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DeepMind • 谷歌大脑

Backpropagation and the brain

Timothy P. Lillicrap • Adam Santoro • Luke Marris • Colin J. Akerman • Geoffrey Hinton

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Introduction:

大脑通过修改神经元之间的突触连接学习，尽管这种突触生理学能过解释该调节过程的规则和过程，但是并不能说明人类大脑内的调节过程中是如何互相协调以实现网络目标的。因为学习从来都不是一个盲目（不计后果）、短视事件的积累过程。如果我们要了解大脑中的学习过程，就需要揭示在整个网络中协调可塑性(orchestrating plasticity)原理。

在机器学习中，研究人员从定义神经网络的架构开始（其中包括神经元的数量及其连接方式）—— 研究人员经常使用具有多层神经元的深层网络（因为事实证明这些架构对于许多不同的任务都非常有效）。 接下来，研究人员便定义一个误差函数，该函数用于量化网络当前实现其目标的程度，然后找寻可以减少误差的学习算法[Fig1]。

在机器学习中，误差反向传播算法是最常使用且最成功的训练深度神经网络算法[Box1]。使用反向传播算法的神经网络是机器学习成功的核心，该技术已经可以在无监督学习、图像识别以及语言翻译领域有很多成功应用。然而，现实中，人脑内的反馈连接常被用于不同的目的(the brain appears to use its feedback connections for different purposes)，并且多以无监督学习呈现，那么我们不禁好奇，反向传播是否可以告知我们大脑中的学习过程?

在这里，我们假设，尽管存在这些明显的差异，大脑仍具有执行反向运算的能力。主要依据是，大脑可以通过反馈连接来诱导神经元活动来计算有效的突触更新，而这些神经元将局部计算出的差异编码为类似反向传播的误差信号。

Credit assignment in networks:

尽管动物出生起就常常表现出某些令人印象深刻的行为（天赋），但它们也展现出只有需要长期的学习才可具有的非凡的壮举。 对于人类，可以是计算机编程或设计视频游戏、 写作和演奏钢琴协奏曲、 学习多种语言的词汇和语法、识别数千个物体、诊断医疗问题并进行血管显微手术。 机器学习的最新研究表明，这些行为取决于强大而通用的学习算法。 因此，我们的兴趣在于试图表达此类学习算法，尤其是它们如何在大脑的多个神经元层中分配。

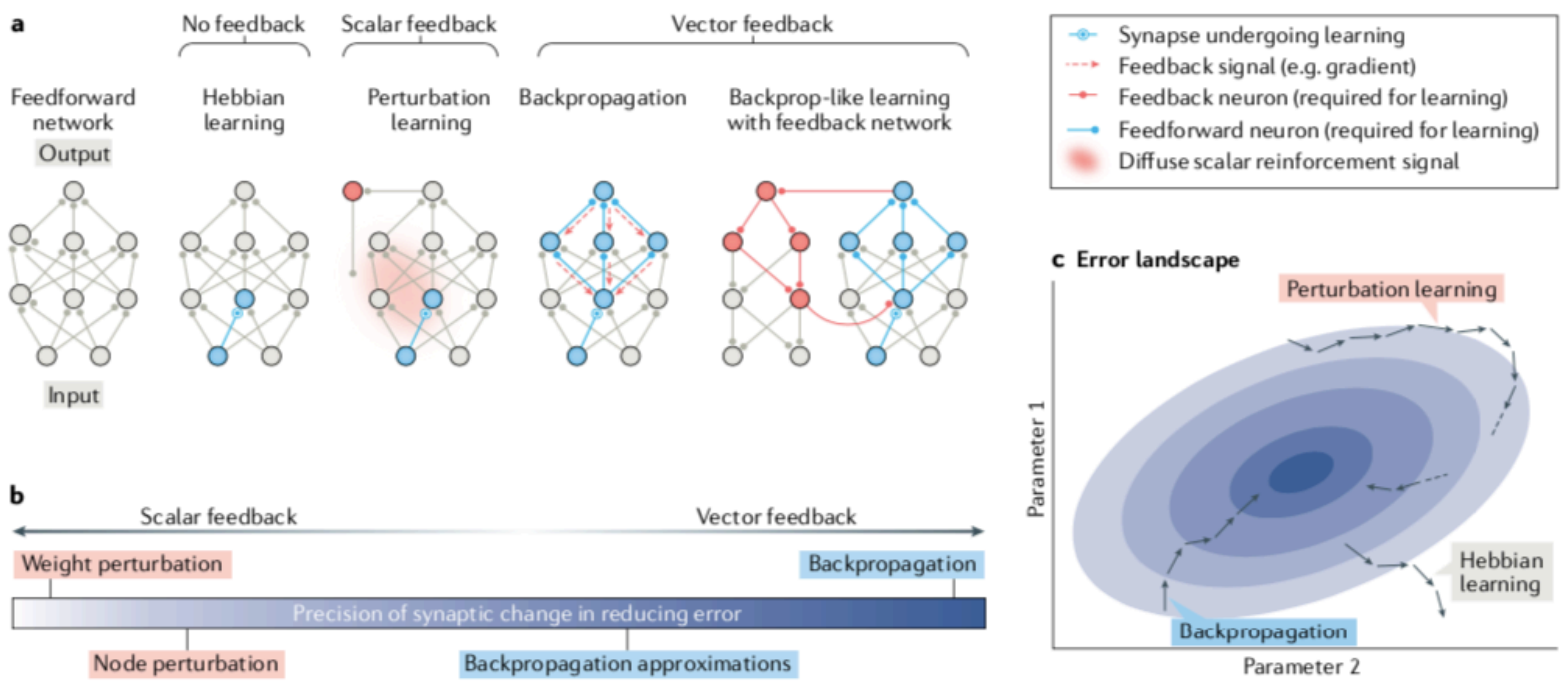
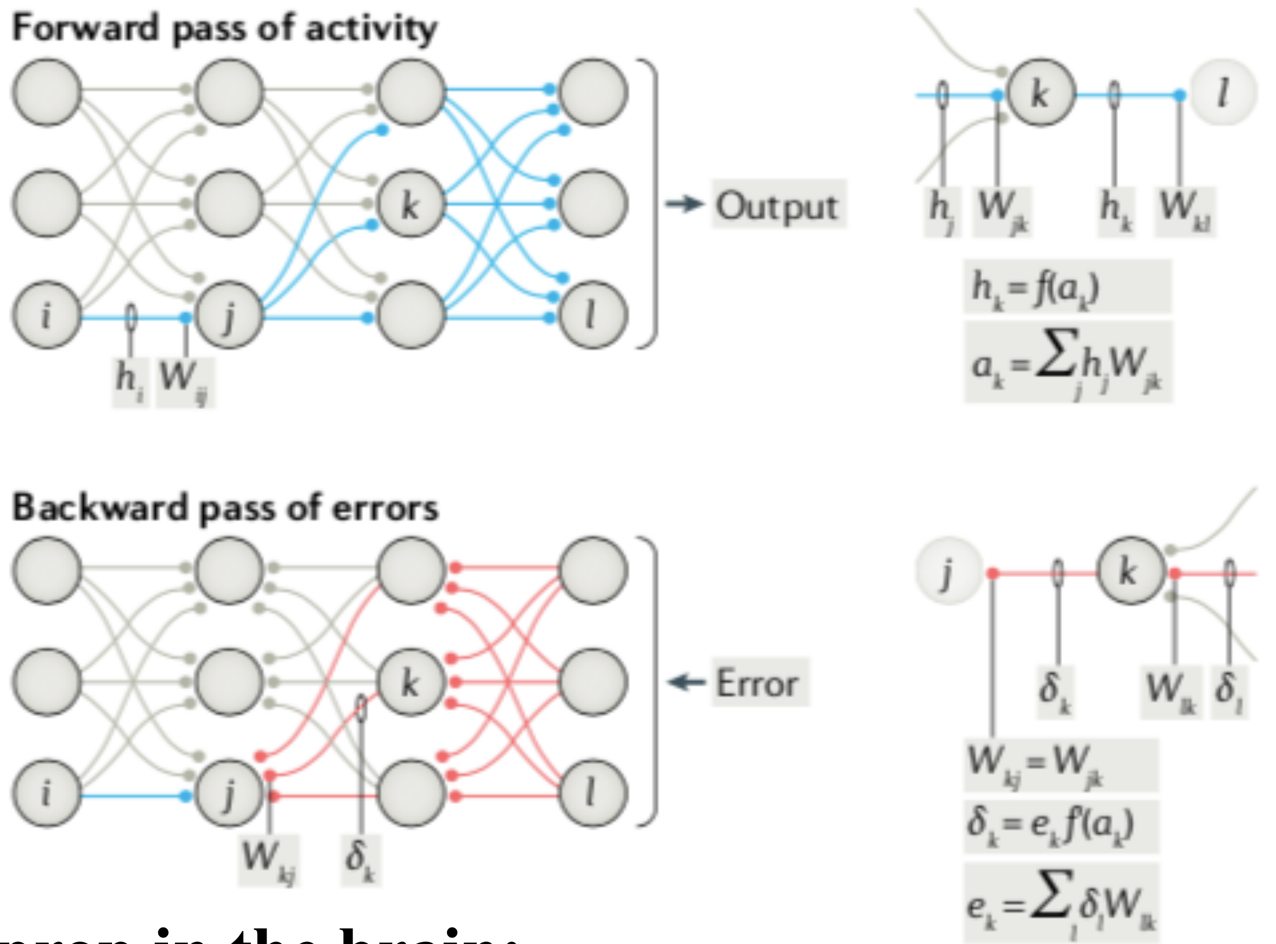


