Predictive scaling laws for spherical rotating dynamos

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SUMMARY
State of the art numerical models of the Geodynamo are still performed in a parameter regime extremely remote from the values relevant to the physics of the Earth’s core. In order to establish a connection between dynamo modelling and the geophysical motivation, it is necessary to use scaling laws. Such scaling laws establish the dependence of essential quantities (such as the magnetic field strength) on measured or controlled quantities. They allow for a direct confrontation of advanced models with geophysical constraints.

We combine a numerical approach, based on a multiple linear regression method in the form of power laws, applied to a database of 102 direct numerical simulations (courtesy of U. Christensen), and a physical approach, based on energetics and forces balances.

We show that previous empirical scaling laws for the magnetic field strength essentially reflect the statistical balance between energy production and dissipation for saturated dynamos. Such power based scaling laws are thus necessarily valid for any dynamo in statistical equilibrium and applicable to any numerical model, irrespectively of the dynamo mechanism.

We show that direct numerical fits can provide contradictory results owing to biases in the parameters space covered in the numerics and to the role of a priori hypothesis on the fraction of ohmic dissipation.

We introduce predictive scaling laws, that is relations involving input parameters of the governing equations only. We guide our reasoning on physical considerations. We show that our predictive scaling laws can properly describe the numerical database and reflect the dominant forces balance at work in these numerical simulations. We highlight the dependence of the magnetic field strength on the rotation rate. Finally, our results stress that available numerical models operate in a viscous dynamical regime, which is not relevant to the Earth’s core.

Key words: Dynamo: theories and simulations; Geomagnetic induction.

1 INTRODUCTION
Many numerical models have been produced over the last few years to try and reproduce characteristics of planetary and stellar magnetic fields. The parameter regime relevant to these natural objects is however out of reach of present days computational resources. In order to assess the reliability of current numerical models and their relevance to natural applications, it is thus necessary to rely on scaling laws, which can be established on the basis of a set of numerical models with varying control parameters and then extended to the regime of geophysical or astrophysical relevance.

Previous empirical scaling laws for the magnetic field strength (Christensen & Aubert 2006) have proven to be remarkably robust. Indeed they seem to be applicable to numerical models irrespectively of the parameter regime, viscous or inertial (Christensen 2010; Schrinner et al. 2012), as well as to natural objects of very different kinds (Christensen et al. 2009). Such scaling laws are constructed on the basis of a statistical balance between energy production and dissipation. It is essential to separate the relative importance of this general assumption – which will necessarily be valid for any dynamo in statistical equilibrium – from additional assumptions which could test the nature of a particular dynamo. An additional key issue is that such existing relations only relate measured quantity. They have no predictive power for numerical models in the sense that the knowledge of control parameters (entering the governing equations) is not sufficient to a priori estimate the strength of the produced magnetic field. We therefore want to introduce predictive scaling laws, which a priori estimate the amplitude of a measured quantity (say the magnetic field strength) as a function of input parameters only.

2 GOVERNING EQUATIONS AND NUMERICAL MODELS
We restrict our study to Boussinesq models of planetary dynamos. The domain consists of a spherical shell, and the aspect ratio between the two bounding spheres is set to \( \xi \equiv r_i/r_o = 0.35 \). The flow is driven by an imposed difference of temperature between the inner and outer boundaries.
The governing equations in the rotating reference frame can then be written—using $L = r_o - r$, as unit of length, $\Omega^{-1}$ as unit of time, $\Delta T$ as unit of temperature, and $\sqrt{\rho \nu \Omega}$ as unit for the magnetic field—as

\[
\begin{align*}
\partial_t u^r + (u^r \cdot \nabla)u^r &= -\nabla \pi^r + E \Delta u^r - 2\epsilon_e \cdot u^r + \frac{Ra E^2}{Pr} \frac{r}{r_o} + (\nabla \times B^r) \times B^r, \\
\partial_t B^r &= \nabla \times (u^r \times B^r) + \frac{E}{Pr} \Delta B^r, \\
\partial_t T^r + (u^r \cdot \nabla)T^r &= \frac{E}{Pr} \Delta T^r, \\
\nabla \cdot u^r &= \nabla \cdot B^r = 0.
\end{align*}
\]

