

# A reconfigurable self-biased optoelectronic transistor for integrated high-fidelity sensing and neuromorphic signal recovery

Xingrou Meng<sup>1,§</sup>, Miao Zhang<sup>1,2,§</sup>, Haoxiang Tian<sup>1</sup>, Weiming Pu<sup>1</sup>, Yi Cui<sup>1</sup>, Kehan Wu<sup>1</sup>, Haonan Sun<sup>1</sup>, Long Chen<sup>1</sup>(✉), Keqin Liu<sup>1,3</sup>(✉), Xianfu Wang<sup>1</sup>(✉)

<sup>1</sup> State Key Laboratory of Electronic Thin Film and Integrated Devices, University of Electronic Science and Technology of China, Chengdu 611737, China

<sup>2</sup> Hongming Electronics, Chengdu 611737, China

<sup>3</sup> Guangdong Provincial Key Laboratory of In-Memory Computing Chips, School of Electronic and Computer Engineering, Shenzhen Graduate School, Peking University, Shenzhen 518055, China

<sup>§</sup> Xingrou Meng and Miao Zhang contributed equally to this work.

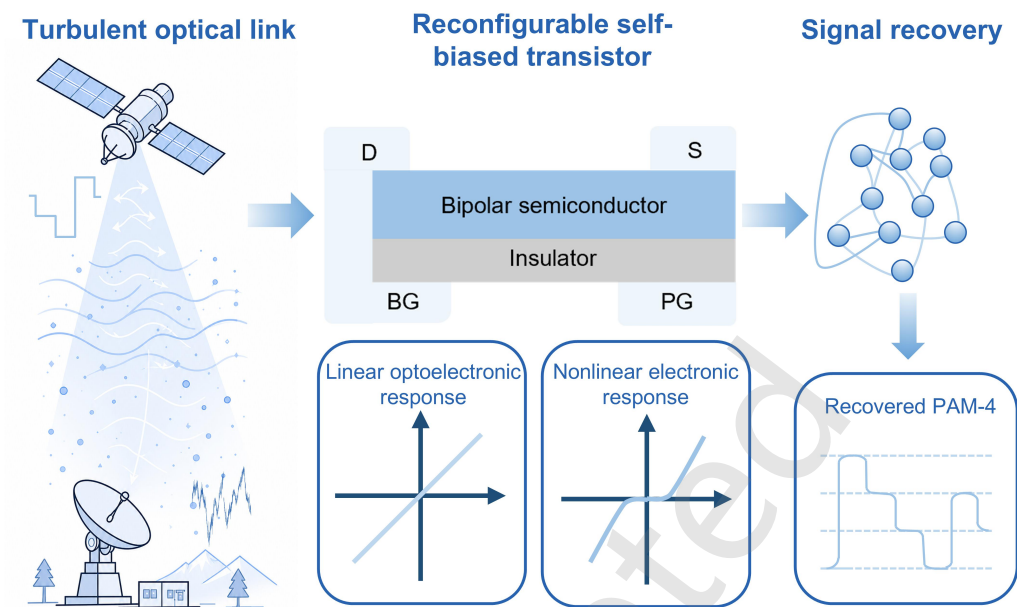
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A reconfigurable self-biased transistor is developed as an integrated linear-nonlinear hardware platform for space-ground optical links, combining high-fidelity linear optoelectronic conversion with nonlinear signal recovery to enable efficient reservoir-computing-assisted recovery of turbulence-distorted PAM-4 optical signals.

# A reconfigurable self-biased optoelectronic transistor for integrated high-fidelity sensing and neuromorphic signal recovery

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<sup>1</sup> State Key Laboratory of Electronic Thin Film and Integrated Devices, University of Electronic Science and Technology of China, Chengdu 611737, China

<sup>2</sup> Hongming Electronics, Chengdu, 611737, China

<sup>3</sup> Guangdong Provincial Key Laboratory of In-Memory Computing Chips, School of Electronic and Computer Engineering, Shenzhen Graduate School, Peking University, Shenzhen 518055, China

<sup>§</sup> Xingrou Meng and Miao Zhang contributed equally to this work.

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✉ Address correspondence to Long Chen, chenlong@uestc.edu.cn; Keqin Liu, kqliu@uestc.edu.cn; Xianfu Wang, xfwang87@uestc.edu.cn



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**ABSTRACT:** Space-ground optical links enable ultra-high-bandwidth and secure long-distance communication but are severely limited by atmospheric-turbulence-induced signal distortion and fading, requiring both high-fidelity linear optoelectronic conversion and nonlinear signal recovery. Neuromorphic computing provides a promising framework for processing temporally complex signals with reduced training cost and improved efficiency. However, its practical deployment in optical communication systems is hindered by the absence of compact and reconfigurable devices capable of simultaneously supporting sensing and processing within a unified hardware platform. Here, we report a reconfigurable self-biased optoelectronic transistor that enables tightly coupled high-fidelity sensing and nonlinear processing at the device level. By leveraging gate-drain coupling and electrostatic doping, the built-in electric field can be dynamically modulated, resulting in reconfigurable carrier transport with continuously tunable linear and nonlinear responses. For high-fidelity optoelectronic conversion, the device exhibits symmetric, bidirectional responses with exceptional linearity ( $R^2 = 0.99$ ) across various wavelengths and illumination intensities. For accurate signal recovery, we present a novel reservoir computing design that employs expansive neurons in place of compressive ones and is directly hardware-realized via the device's nonlinear characteristics, substantially reducing the bit error rate from  $10^{-2}$  (typical of conventional equalizers) to  $10^{-4}$  while lowering the trainable-parameter count to 45.1% and training time to 1.4%. This work establishes a unified, reconfigurable optoelectronic device platform, enabling the practical deployment of neuromorphic computing for robust space-ground optical links.

**KEYWORDS:** neuromorphic computing, reservoir computing, reconfigurable self-biased optoelectronic transistor, space-ground optical links

## 1 Introduction

Space-ground optical links offer a promising pathway to overcoming the bandwidth bottlenecks of traditional microwave communications and establishing a global seamless information network, owing to ultra-wide bandwidth and inherent physical-layer security<sup>[1-3]</sup>. However, the practical deployment of space-ground optical links remains severely constrained by atmospheric turbulence, which is characterized by random refractive-index fluctuations and gives rise to optical scintillation, temporal intensity fluctuations, and turbulence-induced fading, thereby distorting the received optical signals<sup>[4]</sup>. Reliable space-ground optical links therefore require not only high-fidelity optoelectronic conversion for accurate signal acquisition, but also effective recovery of turbulence-distorted temporal signals. In existing systems, these two functions are typically implemented using separate hardware modules: front-end photodetectors perform linear optoelectronic conversion,

while back-end recovery algorithms compensate for signal distortion. Although conventional linear equalizers can provide low-complexity compensation under weak turbulence conditions<sup>[5]</sup>, signal degradation under strong turbulence often exhibits pronounced nonlinearity and temporal correlation, rendering linear recovery methods insufficient for accurate signal reconstruction.

To address these challenges, neural-network-based nonlinear equalization approaches have been increasingly explored for recovering complex distorted optical signals<sup>[6-8]</sup>. Among them, reservoir computing (RC) is a recurrent neural-network framework in which the reservoir provides high-dimensional nonlinear dynamics, while only the linear readout layer is trained, making it well suited for real-time recovery of nonlinear temporal signals. Benefiting from low training cost, hardware efficiency, and strong temporal dynamics, physically implemented RC systems have demonstrated substantial

potential in nonlinear signal recovery<sup>[9]</sup>, time-series prediction<sup>[10-14]</sup>, speech recognition<sup>[15-18]</sup>, physiological signal analysis<sup>[19-21]</sup>, and multimodal information processing<sup>[22-26]</sup>. Importantly, the computational capability of RC systems is fundamentally governed by the nonlinear characteristics of reservoir neurons, which determine the richness of high-dimensional state mapping. Nevertheless, most existing studies primarily focus on engineering short-term relaxation timescales<sup>[23,27,28]</sup> or multimodal functionalities<sup>[23,29]</sup>, whereas the physical regulation of neuronal nonlinearities remains largely unexplored. In particular, conventional reservoir implementations predominantly rely on compressive nonlinear responses, whose limited dynamic expansion capability can restrict temporal separability and nonlinear recovery performance for strongly distorted signals.

At the hardware level, the practical deployment of RC-based space-ground optical communication systems still faces critical challenges. Although multifunctional optoelectronic devices integrating sensing and computing capabilities have recently attracted growing interest for compact intelligent systems<sup>[22,23,30,31,34]</sup>, most existing implementations are primarily optimized for linear optoelectronic conversion<sup>[32,33,35]</sup>, feature extraction<sup>[36-38]</sup>, and recognition tasks<sup>[39-41]</sup>. Their limited nonlinear dynamic tunability severely restricts the capability for reconstructing strongly turbulence-distorted communication signals. Therefore, developing a reconfigurable optoelectronic device that can dynamically switch between linear sensing and nonlinear neuromorphic processing within a unified hardware platform remains highly desirable.