Fig. 1 | **A spectrum of learning algorithms. a** | Left to right: a neural network computes an output through a series of simple computational units. To improve its outputs for a task, it adjusts the synapses between these units. Simple Hebbian learning — which dictates that a synaptic connection should strengthen if a presynaptic neuron reliably contributes to a postsynaptic neuron's firing — cannot make meaningful changes to the blue synapse, because it does not consider this synapse's downstream effect on the network output. Perturbation methods measure the change in error caused by random perturbations to neural activities (node perturbation) or synapse strengths[44] (weight perturbation) and use this measured change as a global scalar reinforcement signal that controls whether a proposed perturbation is accepted or rejected. The backprop algorithm instead computes the synapse update required in order to most quickly reduce the error. In backprop, vector error signals are delivered backward along the original path of influence for a neuron. In the brain, vector feedback might be delivered in a variety of ways, including via a separate network. **b** | Backpropagation and perturbation algorithms fall along a spectrum with respect to the specificity of the synaptic change they prescribe. **c** | Algorithms on this spectrum learn at different speeds. Without feedback, synaptic parameters wander randomly on the error surface. Scalar feedback does not require detailed feedback circuits, but it learns slowly. Since the same signal is used to inform learning at all synapses, the difficulty of deciding whether to strengthen or weaken a synapse scales with the number of synapses in the network: if millions of synapses are changed simultaneously, the effect of one synapse change is swamped by the noise created by all the other changes, and it takes millions of trials to average away this noise[43–46]. The inverse scaling of learning speed with network size makes global reinforcement methods extremely slow, even for moderately sized neural networks. Precise vector feedback via backprop learns quickly. In real networks, it is not possible to make perfect use of the internal structure of the network to compute per-synapse changes, but the brain may have discovered ways to approximate the speed of backprop.



Backprop in the brain:

目前没有直接证据表明人类大脑使用类似反向传播的算法进行学习。但是，之前有研究表明，使用反向传播训练的模型可以解释观测到的神经响应，例如后叶顶皮层和初级运动皮层中的神经元响应。此外，神经科学领域对视觉皮层进行建模的研究提供了新的证据。该研究表明，相比匹配灵长目动物视觉皮层腹侧流中表征的其他模型，使用反向传播训练得到的多层分类模型性能更好[Fig 2].