(1)

Because the governing equations involve nine independent physical parameters ($\alpha, g_0, \Delta T, v, \kappa, \eta, \Omega, \rho, \mu$) and five units (kg, m, s, K, C), owing to the Buckingham $\pi$ theorem, only four independent non-dimensional parameters can be introduced. In our system (eqs 1–3), they are the Ekman number $E = v/(\Omega L^2)$, the Prandtl number $Pr = v/\kappa$, the magnetic Prandtl number $Pm = v/\eta$, and the Rayleigh number $Ra = \alpha g_0 \Delta T L^3/\nu \kappa$, in which $v$ is the kinematic viscosity of the fluid, $\alpha$ the coefficient of thermal expansion, $g_0$ the gravity at the outer bounding sphere, $\kappa = k/(\rho c)$ its thermal diffusivity, and $\eta$ its magnetic diffusivity. Throughout this article, non-dimensional quantities are denoted with a $^\cdot$.

All the simulations used in this work rely on no-slip mechanical boundary conditions and an insulating outer domain. The inner core is insulating in most simulations, and a few simulations involve a conducting inner core with the same conductivity as the fluid.

Our analysis will be tested against a wide database of 185 direct numerical simulations kindly provided by U. Christensen. The data sample is reduced to 102 to only take into account dynamo simulations available at the time. Finally we will use a few additional numerical data published in Morin & Dormy (2009).

These numerical data can be used to test scaling laws guided by physical reasoning. It can also be used to establish direct numerical fits. To this end, we introduce a multiple linear regression approach (Montgomery et al. 2001; Cornillon & Matzner-Lober 2010), detailed in Appendix A.

## 3 Power Based Scalings, Key Parameters and Their Relations

### 3.1 Energy balance between production and dissipation

In order to derive a scaling law for the magnetic field strength, a possible approach introduced by Christensen & Aubert (2006) is to consider the statistical balance between energy production by buoyancy forces and dissipation. Time averaged quantities of a statistically steady dynamo state should obviously satisfy

\[
P = D_y + D_z,
\]

(4)

where $P$ is the power generated by buoyancy forces, $D_y$ is the rate of ohmic dissipation

\[
D_y = \int_V \frac{\eta}{\mu} (\nabla \times B^r)^2 dV,
\]

that is

\[
D_y^* = E_\eta \int_V (\nabla \times B^r)^2 dV^*,
\]

in which $E_\eta = E/\nu m$ is the magnetic Ekman number and $D_y$ is the rate of viscous dissipation

\[
D_z = \int_V \rho \nu (\nabla \times u^r)^2 dV,
\]

that is

\[
D_z^* = E \int_V (\nabla \times u^r)^2 dV^*.
\]

The above quantities are all defined as time averaged over a sufficient amount of time, so that they are steady for a given parameter set.

Following Christensen & Aubert (2006) and introducing the $f_{\text{dnum}}$ coefficient, defined as

\[
f_{\text{dnum}} \equiv \frac{D_y}{D_y + D_z},
\]

(5)

we get

\[
P = \frac{D_y}{f_{\text{dnum}}} = \frac{1}{f_{\text{dnum}}} \int_V \frac{\eta}{\mu} (\nabla \times B^r)^2 dV \sim \frac{1}{f_{\text{dnum}}} \frac{\eta}{\mu} \frac{B^2}{E \nu} V^*,
\]

(6)

where we introduced a typical magnetic field strength $B$ and a magnetic dissipation length scale $\ell_B$, defined again using time averaged quantities as

\[
\ell_B^2 \equiv \frac{\int_V B^2 dV}{\int_V (\nabla \times B^r)^2 dV} = \frac{2}{\eta} \frac{E_{\text{mag}}}{D_y},
\]