Here, we report a WSe<sub>2</sub>-based reconfigurable self-biased optoelectronic transistor that simultaneously enables high-fidelity optical sensing and nonlinear neuromorphic processing within a unified hardware platform. By engineering gate-drain coupling and electrostatic doping to dynamically modulate the built-in electric field and carrier transport behavior in the two-dimensional channel, the transistor simultaneously achieves an ultra-high linear optical response ( $R^2 = 0.99$ ) for distortion-free optoelectronic signal conversion and unique bidirectional rectifying nonlinear electrical characteristics for neuromorphic computing. Thus realizes the integration of dual linear-nonlinear computing capabilities in a single device. Employed as the core neuronal building block for a physical RC system, the transistor leverages its intrinsic physical nonlinearity to directly process turbulence-induced temporal signal distortions. Under strong atmospheric turbulence conditions, the RC system based on this reconfigurable transistor achieves a two-order-of-magnitude reduction in bit error rate (from  $10^{-2}$  to  $10^{-4}$ ) compared with conventional linear equalizers. Meanwhile, compared with other nonlinear equalizers under the same signal recovery task, the proposed device-enabled RC achieves comparable or superior recovery accuracy with substantially reduced model complexity and training cost, lowering the number of trainable parameters to 45.1% and the training time to only 1.4%. This work establishes a high-performance hardware platform for on-chip integrated linear-nonlinear computing and provides a highly promising pathway to realize low-power, high-efficiency integrated neuromorphic systems for future satellite and space-ground optical communication applications.

## 2 Experimental

### 2.1 Device fabrication

WSe<sub>2</sub> and hBN bulk materials were purchased from HQ-graphene, and exfoliated into multilayer flakes on Polydimethylsiloxane (PDMS). The hBN and semiconductor WSe<sub>2</sub> flakes were sequentially transferred onto the bottom gate using a dry transfer method, serving as the dielectric layer and channel materials, respectively. The source and drain electrode pattern were then defined by electron-beam lithography, followed by thermal evaporation (Cr/Au).

### 2.2 Electrical measurements

The electrical characteristics of the device were measured using a probe station (PRCBE DOT) equipped with a semiconductor device parameter analyzer (Keithley 4200A-SCS). The source-measure units integrated into the Keithley 4200A-SCS were used to apply the input voltage signals and record the corresponding electrical response of the device.

### 2.3 Optoelectronic measurements

The device was measured in the probe station (PRCBE DOT) with the lasers (520 nm, 638 nm) and parameter analyzer (Keithley 4200A-SCS). The electrical input signals were applied and the corresponding electrical and photoresponses were measured using the Keithley 4200A-SCS. Scanning photocurrent mapping measurements were performed using a 520 nm laser excitation source with a spatial scanning step of 0.5  $\mu\text{m}$ . The photocurrent signals at different positions were collected using a Keithley 2450 SourceMeter to obtain the spatial distribution of the photocurrent response.

## 3 Results and discussion

### 3.1 Device concept and unified signal processing architecture

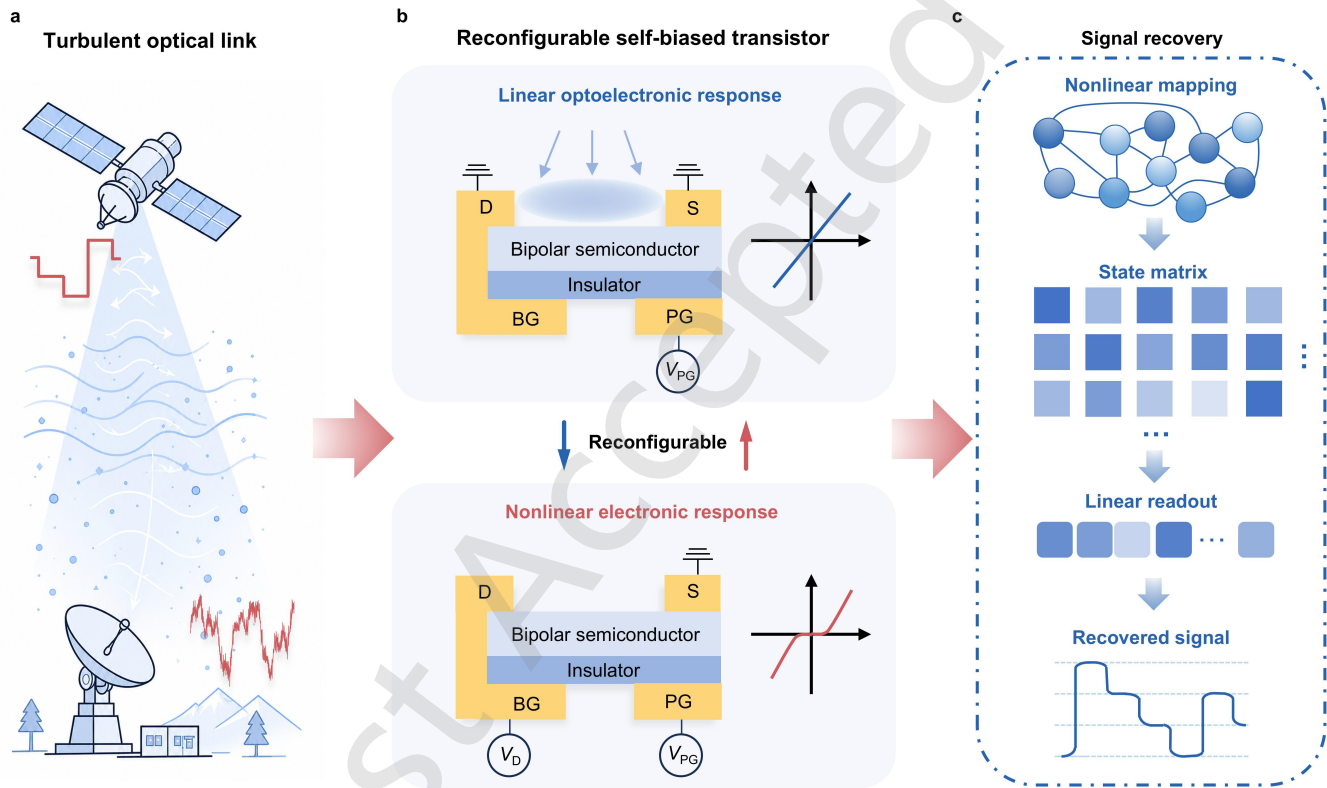
**Figure 1a** illustrates a space-ground optical transmission and processing scheme, where satellite optical signals propagate through atmospheric turbulence characterized by random refractive-index fluctuations, leading to optical scintillation, temporal intensity fluctuations, and turbulence-induced fading in the received signals. To address the demands of signal acquisition and processing in this context, we propose an integrated hardware architecture for high-fidelity reception, nonlinear feature transformation, and subsequent information recovery of turbulence-distorted optical signals. The core concept of this architecture is to unify highly linear optoelectronic conversion and nonlinear electrical computing within a single platform, thereby providing a physical foundation for integrated signal sensing and processing in space-ground optical communication.

To tackle this critical hardware challenge, we propose an architecture of the dynamically reconfigurable linear-nonlinear optoelectronic device and RC system for space-ground optical transmission and processing (**Figure 1b-c**). In this new scheme, a reconfigurable self-biased WSe<sub>2</sub> transistor serves as the core optoelectronic component for integrated neuromorphic computing systems. The dynamic modulation of the built-in electric field within the channel is jointly achieved by gate-drain coupling and electrostatic doping effect, enabling the dynamic reconfiguration of the device between linear optical responses and nonlinear electrical responses (**Figure 1b**). Specifically, the polarity gate (PG) electrostatically tunes the carrier polarity and consequently the rectification direction of the ambipolar WSe<sub>2</sub>

channel, while gate-drain coupling dynamically modulates the channel potential profile during drain-bias sweeping<sup>[25,42-45]</sup>. When voltages are simultaneously applied to both gates, the device operates in a nonlinear mode, exhibiting bidirectional rectifying electrical characteristics. Conversely, under optical stimulation with a voltage applied to the PG, the device operates in a linear mode and exhibits optoelectronic behavior characterized by symmetric linear positive and negative photoconductance.

