

Contents

1	Introduction	1
1.1	Introduction and background	1
1.1.1	The necessity of parametrisation	1
1.1.2	Mathematical formulation of the parametrisation problem	2
1.1.3	Physical processes requiring parametrisation	3
1.1.4	Traditional solutions to the problem and their limitations	4
1.2	Novel approaches to the parametrisation problem	6
1.2.1	Stochastic parametrisation and memory	6
1.2.2	Data-driven parametrisation and machine learning	7
1.3	Simple dynamical systems as testbeds for novel approaches	9
1.3.1	The Lorenz '96 system	9
1.3.2	Statistical models	10
1.3.3	Evaluating parametrisation performance	11
1.3.4	Lessons learnt from Lorenz '96	13
1.3.5	Open questions and the case for more complex dynamical systems	15
1.3.6	Beyond Lorenz '96	16

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Chapter 1

Introduction

1.1 Introduction and background

1.1.1 The necessity of parametrisation

The primary task of general circulation models (GCMs) for Earth’s weather and climate is to simulate the dynamics of the atmosphere and ocean, which are governed by the Navier-Stokes equations. The algorithm chosen to solve these partial differential equations is known as a model’s *dynamical core* (McFarlane 2011). Since analytical solutions to the equations do not exist, the dynamical core necessarily approximates the continuous equations with finite-dimensional, exactly solvable alternatives using one of several possible discretisation schemes (e.g., the finite difference, finite element, finite volume and spectral methods) (Christensen and Zanna 2022). In practice, this usually involves representing the prognostic variables (i.e., those that affect the evolution of the flow) with sets of discrete samples in space and time, whose resolution is constrained by the available computing resources. The unavoidable consequence of discretisation is the loss of information about processes occurring on spatial and temporal scales smaller than the corresponding sampling intervals. These processes are said to be *unresolved*.

It is tempting to naïvely accept the loss of fine-scale information as a necessary sacrifice and hope the dynamical core will still make accurate predictions for the larger, resolved scales. Unfortunately, this too is impossible due to the *nonlinearity* of the governing equations. The reason for this may be seen by considering linear differential equations as a counterexample. If the governing equations were linear, they would allow arbitrary superpositions of solutions, meaning that any given solution could be partitioned into high- and low-frequency components, themselves also solutions. One would thus have the freedom to solve for the low-frequency components alone without compromise. This property may be understood more formally using the Fourier transform, defined for a function f of space and time by

$$\tilde{f}(\omega, \mathbf{k}) = \int dt d^3x e^{i(\mathbf{k} \cdot \mathbf{x} - \omega t)} f(t, \mathbf{x}),$$

which reduces any linear differential equation to an algebraic equation relating the frequency ω to the wave vector \mathbf{k} . Each wavenumber component of the initial state propagates trivially according to its own time dependence $e^{-i(\mathbf{k} \cdot \mathbf{x} - \omega(\mathbf{k})t)}$, *independently of the other components*. If the equations of fluid dynamics were linear, one could safely neglect the fine-scale dynamics because they would have no influence on the coarse scales. In reality, the equations are nonlinear cannot be solved by Fourier transform.

The consequence of the nonlinearity of the equations governing atmospheric and oceanic flows is, therefore, a coupling of the resolved coarse scales to the unresolved fine scales (McFarlane 2011). This fact may be demonstrated more explicitly by applying so-called *Reynolds averaging* to the equations (Christensen and Zanna 2022). Reynolds averaging decomposes each field q into the sum of a coarse-grained (in space or time) or statistical-ensemble-averaged field \bar{q} and a perturbation q' . Note that $\bar{q}' = 0$ by definition.

The coarse-graining operation is assumed to be linear, commute with differentiation and satisfy $\overline{\bar{p}q} = \bar{p}\bar{q}$ for any two fields p and q (Monin and Yaglom 2007). Following the example given by Christensen and Zanna (2022), consider the incompressible Navier-Stokes equations, which have the general form

$$\begin{aligned}\frac{\partial u_i}{\partial t} + u_j \frac{\partial u_i}{\partial x_j} &= \sum f_i, \\ \frac{\partial u_i}{\partial x_i} &= 0\end{aligned}$$

where u_i are the components of the velocity, x_i are the coordinates and f_i are various forces per unit mass. Summation over repeated indices is implied. Applying the decomposition and coarse-graining both sides of the equations yields

$$\begin{aligned}\frac{\partial}{\partial x_i} (\bar{u}_i + u'_i) &= 0 \\ \Rightarrow \quad \frac{\partial \bar{u}_i}{\partial x_i} + \underbrace{\frac{\partial u'_i}{\partial x_i}}_{=0} &= 0 \\ \Rightarrow \quad \frac{\partial \bar{u}_i}{\partial x_i} = \frac{\partial u'_i}{\partial x_i} &= 0\end{aligned}$$

and

$$\begin{aligned}\sum \bar{f}_i &= \overline{\frac{\partial}{\partial t} (\bar{u}_i + u'_i)} + \overline{(\bar{u}_j + u'_j) \frac{\partial}{\partial x_j} (\bar{u}_i + u'_i)} \\ &= \frac{\partial \bar{u}_i}{\partial t} + \underbrace{\frac{\partial u'_i}{\partial t}}_{=0} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} + \bar{u}_j \underbrace{\frac{\partial u'_i}{\partial x_j}}_{=0} + \underbrace{u'_j}_{=0} \frac{\partial \bar{u}_i}{\partial x_j} + \overline{u'_j \frac{\partial u'_i}{\partial x_j}} \\ &= \frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}'_i u'_j}{\partial x_j} - \underbrace{u'_i \frac{\partial u'_j}{\partial x_j}}_{=0} \\ \Leftrightarrow \quad \frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} &= \sum \bar{f}_i - \frac{\partial \bar{u}'_i u'_j}{\partial x_j}.\end{aligned}$$

The physical meaning of this last equation is that the evolution of the coarse-grained velocity field depends not only on itself and the coarse-grained forces, but also on the perturbations via $\bar{u}'_i u'_j$, which does not necessarily vanish. This dependence is a consequence of nonlinearity.

The theoretical discussion in this section establishes that physical processes occurring at one place in the spectrum of temporal and spatial scales are coupled to all the other processes in the spectrum (Franzke et al. 2015). In particular, to ignore the effect of processes not explicitly resolved in numerical models would introduce unacceptable systematic biases, or errors, in the model forecasts. GCMs therefore require parametrisation schemes to estimate the effects of unresolved processes as functions of the available large-scale information (and the parameters of these functions must be chosen appropriately—hence the name “parametrisation”).

1.1.2 Mathematical formulation of the parametrisation problem

In order to make any progress on the parametrization problem, it is necessary to formalise the notion of estimating the “effects” of unresolved processes. I will describe the general approach, which is well-established (see, e.g., Hasselmann 1976; Palmer 2001; Demaeyer and Vannitsem 2018; Brajard et al. 2021), while acknowledging possible alternative conventions where they exist.