(7)

that is

\[
\ell_B^2 = 2 \frac{E_{\text{mag}}}{D_y}, \quad \text{that is} \quad \ell_B^* = 2 E_{\text{mag}}^*/D_y^*.
\]

(8)

This simple reasoning provides the following expression for the magnetic field strength

\[
\frac{B^2}{\mu} \sim f_{\text{dnum}} \ell_B^2 \frac{P}{\eta V^*} = f_{\text{dnum}} \ell_B^2 \frac{P_M}{\eta},
\]

(9)

where $P_M$ is the mass power generated by buoyancy forces $P_M \equiv P/(\rho V)$.

The non-dimensional form of eq. (9) is

\[
Lo \sim f_{\text{dnum}} 1/2 \ell_B^{1/2} \ell_B^* 1/2,
\]

(10)

where $Lo \equiv \left(2 E_{\text{mag}}^*/V^*\right)^{1/2} \equiv B^*$. Expressing a scaling law for $B$ (or its non-dimensional form $Lo$) therefore reduces to relating $P$ and $\ell_B$ to the relevant parameters.

In previous studies $\ell_B$ has often not been introduced as such (but see the review by Roberts & King 2013). Instead it is usually indirectly evaluated by introducing the magnetic dissipation time $\tau_{\text{diss}} \equiv E_{\text{mag}}/D_y = \ell_B^2/(2\eta)$ (see Christensen & Tilgner 2004), or in non-dimensional form $\tau_{\text{diss}}^* \equiv \tau_{\text{diss}}/\tau_{\text{dip}}$, where $\tau_{\text{dip}} \equiv L^2/(\pi^2 \eta)$. This definition leads to $\tau_{\text{diss}}^* = \pi^2/2 \ell_B^2$. Besides, the parameter $f_{\text{dnum}}$ is a rather complex number, which involves both a priori input and a posteriori output model properties. It is usually assumed to be order one in natural dynamos (but see Schrinner 2013), its importance in scaling laws is discussed in Appendix B.
3.2 Power generated by buoyancy forces

Christensen & Aubert (2006) established a relation between $P^*$ and a flux-based Rayleigh number $Rao^*_Q$

$$Ra^*_Q \equiv \frac{1}{4\pi r_0 \rho} \frac{\alpha g r_o \Delta Q}{c \Omega^2 (r_o - r)^2},$$

(11)

where $\Delta Q$ is the difference between the time-average total heat flow $Q$ and $Q'_o = 4\pi \xi T_o (J \cdot s^{-1})$, which corresponds to the diffusive heat flow associated to $T_o(r) = T_o/r + T_b$.

They show that

$$P^* \approx 2\pi \xi \left( \frac{1 + \xi}{1 - \xi}\right) Ra^*_Q,$$

(12)

under the assumptions that the volume integral of the realized temperature gradient can be approximated by its conductive counterpart. The demonstration requires in particular fixed temperature boundary conditions. Relation (12) is well verified for the numerical database used in this study. That is why in the following numerical analysis of scaling laws, the parameter $P^*$ will be replaced by $Ra^*_Q$ with a pre-factor of 7.03 determined by the geometry via the aspect ratio $\xi$.

It is important to stress that $Ra^*_Q$ is an output parameter, and cannot be controlled \textit{a priori} when using fixed temperature boundary conditions. It can however be related to the classical Rayleigh number, which is a control parameter of the problem. Indeed, introducing the Nusselt number $Nu \equiv Q/Q'_o$, which can be rewritten as $Nu = Q_o(r_o)/(4\pi r_o T_o)$ under the statistically steady assumption, relation (11) becomes

$$Ra^*_Q = E^1 \Pr^2 Ra(Nu - 1).$$

(13)

The $Ra^*_Q$ parameter can not be controlled in the problem because it is related to the output parameter $Nu$. Its value is zero at the onset of convection ($Nu = 1$).