By leveraging the linear and nonlinear reconfigurable characteristics of the transistor, effective processing of noisy signals in space-ground optical transmission is achieved. In the signal processing pipeline, the device first operates in a linear mode at the optical input port, enabling high-fidelity photodetection with a large dynamic range by accurately

converting optical signals with different intensity levels into photocurrent. Subsequently, the transistor is reconfigured into a nonlinear electrical mode, where it functions as the nonlinear node of a RC system for distorted signal recovery. Benefiting from the exponential nonlinear response and spatiotemporal dynamics enabled by time-delay feedback, the RC framework projects distorted low-dimensional signals into a high-dimensional feature space, where distorted signal states induced by atmospheric turbulence can be effectively separated and reconstructed. Owing to the rich nonlinear feature transformation performed within the reservoir layer, the output layer requires only a computationally efficient linear regression algorithm to extract target information from the high-dimensional state matrix and accomplish signal demodulation, as illustrated in **Figure 1c**.



**Figure 1.** Architecture of the linear-nonlinear dynamically reconfigurable optoelectronic device and reservoir computing system for satellite optical communication. (a) Schematic of the satellite optical communication scenario and atmospheric turbulence challenges. (b) Principle of dynamic reconfigurability between linear and nonlinear physical mechanisms. (c) Workflow of signal recovery via reservoir computing.

### 3.2 Reconfigurable transistor for nonlinear electrical signal processing

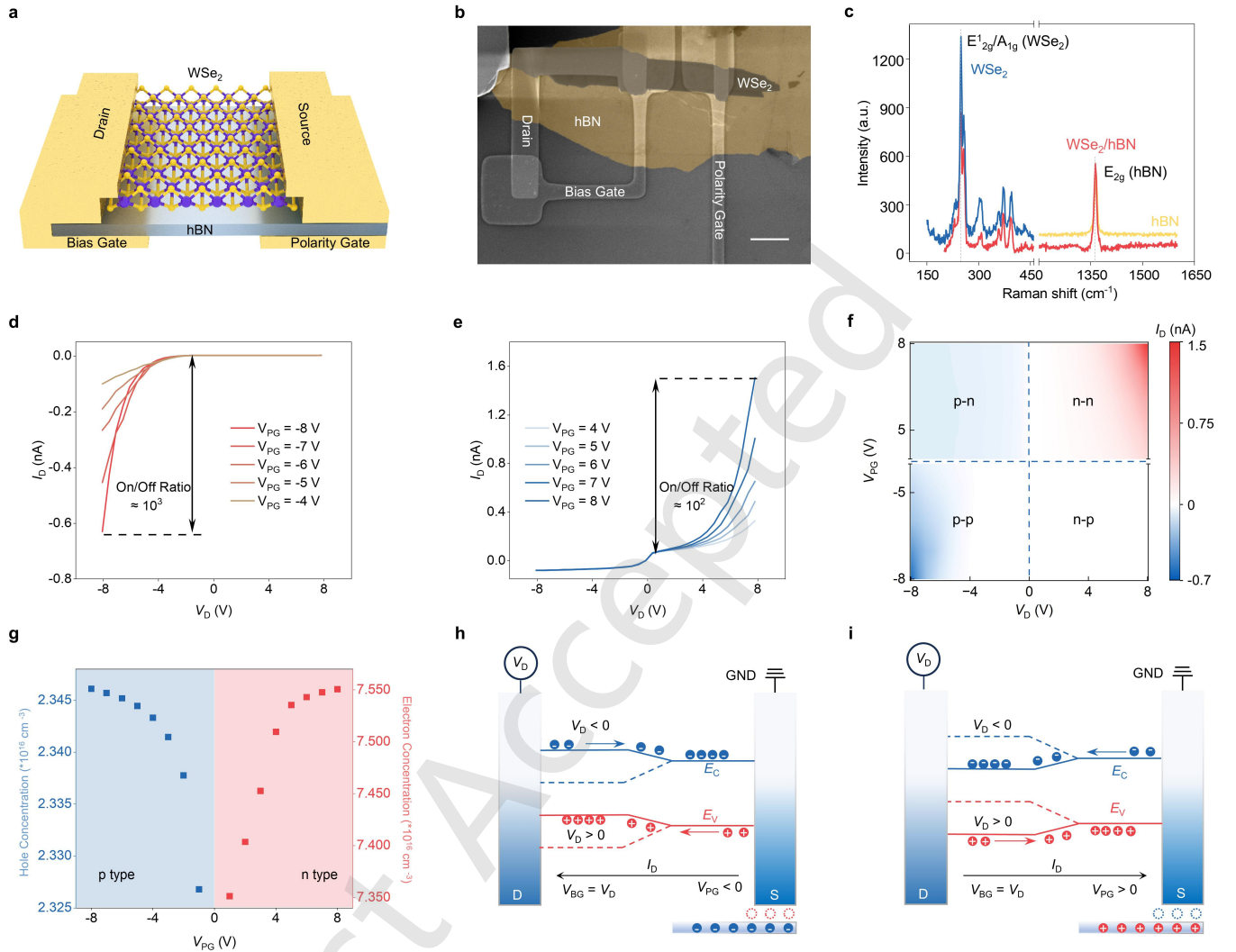
In order to achieve high-performance reconfigurable self-biased transistors, the appropriate selection of semiconductor materials and metal work functions is crucial. **Figure 2a** illustrates the reconfigurable transistor structure used in this study, where high-quality WSe<sub>2</sub> is employed as the channel material, and Cr/Au (5/25 nm) is chosen as the contact metal. During the patterning process, the bias gate and drain are interconnected to form the self-biased structure. As shown in **Figure 2b**, the effective gate-defined WSe<sub>2</sub> channel length is approximately 3.6  $\mu\text{m}$ , with a central gap of approximately 0.4  $\mu\text{m}$  between the two split back gates. The WSe<sub>2</sub> channel width is approximately 1.5  $\mu\text{m}$ . The split back-gate configuration enables spatially selective electrostatic modulation of the WSe<sub>2</sub> channel while leaving its

upper surface unobstructed for optical illumination. The Raman spectrum of the heterostructure shows distinct peaks at 250  $\text{cm}^{-1}$  and 1366  $\text{cm}^{-1}$ , which can be attributed to the E<sub>12g</sub>/A<sub>1g</sub> mode of WSe<sub>2</sub> and the E<sub>2g</sub> mode of hBN, as illustrated in **Figure 2c**.

Electrical measurements reveal that the device operates as a reconfigurable nonlinear diode. The rectification behaviour can be continuously modulated by tuning the gate voltage  $V_{\text{PG}}$ , as demonstrated in **Figure 2d-e**. Switching ratios ( $I_{\text{on}}/I_{\text{near-zero}}$ ) of  $10^3$  and  $10^2$  are achieved for reverse-conducting and forward-conducting rectification, demonstrating reversible modulation of the rectification polarity. By varying the polarity gate voltage  $V_{\text{PG}}$ , both the on-state current and the switching ratio can be systematically tuned. These results highlight the significant influence of  $V_{\text{PG}}$  in controlling the device polarity and electrical characteristics, thereby enabling reversible switching between

distinct operational states. To further demonstrate the electrical reconfigurability of the device, a two-dimensional current mapping was constructed under different  $V_{PG}$  and  $V_D$  conditions, as shown in **Figure 2f**. Four distinct transport states, including p-n, n-n, p-p, and n-p configurations, are identified in the current map. Notably, appreciable current is observed primarily in the n-

n configuration under positive  $V_D$  and in the p-p configuration under negative  $V_D$ , whereas the n-p and p-n states remain nearly nonconductive. This quadrant-selective response provides a direct visualization of the gate-controlled reversal of the rectification polarity.



**Figure 2.** Schematic and electrical characteristics of the WSe<sub>2</sub>-based reconfigurable self-biased transistor. (a) Schematic illustration of the reconfigurable self-biased transistor structure utilizing a WSe<sub>2</sub> channel. (b) SEM image of the fabricated device. Scale bar, 2 μm. (c) Raman spectrum of the heterostructure. (d, e) Electrical characteristics of the reconfigurable WSe<sub>2</sub> self-biased transistor under (d) negative and (e) positive polarity gate voltages. (f) The different current states and transport configurations of the reconfigurable transistor under various  $V_{PG}$  and  $V_D$ , including p-n, n-n, p-p, and n-p states. (g) TCAD simulation results showing the carrier concentration variation under different polarity gate voltages. (h, i) Energy band diagrams of the device under operation with (h) negative and (i) positive polarity gate voltages.