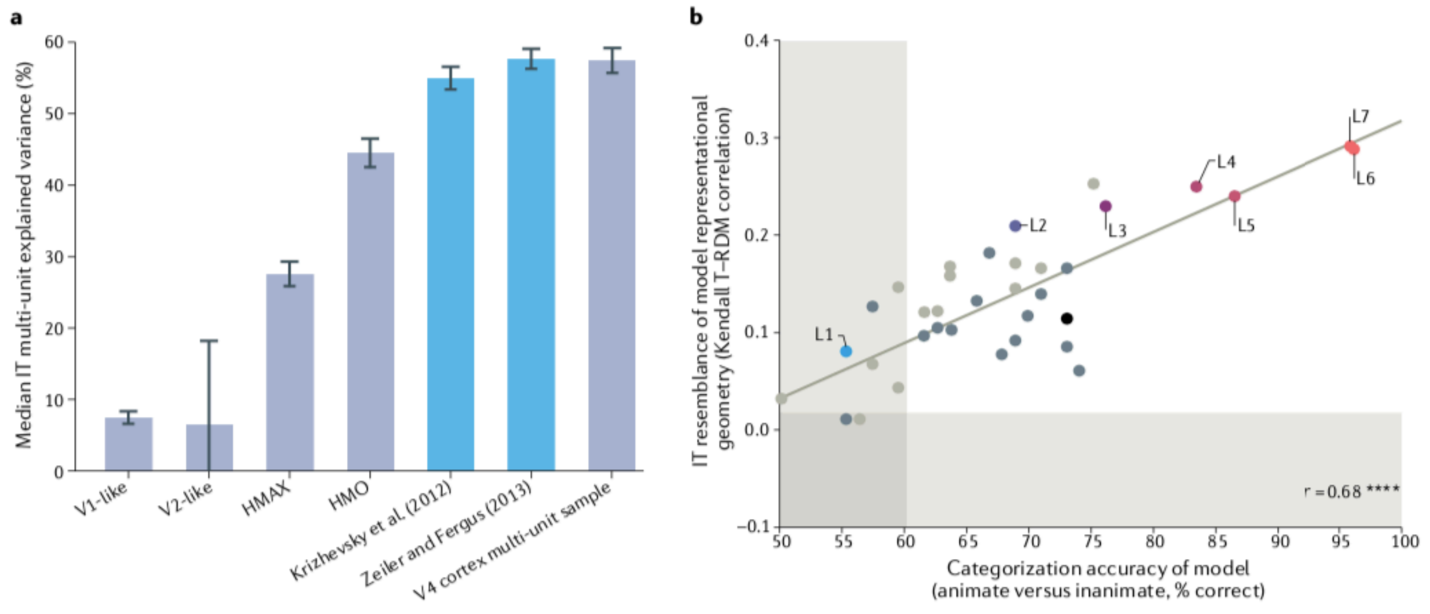


Fig. 2 | **Comparison of backprop-trained networks with neural responses in visual ventral cortex. a** | Cadieu et al.[58] showed that backprop-trained models[12,170] (blue) explain inferior temporal cortex (IT) multi-unit responses better than other models do (grey). **b** | Khaligh-Razavi and Kriegeskorte[70] showed that models with better classification performance more closely resemble IT representations; each unlabelled dot corresponds to a model, whereas the coloured dots L1–L7 correspond to successively deeper network layers. Moreover, neurons in deeper layers within the backprop-trained network have representations that are more similar to those in IT cortex than are neurons in earlier layers of the network. Part **a** adapted from REF.[58], CC-BY-4.0 (https://creativecommons.org/licenses/by/4.0/). Part **b** adapted from REF.[70], CC-BY-4.0 (https://creativecommons.org/licenses/by/4.0/).

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The NGRAD hypothesis:

· 使用神经活动差异来编码误差

（研究者利用活动状态差异来驱动突出变化的学习机制称为NGRAD，而皮层利用NGRAD机制执行对梯度下降近似的想法被称为NGRAD假设）

NGRAD机制基于这样的想法，即较高级活动可以推动较低级活动得到与较高级活动或期望输出更一致的值。然后，较低级活动中出现的变化可以仅使用局部可用信号来计算反向传播的权重更新。因此，其核心理念是自上而下驱动（top-down-driven）的活动可以在层间不出现明显误差信息的情况下驱动学习。