The Earth system may be considered as a dynamical system whose exact evolution is governed by equations of the form

$$\frac{dz}{dt} = \mathbf{F}(\mathbf{z}, t), \quad (1.1.1)$$

where the vector \mathbf{z} contains all the variables needed to fully specify the state of the system and \mathbf{F} is a nonlinear differential operator. One then employs a change of variables $\mathbf{z} \rightarrow (\mathbf{x}, \mathbf{y})$, where \mathbf{x} contains the information or variables that are explicitly resolved by the model being studied and \mathbf{y} contains the unresolved, ‘sub-grid’ information or variables. Practically, \mathbf{x} and \mathbf{y} can be thought of as projections of the full state \mathbf{z} onto lower-dimensional subspaces (Brajard et al. 2021). Alternatively (and more concretely), \mathbf{x} can be obtained by averaging the original variables over several adjacent grid points, with \mathbf{y} being the corresponding residuals (Zacharuk et al. 2018; Alcalá and Timofeyev 2021).

In principle, the change of variables splits (1.1.1) into two parts

$$\begin{aligned} \frac{d\mathbf{x}}{dt} &= \mathbf{G}(\mathbf{x}, \mathbf{y}, t), \\ \frac{d\mathbf{y}}{dt} &= \mathbf{H}(\mathbf{x}, \mathbf{y}, t) \end{aligned}$$

that (still exactly) describe the coupled evolution of the resolved and unresolved variables via nonlinear differential operators \mathbf{G} and \mathbf{H} . The goal of parametrisation is now to derive a new system of equations

$$\frac{d\tilde{\mathbf{x}}}{dt} = \tilde{\mathbf{G}}(\tilde{\mathbf{x}}, t) \quad (1.1.2)$$

whose solution $\tilde{\mathbf{x}}(t)$ approximates the true $\mathbf{x}(t)$ as well as possible without explicitly modelling $\mathbf{y}(t)$. The measure used to compare $\tilde{\mathbf{x}}$ and \mathbf{x} depends on the intended function of the parametrised model; weather forecasting applications that prioritise short-term predictive skill might call for minimisation of the root-mean-square error (RMSE), while climate prediction would be more concerned with the closeness of their probability distributions (including both mean and extreme values).

Before proceeding, it is important to note two assumptions that are implicitly made in writing down (1.1.2). The first is that $\tilde{\mathbf{G}}$ is a *deterministic* function of $\tilde{\mathbf{x}}$. The second is that $\tilde{\mathbf{G}}$ depends only on the value of $\tilde{\mathbf{x}}$ at time t and not earlier times (that is to say, the parametrisation is *memoryless*). Recent research has shown that relaxing these assumptions has the potential to greatly improve the accuracy and reliability of the parametrised model, and this will be discussed in detail in §§ 1.2 and 1.3. However, for the purpose of this basic introduction, I will temporarily follow the traditional approach and retain these assumptions.

There is more than one possible interpretation of $\tilde{\mathbf{G}}(\mathbf{x}, t)$ and its relationship to $\mathbf{G}(\mathbf{x}, \mathbf{y}, t)$. Hasselmann (1976) describes $\tilde{\mathbf{G}}(\mathbf{x}, t)$ as an ensemble average of $\mathbf{G}(\mathbf{x}, \mathbf{y}, t)$, taken over the distribution of all \mathbf{y} that are possible for a given \mathbf{x} , i.e.

$$\tilde{\mathbf{G}}(\mathbf{x}, t) = \langle \mathbf{G}(\mathbf{x}, \mathbf{y}, t) \rangle_{\mathbf{y}}.$$

Demaeyer and Vannitsem (2018) instead assert that the ultimate goal of parametrisation is to literally approximate \mathbf{y} as a function $\boldsymbol{\xi}(\mathbf{x})$, in which case

$$\tilde{\mathbf{G}}(\mathbf{x}, t) = \mathbf{G}(\mathbf{x}, \boldsymbol{\xi}(\mathbf{x}), t).$$

In practice, $\mathbf{G}(\mathbf{x}, \mathbf{y}, t)$ usually separates into a known resolved part $\mathbf{D}(\mathbf{x}, t)$ independent of \mathbf{y} and an unresolved coupling term $\mathbf{C}(\mathbf{x}, \mathbf{y}, t)$. It then suffices to approximate only the unresolved part by a parametrisation $\mathbf{P}(\mathbf{x}, t)$ using one of the above methods, so that the parametrised model reads

$$\frac{d\tilde{\mathbf{x}}}{dt} = \mathbf{D}(\tilde{\mathbf{x}}, t) + \mathbf{P}(\tilde{\mathbf{x}}, t). \quad (1.1.3)$$

1.1.3 Physical processes requiring parametrisation

Following the broad theoretical argument in the previous sections, I now turn to concrete examples of processes that are often represented by parametrisations, restricting the discussion to atmospheric

processes for brevity. This section will give a basic introduction to each process, its effect on the larger-scale behaviour of the climate system and the role of its corresponding parametrisation scheme. The purpose of these examples is to provide real-world context and motivation for current parametrisation research in more idealised settings, which will form one of the main topics of this review.

Cloud microphysics parametrisations model the composition of clouds in terms of the amount of water in the solid (e.g., hail), liquid (cloud droplets and rain) and gaseous phases, and the rate of transitions between these phases. Accurate representation of cloud formation and evolution is crucial for several reasons. First, the interaction of clouds with solar and terrestrial radiation has a major influence on the overall energy balance of the atmosphere (McFarlane 2011). Second, cloud water phase transitions lead to the formation of precipitation, and are a source and sink of latent heat that drives convection (McFarlane 2011). Furthermore, the statistics of cloud formation are linked to global temperatures in a feedback loop; uncertainty in the sign and magnitude of this feedback effect is a major contributor to uncertainty in the sensitivity of global temperatures to increases in atmospheric CO₂ concentration (Andrews et al. 2012; Christensen and Zanna 2022; Stevens and Bony 2013). Microphysical processes occur on the spatial scales of single water droplets and ice particles (of order 10^{-6} m to 10^{-2} m; Lamb (2003)), among the smallest scales in the atmosphere. All atmospheric models must parametrise the amount of cloud water in each phase, the size distribution and concentration of liquid and ice particles, and the resulting rate and type (rain, hail, snow, etc.) of precipitation (Christensen and Zanna 2022).

Moist convection encompasses vertical motions in the atmosphere that are accompanied (and driven) by phase changes of water, and must be parametrised when it occurs on sub-grid scales. Moist convection is generally triggered by warming and moistening at low levels, which create convective instability, and is manifested by narrow updrafts and downdrafts that can rarely be resolved explicitly (McFarlane 2011). Convection transports heat and moisture vertically, removing the instability and generating storms where the condensed water falls out as precipitation; more broadly, it is a key component of the global atmospheric circulation in spite of its small spatial scale (Christensen and Zanna 2022).

It should be noted that parametrisation also encompasses estimation techniques for processes that are too complex to model exactly for reasons unrelated to spatial and temporal resolution (McFarlane 2011). A good example of such a process is *radiative transfer*. Air and its constituent gases, as well as clouds, absorb, emit, reflect and/or scatter solar and terrestrial radiation. This leads to differential heating and cooling that drives the atmospheric circulation. While the theory of radiative transfer is understood well enough to allow precise calculations in principle, the prohibitive computational cost of such calculations necessitates a parametrisation based on simplifying assumptions (the details of which are beyond the scope of this review) (Christensen and Zanna 2022).