To reveal the underlying mechanism of polarity modulation, Technology Computer-Aided Design (TCAD) simulations were performed to investigate the carrier concentration evolution at the metal-semiconductor contact under different  $V_{PG}$ , as shown in **Figure 2g**. The results reveal that negative  $V_{PG}$  enhances hole accumulation, whereas positive  $V_{PG}$  induces electron accumulation in WSe<sub>2</sub>. The carrier concentration gradually increases with increasing gate voltage magnitude and approaches saturation at higher bias, indicating effective electrostatic regulation of the channel polarity by the PG. Finally, the energy band diagram of the device during reconfigurable operation, considering the electrostatic doping induced carrier redistribution under different polarity gate voltages, is illustrated

in **Figure 2h-i**. With a negative  $V_{PG}$  applied, the energy bands at the source side bend upward, leading to hole accumulation and establishing a p-type injection contact. When  $V_D < 0$ , the energy band at the drain side gradually bends upward as  $V_D$  decreases, causing the device to transition from an off state to an on state, exhibiting diode-like behavior (**Figure 2h**). When  $V_D > 0$ , the energy band on the drain side bends downward, preventing holes from crossing the barrier from the source to the drain, keeping the device in the off state. The similar behavior occurs when a positive voltage is applied to  $V_{PG}$  (**Figure 2i**). Thus, the device functions as a reconfigurable self-biased transistor, with its nonlinearity offering significant potential for satellite signal recovery as well as post-processing applications (Supplementary

Figure S1).

### 3.3 Reconfigurable transistor for linear optoelectronic conversion

Space-ground optical transmission and processing require reconfigurable transistors to convert optical signals into electrical signals with high fidelity, thereby demanding a highly linear optoelectronic conversion process to minimize information loss. WSe<sub>2</sub> exhibits a broad optical response across the 200-1000 nm range, enabling detection from ultraviolet to near-infrared wavelengths and supporting diverse applications in multispectral sensing and recognition<sup>[25,30-32]</sup>. Reconfigurable self-biased transistors further enable polarity switching, offering a highly tunable ambipolar optical response across various wavelengths. To evaluate the device's potential for high-fidelity photodetection and in-sensor computing, its optical responses under different intensities, wavelengths, and  $V_{PG}$  is systematically characterized.

Achieving both positive and negative photocurrent is essential for optoelectronic devices, which can be realized by adjusting the direction of the built-in electric field. By tuning the  $V_{PG}$  ( $\pm 5$  V), bidirectional photocurrent responses are successfully demonstrated. Based on this, the dependence of the short-circuit photocurrent on the light intensity is systematically investigated at various wavelengths, as shown in **Figure 3a-b**. To analyze the data, a power-law equation is used for fitting:

$$I_{sc} \propto P^\alpha \quad (1)$$

where  $P$  is the light intensity,  $\alpha$  is the fitting parameter, and  $I_{sc}$  is the short-circuit photocurrent. The extracted value of  $\alpha$  is very close to 1 for both the 520 nm and 638 nm wavelengths, indicating excellent linear mapping between light intensity and photocurrent and ensuring the high-quality acquisition optical information.

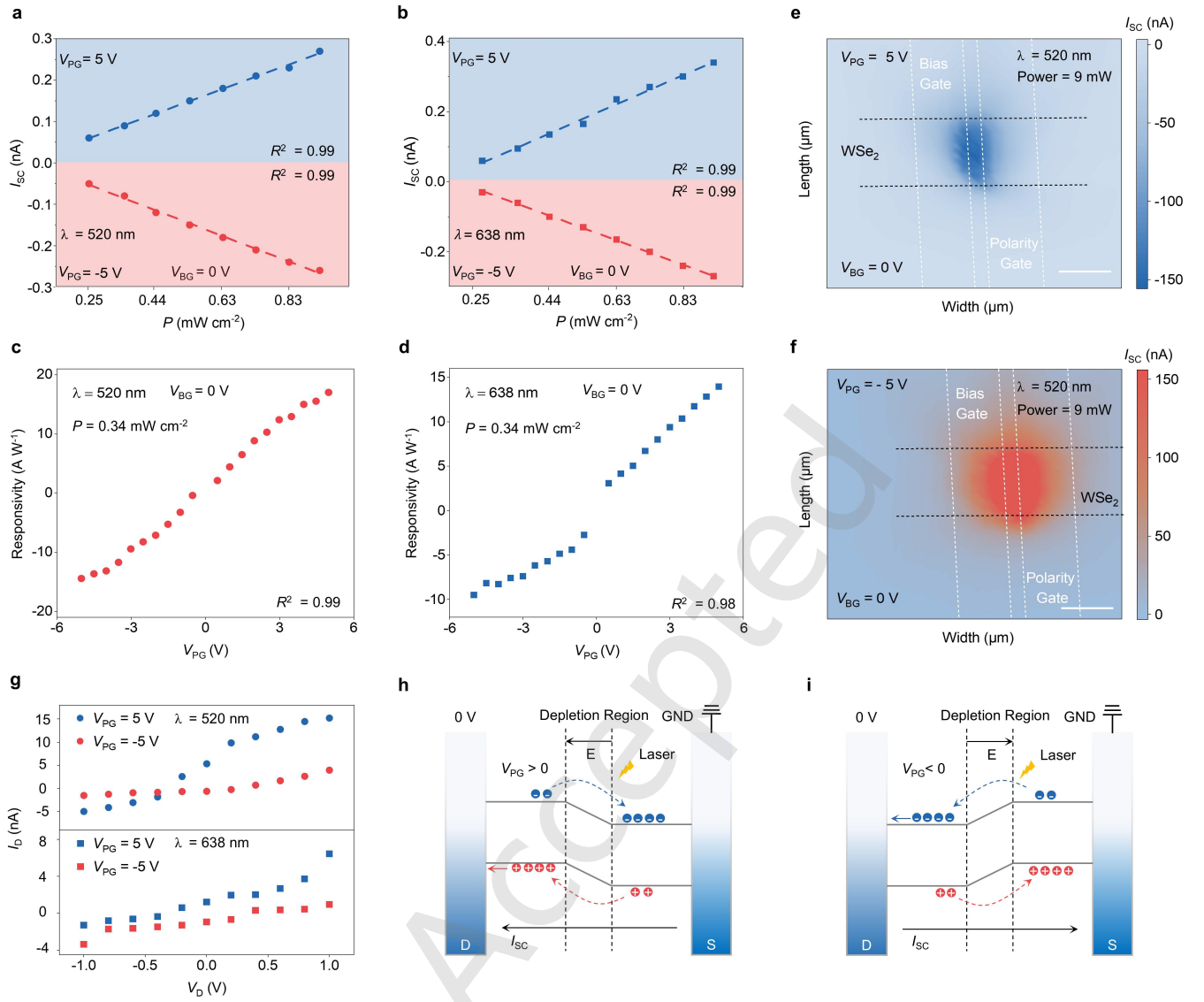
Furthermore, the responsivity of the photocurrent can be modulated by adjusting the strength of the built-in electric field. Thus, the dependence of the responsivity on the  $V_{PG}$  is also investigated. The positive and negative optical responses of the device are measured at various wavelengths under a constant light intensity of  $0.34 \text{ mW cm}^{-2}$ , as shown in **Figure 3c-d**. A positive correlation between responsivity and  $V_{PG}$  is observed, and this relationship is further analyzed through fitting:

$$I_{sc} = PR \propto V_{PG} \quad (2)$$

where  $P$  is the light intensity,  $R$  is the responsivity, and  $I_{sc}$  is the short-circuit photocurrent. The fitting results indicate that the responsivity can vary quite linearly with the applied  $V_{PG}$  ( $R^2 = 0.99$ ) for a given wavelength and light intensity. Moreover, a large linear regime can be maintained under voltages of  $\pm 6$  V. The highly tunable responsivity serves as a hardware foundation for the weight updates in optoelectronic neural networks, thereby establishing a basis for in-sensor convolutional kernels and advanced image processing.

In order to gain a deeper understanding of the optoelectronic conversion process, photocurrent mapping is performed at zero bias under 520 nm laser illumination to characterize the spatial distribution of its photoresponse. The mapping results show that the photocurrent is primarily distributed in the region between the polarity and bias gate, which corresponds to the p-n/n-p junction area (**Figure 3e-f**). This confirms that the photocurrent is mainly generated by the separation of photogenerated carriers due to the built-in electric field in the junction. By applying different  $V_{PG}$  values, both positive and negative photocurrent mappings are clearly observed, validating that the direction of the built-in electric field can be effectively controlled through the polarity gate. Similarly, by sweeping the  $V_D$  with a fixed  $V_{PG}$  ( $\pm 5$  V) under 520 nm and 638 nm light illumination, the positive/negative intersection points with the coordinate axis reveal the tunable bidirectional photocurrent and built-in electric field under the control of polarity gate, as shown in **Figure 3g**.