Note that $Ra^*_Q Nu/(Nu - 1)$ would be an input control parameter in the case of imposed heat flux boundary conditions. The construction of $Ra^*_Q$ would however still involve, even with such boundary conditions, measurements of the Nusselt number, because the temperature difference across the shell becomes a measured quantity.

3.3 Role of the magnetic dissipation length scale $\ell_B$

In the numerical database used in this paper, the dissipation length scale $\ell_B^*$, calculated using eq. (7), varies between 0.02 and 0.10. These values are obviously smaller than those corresponding to the pure dipole decay in the absence of motions $\tau_0^* = 1/2$, that is $\ell_B^* = 1/\pi \lesssim 0.30$. Besides, the range of variation of $\ell_B^*$ is less than one order of magnitude. Thus, as a first approximation, the variations of $\ell_B^*$ can be neglected, namely it can be set to a constant in eq. (10). Using the relation (12), eq. (10) becomes under this assumption

$$Lo \sim f_{\alpha m}^{1/2} Ra^*_Q^{1/2} E^*_m^{1/2}.$$

(14)

Its application to the 102 dynamos database is represented in Fig. 1, and yields the relative misfit $\chi_{rel} = 0.433$. Relation (14), which simply corresponds to the energy balance between production and dissipation with $\ell_B$ approximated as a constant, already provides a good fit to the numerical data. This implies that empirical fits of the magnetic field strength previously obtained in the literature mainly reflect this simple balance between energy production and dissipation, combined with an improved description of the magnetic dissipation $\ell_B$ than a simple constant, which is however not essential.

Figure 1. The Lorentz number corrected for the relative fraction of Ohmic dissipation versus a combination of the flux-based Rayleigh number, the Ekman number and the magnetic Prandtl number: eq. (14). This simple scaling law only reflects the statistical balance between energy production and dissipation, combined with a constant $\ell_B$. Points correspond to the full 102 dynamos database, open squares indicate the subset used in Christensen & Aubert (2006).

The statistical balance between both terms of the right-hand side of the dimensional form of the induction eq. (2) yields to $uB/\ell \sim \eta B/\ell_B^2$, where we introduced a typical velocity field strength $u$, and $\ell$ has the dimension of a length scale which depends on correlations between the norm and direction of $u$ and $B$. The length scales $\ell_B$ and $\ell$ are thus related by

$$\ell_B \sim \eta^{1/2} u^{-1/2} \ell^{1/2},$$

(15)

which can be normalized as

$$\ell_B^* \sim \xi^{1/2} u^{*1/2} \ell^{*1/2}, \quad \text{or} \quad \ell_B^* \sim E^{1/2}_{\ell_B^*} Rm^{-1/2} \ell^{*1/2},$$

(16)

where $Rm$ is the magnetic Reynolds number, and $Ro$ is the Rossby number, defined as $Ro \equiv (2 E_{kin}/V^2)^{1/2} \equiv u^*$. with

$$E_{kin} \equiv \int_V \frac{\rho u^2}{2} dV,$$

that is $E_{kin} \equiv \int_V \frac{u^2}{2} dV^*.$

(17)

The magnetic dissipation length scale $\ell_B$ is thus an output parameter, in so far as it is related to both the characteristic velocity $u$ of the flow (measured by Ro or Rm) and the length scale $\ell$ (see Appendix C1).

3.4 Existing scaling laws for the magnetic field strength and their physical interpretation

Christensen & Aubert (2006) introduced two seminal scaling laws

$$Lo \sim f_{\alpha m}^{1/2} Ra^*_Q^{0.34},$$

(18)

and its optimised form

$$Lo \sim f_{\alpha m}^{1/2} Ra^*_Q^{0.32} Pm^{0.11}.$$

(19)

Their application to the 102 dynamos database is represented in Fig. 2, and yields the relative misfits $\chi_{rel} = 0.256$ and $\chi_{rel} = 0.152$, respectively. The corresponding assumption on the magnetic dissipation length scale $\ell_B^*$ is detailed in Appendix C2. It respectively
yields
\[ \ell_B^* \sim Rm_{Q}^{-0.16} E_{\eta}^{1/2}, \quad \text{and} \quad \ell_B^* \sim Rm_{Q}^{-0.18} E_{\eta}^{1/2} Pm_{-0.39}, \] (20)

which are represented in Fig. 3 (see Appendix C2 for discussion).