1.1.4 Traditional solutions to the problem and their limitations

With the examples of cloud microphysics, moist convection and radiative transfer in mind, I now broadly review the traditional approaches used to construct parametrisation schemes in practice. In particular, this section will identify the key assumptions upon which many traditional schemes are founded, and the circumstances under which the assumptions may be violated. This will motivate research into novel approaches.

A parametrisation scheme is traditionally constructed by formulating a simplified, easily solvable and deterministic conceptual model of the physical process in question. The solution of this model is then used to estimate the effect of the process on the coarse-scale state of the parent model, known as the *unresolved tendency* (McFarlane 2011). For example, the earliest convective parametrisation was developed by Manabe, Smagorinsky, and Strickler (1965) and simply assumed that the net effect of convection is to relax the vertical structure of the atmosphere towards a neutrally stable state whenever it becomes convectively unstable. One obvious deficiency of simple conceptual models is that they cannot possibly capture the full range of variability in the processes they simulate. One major branch of modern parametrisation research therefore studies *data-driven* schemes that instead use observational or high-resolution simulated data to fit empirical models for the unresolved processes, naturally capturing a wider range of variability

(Christensen and Zanna 2022). Data-driven parametrisation will be discussed in much further detail in the next section.

In general, a traditional parametrisation scheme aims to capture the net unresolved tendency due to all occurrences of the unresolved process (e.g., all convective updrafts and downdrafts) within each grid cell of the parent model. A deterministic prediction of this type is valid when each grid cell contains many independent realisations whose varying contributions may be expected to yield a reliable average tendency. This requires a *scale separation* between the unresolved process and the resolution of the parent model. Scale separation breaks down when model development and increases in available computing resources allow simulations at resolutions approaching the previously unresolved scales. In this case, knowledge of the coarse-scale state cannot be expected to uniquely determine the unresolved tendency because the process is only realised a few times in each grid cell. The resulting (seemingly) random nature of the true unresolved tendency motivates stochastic treatments (McFarlane 2011; Christensen and Zanna 2022; Berner et al. 2017). These will be discussed in the next section.

The conceptual models core to traditional parametrisations usually contain free parameters that are determined from the coarse-scale model state using additional assumptions called *closures*. Closures often postulate a state of quasi-equilibrium between the unresolved processes and their large-scale environment, such as a balance between the accumulation of convective available potential energy (CAPE) and its removal by convection, or between the horizontal convergence of moisture at low levels and its convective transport to higher levels (McFarlane 2011; Christensen and Zanna 2022; Palmer 2019). However, there is no guarantee that such an equilibrium exists; in fact, it has been demonstrated that the CAPE balance is violated by fluctuations on sub-diurnal time scales (Donner and Phillips 2003) and by midlatitude continental convection (Zhang 2002). Newer parametrisation schemes have allowed departures from equilibrium by representing the unresolved processes in a prognostic rather than diagnostic manner (i.e., allowing the processes to have their own self-governing time dependence rather than calculating them from the large-scale state at each time step independently of their values at the previous step) (Rio, Del Genio, and Hourdin 2019; Berner et al. 2017). This creates *memory* or *latency* in the parametrised tendencies, meaning that the tendencies have some nonzero response time when subjected to sudden changes in the large-scale state. Memory will be discussed further in the next section.

Parametrisation schemes commonly suffer from several other issues that I will briefly address here. Firstly, while the division of the general atmospheric dynamics into a set of separately parametrised processes (microphysics, convection, etc.) is physically motivated, it remains somewhat arbitrary because these processes, strictly speaking, form a continuum without well-defined boundaries (Christensen and Zanna 2022; McFarlane 2011). It is a goal of contemporary research to unify the parametrisations as much as possible. Secondly, given the importance of future climate projections, it is natural to ask whether the parametrisation schemes that have been developed and tuned on today's climate remain valid as the climate changes over decade- to century-long simulations. This is a matter of particular concern for data-driven parametrisations, since there is little reason to trust empirical models once they are extrapolated beyond the range of the data originally used to fit them (Christensen and Zanna 2022). Finally, unless very special care is taken, parametrisation schemes can cause the parent model to violate known physical conservation laws (e.g., mass, energy and momentum) (Christensen and Zanna 2022). Efforts to resolve this issue are ongoing.

1.2 Novel approaches to the parametrisation problem

Since the 1990s, the limitations identified in § 1.1.4 have prompted many to reconsider the principles upon which parametrisation schemes are founded. The main advance has been the development of stochastic parametrisations that incorporate random noise in the predicted tendencies. More recently, others have approached the problem from an entirely new direction, developing data-driven parametrisations that learn to predict the tendencies empirically. This section will introduce the stochastic and data-driven approaches in general terms while omitting the technical details of individual implementations, the aim being to contextualise and motivate the study of these approaches in more idealised frameworks in § 1.3. Other methods (such as superparametrisation) exist but are beyond the scope of this review.

1.2.1 Stochastic parametrisation and memory

The potential value of stochasticity for climate modelling was first established by Hasselmann (1976), whose seminal paper sought to explain the characteristics of long-term climate variability. Knowing that climate depends on interactions between all components of the Earth system (atmosphere, ocean, cryosphere, biosphere, etc.), Hasselmann argued that the effect of the more rapidly-evolving atmosphere on the other, more slowly-varying components is that of a stochastic forcing. Owing to their long response time, the slowly-varying components effectively integrate this stochastic forcing, allowing long-term climate variability to be characterised as a type of random walk process akin to the Brownian motion of a massive particle in a fluid.

Further motivation for stochastic parametrisation in particular stems from the need to reliably estimate uncertainties in weather forecasts and climate projections. Weather forecasting centres typically propagate initial condition uncertainties (due to imperfect observations) through to the final forecast in a Monte Carlo fashion, by initialising an ensemble of model runs with perturbed initial conditions and measuring the spread of the resulting forecasts. It has been observed that deterministic models produce systematically under-dispersed ensembles that fail to span the range of actual weather outcomes, indicating that these models are failing to capture additional sources of variability (Palmer et al. 2005; Berner et al. 2017; Palmer 2019). Knowing that poor scale separation and departures from quasi-equilibrium should preclude deterministic relationships between unresolved tendencies and the large-scale state (see § 1.1.4), it should seem highly likely that deterministic parametrisation contributes to this deficiency.

The principle of stochastic parametrisation is, therefore, that unresolved tendencies should be randomly sampled from an appropriate distribution at each point in space and time, not simply set to the mean of the distribution (Franzke et al. 2015). This choice has now been theoretically justified using statistical mechanical arguments; most notably, Wouters and Lucarini (2012, 2013) showed that, assuming a weak coupling to the resolved variables, the effect of unresolved dynamics should be parametrised by a combination of deterministic and stochastic terms, as well as a *non-Markovian* memory term depending on the past states of the resolved variables.

