions were stable and to exclude major batch effects, we first compared the responses of the control datasets (Ctrl 1 vs. Ctrl 2). To this end, we computed the difference between the Ctrl 1 and Ctrl 2 mean responses ($\Delta R_{(Ctrl2-Ctrl1)}$) to chirp and moving bar stimuli for each cell of every RGC type. This allowed us to quantify if and how the responses changed over the time-course of an experiment (cf. protocol in Fig. 1e). Here, we only considered RGC types with >10 paired cells (21/32).

Surprisingly, while the majority of RGC types featured stable responses (e.g., G_1, G_{21}; Fig. 3a), a substantial number of RGC types (∼34%) changed their responses to chirp and/or moving bar stimuli in the absence of any pharmacological perturbation in a highly reproducible manner (Fig. 3b). For instance, for Ctrl 2, G_{23} showed reduced responses, whereas G_{31} showed an increased response activity. Interestingly, cells assigned to the functional groups of 'Off' and 'Fast-On' RGC types displayed exclusively stable responses, whereas 'On-Off', 'Slow-On', and 'Uncertain RGCs' included types with changing responses (50%, 50%, and 67%, respectively). This diversity argues against a systematic effect (such as, e.g., general run-down) and for a cell type-specific phenomenon, which in the following we refer to as 'adaptational response changes'.

NO affects retinal output in a highly type-specific manner. Next, we investigated the effects of NO on the RGC responses. As with the control dataset, we computed the cell-wise response differences between Ctrl 1 and NO responses ($\Delta R_{(NO-Ctrl1)}$). Similar to the control dataset, the majority of RGC types displayed stable responses (e.g., G_2, G_{17}; Fig. 3c), while a smaller fraction (∼43%) changed their responses significantly (e.g., G_{28}, G_{32}; Fig. 3d) following the NO perfusion. We found that the percentage of changing types per functional group was similar to that in the control dataset: 'Off' (0%), 'Fast On' (34%), 'On-Off' (50%), 'Slow On' (66%), and 'Uncertain RGCs' (66%). This raised the question if the observed changes in the NO dataset indeed reflected NO-induced modulations or mostly adaptational response changes (as observed in the control dataset). We therefore tested for each RGC type if the re-

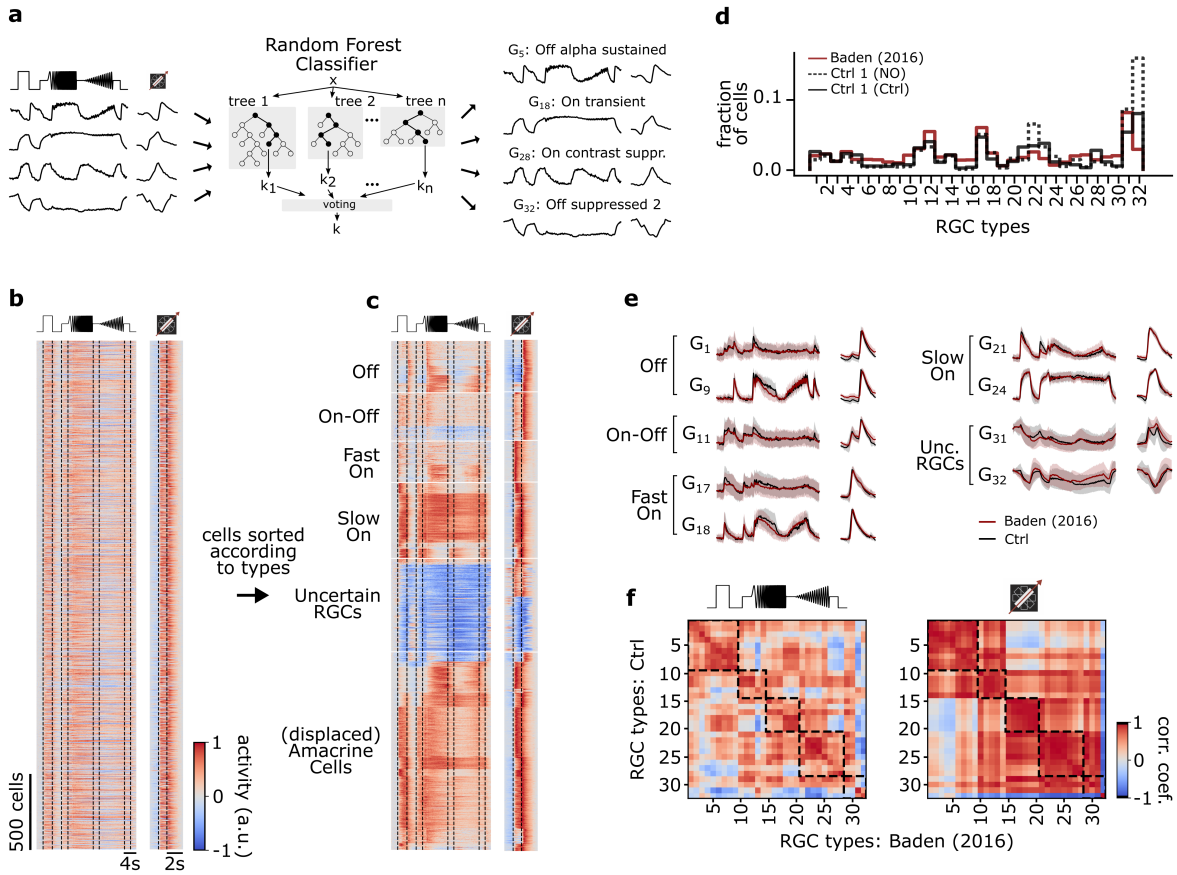

Fig. 2. Functional classification of mouse RGC types. (**a**) Illustration of the random forest classifier (RFC) to predict cell type labels for Ctrl 1 of both datasets. For each cell, Ca^{2+} responses to chirp and moving bar, soma size, and p-value of permutation test for direction selectivity (left) constitute the input to the RFC (centre) to predict a cell type label, i.e., a type G_X (right). For details, see Methods and (79). (**b**) Pooled heat map of unsorted cell responses to chirp and moving bar stimulus from both Ctrl 1 datasets after quality filtering (QI_{MB}>0.6 or QI_{chirp}>0.45, and classifier confidence score ≤ 0.25). Color bar indicates normalized response activity. (**c**) Heat map from (b), but sorted according to their assigned type. (**d**) Distribution of RGC types predicted by the RFC classifier for both Ctrl 1 of control pair (Ctrl 1 (Ctrl); solid black), of DETA/NO pair (Ctrl 1 (NO); dotted black), and for the training dataset from Baden et al. (5) (red). (**e**) Representative RGC type mean responses to chirp and moving bar (Ctrl, black; training dataset, red). (**f**) Correlation matrix of type mean responses per RGC type between Ctrl and training dataset for chirp (left) and moving bar (right). Dashed boxes indicate functional groups (Off, On-Off, Fast On, Slow On, and Uncertain RGCs; see (5)). Color bar indicates correlation coefficient.

sponse changes observed for control ($\Delta R_{(Ctrl2-Ctrl1)}$) and NO ($\Delta R_{(NO-Ctrl1)}$) were significantly different (Fig. 3e). To our surprise, this was only the case for G_{32} ('Off suppressed 2') RGCs, suggesting highly type-selective NO effects – at least for temporal responses to chirp and moving bar stimuli.