Relation (18) and its optimized form (19) are empirical laws obtained using numerical experiments. The physical interpretation of relation (18), as provided by Christensen & Aubert (2006), is based on two assumptions: the empirical scaling law for the magnetic dissipation time \( \tau_{\eta}^* \sim Rm^{-1} \) (Christensen & Tilgner 2004), which is equivalent to assuming \( \ell^* \sim 1 \) (see Appendix C1), and their empirical fit \( Ro \sim Rm_{Q}^{0.41} \) (eq. 30 in Christensen & Aubert 2006). Using eq. (16), these two assumptions provide \( \ell_B^* \sim Rm_{Q}^{-0.21} E_{\eta}^{1/2} \). This last expression can then be injected in eq. (10), to yield \( Lo \sim f_{\text{ohm}}^{1/2} Rm_{Q}^{0.29} \). Thus, their demonstration leads to an exponent of \( Rm_{Q} \) equal to 0.29, which is only slightly lower than their optimal exponent 0.34 in (18).

Christensen (2010) proposed a modified interpretation: while retaining the assumption \( \ell^* \sim 1 \), he replaced the scaling law for \( Ro \) by the one resulting from mixing length theory (balance between inertia and buoyancy). This theory, usually applied for turbulent convection in stars (Stevenson 1979; Kippenham & Weigert 1990), provides \( Ro \sim Rm_{Q}^{1/3} \). It leads to \( Lo \sim f_{\text{ohm}}^{1/2} Rm_{Q}^{1/3} \), which is closer to the original fit (18) obtained by Christensen & Aubert (2006).

Instead, Jones (2011) based his physical reasoning on the inertial scaling law \( Ro \sim Rm_{Q}^{2/5} \) (derived from the so-called IAC balance, see Aubert et al. 2001), and obtained \( Lo \sim f_{\text{ohm}}^{1/2} Rm_{Q}^{0.30} \). The assumptions of inertial scaling laws for \( Ro \) made by both Christensen (2010) and Jones (2011) however do not seem relevant to dipolar numerical dynamos (see Section 4.5 of this paper; and Christensen & Aubert 2006; Soderlund et al. 2012).

More recently, Davidson (2013) studied analytically the asymptotic limit expected to be relevant to planetary dynamos. In this limit, viscosity is negligible, which implies a vanishing viscous dissipation \( (f_{\text{ohm}} \sim 1) \), and inertial forces do not enter the dominant forces balance (small Rossby number limit). Davidson’s argument relies on a dimensional analysis. On the right-hand side of eq. (9), with \( f_{\text{ohm}} \sim 1 \), both \( Pm \) and \( \ell_{B}/\eta \) are assumed to be independent on \( \Omega \). This implies that \( B^2/ (\rho \mu) \) only depends on \( L \) and \( Pm \), and thus

\[ \frac{B^2}{\rho \mu} \sim L^{2/3} Pm_{-2/3}, \] (21)

(see eq. 6 in Davidson 2013). In order to account for viscous effects in numerical simulations, Davidson (2013) then replaces \( Pm \) with \( f_{\text{ohm}} Pm \) in (21), which leads to

\[ \frac{B^2}{\rho \mu} \sim L^{2/3} (f_{\text{ohm}} Pm)^{2/3}, \] (22)
different prefactors for dipolar and multipolar dynamos, despite of their different induction mechanisms (Christensen 2010; Schrinner et al. 2012).