The simplest and earliest approach to stochastic parametrisation is the method of *stochastically perturbed parametrisation tendencies* (SPPT), which takes an existing deterministic parametrisation and randomly scales its output with a multiplicative noise field (Palmer 2019; Christensen 2020). Re-using the notation of § 1.1.2, an SPPT model for the resolved variables \mathbf{x} takes the form

$$\frac{d\mathbf{x}}{dt} = \mathbf{D}(\mathbf{x}, t) + [I + \text{diag}(\mathbf{e})]\mathbf{P}(\mathbf{x}, t),$$

where \mathbf{P} is the existing deterministic parametrisation, \mathbf{e} is a mean-zero random vector with the same length as \mathbf{x} and I is the identity matrix. The choice of multiplicative (and thus inherently state-dependent) rather than additive noise is intuitively motivated by the expectation that variability in the effect of unresolved processes should be greatest when those processes are most active (Franzke et al. 2015). Christensen (2020) performed a comparison of high-resolution simulations to parametrised single-column model output which justified the use of multiplicative perturbations.

In GCMs, where the variables being modelled have spatial dependence, the multiplicative perturbation takes the form of a random *field* $e(x, y, t)$. It has been argued that this random field should be spatially and temporally correlated (in contrast to uncorrelated “white” noise) in order to emulate the organisation of unresolved processes on larger scales and their persistence in time (Christensen and Zanna 2022; Franzke et al. 2015). In particular, perturbations that explicitly depend on their own past values constitute a type of memory, albeit distinct from the memory term advocated by Wouters and Lucarini (2012, 2013), which would instead couple the perturbations to the past values of the large-scale variables.

Stochastic parametrisations have several known advantages over their deterministic counterparts, and are now implemented in operational weather forecast models. They have been found to remedy the aforementioned issues of ensemble underdispersion and prediction unreliability (Palmer et al. 2005; Berner et al. 2017), and (as of 2009) even make the skill of five-day forecasts comparable to that of deterministically parametrised two-day forecasts (Palmer 2019). Despite the zero-mean nature of the noise, it has been shown that stochastic parametrisations can reduce systematic model biases (“noise-induced drift”; Palmer et al. (2005)) and stabilise the simulation of regime-based behaviour (such as the El Niño–Southern Oscillation) in the climate system (Berner et al. 2017).

Reviewing the field, Palmer (2019) identifies outstanding issues for further research. The main concern is the lack of rigour in most stochastic schemes; SPPT, for example, modifies existing deterministic schemes *ad hoc* rather than incorporating stochasticity *ab initio* in the development process. More objective approaches are yet to gain widespread acceptance. This motivates both data-driven methods and further testing using simpler dynamical systems where objectivity is more feasible.

1.2.2 Data-driven parametrisation and machine learning

The fitting of predictive statistical models to data is, of course, ubiquitous in the sciences, but attempts to use such models as parametrisation schemes and couple them into fully fledged GCMs are a relatively new phenomenon—certainly more so than stochastic parametrisations. The prerequisite for all data-driven parametrisations is obviously training data: mathematically, an approximate solution of (1.1.1) of sufficient accuracy and resolution to be considered “truth” for the application at hand. Training data are typically derived from high-resolution simulations, such as regional weather model runs or large eddy simulations (LES). The other ingredient is the imperfect low-resolution model that will later be augmented by parametrisation.

To generate an appreciation of how these data might be used to construct a parametrisation in practice, I roughly follow the argument and notation of Brajard et al. (2021). Define a map \mathcal{M} that takes each state $\mathbf{z}(t)$ in the training dataset to the state $\mathbf{z}(t + \delta t)$ at the next time step. Similarly, denote by \mathcal{M}^r the low-resolution model (the superscript *r* meaning “reduced”), which maps a low-resolution state $\mathbf{x}(t)$ to a prediction for $\mathbf{x}(t + \Delta t)$, where Δt is not necessarily equal to δt (usually larger). The spaces of high- and low-resolution states, having different dimensions, may be linked by an operator $\langle \cdot \rangle$ that projects high-resolution states onto the low-resolution state space. Practically, the projection operation is simply a coarse-graining of \mathbf{z} by averaging values at adjacent grid points to match the resolution of \mathbf{x} . Now, for each state \mathbf{z} in the training dataset, one may compute the difference

$$\epsilon(\mathbf{z}) = \frac{\langle \mathcal{M}(\mathbf{z}) \rangle - \langle \mathbf{z} \rangle}{\delta t} - \frac{\mathcal{M}^r(\langle \mathbf{z} \rangle) - \langle \mathbf{z} \rangle}{\Delta t}$$

between the coarse-grained true tendency (on the left) and the tendency predicted by the coarse model when it sees the same state (on the right). This is the unresolved tendency. Knowledge of $\langle \mathbf{z} \rangle$ alone does not uniquely determine ϵ because $\langle \mathcal{M}(\mathbf{z}) \rangle$ depends on the original \mathbf{z} . However, if one can fit a statistical model \mathbf{P} to the dataset of $(\langle \mathbf{z} \rangle, \epsilon)$, then $-\mathbf{P}(\mathbf{x}(t))\Delta t$ will be able to serve as an estimate of the error incurred by the coarse model in predicting $\mathbf{x}(t + \Delta t)$ given $\mathbf{x}(t)$. This motivates the construction of a parametrised model \mathcal{M}^p , defined by

$$\mathcal{M}^p(\mathbf{x}) = \mathcal{M}^r(\mathbf{x}) + \mathbf{P}(\mathbf{x})\Delta t$$

that simply subtracts the estimated error at each time step of the coarse model. In theory, the solution $\mathbf{x}(t)$ obtained by iteration of \mathcal{M}^P will be more accurate than that obtained by iteration of the unparametrised \mathcal{M}^r .

The current method of choice for constructing P in weather and climate modelling contexts is machine learning (ML). I will briefly introduce the key concepts, strengths and weaknesses of ML, following Beucler et al. (2022). ML encompasses a broad class of algorithms that programmatically and autonomously develop and apply rules for performing tasks, such as image classification, removing the need for a human to explicitly program the rules. They do this using supplied *training data* that exemplify the task to be performed. When it comes to data-driven parametrisation, the task is function approximation or regression, and the relevant algorithms usually require a training dataset of example inputs (i.e., coarse-scale variables) *labelled* with the desired outputs (i.e., unresolved tendencies). One commonly-used class of algorithms called *neural networks* consist of layers of inter-communicating calculation nodes called neurons and learn to approximate functions by optimising sets of weights associated with the neurons. Another type of algorithm is the *random forest*, which approximates functions by passing the inputs through a series of nested *if/else* decision trees.

The distinguishing advantage offered by ML data-driven parametrisations is their ability to systematically capture complex relationships without relying on artificially simplified physical models derived by humans (Irrgang et al. 2021; Beucler et al. 2022). In addition to constructing new parametrisations from scratch, ML has been used to emulate the action of existing parametrisation schemes in GCMs (e.g., Gentine et al. 2018). These ML emulators have the potential to reduce the computational burden that parametrisation usually imposes, leaving more resources for other tasks such as calling the parametrisation scheme more frequently or increasing the model resolution (Beucler et al. 2022). Furthermore, the ability to emulate multiple existing schemes at once is a step towards unifying the parametrisation of unresolved processes (a long-standing issue; see § 1.1.4).