To elucidate the operating mechanism, the energy band diagram of the device during illumination is illustrated in **Figure 3h-i**. A positive  $V_{PG}$  shifts the source-side energy band downward, establishing a junction region and a built-in electric field with the drain side. Under illumination, the photogenerated electrons and holes move toward the source and drain sides, respectively, resulting in a photocurrent flowing from the source to drain (**Figure 3h**). Conversely, a negative  $V_{PG}$  reverses the built-in electric field, driving a photocurrent from the drain to the source (**Figure 3i**). The above reconfigurable linear response of the self-biased transistors is crucial for achieving high fidelity optical signal conversion and in-sensor processing applications (Supplementary Figure S2)



**Figure 3.** Linear optical response and underlying physical mechanism of the reconfigurable self-biased transistor. (a, b) Short-circuit photocurrent ( $I_{sc}$ ) as a function of intensity at  $V_{PG} = \pm 5$  V under (a) 520 nm and (b) 638 nm illumination. (c, d) Responsivity as a function of the polarity gate voltage under (c) 520 nm and (d) 638 nm illumination.  $R^2$  denotes the coefficient of determination for the corresponding fits. (e, f) Photocurrent mapping under zero bias gate voltage and different polarity gate voltages. Scale bar, 5  $\mu\text{m}$ . (g) Verification of reconfigurable built-in electric field modulated by polarity gate voltage under 520 nm and 638 nm illumination at higher optical power. (h, i) Schematic energy band diagrams of the device under different polarity gate voltages.

### 3.4 Integrated reconfigurable system for space-ground signal recovery via reservoir computing

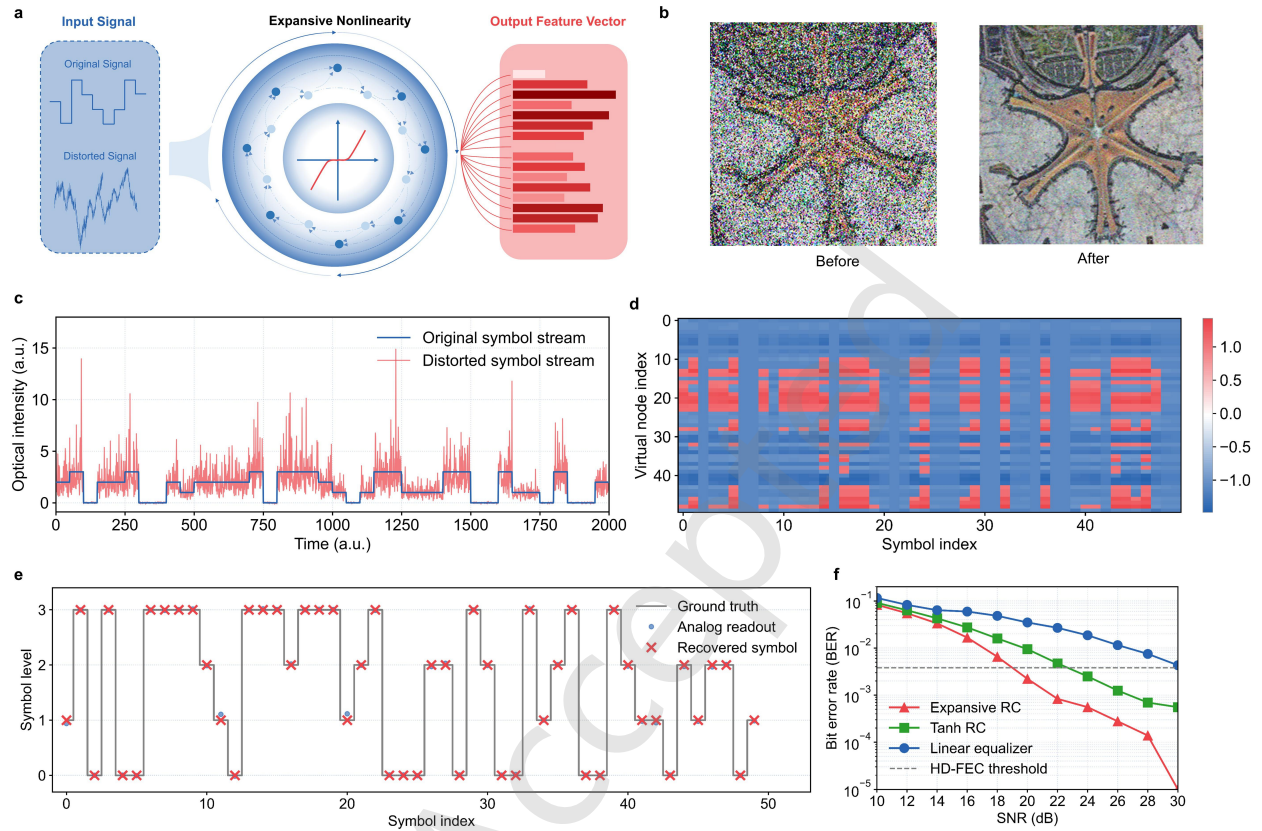
To achieve reliable space-ground optical transmission and processing, optical signals from satellites first undergo high-fidelity linear optoelectronic conversion, followed by advanced signal recovery techniques to mitigate turbulence-induced distortions. Given the complex dynamics and temporal correlation of atmospheric turbulence, conventional linear equalizers are often insufficient for accurate signal recovery, whereas neural-network-based nonlinear equalizers typically require a large number of trainable parameters and long training time. Significantly, the nonlinear dynamics and temporal correlation inherent in atmospheric turbulence are a perfect match for the two pivotal attributes of reservoir computing. Nevertheless, the signal recovery capability of RC critically depends on the nonlinear characteristics of the reservoir nodes. Conventional RC systems generally rely on compressive nonlinearities, such as tanh activation, which tend to saturate

and thereby limit feature separability under strongly distorted channel conditions. In contrast, the proposed self-biased transistor intrinsically exhibits expansive nonlinearity, enabling continuous amplification of subtle signal differences and enhanced high-dimensional feature mapping. Accordingly, a RC system with expansive neurons is constructed to characterize the dynamic evolution of turbulent systems and achieve high-fidelity recovery of turbulence-impaired optical signals.

The signal recovery performance of reservoir computing systems for 4-level pulse amplitude modulation (PAM-4) signals under atmospheric turbulence conditions is systematically investigated. The overall signal recovery architecture is illustrated in **Figure 4a**. The space-ground optical signals subjected to random perturbations are expanded into high-dimensional features via the spatiotemporal reservoir layer. The cyclic connection of the system is realized through a time-delay feedback, where the output of the physical node at the current moment is superimposed with the new input signal after a

specific time delay ( $\tau$ ). This recursive structure establishes a tight coupling relationship among virtual nodes, endowing the system with a “fading memory” property. 50 virtual nodes are chosen for this task, which are implemented by the nonlinear self-biased transistor via a time-multiplexing mechanism, significantly conserving hardware resources. Through repeated iterations involving the nonlinear node and the time-delay

feedback, features from the original signal are nonlinearly mixed and mapped onto the state fluctuations of all virtual nodes. Since the reservoir layer has already completed the complex nonlinear transformations, the output layer requires only a simple linear regression to precisely extract target information from the high-dimensional state matrix (see Supplementary Note 1 for more details).



**Figure 4.** Reservoir-computing-based PAM-4 signal recovery and performance evaluation for space-ground optical links. (a) Schematic architecture of spatiotemporal processing in reservoir computing system with expansive neurons. (b) Demonstration of distorted images recovery via reservoir computing (<https://www.cpeos.org.cn/home/>). (c) Severe time-domain distortion of PAM-4 signals induced by atmospheric turbulence channels. (d) Heat map of high-dimensional spatiotemporal evolution and feature separation of internal reservoir states. (e) Recovered PAM-4 symbol sequence compared with the ground truth. (f) BER performance comparison as a function of SNR for the expansive RC enabled by our device (red curve), conventional Tanh RC (green curve), and the traditional linear equalizer (blue curve).