4 PREDICTIVE SCALING LAWS FOR THE MAGNETIC FIELD STRENGTH

Power based scaling laws, discussed in the previous section, properly describe the numerical database. However they only relate together measured quantities. We now want to express scaling laws which only involve input parameters on the right-hand side. Such scaling laws will be referred to as ‘predictive’ in the sense that they estimate the strength of a measured quantity, say the magnetic field strength, as a function of input parameters only (i.e. parameters that explicitly enter the governing equations), and can therefore be used before any simulation is performed (as opposed to scaling laws involving measured quantities such as $Ra_\ell$ and $f_{\text{shm}}$).

4.1 Control parameters

Only four non-dimensional parameters can be introduced in the governing equations (1–3). In our formulation, these are the Ekman number $E$, the Prandtl number $Pr$, the magnetic Prandtl number $Pm$ and the Rayleigh number $Ra$ (see Section 2). According to the Buckingham π theorem, any additional non-dimensional quantity, for example the Elsasser number $\Lambda \equiv Lo^2 Pm/\epsilon$, can therefore be expressed as a function of the above four non-dimensional control parameters. The choice of non-dimensional parameters is however non-unique (for example, the Roberts number $q \equiv \kappa/\eta$ could be used instead of the magnetic Prandtl number $Pm \equiv \nu/\eta$).

Stelzer & Jackson (2013) opened the way to a predictive scaling by expressing $Nu - 1$, $Ro$ and $Lo/f_{\text{shm}}^{1/3}$ as a function of $Ra$ instead of $Ra_\ell$ (see their section 5). Their approach however is bound to fail for small values of $Ra$ as all these measured quantities obviously vanish below the onset of convection or dynamo action.

Instead of using the Rayleigh number as control parameter, it is thus natural to introduce the distance to an instability threshold. We thus introduce $Ra_a$ and $Ra_\ell$, which respectively correspond to the onset of convection and dynamo action (see Appendix E for $Ra_a$). The measured quantities $Nu - 1$ and $Ro$ are expected to vanish at the onset of convection $Ra = Ra_a$, and $Lo$ at the onset of dynamo action $Ra = Ra_\ell$.

The quantity $Ra - Ra_a$, therefore provides a natural control parameter for hydrodynamic quantities such as $Nu - 1$ and $Ro$. This control parameter, even though natural, is however biased because of the strong dependence of the critical Rayleigh number $Ra_a$ on $E$ and $Pr$. This dependence, first formulated and investigated by Chandrasekhar (1961) in the cartesian geometry, has been extensively studied. Especially, Roberts (1968) then Busse (1970) studied the limit $E \ll 1$ in a spherical geometry. In a perturbative cylindric model for a uniformly heated fluid, Busse (1970) proposed

$$Ra_a \sim E^{-4/3} \left( \frac{Pr}{1 + Pr} \right)^{4/3}.$$  

This solution, valid in the limit of asymptotic Ekman numbers, is consistent with several other studies: for example, Carrigan & Busse (1983) (experimental convection study in a differentially heated spherical shell), Jones et al. (2000) (uniformly heated fluid in a sphere), Takehiro et al. (2002) (fixed heat flux boundary conditions), Dormy et al. (2004) and Zhang & Liao (2004). It is validated to a certain extent against the finite Ekman number numerical database.
used in this paper. The corresponding misfit is $\chi_{\text{rel}} = 0.319$ and it is represented in Fig. 5(a). Note that a dependence on $\Pr/(1 + \Pr)$ remains. The optimised scaling law obtained with our database is $R_{a} \simeq 17.78 E^{-1.19} (\Pr/(1 + \Pr))^{0.58}$, with $\chi_{\text{rel}} = 0.061$ (95 per cent confidence intervals in Table 2): the optimised exponent is slightly weaker (in absolute value) than those predicted by the asymptotic calculus of Busse (1970), which indicates that these models are still not in an asymptotic limit.