Next, we leveraged the control dataset to disentangle NO-induced from adaptational effects at the level of the response features. To this end, we subdivided the chirp stimulus into six feature segments ((1) On, (2) Off, (3) low frequency, (4) high frequency, (5) low contrast, (6) high contrast), and the moving bar into two ((7) On, (8) Off) (Fig. 4c). Then, for every cell type and every stimulus feature, we computed the difference of the mean responses between the first and second recording separately for the control (Fig. 4a; left panel) and NO dataset (Fig. 4a; middle panel). To isolate NO-induced effects, we computed the differences ($\Delta R_{(NO-Ctrl1)} - \Delta R_{(Ctrl2-Ctrl1)}$; Fig. 4a; right panel), based on the assumption that the adaptational component of the changes would be similar for both datasets. Through this analysis, we found three response behaviors across the RGC types: (1) not NO-affected/stable, (2) showing cell type-specific adaptation, and (3) NO-affected (Fig. 4b).

As before, we found that only G_{32} is strongly affected by NO; it showed barely any adaptational response changes, yet its activity increased during NO application (Fig. 4b; (3)). This increase in activity was statistically significant for the chirp's On step (1) and during both the frequency and contrast modulations ((3)-(6)), as well as for the moving bars trailing edge (8) (for tests, see Fig. 4 legend), suggesting that NO reduces the cell's inhibition by temporal contrast.

Interestingly, a cell type that is also suppressed-by-contrast, G_{31} ('Off suppressed 1'), displayed a similar behavior during the NO application (Fig. 4a). However, G_{31} showed this response change for most features already in the control, suggesting that this effect was primarily adaptational (Fig. 4a; right panel). Still, our analysis suggests that NO had a significant effect though different from what we observed for G_{32}: in G_{31} the response to the chirp's Off step (2) increased, whereas that to the moving bar's leading edge (7) decreased. Note that it is possible that additional NO effects on G_{31} may have been 'masked' by the strong adaptational response

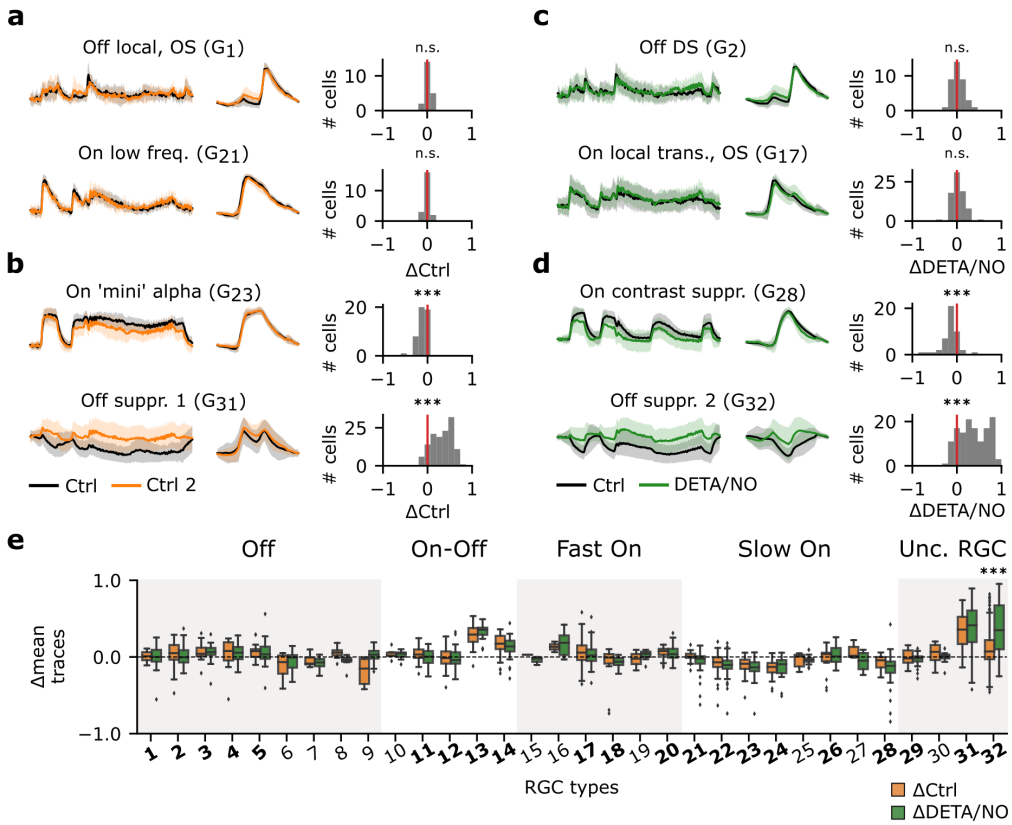

Fig. 3. Certain RGC types are affected by adaptational and/or NO-induced effects, others are unaffected. (**a**) Left: Two representative mean calcium responses of paired RGC types showing no differences between Ctrl 1 (black) and Ctrl 2 (orange) (top: G_1; bottom: G_{21}). Right: Corresponding histograms displaying the trace differences between paired cell responses of the respective cell types. Zero indicates no difference between the response of the same cell across both recordings, whereas negative values indicate a decreased and positive ones an increased activity. (**b**) Two representative RGC types that show decreased (top: G_{23}) and increased (bottom: G_{31}) response activity during Ctrl 2. (**c**) As in (a), but between paired Ctrl 1 (black) and DETA/NO (green) (top: G_2; bottom: G_{17}). (**d**) As (c), but showing two cell types that display a decreased (top: G_{28}) and increased (bottom: G_{32}) activity when perfused with DETA/NO. ***: p<0.001; One-sample T-test. (**e**) Box plots of trace differences of all paired cells of all RGC types from control (Ctrl 1 & Ctrl 2; orange) and NO dataset (Ctrl & DETA/NO; green). Bold numbers indicate RGC types with >10 paired cells per dataset and condition. Dashed line shows zero baseline, i.e., no difference between traces. Gray and white background blocks summarize the larger functional groups for better visualization (Off, On-Off, Fast On, Slow On, Uncertain RGCs). ***: p<0.001; Mann-Whitney U-Test and Bonferroni correction for multiple tests.

changes.