ML parametrisations are not without their issues; they are known to be prone to overfitting and often cause their host models to become numerically unstable. They are also, by their very nature, far more difficult to interpret than traditional schemes. It is therefore very difficult to determine *a priori* whether or not they will continue to be valid in climate conditions outside the bounds of their training datasets (Irrgang et al. 2021; Beucler et al. 2022). “Interpretable” or “explainable” ML is an active area of research that aims to address these issues. Another active research topic is “physics-guided ML”, the aim of which is to augment ML with known physical constraints and conservation laws that would otherwise be violated (e.g., Yuval, O’Gorman, and Hill 2021).

1.3 Simple dynamical systems as testbeds for novel approaches

Historically, it has been common practice to develop and test new parametrisation techniques using simpler dynamical systems that share the key nonlinear, multi-scale and chaotic properties of the climate system. These analogue systems provide testbeds where the parametrisation problem is more tractable, avoiding the expense, effort and technicalities of fully-fledged climate models. The simplicity of these systems also helps to ensure the reproducibility of the results obtained. This section will review the progress that has been made using simple analogue systems and argue that, considering the outstanding issues identified in §§ 1.1 and 1.2, further research using these systems may yet be warranted. The relevant techniques for constructing and testing parametrisation schemes in simple model frameworks, and the remaining open questions, will be discussed in order to inform future research.

1.3.1 The Lorenz '96 system

The Lorenz '96 model (henceforth L96) was proposed by eminent meteorologist Edward N. Lorenz in a 1995 paper (Lorenz 1995) on the growth of errors in solutions of dynamical systems and the resulting limits of predictability for those systems. Lorenz proposed to mimic the multi-scale nature of the climate system by coupling two dynamical systems with different characteristic time scales. Following his notation, there is a discrete set of “slow” variables $\{X_k\}_{k=1}^K$, each of which has an associated discrete set of “fast” variables $\{Y_{j,k}\}_{j=1}^J$. The indices of the slow variables are periodic ($X_{K+1} = X_1$ and $X_0 = X_K$) and the sets of fast variables are arranged end-to-end so that $Y_{J+1,k} = Y_{1,k+1}$ and $Y_{0,k} = Y_{J,k-1}$. The intuition is that the variables represent samples of a field along a latitude circle, as shown in Figure 1.1 (a reproduction of Figure 1 by Russell et al. (2017)). The evolution of the system is governed by the ordinary differential equations

$$\frac{dX_k}{dt} = -X_{k-1}(X_{k-2} - X_{k+1}) - X_k + F - \frac{hc}{b} \sum_{j=1}^J Y_{j,k}, \quad (1.3.1a)$$

$$\frac{dY_{j,k}}{dt} = -cY_{j+1,k}(Y_{j+2,k} - Y_{j-1,k}) - cY_{j,k} + \frac{hc}{b} X_k. \quad (1.3.1b)$$

The constant $c \geq 1$ dictates the ratio of the time scale of the Y variables to the time scale of the X variables, b the typical magnitude of X relative to Y , h the strength of the coupling between the two subsystems and F the constant forcing applied to each X variable.

As discussed in § 1.1.2, the objective is to find $P_k(X_1, \dots, X_K) \approx -(hc/b) \sum_{j=1}^J Y_{j,k}$ such that the solution of the parametrised system

$$\frac{dX_k}{dt} = -X_{k-1}(X_{k-2} - X_{k+1}) - X_k + F + P_k(X_1, \dots, X_K)$$

approximates as accurately as possible the true X_k obtained by solving (1.3.1). The simple form of L96 allows one to generate a training dataset by numerically solving (1.3.1) and directly diagnosing the unresolved tendency of X_k as

$$U_k(t) = \frac{X_k(t + \Delta t) - X_k(t)}{\Delta t} - [-X_{k-1}(X_{k-2} - X_{k+1}) - X_k]. \quad (1.3.2)$$

As we shall see, it is usually assumed that P_k depends only on X_k (i.e., the parametrisation is *local*) but may also depend on the value of X_k at earlier times. The symmetry of (1.3.1) under shifts of the k index implies that all the X_k have the same long-term statistics, so it suffices to aggregate all the U_k into a single training dataset and use the resulting parametrisation for all the X_k rather than constructing a separate parametrisation for each variable.

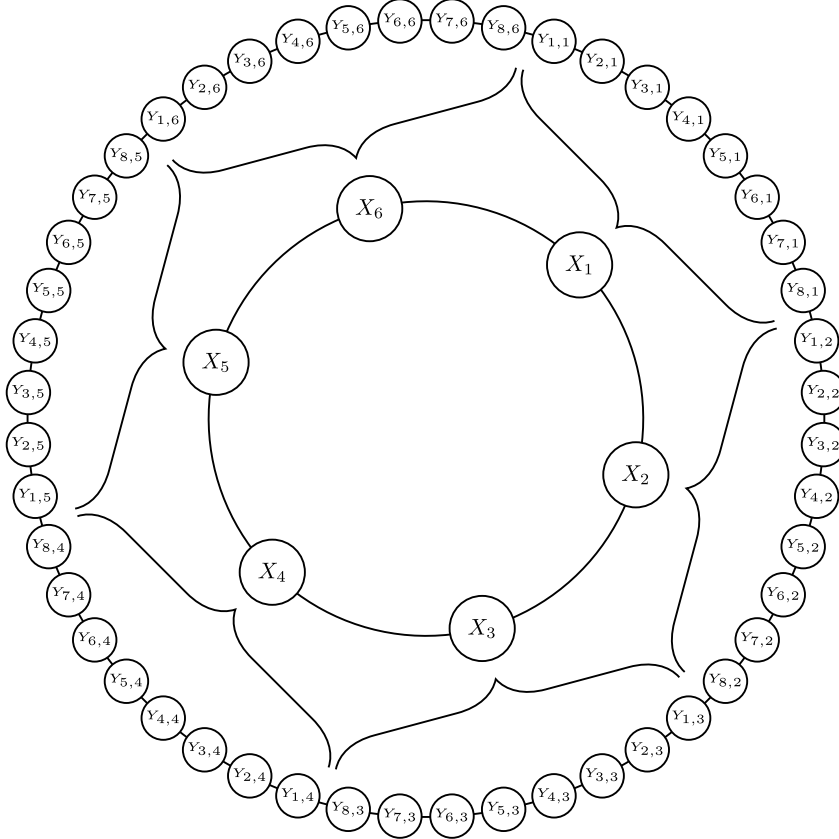


Figure 1.1: Illustration of the periodic arrangement of the L96 variables, with the slow variables X_k arranged in a circle. Each slow variable is coupled to a neighbouring subset of the similarly arranged fast variables $Y_{j,k}$. Reproduced from Russell et al. (2017), Figure 1.

1.3.2 Statistical models

Constructing a data-driven parametrisation scheme for L96 requires first choosing the structure of the scheme and then using the training dataset to find the optimal values of the associated free parameters. The simplest structure, popularised in an influential paper by Wilks (2005), consists of a polynomial regression of U against X as a deterministic base, modified by stochastic noise. Wilks' scatterplot of U and X and quartic polynomial least-squares regression, shown in Figure 1.2, confirm that such a structure is reasonable.