In practice, the numerical experiments used in this study are performed for values of $R_{a}$ of the order of 10 times the critical value (see Fig. 5b). Indeed, only dynamos with $Nu > 2$ are considered in the database (see Christensen & Aubert 2006), on the other hand, for obvious computational reasons associated with small scale motions, $R_{a}$ is never very far from the onset in numerical models. As a result, the values of $R_{a}$ are strongly correlated with the values of $R_{a_{c}}$. It follows that $R_{a}$ is in fact close to $R_{a} - R_{a_{c}}$: in the numerical database, $R_{a} \approx 1.11 (R_{a} - R_{a_{c}})$ with a relative misfit $\chi_{\text{rel}} = 0.052$ (see Fig. 5c). This last relation, which traduces a bias in the database, explains why Stelzer & Jackson (2013) obtained satisfying fits of $R_{o}$ and $Nu - 1$ as a function of $R_{a}$ (without introducing the distance to the onset of convection).

The strong dependence of $R_{a_{c}}$ on the Ekman number introduces a very large variation of the control parameter $R_{a} - R_{a_{c}}$, spanning over five orders of magnitude in the numerical database. This is somewhat fictitious as the parameter $R_{a}/R_{a_{c}}$ would only vary over one order of magnitude. We thus introduce $\tilde{R} = R_{a}/R_{a_{c}}$ and our new control parameter will thus be $\tilde{R} - 1$ (as $\tilde{R}_{c} = 1$). This new control parameter filters out the Ekman and Prandtl number dependences (the Ekman dependence is highlighted in Fig. 5d).

To measure the distance to the onset of dynamo action, we also introduce the control parameter $\tilde{R} - \tilde{R}_{d}$, where $\tilde{R}_{d} \equiv R_{a_{d}}/R_{a_{c}}$ is a function of $E$, $Pr$ and $Pm$ only. Nevertheless, whereas $R_{a_{d}}$ is known for all numerical experiments in the database provided by U. Christensen, this is not the case for the critical value at the onset of dynamo action $R_{a_{d}}$. It can be estimated through a linear interpolation of $Lo^{2}$ as a function of $R_{a}$ near the onset of dynamo action (see Appendix E). Such an estimate could only be performed for seven sets of $E$, $Pr$ and $Pm$ in the database (see Table 1), which corresponds to 33 numerical simulations. It is extended to 42 simulations thanks to nine additional direct numerical simulations extracted from Morin & Dormy (2009) and corresponding to the set $E = 3 \times 10^{-4}$, $Pr = 1$ and $Pm = 3$.

Our four control parameters therefore are: the Ekman number $E$, the Prandtl number $Pr$, the magnetic Prandtl number $Pm$ and the relative distance to either the onset of convection or of dynamo action, $\tilde{R} - 1$ and $\tilde{R} - \tilde{R}_{d}$, respectively.
4.2 Direct numerical fit versus forces balances

Empirical scaling laws deduced from the multiple linear regression method applied to numerical data have to be considered carefully for two main reasons. First, the ranges of some input parameters are highly correlated, which introduces bias in scaling laws. It is the case for the Ekman number and the magnetic Prandtl number. The minimal value of \( P_m \) required for dynamo is indeed dependent on \( E \) (see Christensen & Aubert 2006). This cannot be distinguished from \( E^{2/3} \) as shown in Fig. 7(a) and in King & Buffett (2013) (see also Soderlund 2012). The lengthscale \( \ell^* \) corresponds to the characteristic length scale of the flow calculated as the mean scale of the kinetic energy spectrum (see Christensen & Aubert 2006). This length scale is very similar to our \( \ell^* \), introduced in Appendix B1.

Supposing, as do Petrelis & Fauve (2001), that \( \ell^* \sim 1 \), this leads in non-dimensional form to

\[
\Lambda \sim \left( R_m - R_m' \right) E, 
\]

where \( R_m' \) corresponds to the critical value of \( R_m \) at the onset of dynamo action.