Notably, RGC types that were assigned to the group of the so-called 'Slow On' types (G_{21}-G_{28}), which exhibit strong and sustained responses during the frequency and contrast sequences of the chirp stimulus, showed a decrease in activity in both datasets (e.g., G_{24}; Fig. 4b; (2); bottom). Consequently, the changes in these response features ((3)-(6)) are likely adaptational (Fig. 4a) – as the changes can be found in the control (Fig. 4a; left panel) as well as in the NO dataset (Fig. 4a; middle panel), but not in the difference (Fig. 4a; right panel). Our conclusion that both adaptational and NO-mediated effects on RGC responses are highly cell type-selective is further supported by the fact that we also found several RGC types that showed stable responses during control and NO application (Fig. 4b; (1)).

Taken together, our analysis revealed that the adaptational and NO-induced effects occurred on a feature-specific as well as cell type-specific level. On the one hand, several 'Slow On' types showed adaptational effects in response to temporal frequency and contrast features, while other features were not affected. On the other hand, at least one distinct RGC type (G_{32}) displayed an significantly increased response modulation of most features during the NO application; hence hinting towards an effect of NO on response suppression, as in the case of G_{32} is elicited by temporally changing stimulus contrast.

Clustering of G_{32} responses reveals three functionally distinct RGC types with different NO-sensitivity. According to Baden et al. (5), G_{32} features a coverage factor of ∼4. As the average coverage factor of mouse RGCs was estimated to be ∼2 (5, 84), G_{32} likely consists of several RGC types. To test this, we performed Mixture of Gaussian clustering of the RGC cells assigned as G_{32} (Fig. 5a-c) using the Ctrl 1 responses to chirp and moving bar stimuli from both datasets (Fig. 5a). We found three distinct clusters – all suppressed-by-contrast but to different degrees (Fig. 5d,e).

All three G_{32} clusters showed little to no adaptation for the control dataset, but displayed differential modulations in response to NO application, with cluster 1 exhibiting the strongest NO effect (Fig. 5f,g; left) for both stimuli. The NO effect was statistically significant in clusters 1 and 2 – both for mean trace difference and correlation (Fig. 5g; left and

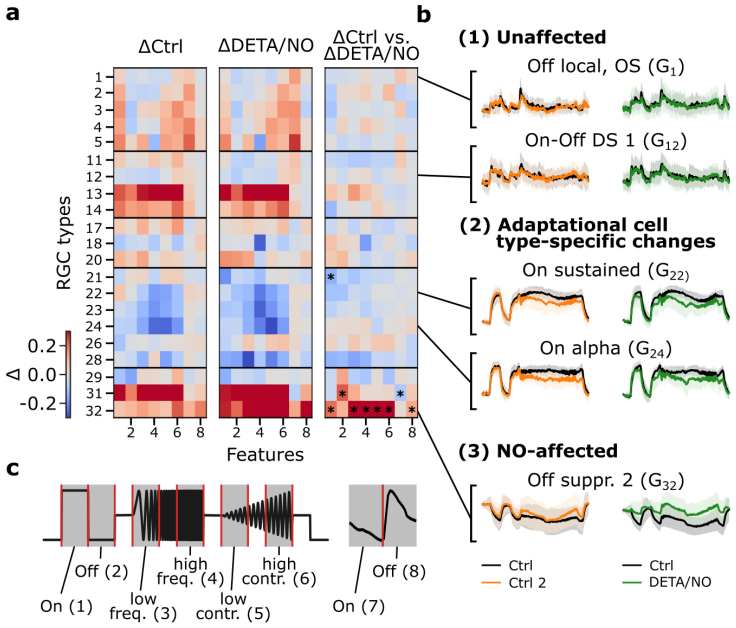

Fig. 4. Disentangling NO-induced effects from adaptational response changes reveals type-specific NO modulation. (**a**) Left: Difference between paired Ctrl 2 and Ctrl 1 RGC traces per type subdivided into 8 features ($\Delta R_{(Ctrl2-Ctrl1)}$). Color-code indicates response increase (red), no change (white) and decrease (blue) for Ctrl 2. Middle: Difference between DETA/NO and Ctrl ($\Delta R_{(NO-Ctrl1)}$). Right: Difference between the two heatmaps ($\Delta R_{(NO-Ctrl1)} - \Delta R_{(Ctrl2-Ctrl1)}$). Asterisks indicate significant differences of the trace differences of all cells per feature and per cell type between $\Delta Ctrl$ and $\Delta DETA/NO$ using independent two-sided T-test and Bonferroni correction for multiple tests. (**b**) Example chirp traces categorized into unaffected (top two types: G_1, G_{12}), adaptational (two middle types: G_{22}, G_{24}) and NO-affected (bottom: G_{32}). Left traces show exemplary responses per type from the control dataset (black: Ctrl 1; orange: Ctrl 2) and NO dataset (black: Ctrl; green: DETA/NO). (**c**) Subdividing the chirp (left) and moving bar (right) stimuli into 8 features for detailed feature analysis. The chirp is subdivided into 6 features ((i) on, (ii) off, (iii) low frequency, (iv) high frequency, (v) low contrast and (vi) high contrast); the moving bar into 2 ((vii) on and (viii) off).

right, respectively) – but not in cluster 3.

Since the prominent feature of these RGC types is suppression by stimulus contrast, we compared their suppression strength between the conditions using a suppression index (SI; see Methods). Here, we found that in cluster 1, SI did not change between Ctrl 1 and Ctrl 2, but was significantly reduced with NO. In fact, with NO, these cells lost their suppressive feature and were rather excited than suppressed by the stimuli. Cluster 2 displayed significant differences in SI in both control and NO dataset.

Taken together, our data indicate that G_{32} may consist of three suppressed-by-contrast RGC types and that in at least two of them, the contrast suppression is strongly modulated by NO. This subdivision of G_{32} into three types is supported by its high coverage factor (5, 84).