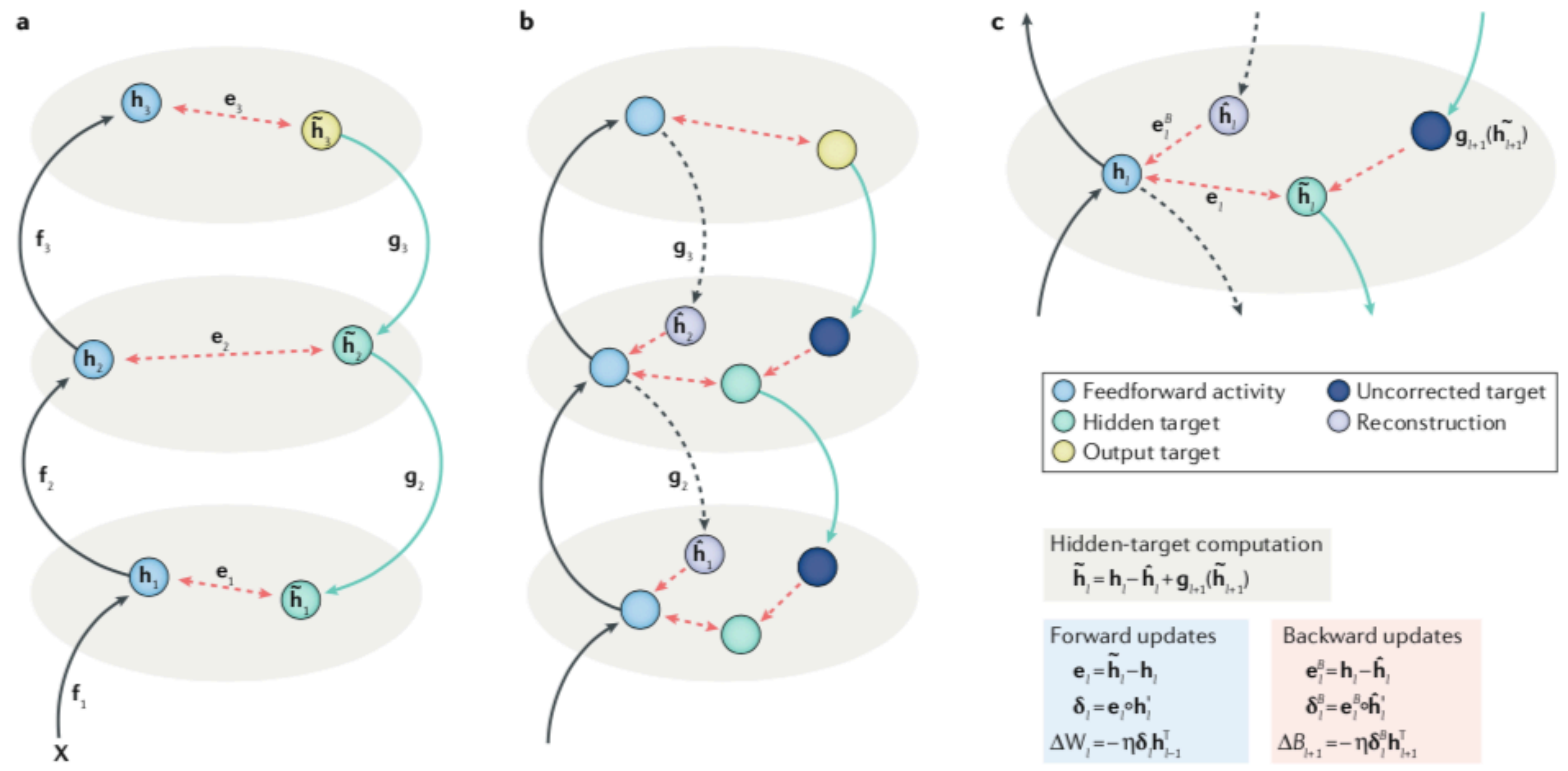


Fig. 3 | **Target propagation algorithms. a** | Schematic of target propagation that uses perfect inverses, $\mathbf{g}_l(\cdot) = \mathbf{f}_l^{-1}(\cdot)$, at each layer. For illustration, high-dimensional activity vectors at each layer are represented as points in a 2D space. Local layer-wise errors, $\mathbf{e}_l = \tilde{\mathbf{h}}_l - \mathbf{h}_l$, are computed between the forward-pass activities ($\mathbf{h}_l$; blue) and the top-level ($\tilde{\mathbf{h}}_3$; yellow) and induced ($\tilde{\mathbf{h}}_l$; green) targets. Synaptic weights, W_l, associated with the forward mapping $\mathbf{f}_l(\cdot)$ are updated in order to move the forward activity vectors closer to the targets. **b** | Difference target propagation helps correct for the fact that the feedback connections may not implement perfect inverses. For each layer, $\mathbf{h}_l$, we compute a reconstruction, $\hat{\mathbf{h}}_l$, from the layer immediately above via $\mathbf{g}_{l+1}(\cdot)$. Then, to compensate for imperfections in the auto-encoders, we add the reconstruction error, $\mathbf{e}_l^B = \mathbf{h}_l - \hat{\mathbf{h}}_l$, to the uncorrected target $\mathbf{g}_{l+1}(\tilde{\mathbf{h}}_{l+1})$ (dark blue), computed from the layer above in the backward pass. **c** | Schematic for a single layer of difference target propagation. Forward synaptic weights, W_l, are updated in order to move the forward-pass hidden activity closer to the corrected hidden target. Note that the light purple, dark blue and green circles do not represent separate sets of neurons, but rather different stages of processing performed in the same neurons. Backward synaptic weights, B_{l+1}, are updated in order to reduce auto-encoder reconstruction errors. The hidden target, $\tilde{\mathbf{h}}_l$, is computed as a mixture of the bottom-up activity with top-down feedback. Crucially, errors are computed with signals local to the neurons in each layer, rather than propagated between layers as in backprop.

Implementation:

大脑如何近似反向传播，现有的NGRAD或许能提供较为高级的见解，但是关于如何在神经组织中实施这种算法仍有许多疑问。

为了在神经回路中发挥作用，NGRAD必须具备以下能力：协调前馈和反馈途径之间的相互作用，计算神经活动模式之间的差异以及利用这种差异进行适当的突触更新。 目前尚不清楚生物回路如何支持这些操作，但是最近的实证研究为这些实施要求提供了一组潜在的解决方案。