**Table 1.** Comparison of recovery accuracy, model complexity, and computational efficiency among the proposed device-enabled RC, conventional RC, and representative neural-network-based nonlinear equalizers. The “best epoch” denotes the training epoch corresponding to the minimum validation loss. For the RC models, the output-layer weights are obtained through a one-step linear regression.

| Model       | Params | Best val BER | Test BER | Best epoch | Train time (s) | Infer time ( $\mu\text{s}/\text{symbol}$ ) |
|-------------|--------|--------------|----------|------------|----------------|--------------------------------------------|
| This Work   | 51     | 0.001        | 0.0033   | 1          | 0.2542         | 0.1515                                     |
| RC (tanh)   | 51     | 0.001        | 0.0043   | 1          | 0.3470         | 0.1503                                     |
| MLP         | 781    | 0.002        | 0.0047   | 24         | 26.2671        | 0.2483                                     |
| 1D-CNN      | 113    | 0.001        | 0.0037   | 27         | 21.5740        | 0.3849                                     |
| Transformer | 1769   | 0.001        | 0.0030   | 44         | 106.8546       | 5.0586                                     |
| GRU         | 273    | 0.001        | 0.0030   | 23         | 18.8123        | 0.4057                                     |
| LSTM        | 361    | 0.001        | 0.0043   | 20         | 28.8147        | 0.4617                                     |

To better illustrate the implementation process of signal recovery, the internal working states of the reservoir are further elucidated in **Figure 4c-e**. The distorted optical signals caused by the atmospheric turbulence are shown in **Figure 4c**. Under a

turbulence intensity of  $\sigma_R^2 = 0.3$ , affected by both log-normal fading and additive noise, the received PAM-4 signal (red solid line) undergoes severe distortion in the time domain. Its four ideal amplitude levels (blue lines) are severely aliased, rendering

traditional threshold decision-making ineffective. To address this, the received signal is injected into the reservoir computing system, and the spatiotemporal evolution of its internal states is shown in **Figure 4d**. This figure displays the high-dimensional dynamic responses after the input signal is scattered to 50 virtual nodes (an optimal value determined in Supplementary Figure S3) through a masking process. Distinct state striations can be clearly observed in the heat map, indicating that the expansive nonlinearity of the proposed transistor effectively enlarges subtle differences among originally aliased signals and maps them into linearly separable feature patterns within the high-dimensional state space. This process provides abundant fingerprint-like dynamic features for subsequent signal classification and recovery.

Consequently, the signal recovery performance based on the aforementioned feature mapping is shown in **Figure 4e**. The analog output of the readout layer (blue dots) exhibits strong clustering, tightly distributed around the ideal integer levels (0, 1, 2, 3), and the final decision symbols (red crosses) align perfectly with the true transmitted symbols (gray lines). This demonstrates that the system effectively suppresses amplitude fluctuations caused by channel noise and turbulence. To further explore the ultimate robustness of the system, a large-scale data transmission test was conducted under moderate turbulence intensity ( $\sigma_R^2 = 0.15$ ). Experimental results indicate that during the transmission of 100000 bits (corresponding to 50,000 PAM-4 symbols), the system achieved zero-error transmission. This result implies that without applying forward error correction the actual BER is already below the order of  $10^{-4}$ , confirming the ability of expansive nonlinearity to amplify and separate minute signal differences in the non-saturation region.

The influence of reservoir-node nonlinearity on signal recovery performance is quantitatively illustrated in **Figure 4f**. The plot compares the BER as a function of signal-to-noise ratio (SNR) for the proposed expansive RC enabled by our device (red curve), conventional Tanh RC (green curve), and the traditional linear equalizer (blue curve). Here, a BER of  $3.8 \times 10^{-3}$  is used as the threshold for hard-decision forward error correction (HD-FEC). And a BER below this threshold indicates that the recovered signal falls within the HD-FEC correctable range, thereby supporting reliable signal transmission. Analysis reveals that the linear equalizer is limited by its linear compensation capability and struggles to address turbulence-induced nonlinear fading and temporally correlated distortions. As a result, its BER decreases slowly and fails to fall below this threshold. In contrast, RC can enhance the feature separation capability of distorted signals through high-dimensional nonlinear state mapping. Further comparison shows that conventional Tanh RC is limited by the saturation effect of compressive nonlinearity, whereas the proposed expansive RC can continuously amplify subtle signal differences, achieving lower BER and reaching the HD-FEC threshold at a lower SNR. This indicates that expansive nonlinearity provides stronger dynamic mapping and feature separation capabilities than both linear equalization and conventional compressive RC.

Beyond recovery accuracy, practical deployment of intelligent signal recovery systems also requires low model complexity and high training efficiency. Therefore, the proposed device-enabled RC was further benchmarked against conventional RC and neural-network-based nonlinear equalizers, including multilayer

perceptron (MLP), one-dimensional convolutional neural network (1D-CNN), transformer, gated recurrent unit (GRU) and long short-term memory (LSTM), under the same PAM-4 recovery task. As shown in **Table 1**, all models were evaluated under identical turbulence intensity ( $\sigma_R^2 = 0.3$ ), training protocol, and test conditions. The proposed RC uses 50 virtual nodes and trains only the linear readout layer, requiring only 51 trainable parameters. Despite its low complexity, it achieves a test BER of 0.0033, outperforming conventional RC (0.0043), MLP (0.0047), 1D-CNN (0.0037), and LSTM (0.0043), while remaining comparable to Transformer and GRU (0.0030). Compared with the lightest neural-network baseline, 1D-CNN, the trainable-parameter count is reduced from 113 to 51, corresponding to 45.1%. In addition, its training time is only 0.2542 s, which is 1.4% of that required by GRU. These results demonstrate the superior trade-off of the proposed device-enabled RC among recovery accuracy, model complexity, and training efficiency.

To further demonstrate the robustness and general applicability of the proposed hardware RC system, the satellite signal recovery performance under highly complex channel conditions is demonstrated in **Figure 4b**. The left panel shows the degraded image after simulated long-distance transmission, where the signal is jointly impaired by atmospheric turbulence and stochastic noise, leading to severe blurring and a markedly reduced SNR. In contrast, the right panel presents the image recovered by the physical reservoir computing system. Leveraging the transistor's intrinsic nonlinear mapping capability and short-term memory, the system effectively suppresses background noise while faithfully reconstructing texture details and edge features. These results clearly validate the robustness of the proposed system against strong nonlinear channel impairments.

Building on the high-performance reservoir-based signal recovery system, a downstream image classification network was constructed to evaluate classification performance before and after signal restoration, as detailed in Supplementary Figure S4. Although turbulence reduces recognition accuracy to 81.77%, the RC-based system effectively restores performance to 94.3%, approaching the ideal baseline of 95.7% and demonstrating robust resilience against signal distortions, highlighting its potential as a versatile platform for space-ground optical transmission and processing.

## 4 Conclusion

In summary, we have successfully demonstrated a WSe<sub>2</sub>-based reconfigurable self-biased transistor designed to overcome the need for compact and reconfigurable hardware capable of integrating high-fidelity optical sensing and nonlinear signal processing. By exploiting the gate-drain coupling and electrostatic doping to modulate the built-in electric field, the device achieves continuously tunable carrier transport, enabling both highly linear optoelectronic conversion and nonlinear neuronal responses within a single device. The transistor exhibits excellent optical linearity with  $R^2 = 0.99$ , supporting reliable optoelectronic signal conversion under different illumination conditions. When used as the core neuronal element in a reservoir computing system, it enables robust recovery of turbulence-distorted PAM-4 signals, reducing the BER from  $10^{-2}$  to  $10^{-4}$ . Compared with representative neural-network-based nonlinear equalizers, the proposed device-enabled RC

reduces the trainable-parameter count to 45.1% and the training time to 1.4%, demonstrating an advantageous balance among recovery accuracy, model complexity, and computational efficiency. This work provides a unified and reconfigurable optoelectronic device platform for efficient neuromorphic signal processing in future space-ground optical communication systems.

**Electronic Supplementary Material:** Supplementary material (Further details on simulation details of the reservoir computing system, leveraging nonlinear electrical characteristics of reconfigurable self-bias transistors for image processing, multispectral image processing and recognition, parameter sweep and optimization of the reservoir, quantitative evaluation on handwritten letter dataset) is available in the online version of this article at <https://doi.org/10.26599/NR.2026.94909153>.

### Data availability

All data needed to support the conclusions in the paper are presented in the manuscript and the Electronic Supplementary Material. Additional data related to this paper may be requested from the corresponding author upon request.

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### Declaration of competing interest

All the contributing authors report no conflict of interests in this work.

### Author contribution statement

X. R. M.: Experimental design, data curation, neural network simulation, project administration, writing manuscript. M. Z.: Experimental design, investigation, data curation, project administration, writing manuscript. H. X. T.: Investigation, data curation. W. M. P.: Investigation, data curation. Y. C.: Experimental design, data curation. K. H. W.: Experimental design, data curation. H. N. S.: Experimental design, data curation. L. C.: Project administration, supervision, formal analysis. K. Q. L.: Supervision, formal analysis, review manuscript, funding acquisition. X. F. W.: Supervision, project administration, funding acquisition, review manuscript. All authors have approved the final manuscript.

### Informed consent

Not applicable.

### Ethics statement

Not applicable.

### Use of AI statement

None.