NO does not affect RGC receptive field properties. So far, we focused on effects in the temporal response domain, where we found that mainly G_{32} types were affected by an increase in NO levels. However, NO has been shown to affect electrical coupling, e.g., by reducing conductance between AII ACs and On-cone BCs (66), and hence may alter receptive field (RF) properties. Therefore, we next investigated the effects of NO on the spatial RFs (sRFs) of the individual RGC types. To this end, following the same experimental paradigm as described earlier, we recorded RGC responses to binary dense noise. Next, we computed their sRFs for both recording conditions (Fig. 6a) using spike-triggered averaging (85), obtaining control and NO sRFs, and then fitted a Gaussian to each sRF's center (Fig. 6a). We focused the following analysis on RGC types with reliable sRF estimates (see Methods). These included types in all five larger RGC groups (5): G_5 for Off; G_{11}, G_{12}, and G_{14} for On-Off; G_{17} for Fast On; G_{23}, G_{24}, G_{26}, and G_{27} for Slow On; G_{31} and G_{32} for Uncertain RGCs. In these types, sRFs were very stable in both control and NO condition.

Using the difference in sRF center diameter between control and NO as a metric (Fig. 6b), we did not find NO to cause any significant changes in sRF size in any of the analysed RGC types. Next, we tested if the sRF surround was affected by NO, because a modulation of inhibitory synaptic input and/or electrical coupling may cause a change in surround strength. As a measure of surround strength, we computed a surround index (see Methods) of control and NO sRFs (Fig. 6c). Like with the sRF center diameter, we did not find significant differences for any of the analysed RGC types. Surprisingly, also G_{32} did not show NO-mediated differences in its sRF properties, implying that NO may only affect its temporal response, but not its RF organization.

Taken together, at least for the tested RGC types, we did not detect any significant NO effects neither on sRF center size not surround strength.

Discussion

We used two-photon Ca^{2+} imaging to record RGC responses to various visual stimuli to investigate the neuromodulatory effects of elevated NO levels on the signal processing across

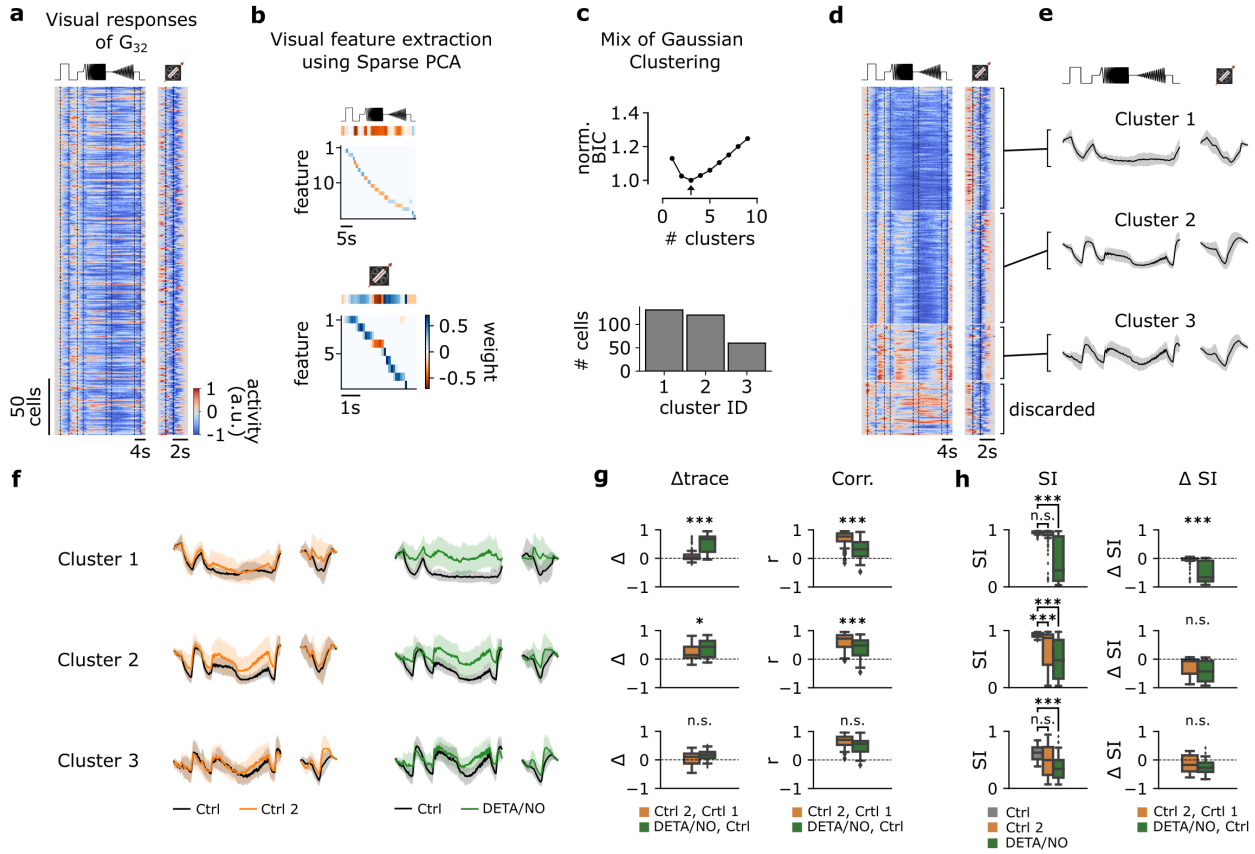

Fig. 5. Functional clustering of the G_{32} reveals three distinct types that are differently affected by NO. (**a**) Visual responses of G_{32} cells recorded from several experiments in response to the full-field chirp (left) and moving bar (right) stimuli. (**b**) Visual features extracted from chirp (top) and moving bar (bottom) stimuli using sparse PCA on the responses. Color indicates weight of each feature. (**c**) Top: Bayesian Information Criterion (BIC) as function of number of clusters. Arrow indicates lowest BIC and the number of clusters to choose. Bottom: Number of cells per predicted cluster. (**d**) Cells sorted according to their assigned cluster. Cells at the bottom were discarded. (**e**) Mean responses of the 3 corresponding clusters for the chirp (left) and moving bar (right). (**f**) Left: Paired mean responses of the 3 clusters to Ctrl 1 (black) and Ctrl 2 (orange). Right: Cluster mean responses to Ctrl 1 (black) and DETA/NO (green) (**g**) Left: Trace difference between Ctrl 2 & Ctrl 1 (orange) and DETA/NO & Ctrl (green) for the 3 clusters (cluster 1-3 from top to bottom). Right: Correlation coefficient between Ctrl 2 & Ctrl 1 (orange) and DETA/NO & Ctrl 1 (green) for the 3 clusters. ***: p<0.001; independent T-test & Mann-Whitney U-Test. (**h**) Left: Suppression index (SI) computed for Ctrl 1 (gray), Ctrl 2 (orange) and DETA/NO (green) for the 3 clusters. ***: p<0.001; Kruskal-Wallis test & Dunnett's test. Right: Difference of SI between Ctrl 2 & Ctrl 1 (orange) and DETA/NO & Ctrl 1 (green). ***: p<0.001; independent T-test & Mann-Whitney U-Test.