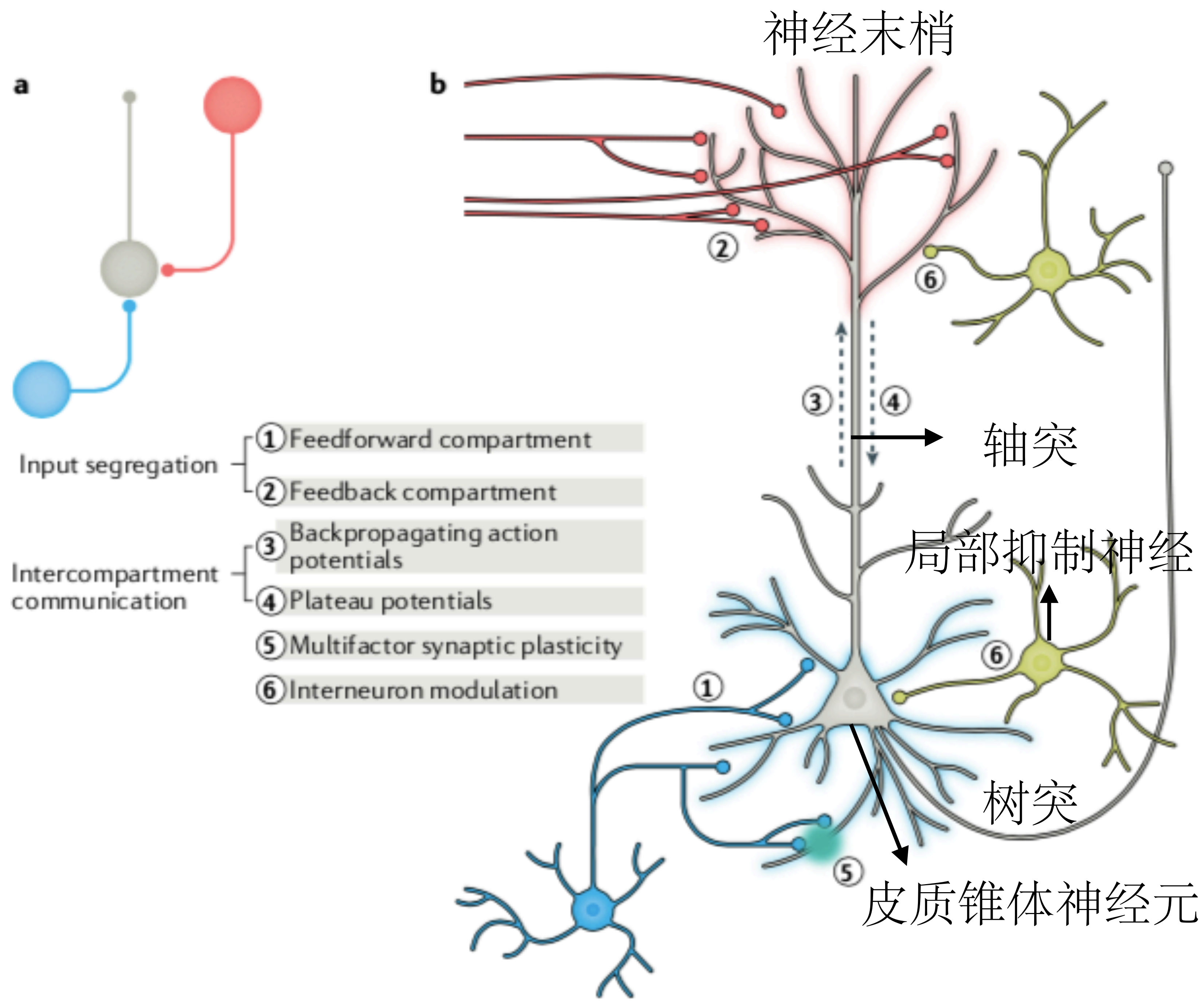


Fig. 4 | **Empirical findings suggest new ideas for how backprop-like learning might be approximated by the brain. a** | When backprop was first published, a neuron (grey cell) was typically conceived of, and modelled, as a single voltage compartment into which feedforward signals (blue; for example, from a lower-order cortical area) and feedback signals (red; for example, from a higher-order cortical area) would arrive undifferentiated. **b** | A contemporary schematic of a cortical pyramidal neuron (grey cell). Feedforward (**1**) and feedback (**2**) inputs are thought to be treated differently. They arrive at different compartments of the cell (for example, the basal and apical dendrites, respectively) and may be electrotonically segregated. Compartments can communicate selectively via backpropagating action potentials that are triggered by spikes in the soma and via calcium-spike-induced plateau potentials generated in the apical dendrite (**3** and **4**). Plasticity in one compartment may depend on both local synaptic events and events triggered in another compartment (**5**). For example, 'forward' basal synaptic plasticity may be altered by the arrival of apically generated plateau potentials. Finally, local inhibitory neurons (yellow cells) can regulate the communication between the subcellular compartments and can themselves be differentially recruited by higher-order inputs, and thus can modulate the interactions between the forward and backward pathways (**6**).

Report

2020.4.27

張慕琪

Methods

实验设计:

已完成图片记录：time series (Beijing, China); Maps_differences;
taylor diagram (Beijing, China), histogram(Beijing, China)

待完成绘图:

1. future time series(Beijing, *China*);
2. future maps(*2090-2100, 2090s-1990s*).

时间：Train & validation (=historical), test (future projection)

数据：CCSM, GMFD, ANN(before BC) , ANN(after BC), Linear

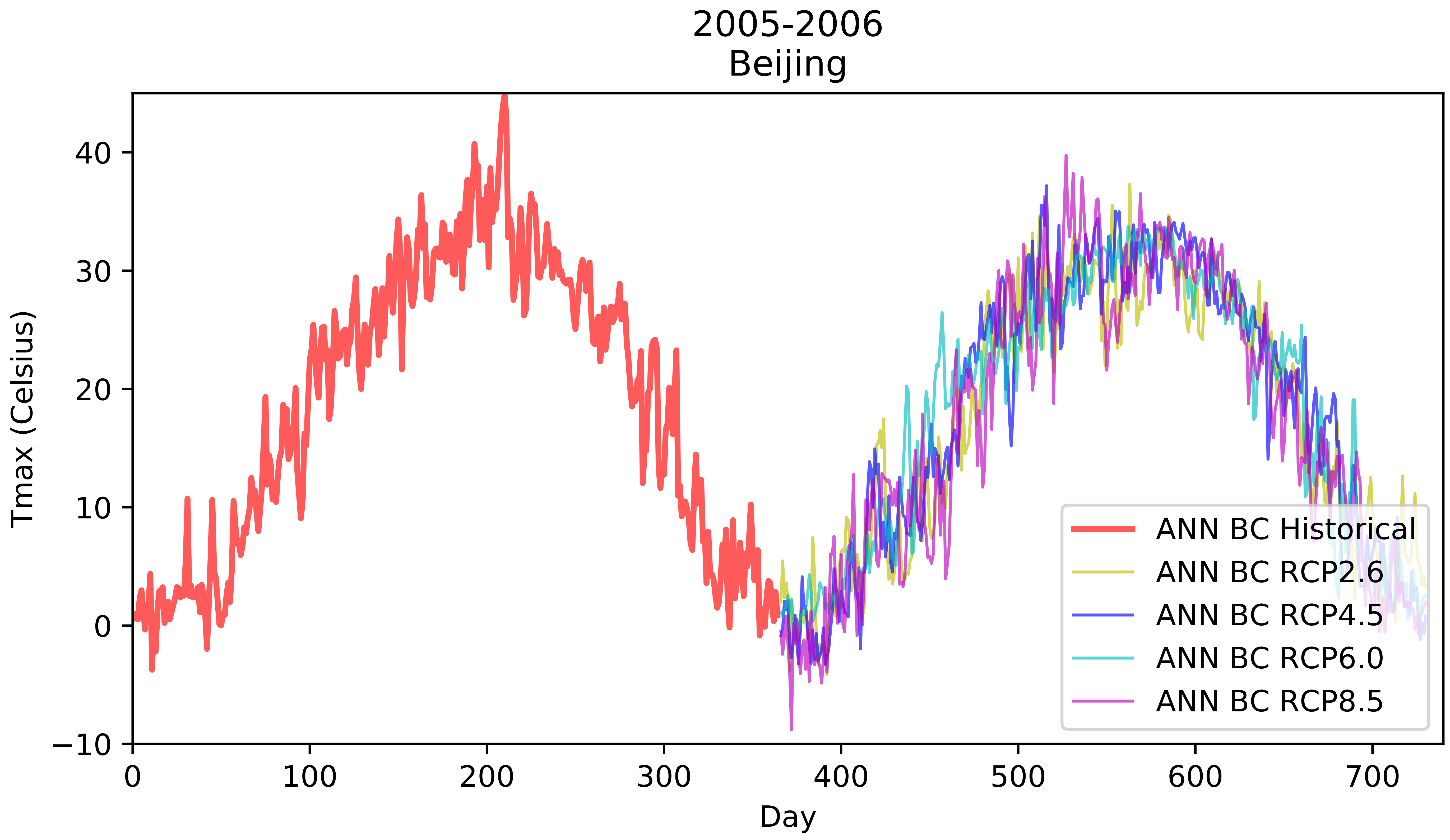
变量:

·Temperature

Results

Time series Beijing Future

Tmax




```
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ann_rcp26 = 28.999779
ann_rcp45 = 31.257303
ann_rcp60 = 32.004745
ann_rcp85 = 28.86967
```
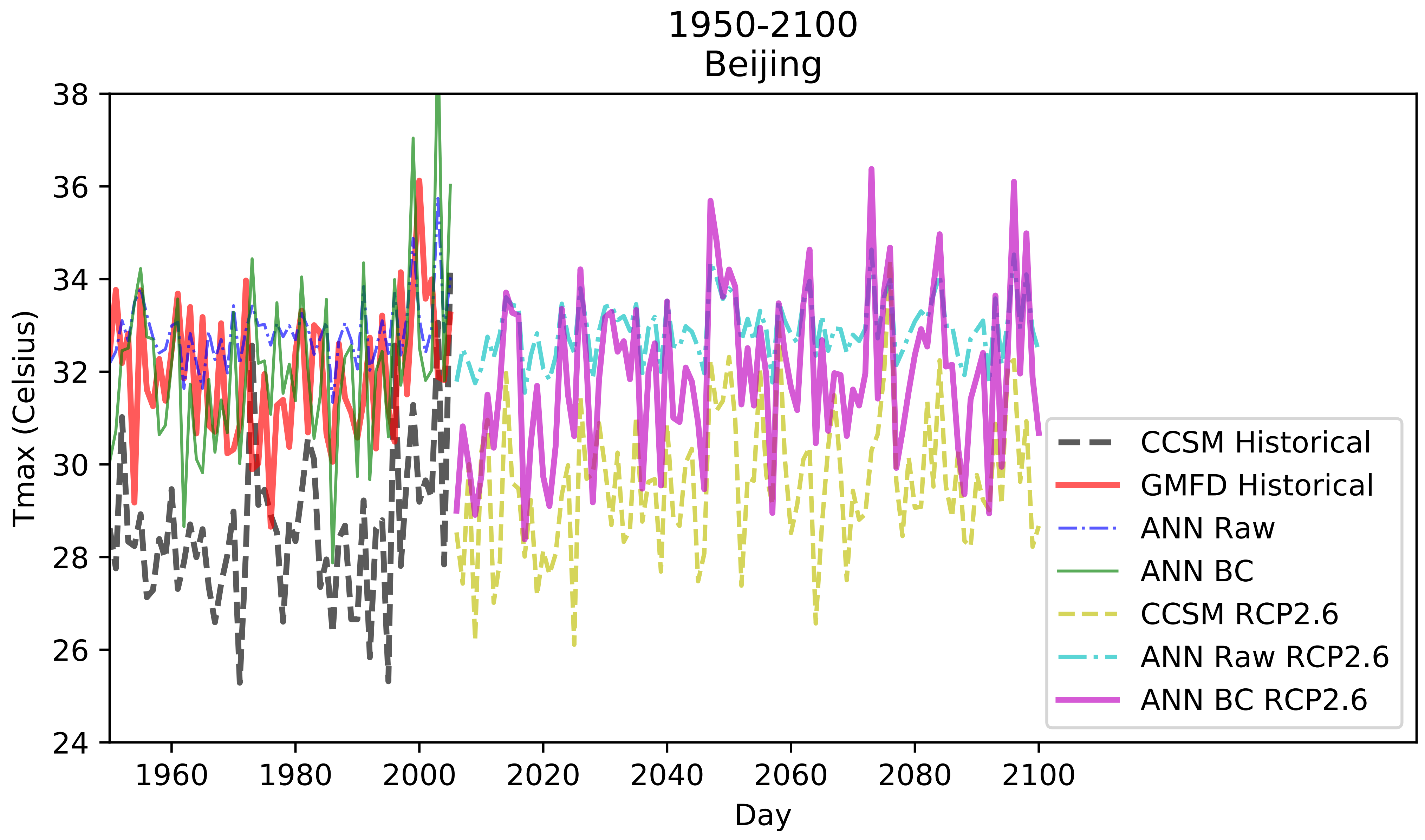
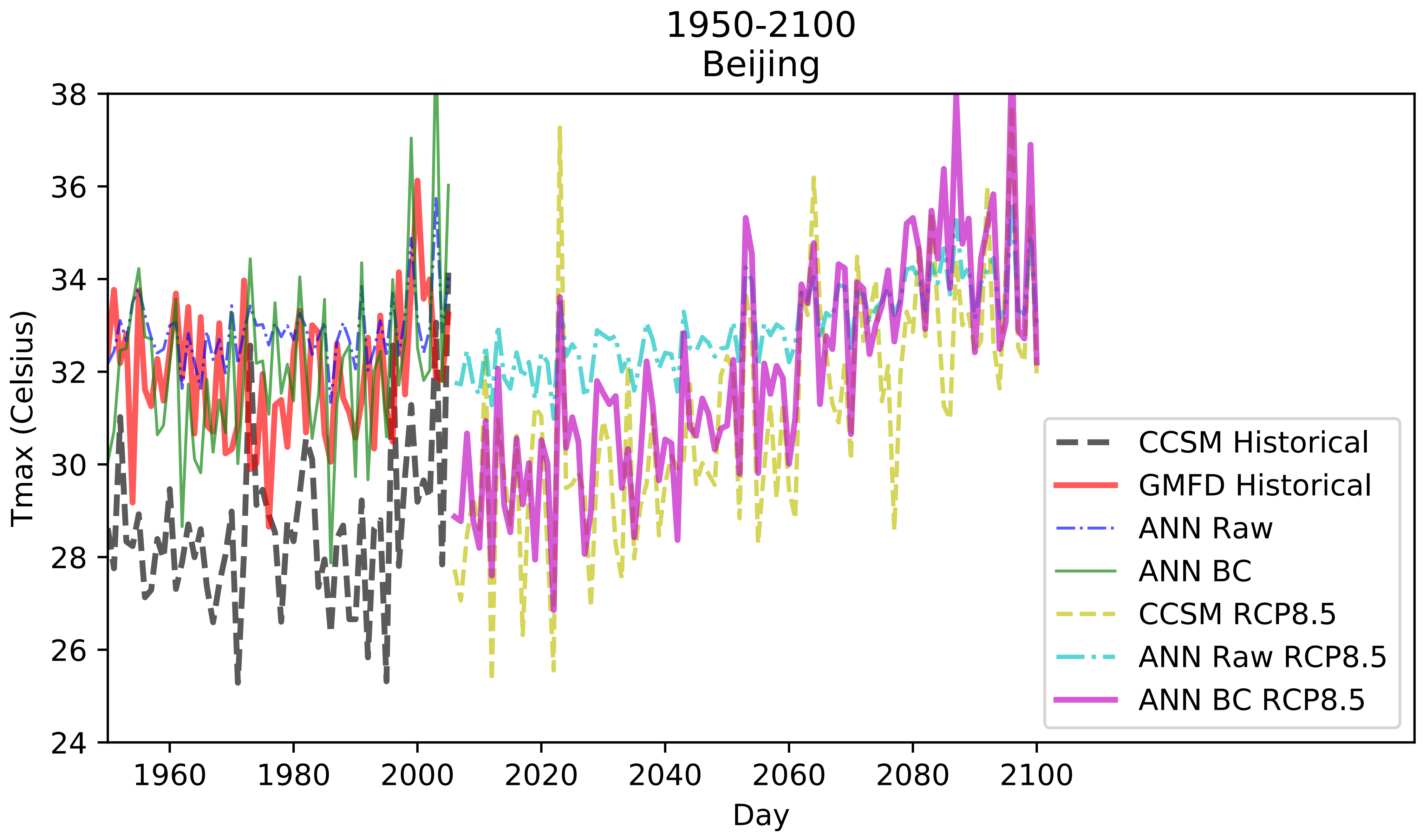