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## Electronic Supplementary Material

### A reconfigurable self-biased optoelectronic transistor for integrated high-fidelity sensing and neuromorphic signal recovery

Xingrou Meng<sup>1,§</sup>, Miao Zhang<sup>1,2,§</sup>, Haoxiang Tian<sup>1</sup>, Weiming Pu<sup>1</sup>, Yi Cui<sup>1</sup>, Kehan Wu<sup>1</sup>, Haonan Sun<sup>1</sup>, Long Chen<sup>1,✉</sup>, Keqin Liu<sup>1,3,✉</sup>, Xianfu Wang<sup>1,✉</sup>

<sup>1</sup> State Key Laboratory of Electronic Thin Film and Integrated Devices, University of Electronic Science and Technology of China, Chengdu 611737, China

<sup>2</sup> Hongming Electronics, Chengdu 611737, China

<sup>3</sup> Guangdong Provincial Key Laboratory of In-Memory Computing Chips, School of Electronic and Computer Engineering, Shenzhen Graduate School, Peking University, Shenzhen 518055, China

<sup>§</sup> Xingrou Meng and Miao Zhang contributed equally to this work.

✉ Address correspondence to Long Chen, chenlong@uestc.edu.cn; Keqin Liu, kqliu@uestc.edu.cn; Xianfu Wang, xfwang87@uestc.edu.cn.

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## Supplementary Note 1: Simulation details of the physical reservoir computing system

### Atmospheric turbulence channel modeling

To rigorously evaluate the system's robustness, we simulated the space-ground optical transmission and processing link under atmospheric turbulence. The channel fading coefficient  $h(t)$  is modeled using the Log-normal distribution, which is widely adopted for weak-to-moderate turbulence regimes. The received signal intensity  $I_{rx}(t)$  is expressed as:

$$I_{rx}(t) = I_{tx}(t) \cdot h(t) + n(t)$$

where  $I_{tx}(t)$  represents the transmitted PAM-4 signal, and  $n(t)$  denotes additive white Gaussian noise (AWGN). The fading coefficient  $h(t)$  follows:

$$h(t) = \exp(X), \quad X \sim N(-\sigma_R^2/2, \sigma_R^2)$$

In our simulation (Python environment), the turbulence strength is set to  $\sigma_R^2 = 0.3$  (indicating strong fluctuation), and the noise level is set to 0.05.

### Device nonlinearity model

The core of the reservoir computing system is the reconfigurable optoelectronic device. Based on the experimental electrical characteristics shown in Figure 2, we modeled the device's transfer function as an expansive nonlinearity. The mathematical expression used in the simulation is:

$$f(x) = \text{sgn}(x) \cdot (e^{|x|} - 1)$$

To reflect physical constraints, a saturation limit (ranging from -0.6 V to 1.5 V) is applied to the input  $x$  before the exponential transformation. This expansive nature is critical for separating aliased signal levels.

### Time-multiplexing reservoir construction

We implemented a delay-based reservoir architecture where a single physical node is time-multiplexed to create  $N$  virtual nodes. The dynamics of the  $j$ -th virtual node at the  $i$ -th symbol step, denoted as  $x_i(j)$ , is governed by:

$$x_i(j) = f(\alpha \cdot I_{rx,i} \cdot M_j + \beta \cdot x_i(j-1))$$

where:

$N = 50$  is the number of virtual nodes (corresponding to the sampling rate).

$I_{rx,i}$  is the averaged input signal for the current symbol.

$M_j$  is the input mask value for the  $j$ -th node, drawn from a uniform distribution  $U[-0.5, 0.5]$ .

$\alpha = 0.15$  is the input gain scaling the optical drive.

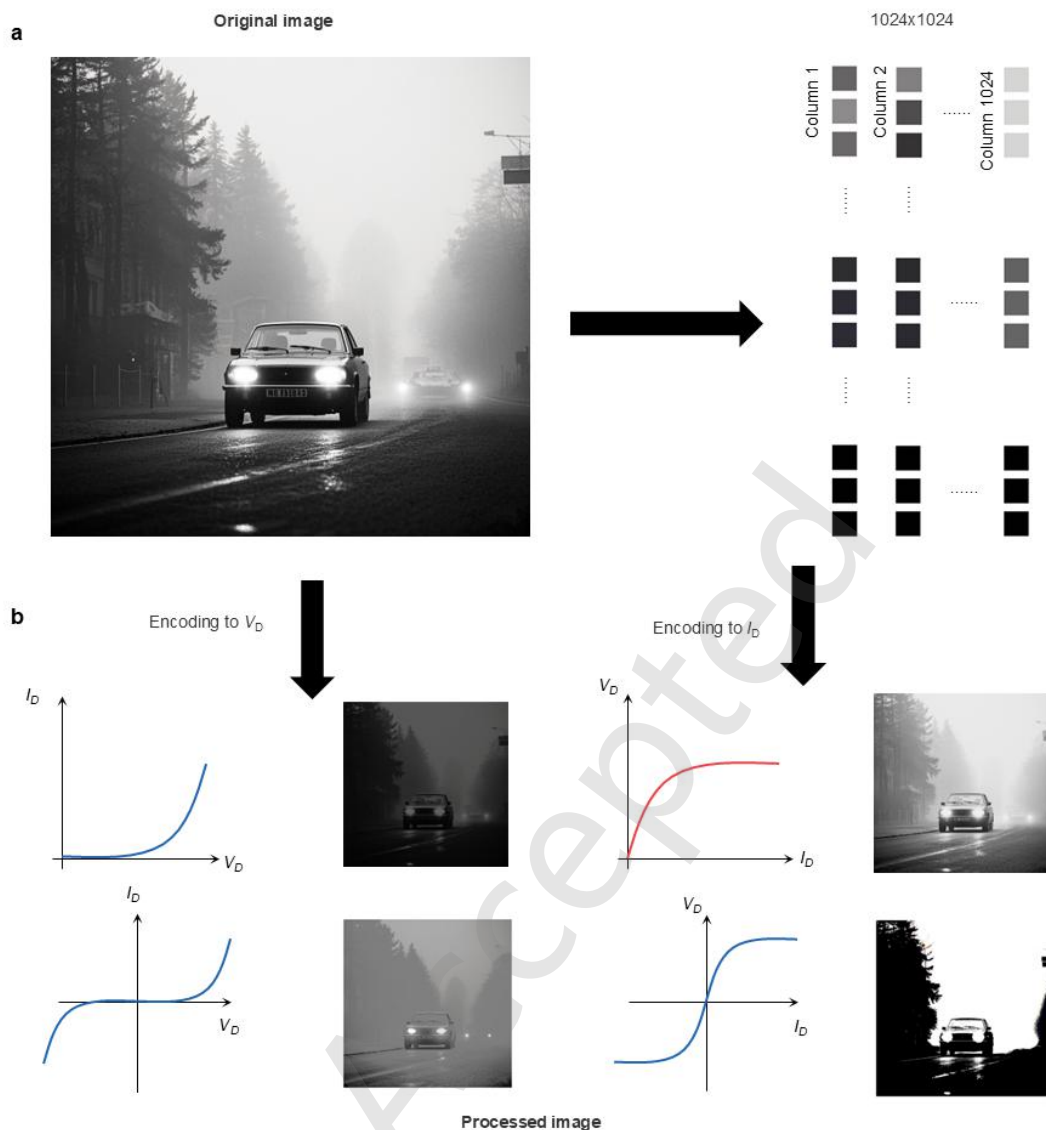
$\beta = 0.1$  is the feedback gain representing the temporal coupling strength.

$x_i(j-1)$  represents the state of the previous virtual node (for  $j=0$ , it connects to the last state of the previous symbol  $x_{i-1}(N-1)$  due to the delay loop).

## Supplementary Section 1. Leveraging nonlinear electrical characteristics of reconfigurable self-bias transistors for image processing

Image processing and recognition play a crucial role in areas such as autonomous driving and medical imaging<sup>[1-4]</sup>. By leveraging the electrical characteristics of reconfigurable self-bias transistors, four image enhancement functions can be achieved.

A  $1024 \times 1024$  image is selected as the input signal to the device, as shown in **Figure S1(a)**. Due to its voltage-current characteristics, which exhibit the nonlinear behavior of an exponential function, it can be effectively used for image processing. **Figure S1(b)** illustrates the image enhancement effects achieved by leveraging the device's electrical properties and various encoding and processing methods. The first method utilizes the device's output characteristics in the  $V_{PG} > 0$  region, where the image's color intensity range of 0-255 is linearly mapped to the 0-8 V range as input. The device's current  $I_D$  is collected as the output, and this  $I_D$  is then linearly divided into the range 0-255 to form the new color intensity, thereby enhancing the image's dark details. The second method linearly encodes the image's color intensity into the -8 V to 8 V range as input, reverses the polarity of  $V_{PG}$ , and linearly encodes the output  $I_D$  from negative to positive into the 0-255 range as the new color intensity output, thus achieving grayscale processing of the image. The third method leverages the  $V_{PG} > 0$  region output characteristics by linearly encoding the image's color intensity as  $I_D$ , which is used as input. The voltage between the source and drain is then output and converted into the 0-255 range, effectively enhancing the bright details of the image. The fourth method adjusts the  $V_{PG}$ , linearly maps the 0-255 range to positive and negative currents as input, and the resulting source-drain voltage is linearly mapped from negative to positive into the 0-255 range. This encoding and processing approach achieves contrast stretching of the image. The image processing methods described here are of great significance for achieving low-power, multifunctional image processing modes.