RGC types in the mouse retina. To our surprise, already without pharmacological perturbation, we found that about one third of the RGC types displayed highly reproducible and cell type-specific response changes during the course of an experiment – a finding of potentially high relevance especially for pharmacological experiments in the *ex vivo* retina. Accounting for these adaptational changes enabled us to isolate NO-related effects on RGC responses. Here, we revealed that mainly the RGCs assigned to G_{32} ('Off suppressed 2') were affected by NO, which strongly reduced the response suppression and rendered the cells more active. Further, we demonstrated that G_{32} likely consists of three types – consistent with its high coverage factor (5) – that were all differentially modulated by NO. Finally, for a representative subset of RGC types, we showed that elevating NO levels has no discernible effect on sRF size or surround strength. Together, our data suggest that NO specifically modulates response suppression in a group of contrast-suppressed RGC types. Additionally, our study demonstrates the need for recording paradigms that takes adaptational, non-drug-related response changes into account when analysing potentially subtle pharmacological effects.

Nitric oxide as a modulator in the retina. Neuronal nitric oxide synthesis (nNOS) has been detected in different retinal cell classes (49–57). In the mouse retina, light-dependent NO production seems to mainly occur in specific AC types (36). The main NO-sensor (NO-GC), which connects NO to intracellular cGMP signalling (55, 60, 86, 87) is present in all retinal layers (70). This and earlier findings of NO modulating response gain in BCs (68, 69) and RGCs (71), led us to expect global NO effects on retinal output. What we found instead was a highly selective effect in a distinct group of likely three types of RGCs formerly amalgamated in G_{32} (5). Specifically, NO affected these types in a similar way, yet differentially by increasing their activity and partly eliminating their characteristic feature of being suppressed by temporal contrast. Notably, the NO effect was only visible in their temporal responses; we did not detect changes in their sRF properties. This RGC type-selectivity of NO neuromodulation is reminiscent of a recent study, where dopamine was

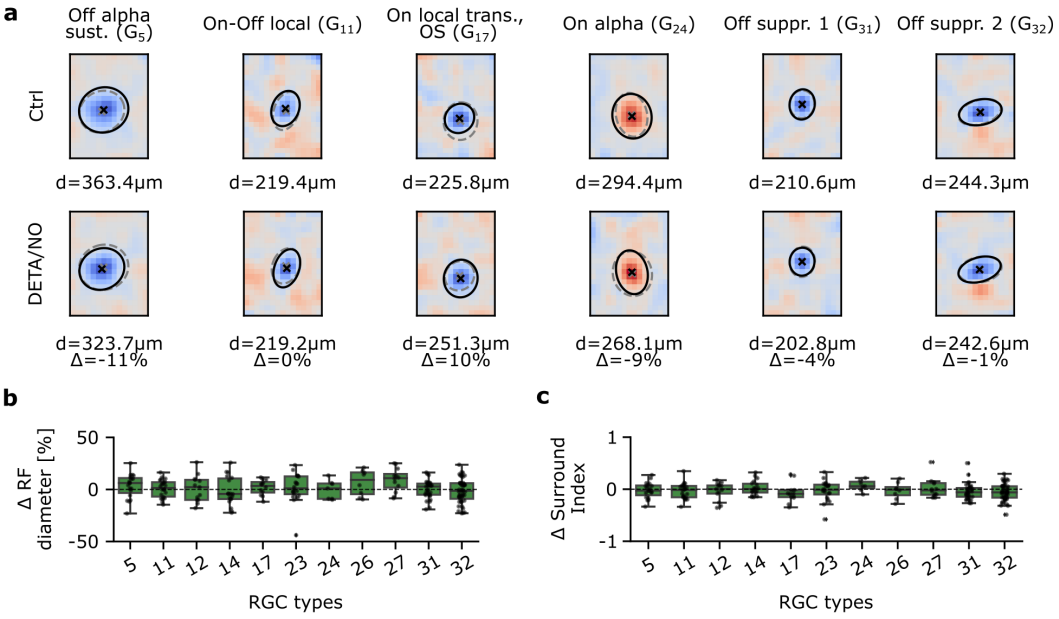

Fig. 6. Spatial receptive fields are not affected by NO across various RGC types. (**a**) Representative estimated spatial receptive fields (sRF) of six RGC types. Top: Estimated sRFs to Ctrl 1. Cross indicates RF center; solid line indicates outline of the Gaussian fit of the RF center; dashed outline indicates corresponding Gaussian fit of the same cell to DETA/NO. Bottom: Same as top, but of DETA/NO condition. (**b**) RF diameter difference in percentage between DETA/NO and Ctrl 1. Only types with more than 5 paired cells were included. One-sample T-test. (**c**) Surround index difference between DETA/NO and Ctrl 1. Only types with more than 5 paired cells were included. One-sample T-test.

found to modulate distinct response features of specific RGC types (48).

To ensure reliable RGC type classification, our set of visual stimuli was restricted to artificial ones (full-field chirps, moving bards, and dense noise). Such artificial stimuli probe the stimulus space in a rather selective and limited fashion. Hence, we cannot exclude that we missed NO effects that may have come apparent for other, more complex stimuli. Specifically, natural images or movies, stimuli that are closer to what the retina evolved to process (88), may be needed for a more complete picture of the functional implication of retinal neuromodulation. That natural stimuli can reveal novel nonlinear properties of retinal functions was demonstrated, for example, by Goldin et al. (89), who showed that a RGC's contrast selectivity can be context-dependent. Similarly, Höfling et al. (90) recorded natural movie-evoked RGC responses to train a convolutional neural network, which through *in silico* experiments allowed them to discover that transient suppressed-by-contrast RGC (G_{28}) feature centre color-opponent responses and may signal context changes. These studies highlight that future studies on neuromodulators should also employ natural stimuli.

Another important aspect to consider when studying NO neuromodulation in the retina is the level of light adaptation. Several studies proposed that NO facilitates the transition across light levels (66, 68, 69), especially to photopic conditions (36). Since we employed two-photon imaging, which inevitably results in a certain level of background 'illumination' (see discussion in (75, 91)), our experiments were performed in the low photopic range. Therefore, it is possible that NO-mediated neuromodulation serves different, light-level dependent functions: more globally during the transition from scotopic to mesopic/photopic, and more cell type-specific in the photopic regime – as we reported here.