Results

Time series Beijing Future

Tmax

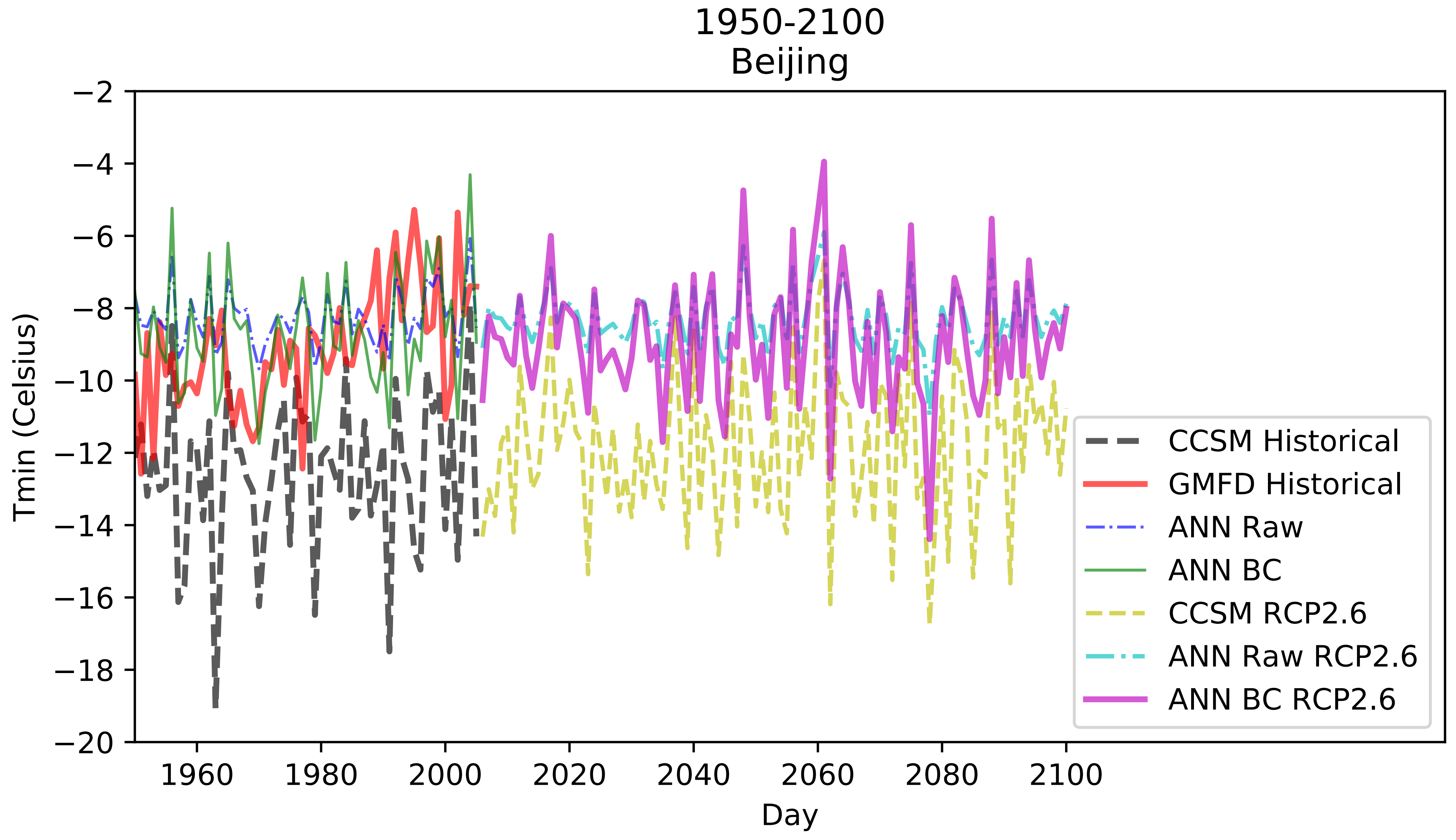


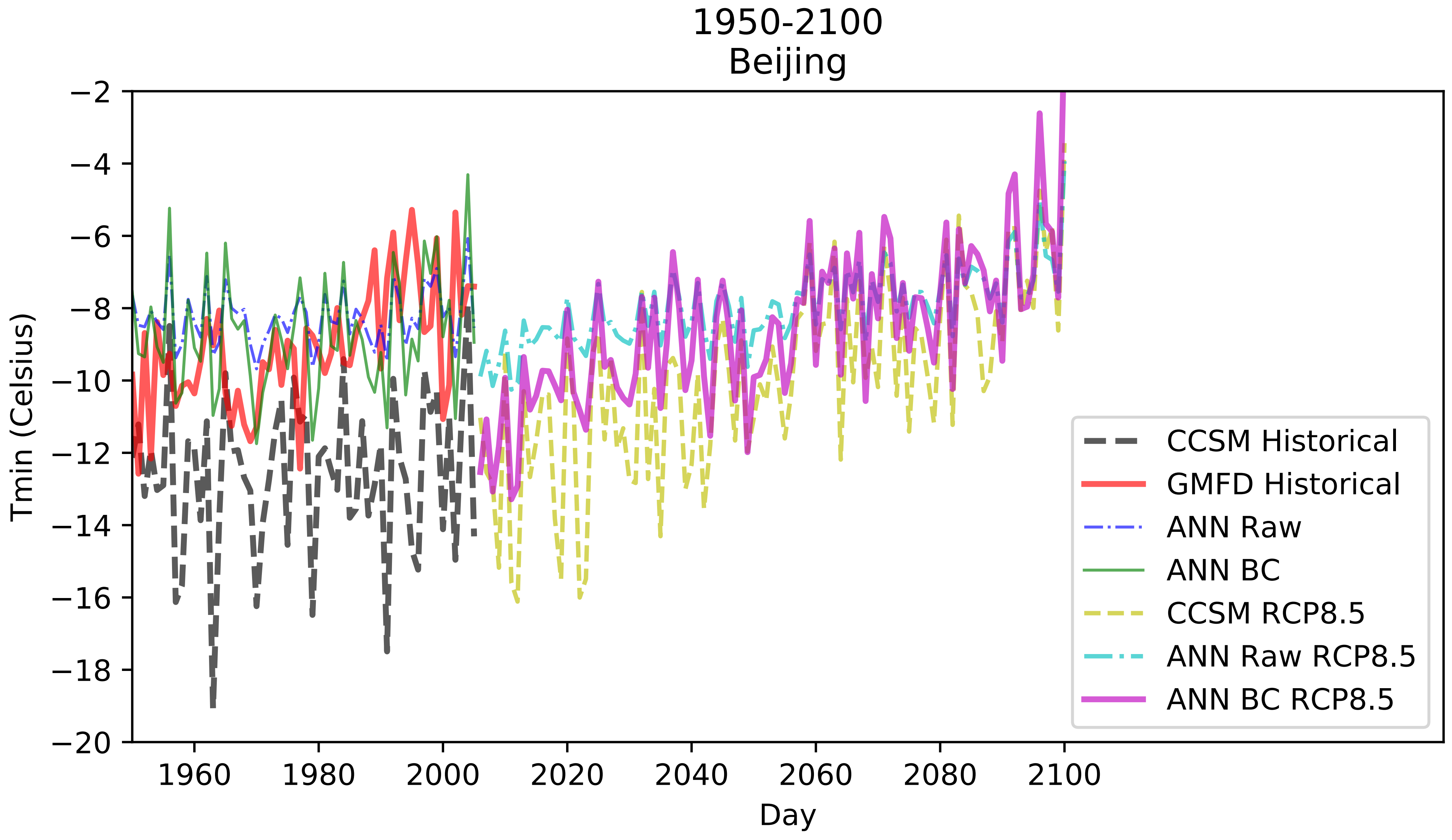


Results

Time series Beijing Future