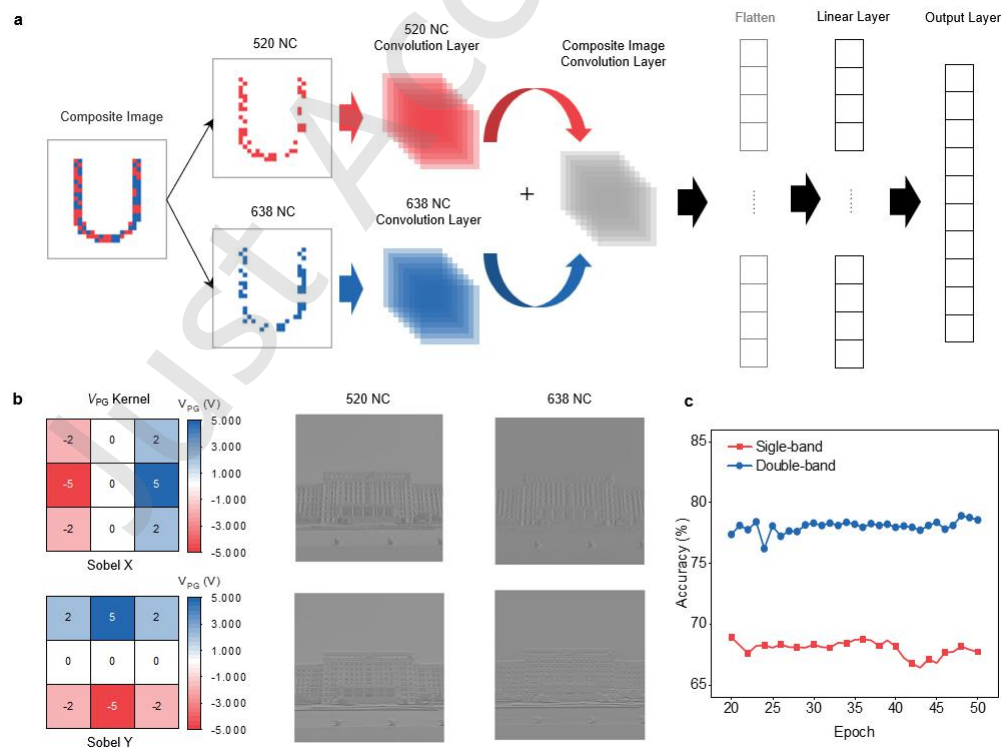


**Supplementary Figure S1. Image processing and enhancement leveraging device electrical nonlinearity.** **a.** Original input image used for the processing demonstrations. **b.** Four distinct image enhancement functions achieved by leveraging the device's reconfigurable nonlinear electrical characteristics.

## Supplementary Section 2. Multispectral image processing and recognition

The ambipolar reconfigurable device, based on a split-gate structure, is characterized by linear positive and negative photoconductivity, thereby enabling applications in fields such as image edge detection and matrix multiplication<sup>[5,6]</sup>. By leveraging the response of semiconductor materials to distinct optical wavelengths, recognition accuracy for specific tasks can be effectively enhanced. As illustrated in **Figure S2(a)**, the input image is composed of light from two distinct bands: 520 nm and 638 nm. Utilizing the intrinsic optical response of the device, convolution operations are executed separately for the 520 nm and 638 nm bands, with the resulting outputs subsequently summed. Following a fully connected operation, image classification and recognition are achieved.

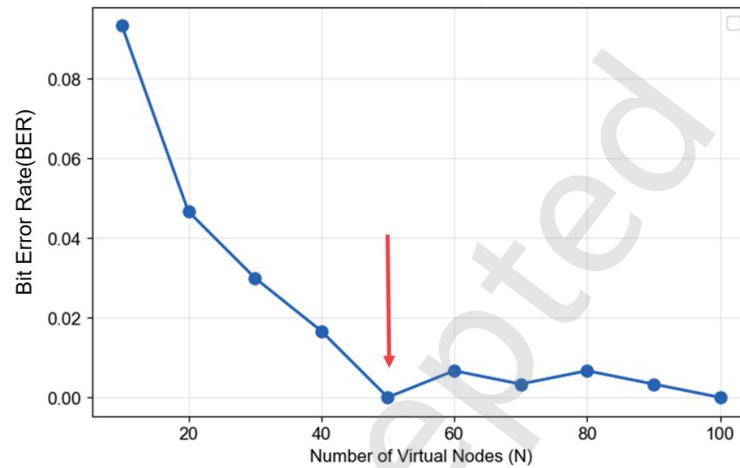
In **Figure S2(b)**, edge detection results for images under different optical bands are presented, demonstrating robust detection performance. Furthermore, the reconfigurable self-biased transistor can be utilized to implement in-sensor multi-band convolution networks, thereby yielding superior recognition accuracy compared to single-band counterparts. To validate this, the Fashion-MNIST dataset was grayscale-processed, and appropriate noise was introduced to the processed images. These were then fused with the original grayscale images to simulate interference from specific light bands in complex environments. Following dataset reconstruction, simulation tests indicated that the recognition accuracy for the single-band method was limited to approximately 66%. In contrast, recognition accuracy under dual-band conditions was improved by approximately 12%, demonstrating that under identical training conditions, the test accuracy of the dual-band method is significantly higher than that of the single-band method (**Figure S2(c)**).



**Supplementary Figure S2. Multispectral image processing and recognition applications based on the split-gate ambipolar reconfigurable device.** **a.** Schematic of the in-sensor dual-band convolution recognition workflow. **b.** Demonstration of multi-band edge detection. **c.** Quantitative comparison of recognition accuracy in noisy environments.

### Supplementary Section 3. Parameter sweep and optimization of the reservoir

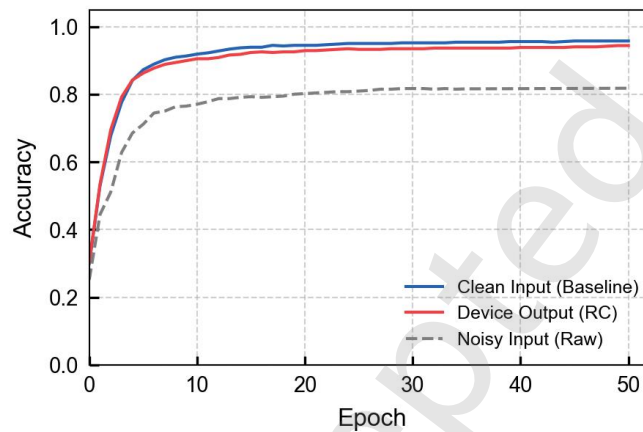
The relationship between the number of  $N$  and the BER exhibits a clear downward trend that saturates after an optimal point. Initially, increasing  $N$  significantly improves performance by expanding the dimensionality of the feature space, achieving error-free transmission at  $N=50$ . Beyond this point, further increasing the sampling rate yields diminishing returns. While  $N=100$  also achieves zero error, the minor fluctuations observed between  $N=60$  and  $N=90$  suggest that the system approaches a limit where high-frequency noise sensitivity begins to interfere with stability. Therefore,  $N=50$  is identified as the optimal operating point, balancing high computational dimensionality with physical bandwidth efficiency.



Supplementary Figure S3. Impact of the number of virtual nodes ( $N$ ) on the BER.

## Supplementary Section 4. Quantitative evaluation on handwritten letter dataset

As illustrated in Supplementary Figure S4, we evaluated the system's performance in a downstream image classification task using the handwritten letter dataset. The recognition model was implemented as a simple single-layer perceptron to test the linear separability of the output features. Under ideal noise-free conditions, the baseline recognition accuracy is 95.7%. Upon the introduction of atmospheric turbulence, however, the recognition accuracy using traditional processing methods degrades precipitously to 81.77% due to feature distortion. In contrast, after processing via the proposed reservoir computing system, the simple single-layer perceptron successfully extracts features from the recovered signals, restoring the accuracy to 94.3%. This result confirms that the device's expansive nonlinearity effectively amplifies and separates minute signal differences, enabling remote sensing recognition performance that approaches ideal levels with minimal computational complexity.



Supplementary Figure S4. Comparison of classification accuracy between turbulence-distorted and restored images.

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