Adaptational, cell type-specific response changes. Every recording method introduces technique-specific biases that have to be considered in the data analysis and interpretation. For two-photon imaging with fluorescent Ca^{2+} sensors, these potential biases include Ca^{2+} buffering, sensor bleaching by the excitation laser and, in the case of bulk-loading with synthetic dyes (as in our experiments; see also (92)), slow leakage of indicator from the cells. In retinal imaging, additional potentially confounding factors are an excitation laser-induced baseline activity and photoreceptor bleaching (76, 91). These biases are expected to be systematic, e.g., causing a decrease in signal-to-noise ratio across (RGC) responses (i.e., run-down). To account for this, we established a recording paradigm that produced a control and a NO dataset consisting of paired RGC responses.

When analyzing the control dataset, we were surprised by finding response changes in approx. a third of the RGC types already in the absence of the NO donor. These changes were consistent for a particular type but differed between types. Typically, we did not observe a simple overall decrease or increase in activity, but rather selective changes of response

features: For instance, in G_{24} (Slow On) only its response to high frequency and low contrast was reduced, while the remaining response features were not affected. Together, this strongly argues against a systematic, recording technique-related bias. Currently, we can only speculate about the mechanism(s) underlying this type-specific adaptation. The most parsimonious explanation may be related to the *ex vivo* condition of the retina: While we allowed the tissue to settle and adapt to perfusion medium, light level, temperature etc. for approx. 25 min, extracellular signaling molecules, such as neuromodulators, may be depleted and washed out over the course of the experiment, resulting in differential adaptation of various RGC types. In any case, as type-selective adaptations can confound the recorded responses in a complex manner, a paired recording paradigm as the one described here, is recommended – in particular for pharmacological experiments.

Combining population imaging, RGC classification and paired recordings to study neuromodulation of retinal output. In this study, we investigated the neuromodulatory effects of NO on the retinal output signal. To this end, we combined experimental and computational approaches to dissect NO-mediated effects at the RGC type-level. The latter is important for understanding neuromodulator function for early vision, because the visual information is sent to the brain via parallel feature channels, represented by >40 RGC types in the mouse retina (5, 6, 84, 93). We demonstrated that our approach enable to distinguish adaptational from actual NO-induced effects using a rather simple and straightforward linear analysis (i.e., focusing on mean trace or RF size differences), which means that we may have missed potential non-linear effects. However, the presented pipeline for analyzing neuromodulation in neural circuits constitutes a framework that can be easily extended by applying more advanced analyses.

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Methods

Animals and tissue preparation. All animal experiments were conducted at the University of Tübingen and were performed according to the laws governing animal experimentation issued by the German Government as well as approved by the institutional animal welfare committee of the University of Tübingen. For all experiments, we used retinae (n=26) from C57Bl/6 J mice (n=14; JAX 000664) of either sex between the age of 4-16 weeks. All animals were kept in the local animal facility and housed under the standard 12h/12h day/night cycle at 22°C and a humidity of 55%.

The following procedures were carried out under very dim red (> 650 nm) light. Before each imaging experiment, the animal was dark-adapted for >1 h, then anesthetized with isoflurane (CP-Pharma) and sacrificed by cervical dislocation. Immediately after, the eyes were enucleated with a dorsal cut as orientation landmark and hemisected in carboxygenated (95% O2, 5% CO2) artificial cerebrospinal fluid (ACSF) solution containing (in mM): 125 NaCl, 2.5 KCl, 2 $CaCl_2$, 1 $MgCl_2$, 1.25 NaH_2PO_4, 26 $NaHCO_3$, 20 glucose, and 0.5 L-glutamine at pH 7.4. Sulforhodamine-101 (SR101, 0.1 µM; Invitrogen) was added to the ACSF to reveal blood vessels and damaged ganglion cell layer (GCL) cells in the red fluorescence channel (75). The carboxygenated ACSF was constantly perfused through the recording chamber at 4 ml/min and kept at ∼36°C throughout the entire experiment. After the dissection, retinae were bulk-electroporated with the synthetic fluorescent calcium indicator Oregon-Green 488 BAPTA-1 (OGB-1; hexapotassium salt; Life Technologies) (92). To electroporate the GCL, the dissected retina was flat-mounted with the GCL facing up onto an AnodiscTM (#13, 0.1 µm pore size, 13 mm diameter, Cytiva), and then placed between two 4 mm horizontal platinum disk electrodes (CUY700P4E/L, Nepagene/Xceltis). The lower electrode was covered with 15 µl of ACSF, while a 10 µl drop of 5 mM OGB-1 dissolved in ACSF was suspended from the upper electrode and lowered onto the retina. Then, nine electrical pulses (∼9.2 V, 100 ms pulse width, at 1 Hz) from a pulse generator/wide-band amplifier combination (TGP110 and WA301, Thurlby handar/Farnell) were applied and then, the electroporated retina on the Anodisc was transferred into the recording chamber, whereby the dorsal edge of the retina pointed away from the experimenter. The retina was left there for 30 min to recover, as well as adapted to the light stimulation by displaying a binary dense noise stimulus (20 x 15 matrix, 40x40 μm^2 pixels, balanced random sequence) at 5 Hz before the recordings started.

Pharmacology. All used drugs were added to the carboxygenated, perfused ACSF solution 15min prior to the second recording of the GCL scan fields. For the drugs, the respective concentrations were used (in µM): 100 (Z)-1-[N-(2-aminoethyl)-N-(2-ammonioethyl)amino]diazen-1-ium-1,2-diolate (DETA/NO) and 1 strychnine. The ACSF solution with and without drug application was always kept at ∼36°C.

Two-photon calcium imaging. For the functional calcium imaging experiments, a MOM-type two-photon microscope (designed by W. Denk, MPI, Heidelberg; purchased from Sutter Instruments/Science Products) (75, 76) was employed. The microscope was equipped with a mode-locked Ti:Sapphire laser (MaiTai-HP DeepSee, Newport Spectra-Physics) tuned to 927 nm (ideal wavelength to excite OGB-1), two photomultiplier tubes serving as fluorescence detection channels for OGB-1 (HQ 510/84, AHF/Chroma) and SR101/tdTomato (HQ 630/60, AHF), and a water immersion objective (CF175 LWD×16/0.8W, DIC N2, Nikon, Germany). To acquire images, custom-made software (ScanM by M. Müller and T. Euler) running under IGOR Pro 6.3 for the operating system Microsoft Windows (Wavemetrics) was used and time-lapsed 64 x 64 pixel image scans ($\sim$100 µm^2) at 7.8125 Hz were taken. Routinely, the optic nerve position and the scan field position were recorded to reconstruct their retinal positions. High-resolution images (512 x 512 pixel images) were recorded to support semi-automatic ROI detection.