Denote the deterministic polynomial part of the parametrisation by $P_{\text{det}}(X)$. Wilks' proposal was to then model the residuals as an additive, mean-zero noise term $e(t)$, independent of X and updated at each time step, so that

$$P(X) = P_{\text{det}}(X) + e(t). \quad (1.3.3)$$

Arnold, Moroz, and Palmer (2013) and later Christensen, Moroz, and Palmer (2015) considered the SPPT method (see § 1.2.1), where instead

$$P(X) = [1 + e(t)]P_{\text{det}}(X). \quad (1.3.4)$$

The most common form for $e(t)$ in both (1.3.3) and (1.3.4) is that of a *first-order autoregressive* or AR(1) model

$$e(t) = \phi e(t - \Delta t) + \sigma z \quad (1.3.5)$$

where $\phi \in [0, 1]$ and $\sigma \geq 0$ are constants and z is drawn independently from the standard normal distribution at each time step. The AR(1) model introduces memory by having $e(t)$ relax from its value

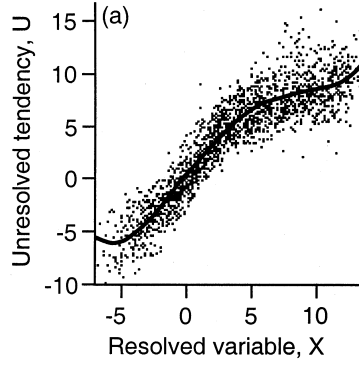


Figure 1.2: Scatterplot of unresolved tendencies U against large-scale variables X in L96 (black dots), and corresponding quartic polynomial least-squares regression (black line). Data are for forcing $F = 18$. Reproduced from Figure 2a of Wilks (2005).

at the previous time step towards zero, while also adding independent random jumps with standard deviation σ . AR(1) noise is commonly also referred to as *red* noise. The two important special cases of an AR(1) model are $\phi = 0$, which reduces $e(t)$ to white noise without memory, and $\phi = \sigma = 0$, which results in a deterministic parametrisation $P(X) = P_{\text{det}}(X)$. The best estimates of ϕ and σ are straightforwardly obtained by examining the autocorrelation and standard deviation of the residual time series $U(t) - P_{\text{det}}(X(t))$ in the training dataset (see Arnold, Moroz, and Palmer (2013) and Wilks (2011, Chapter 9) for details).

It must be noted that the additive and SPPT schemes (1.3.3) and (1.3.4) are inherently limited by their simple form. The additive scheme assumes that the variance of the unresolved tendency is independent of the value of X , and SPPT implies that the variance vanishes when $P_{\text{det}}(X) = 0$. Inspection of Figure 1.2 indicates that neither of these conditions is strictly satisfied. Arnold, Moroz, and Palmer (2013) therefore proposed two possible modifications of (1.3.3), with the standard deviation of $e(t)$ being a linear function of either $|X(t)|$ or $|P_{\text{det}}(X(t))|$.

Other studies have experimented with more complex statistical models for the unresolved tendencies. Chorin and Lu (2015) tested NARMAX (nonlinear autoregression moving average with exogenous inputs), a model which represents the tendency as a function of (i) the tendencies estimated at previous time steps (autoregression), (ii) the current and previous values of X (nonlinear; exogenous data), (iii) independent Gaussian noise and (iv) the previous values of the Gaussian noise (moving average). The motivation for NARMAX is that it may be able to capture more complex relationships and memory effects by using more predictors and free parameters. Crommelin and Vanden-Eijnden (2008) and Kwasniok (2012) used Markov chain models, which approximate the continuous range of possible unresolved tendencies U for a given X by a discrete set of allowed states. The model transitions from state to state according to a set of probabilities that depend on X and are estimated from the training dataset. The latest studies have tested machine learning algorithms for L96, reflecting the increasing research interest in ML-based parametrisation schemes for GCMs (see § 1.2.2). Gagne II et al. (2020) used generative adversarial networks (GANs), which involve pairs of competing neural networks and have the advantage of being stochastic with no need for *ad hoc* perturbations. Bhouri and Gentine (2023) used deterministic but memory-based neural networks trained to directly optimise short-term forecast accuracy without requiring the calculation of the unresolved tendencies U in the training dataset.

1.3.3 Evaluating parametrisation performance

After choosing and fitting a parametrisation scheme, the next step is to assess its performance. It is important to recognise that there are several contexts in which one might want a parametrisation to perform well. The first important distinction is between *offline* and *online* testing. Offline testing

involves feeding large-scale states into the parametrisation scheme from a pre-computed test dataset that was not used for training (such as a new high-resolution simulation) and measuring the level of agreement between the tendencies predicted by the scheme and the true tendencies. Online testing, on the other hand, involves coupling the parametrisation scheme into the host model and comparing the output of the parametrised model to the corresponding “truth” solution (which might be the output of a high-resolution unparametrised model). Online performance can further be assessed for short-term (“weather”) forecasts or long-term (“climate”) predictions. The reliability of ensemble forecasts (see § 1.2.1) must also be determined. As we shall see, the extent to which good performance in more than one category is achievable is a topic of ongoing research.

Offline testing

Offline testing is rarely documented in the L96 literature because it is somewhat more straightforward than online testing. The aim is to ensure that the parametrisation scheme accurately captures the distribution of unresolved tendencies that exist in the true solution. Gagne II et al. (2020) achieved this by integrating the full system (1.3.1) to obtain a test dataset and estimating the time-aggregated probability density functions (PDFs) of the true unresolved tendencies (1.3.2) and the tendencies predicted by the parametrisation schemes. They then expressed the difference between these distributions as a scalar quantity using the Hellinger distance, defined for two PDFs p and q by

$$H(p, q) = \frac{1}{2} \int dx \left(\sqrt{p(x)} - \sqrt{q(x)} \right)^2. \quad (1.3.6)$$

Forecast performance

When evaluating online forecast accuracy for L96, studies are primarily concerned with the agreement between a “truth” (or verification) solution of (1.3.1) and the mean of an ensemble of independently realised, stochastically parametrised forecasts starting from the same or nearby initial conditions. This reflects standard practice in operational numerical weather prediction. A standard approach is to calculate the root mean square error (RMSE)

$$\text{RMSE}(t) = \left(\left\langle \sum_k (X_k^{\text{ens}}(t) - X_k^{\text{ver}}(t))^2 \right\rangle \right)^{1/2}$$

between the ensemble mean forecast $X_k^{\text{ens}}(t)$ and the verification $X_k^{\text{ver}}(t)$, where the mean $\langle \cdot \rangle$ is taken over many forecast-verification pairs with a range of initial conditions (Crommelin and Vanden-Eijnden 2008; Gagne II et al. 2020).

An alternative for single-integration (non-ensemble) forecasts is to take the mean over time, from the initial time up to time t (Bhouri and Gentine 2023). Another accuracy metric is the anomaly correlation (ANCR), which is the Pearson correlation coefficient

$$\text{ANCR}(t) = \left\langle \frac{\sum_k A_k^{\text{ens}}(t) A_k^{\text{ver}}(t)}{[\sum_k A_k^{\text{ens}}(t)^2 \sum_k A_k^{\text{ver}}(t)^2]^{1/2}} \right\rangle$$

between the forecast anomaly $A_k^{\text{ens}}(t) = X_k^{\text{ens}}(t) - \langle X_k^{\text{ver}}(t) \rangle_t$ and the verification anomaly $A_k^{\text{ver}}(t) = X_k^{\text{ver}}(t) - \langle X_k^{\text{ver}}(t) \rangle_t$, again averaged over forecast-verification pairs (Crommelin and Vanden-Eijnden 2008). Other studies (Kwasniok 2012; Arnold, Moroz, and Palmer 2013) have used more complex skill scores to assess forecast accuracy.