Tmin



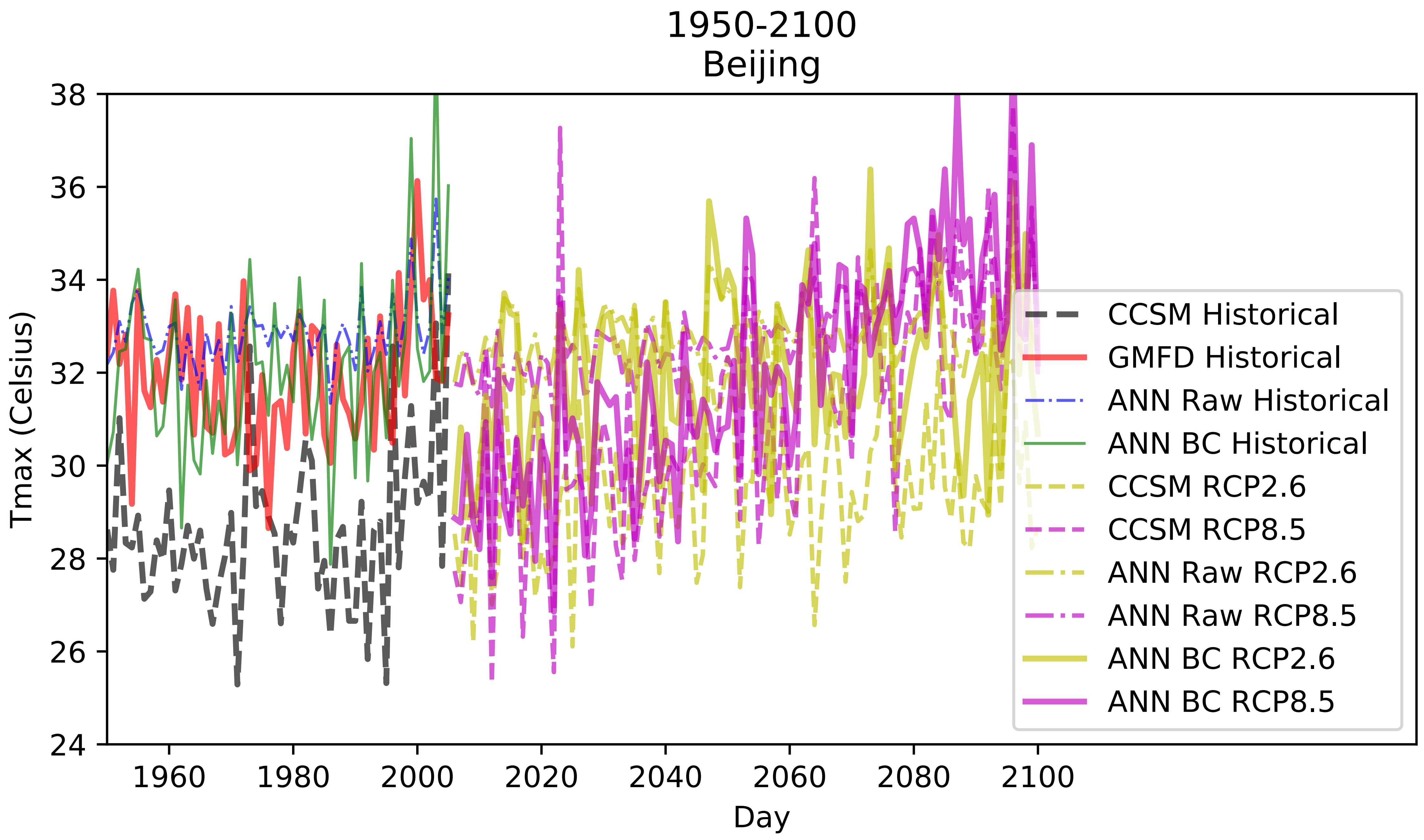


谢谢

Results

Time series Beijing Future

Tmax



Results

Time series Beijing Future

Tmin