Light stimulation for two-photon calcium imaging. For the light stimulation of the retinal tissue, a digital light processing (DLP) projector (lightcrafter (LCr), DPM-E4500UVBGMKII, EKB Technologies Ltd) was used to display the visual stimuli through the objective onto the retina, whereby the stimulus was focused on the photoreceptor layer (94). The LCr was equipped with a light-guide port to couple in external, band-pass filtered green and UV light-emitting diode (LEDs; green: 576 BP 10, F37-576; UV: 387 BP 11, F39-387; both AHF/Chroma). The band-pass filter was used to optimize the spectral separation of mouse M- and S- opsins (390/576 Dualband, F59-003, AHF/Chroma). Both LEDs were synchronized with the scan retracing of the microscope. Stimulator intensity (as photoisomerization rate, 10^3 P*s^{-1} per cone) was calibrated to range from $\sim$0.5 (black image) to $\sim$20 for M- and S-opsins, respectively. A steady illumination of $\sim 10^4$ P*s^{-1} per cone was present during the scan recordings due to the two-photon excitation of photopigments (75, 76).

In total, 3 types of light stimuli were used for the imaging of calcium in the GCL: (1) full-field chirp stimulus (700 µm ⌀; see details here ref. (5)), (2) bright moving bar (0.3 x 1 mm) at 1 mm s^{-1} in eight directions to probe direction and orientation selectivity, and (3) random binary noise with a checkerboard grid of 20 x 15 checks and a check size of 40 µm at 5 Hz for 5 min to map receptive fields. Before each stimulus was presented, the baseline was recorded after the laser started scanning for at least 30 s to avoid immediate laser-induced effects on the retinal activity (75, 76, 95).

Data Analysis of two-photon calcium imaging recordings. Image extraction and semi-automatic region-of-interest (ROI) detection were performed using Igor PRO 8. All analyses were organized and performed in a custom-written schema using DataJoint for Python http://datajoint.github.io/; D. Yatsenko, Tolias lab, Baylor College of Medicine.

Preprocessing. After the Ca^{2+} were extracted from individual ROIs, as described elsewhere (5, 95), the raw traces were detrended by subtracting a smoothed version of the trace from the raw one. Detrending was necessary to remove slow drifts in the signal that were unrelated to the light-induced response. The smoothed version was the trace was computed by applying a Savitzky-Golay filter (96) of 3rd polynomial order and a window length of 60 s using the Python SciPy implementation $scipy.signal.savgol_filter$ (97).

$$r_{detrend} = r_{raw} - r_{smooth}$$

Lastly, the baseline activity (mean of the first eight samples) was subtracted, the mean activity $r(t)$ was computed and then traces were normalized such that:

$$\max_t(|r(t)|) = 1$$

Inclusion criterion. To include reliable cell responses for the performed analyses, two consecutive quality filtering steps were applied. At first, the response quality criterion, also termed quality index (QI), was computed for the moving bar ($QI_{MB} > 0.6$) and full-field chirp ($QI_{chirp} > 0.45$). Cells that passed either one of these two QIs in both recording conditions were included, otherwise they were discarded in the following analyses. As in Baden et al. (5), the quality index is defined as follows:

$$QI = \frac{Var[\langle C \rangle_r]_t}{\langle Var[C]_t \rangle_r}$$

where C is the T by R response matrix (time samples by stimulus repetitions) and $\langle\rangle_x$ and $Var[]_x$ denote the mean and variance across the indicated dimension x, respectively. As a second step, cells were assigned to a RGC group using the RGC classifier, which returned the RGC group index and a confidence score (i.e., assignment probability to the predicted RGC group by the random forest classifier (79)). Only cells that were assigned to one of the RGC groups (i.e., RGC index 1 - 32) were included, whereby cells assigned to a displaced AC group (i.e., RGC index 33 - 46) were rejected. Cells that exceeded the confidence score threshold of > 0.25 were included.

Suppression index. For each cell, the suppression index (SI) was measured by comparing the (absolute) negative area under the curve (AUC_{neg}) of the chirp and moving bar responses with the total area under the curve (AUC_{neg}+AUC_{pos}) of the entire response trace. For the absolute AUC_{neg}, the response was clipped for value <0.

$$SI = \frac{|AUC_{neg}|}{|AUC_{neg}| + |AUC_{pos}|}$$

Trace difference Δ. To compute the trace difference between the paired responses per cell, we subtracted the first response average to the chirp and moving bar stimuli, i.e., Ctrl 1, from the second recorded light-induced response, i.e., either NO or Ctrl 2. For the cell type-specific analysis, we computed the

average trace differences per cell. For the feature-based analysis, we computed the average trace differences per feature and per cell type.

On-Off Index. The On-Off index was computed as

$$OOI = \frac{\langle r_{on} \rangle_t - \langle r_{off} \rangle_t}{\langle r_{on} \rangle_t + \langle r_{off} \rangle_t}$$

where r_{on} and r_{off} are defined as the separated time components of the moving bar response into its On- and Off-component. For each component, we computed the mean value of the discrete differences along the time axis clipped between 0 and 1 to estimate if there is a response to the particular feature.

Classification of functional retinal ganglion cell types. For the functional classification of RGC types, we used a previously published RGC classifier (79). The classifier, which uses a random forest classifier, was trained, validated and tested on previously published RGC type responses (5). As input to the classifier, we used the responses to the standard set of stimuli, i.e., full-field chirp and moving bar, as well as soma sizes (separates alpha and non-alpha types) and the p-values of the permutation test for direction selectivity (separates DS and Non-DS types). For every cell, the RGC classifier outputs its type index and the confidence scores for all 46 types. The confidence score, as described in 'Inclusion criterion' was used as quality criterion.