Recall from § 1.2.1 that an ensemble forecast is said to be reliable if the spread of the ensemble members is an accurate estimate of the uncertainty in the ensemble mean. In the context of L96, there are two ways to measure reliability. The first (Wilks 2005; Crommelin and Vanden-Eijnden 2008; Kwasniok 2012) is to sort the states X_k of the ensemble members at the chosen lead time from largest to smallest (or

vice versa), and find the rank that the truth state would occupy within the list. The ranks from many ensemble forecasts are aggregated and their distribution plotted on a *rank histogram*, which should ideally be uniform for a well-dispersed ensemble. A U-shaped rank histogram indicates underdispersion; that is, the truth too frequently lies at the extreme ends of or outside the ensemble. An inverted U shape indicates the opposite (overdispersion). Another method is to simply compare the ensemble standard deviation and the RMSE, which should be roughly equal for a reliable forecast (Arnold, Moroz, and Palmer 2013; Gagne II et al. 2020).

Climate prediction performance

There are several classes of metrics and methods available for assessing the accuracy of long-term climate predictions made by parametrised L96 models. The simplest is to compare the low-order moments (mean, variance) of the long-term distributions of X between the parametrised and truth solutions. However, it is often the case for the relatively simple L96 model that parametrised models reproduce these moments quite accurately (Wilks 2005), motivating comparison of the entire PDFs—a more stringent test. In addition to visual comparison of the PDFs, one can use scalar measures such as the Hellinger distance (1.3.6) (Arnold, Moroz, and Palmer 2013; Gagne II et al. 2020) and the Kolmogorov-Smirnov statistic

$$D_n = \max_X |\Psi_{\text{true}}(X) - \Psi_{\text{model}}(X)|,$$

which is the maximum absolute difference between the cumulative distribution functions Ψ of X in the truth and parametrised models (Wilks 2005; Chorin and Lu 2015; Kwasniok 2012). As a diagnostic tool, it is also possible to compare the joint distributions of X and the unresolved tendency U between the truth and parametrised models (Gagne II et al. 2020).

Another approach is to study the correlation and spectral properties of X . In the time domain, one can compute the autocorrelation function $\langle X_k(t)X_k(t+\tau) \rangle_{t,k}$ or the cross-correlation $\langle X_k(t)X_{k+1}(t+\tau) \rangle_{t,k}$ between neighbouring variables and compare these to their truth counterparts (Crommelin and Vanden-Eijnden 2008; Kwasniok 2012; Chorin and Lu 2015; Gagne II et al. 2020). Gagne II et al. (2020) applied the continuous wavelet transform (CWT) to the $X(t)$ time series to measure the amount of power in the signal as a function of oscillation period. Similar analyses may be performed in “space” by computing the autocorrelation $\langle X_k(t)X_{k+n}(t) \rangle_{t,k}$ with respect to shifts in the k index (Gagne II et al. 2020) or by taking a discrete Fourier transform of X_k with respect to k and deriving wavenumber statistics (Crommelin and Vanden-Eijnden 2008; Kwasniok 2012).

1.3.4 Lessons learnt from Lorenz ’96

Now that the statistical models and analysis techniques for L96 parametrisation have been surveyed, I shall review the results of previous studies, focusing on key conclusions that have potential implications for more complex dynamical systems. The common objective in many studies has been to determine the value added by stochasticity and memory. The general consensus is that parametrisations with white noise outperform purely deterministic ones, and that adding memory via red noise or dependence on past large-scale states gives a further advantage over white noise (Wilks 2005; Arnold, Moroz, and Palmer 2013; Gagne II et al. 2020). The advantages of stochasticity and memory include improvements in the skill and reliability of ensemble forecasts and in the accuracy of climatological probability distributions. Arnold, Moroz, and Palmer (2013) additionally found that parametrisations with state-dependent noise have the potential to produce more skilful forecasts than those with state-independent additive noise. This was only observed under conditions of small time-scale separation between the resolved and unresolved variables (i.e., $c \sim 1$ in (1.3.1)); it appeared that simple additive noise was sufficient for larger scale separation. A representative illustration of the conclusions for short-term forecasting and climate prediction are respectively given by Figures 6 and 10 of Arnold, Moroz, and Palmer, which are reproduced here as Figures 1.3 and 1.4.

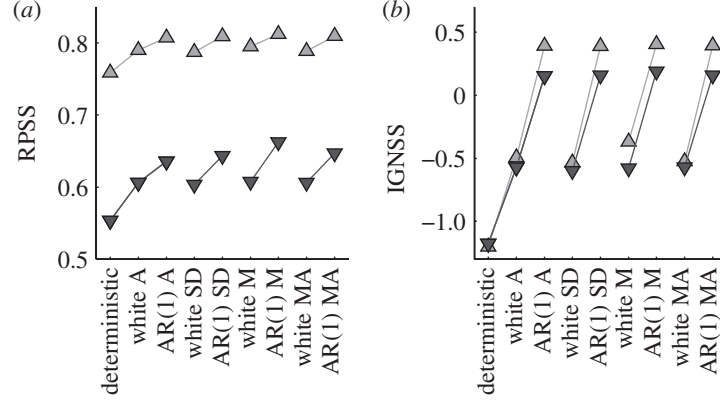


Figure 1.3: Reproduction of Figure 6 by Arnold, Moroz, and Palmer (2013), showing a comparison of ensemble forecast skill for parametrisations with different types of noise. Skill is measured by the ranked probability skill score (RPSS; panel (a)) and ignorance skill score (IGNSS; panel (b)); higher values indicate better skill. The deterministic parametrisation is a cubic polynomial regression and added noise is either white or generated by an AR(1) process. Acronyms indicate the method used to introduce the noise; A = “additive”, SD = “state-dependent” (noise standard deviation a linear function of $|X|$), M = “multiplicative” (SPPT) and MA = “multiplicative and additive” (noise standard deviation a linear function of $|P_{\text{det}}(X)|$). Upright light grey triangles indicate results obtained under conditions of larger time scale separation ($c = 10$ in (1.3.1)) and inverted dark grey triangles indicate smaller time scale separation ($c = 4$). It is clear that schemes with white noise outperform deterministic ones, and schemes with AR(1) noise outperform those with white noise.

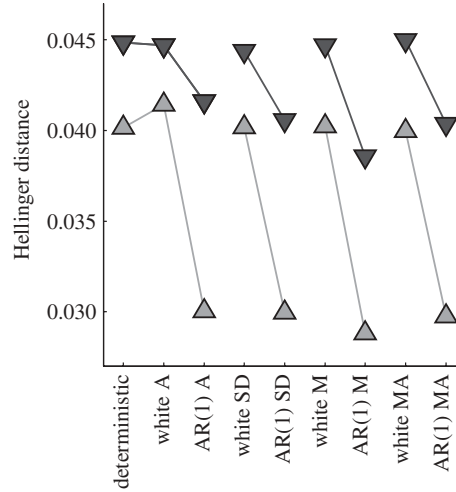


Figure 1.4: Reproduction of Figure 10 by Arnold, Moroz, and Palmer (2013), comparing the accuracy with which parametrisations with different types of noise reproduce the true climatological PDFs of the resolved variables. Accuracy is measured by the Hellinger distance between the modelled and true PDFs; lower values indicate higher accuracy. The labels on the horizontal axis and the markers have the same meaning that they do in Figure 1.3. A clear improvement in accuracy is given by the schemes with AR(1) noise.

Some studies have obtained results that conflict with the aforementioned consensus. Firstly Arnold, Moroz, and Palmer (2013) found no appreciable difference in climatological PDF accuracy between their white noise and deterministic schemes; this is evident in Figure 1.4. Analogously, Christensen, Moroz, and

Palmer (2015) similarly found no significant difference between white noise and deterministic schemes in terms of their ability to reproduce regime behaviour and predict the system’s response to changes in the external forcing parameter F . Gagne II et al. (2020), who constructed parametrisations using generative adversarial networks, came to the unexpected conclusion that using temporally correlated red noise may degrade the accuracy of ensemble forecasts via an accumulation of noise-induced error and have little benefit over white noise for climate prediction accuracy.

Several authors have postulated general interpretations of these results that may be relevant to the parametrisation problem in dynamical systems beyond L96. Arnold, Moroz, and Palmer (2013) attributed the apparent superiority of memory-based parametrisations to a potential for subgrid-scale processes to influence the resolved state on scales much larger than the grid scale at which the host model is truncated; memory captures this spatial and temporal correlation or persistence. Christensen, Moroz, and Palmer (2015) agreed with this assessment on the basis of their results. They also argued that the persistence of correlated noise is necessary to drive regime transitions that would otherwise be underrepresented. Observing that stochastic parametrisation improved the prediction of responses to changes in forcing, they further argued that stochastic data-driven parametrisations are generally more likely to function well in changed climate conditions outside the range of their training datasets.

1.3.5 Open questions and the case for more complex dynamical systems

To conclude this section on data-driven parametrisation for L96, I will draw on the key messages and conclusions in the literature to motivate further research of the same kind in models of intermediate complexity.

Generally speaking, many parametrisation approaches of varying complexity have shown promise when applied to L96; all the studies mentioned in § 1.3.2 were able to construct a scheme that reproduced the properties of interest without egregious errors. Indeed, some of the more recent and complex approaches have shown only marginal improvements over the original regression-based approach introduced by Wilks (2005). Gagne II et al. (2020) attributed this to the simplicity of L96, which only considers the evolution of a single field in one discrete spatial dimension. There is hope that applying the L96 methods to dynamical systems with more prognostic variables, spatial dimensions and degrees of freedom may reveal deficiencies that were inconsequential in L96 and thus give researchers more discriminative power in choosing approaches for application to full GCMs.

Several specific findings in L96 studies raise other questions that also motivate a change of focus to more complex dynamical systems. The first is the observation by Crommelin and Vanden-Eijnden (2008) that the advantage of their conditional Markov chain parametrisation over the regression-based approach was greatest under conditions of small time-scale separation and diminished with increasing scale separation. Arnold, Moroz, and Palmer (2013) drew a similar conclusion regarding the difference between stochastic and deterministic regression-based schemes. These findings are consistent with the expectation that the net effect of subgrid-scale processes should become increasingly unpredictable as resolution increases and the size of the sample of small-scale events decreases (see § 1.1.4). This is another piece of evidence that more realistic fluid models, which do not have such a clean separation between “resolved” and “unresolved” variables, will be more discriminating and allow the best approaches to show their full potential.

An open question of importance for real-world modelling concerns the extent to which parametrisation schemes that result in accurate weather forecasts tend to also produce accurate climate predictions (Christensen and Berner 2019). Another asks whether a scheme’s offline performance is a good indicator of its online performance once coupled into a model. Gagne II et al. (2020) addressed these questions by testing a collection of GAN parametrisations with different predictors and types of noise (see Figure 1.5), with the results suggesting an affirmative answer for the former and a negative answer for the latter. The verification of these conclusions would be a worthwhile goal for further research using other dynamical systems. Other possible goals could be to more clearly assess the ability of data-driven parametrisation schemes to adapt to unseen climate conditions (Christensen, Moroz, and Palmer 2015).

and to explore and exploit the potential for data-driven schemes to correct numerical errors in addition to modelling unresolved processes (Bhouri and Gentile 2023).

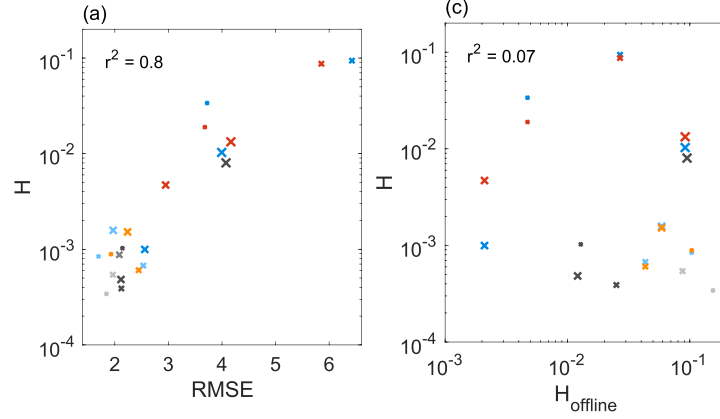


Figure 1.5: Reproduction of Figures 11a and 11c by Gagne II et al. (2020). Panel (a) compares ensemble mean weather forecast accuracy (measured by RMSE) to climatological PDF accuracy (measured by the Hellinger distance H) for a collection of GAN parametrizations with different predictors and types of noise. Panel (c) performs a similar comparison with offline performance (measured by the Hellinger distance between the PDFs of the true and predicted tendencies) taking the place of RMSE.

1.3.6 Beyond Lorenz '96

The transition from L96 to more complex systems necessarily gives rise to several technicalities that must be addressed. The most pressing of these is the fact that increasing the number of degrees of freedom in the host model will greatly increase the number of predictors available for parametrizations to use. Models with more than one prognostic variable will also require separate parametrizations for each one. Without judicious simplifications, the problem of constructing a rigorous data-driven parametrization will quickly become intractable. Crommelin and Vanden-Eijnden (2008) give an insightful discussion of this issue as it relates to Markov chain parametrizations.

Another complication is that the “spatial” dimension in L96 is discrete, while the dynamical systems being parametrized in weather and climate modelling (i.e., fluid flows) have continuous spatial dimensions. While it is well established that there is little benefit in using stochastic parametrizations with spatially correlated noise for L96, spatial correlation is expected to be a much more important consideration in spatially continuous systems (Arnold, Moroz, and Palmer 2013). One might also ask whether it will be beneficial to construct spatially nonlocal schemes where the tendency predicted at each point also depends on the values of the large-scale variables at neighbouring points (potentially capturing the gradients of these variables).

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