Receptive field estimation. We mapped receptive fields (RFs) of RGCs using the RF python toolbox *RFEst* (98), following the procedure in (5) with few modifications. The binary dense noise stimulus (20 × 15 matrix, (40 µm)^2 pixels, balanced random sequence; 5 Hz) was centered on the recording field. We computed the temporal gradients of the Ca^{2+} signals from the detrended traces and clipped negative values:

$$\dot{c} = \max(0, \dot{r}_{detrend})$$

The stimulus $S(t)$ and the clipped temporal gradients c were upsampled to 10 times the stimulus frequency to compute the gradient-triggered average stimulus:

$$\boldsymbol{F}(x,y,\tau) = \int_{t=0}^{T} \dot{c}(t) \boldsymbol{S}(x,y,t+\tau)$$

where $\boldsymbol{S}(x,y,t)$ is the stimulus, τ is the lag ranging from approximately -0.20 to 1.38 seconds, and T is the duration of the stimulus. We smoothed these raw RF using a 5 × 5 pixel and 1 pixel standard deviation Gaussian window for each lag. Then we decomposed the RF into a temporal ($F_t(\tau)$) and spatial ($\boldsymbol{F}_s(x,y)$) component using singular value decomposition and scaled them such that $\max(|F_t|) = 1$ and $\max(|\boldsymbol{F}_s|) = \max(|\boldsymbol{F}|)$. For each spatial RF $\boldsymbol{F}_s$, we fit a 2D Difference of Gaussians using the python package *astropy* (99). The mean and covariance matrices of the center and surround Gaussian fits were tied, except for a linear scaling of the covariance matrix. We defined the polarity $p \in \{-1, 1\}$ of the spatial RF as the sign of the model fit at its mean. Next, we computed the center RF of the spatial RF as $\boldsymbol{F}_s^c = \max(0, p \cdot \boldsymbol{F}_s)$. The surround index was computed as:

$$RF_{surround} = \frac{\sum_{x,y}(\boldsymbol{F}_s - \boldsymbol{F}_s^c)}{\sum_{x,y}(|\boldsymbol{F}_s|)}.$$

To measure the center RF size, we fit a 2D Gaussian to the center RF, with the mean fixed to the one obtained from the Difference of Gaussians fit. The area covered by two standard deviations of this Gaussian fit was used as the RF size.

Functional clustering. The functional clustering was based on a similar approach as in (5). The clustering was only applied on RGC types previously classified as G_{32} and only recorded in Ctrl 1. First, visual features from the full-field chirp and moving bar Ca^{2+} responses were extracted using sparse principal component analysis (100). After optimizing the alpha parameter for each stimulus, each cell's dimensionality was reduced to 30 features, whereby the chirp covered 21 and the moving bar 9 features. Alpha was optimized in a way that every part of each stimulus was represented by one feature to increase interpretability. Each feature was standardized across cells before clustering. Then, the features were used to cluster the cells using a Mixture of Gaussian model. The ideal number of clusters was chosen based on the cross-validated Bayesian Information Criterion. Additionally, cluster coherence was computed and validated using intra- and inter-cluster correlation, as well as the influence of potential batch effects, i.e., a single cluster originates from a single retina or scan field, but is found across several ones. Then, the model was used to predict cell types labels. Finally, cluster 3 showed a high signal-to-noise ratio, thus cells were re-clustered, which originated in three clusters, whereby two showed high variability in their chirp and moving bar responses. These cells were discarded in the further analysis to clean this cluster from potential contamination.

Statistical analysis. To quantify the differences between traces, a Shaprio-Wilk test was used to test for normality and then either the two-sided t-test (if normally distributed) or the non-parametric Wilcoxon signed-rank test (Mann-Whitney U Test). To determine α, Bonferroni correction was used, depending on the number of tests performed. To test the difference between traces against zero, we either used the t-test or the non-parametric Wilcoxon signed-rank test, depending on the distribution. A one-sampled T-test was performed to test the mean against a population mean of zero in order to quantify if the mean difference diverges from zero. For the statistical comparison of the suppression index between conditions per cluster, the non-parametric Kruskal-Wallis one-way analysis of variance and post-hoc Dunnett's test and Bonferroni correction to determine the statistical significance between conditions was used.

Data and code availability. Data, light stimuli, as well as all custom analyses including code and notebooks to reproduce analyses will be made available at https://github.com/eulerlab upon journal publication.

Author contributions. D.G., T.S.K., Z.Z., T.E. and T.S. designed the study; D.G. performed imaging experiments, supported by R.A. and T.S.K.; D.G. performed pre-processing; D.G. analysed the data with the help of J.O. and M.A.G.; Z.Z. helped to maintain the experimental setup; D.G. wrote the manuscript with the help from T.E., T.S., J.O., M.A.G. and O.M.

Supplementary Material

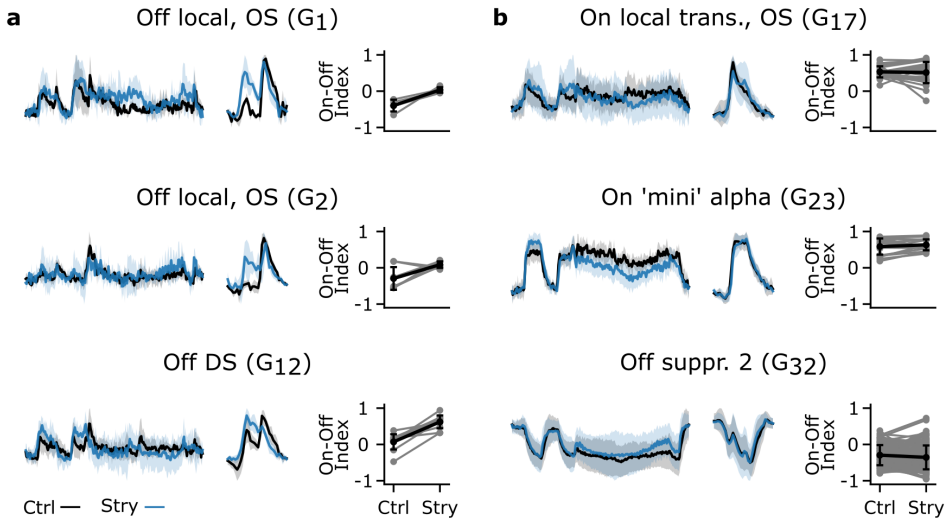

Fig. S1. Testing the effects of strychnine on different RGC type responses. (a) Left: Representative mean calcium responses of paired RGC types between Ctrl (black) and Strychnine-application (blue) (top: G_1; middle: G_2; bottom: G_{12}) exhibiting Off-responses. Right: Corresponding On-Off indices of paired RGCs for the Ctrl and Strychnine condition. **(b)** Left: As **(a)**, representative mean calcium responses of paired RGC types between Ctrl (black) and Strychnine-application (blue) (top: G_{17}; middle: G_{23}; bottom: G_{32}) exhibiting mainly On-responses and a suppressed-by-contrast component. Right: Corresponding On-Off indices of paired RGCs for the Ctrl and Strychnine condition.