While the length scale \( \ell^* \) necessarily varies over a limited range in the numerical database (see Fig. 7a and the discussion at the end of Section 3.4), a finer description can be achieved by retaining viscous effects and neglecting inertial forces. The equilibrium between the curl of the Coriolis force and the viscous force indeed yields

\[
\tilde{\ell}^* \sim E^{1/3}. 
\]

This last relation properly describes the database used in the present paper, as shown in Fig. 7(a) and in King & Buffett (2013) (see also Roberts & King 2013). The lengthscale \( \tilde{\ell}^* \) clearly depends on \( E^{1/3} \) and not on \( E^{1/2} \), the latter being the typical scale of boundary layers. Thus, viscous effects play a non-negligible role in the bulk of the flow. This indicates that present numerical simulations are not in a dynamical regime relevant to the Earth’s core (see also Soderlund et al. 2012). The \( E^{1/3} \) scale would represent less than 100 m for geophysical values. Besides, the mild dependence of \( \tilde{\ell}^* \) on the Rossby number (see Fig. 7b) shows that the assumption that inertia is small compared to viscous effects is verified by numerical models.

If one uses (27) for the length scale \( \tilde{\ell}^* \) in relation (25) (see Fauve & Petrelis 2007), this yields

\[
\Lambda \sim \left( R_m - R_m' \right) E^{1/3}. 
\]

An alternative forces balance, known as the strong field balance, and assumed to be valid for the Earth’s core, consists in assuming a balance between the Lorentz force and the viscous force associated to the flow modification (Petrelis & Fauve 2001). It yields the equilibrium

\[
\Lambda \sim \left( R_m - R_m' \right) E, 
\]

where \( R_m \) corresponds to the critical value of \( R_m \) at the onset of dynamo action.

4.3 Magnetic field strength as a function of the flow amplitude

A first step in our reasoning consists in expressing the magnetic field strength as a function of the flow amplitude. In experimental physics, one usually controls the peak velocity of a flow driven say by propellers. For this reason, earlier theoretical work often focused on the relation between the produced magnetic field and the velocity field. A first approach is to consider dynamos which bifurcate from a laminar flow. One assumes that in such cases, a dominant balance exists between the Lorentz force and the viscous force associated to the flow modification (Petrelis & Fauve 2001).

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\Lambda \sim \left( R_m - R_m' \right) E^{1/3}. 
\]

An alternative forces balance, known as the strong field balance, and assumed to be valid for the Earth’s core, consists in assuming a balance between the Lorentz force and the modification of the.
Coriolis force. It provides (see Petrelis & Fauve 2001) in non-dimensional form
\[ \Lambda \sim (Rm - Rm_0). \]  
(29)

Each of the relations (26), (28) and (29) can be tested against the 42 dynamos database (see Fig. 8), and yields the relative misfits \( \chi_{rel} = 1.438 \), \( \chi_{rel} = 0.891 \), and \( \chi_{rel} = 2.081 \), respectively. The best scaling law fitting the numerical data is therefore (28). It is consistent with the fact that viscous effects have been shown to play a non-negligible role in the bulk of the flow in numerical models.

This result can be compared to the output of a direct numerical fit. The values of the magnetic Reynolds number at the onset of dynamo action corresponding to seven sets of E, Pr and Pm in the database have been estimated by a linear interpolation of Lo \(^2\) as a function of Rm (see Table 1 and Appendix E). The multiple linear regression approach applied to the 42 dynamos database provides the following scaling law for the Elsasser number \( \Lambda \) as a function of \( (Rm - Rm_0) \) and E (95 per cent confidence intervals given in Table 3): \(^1\)

\[ \Lambda \sim 10.24 (Rm - Rm_0)^{1.09} E^{0.52}, \text{ with } \chi_{rel} = 0.698. \]  
(30)

The physically derived scaling law (28) is consistent with the empirical scaling law (30) for the dependence on \( (Rm - Rm_0) \). The optimal exponent of E is larger than the 1/3 value predicted by (28), and remains to be investigated.

Fig. 10(a) represents relation (28) applied to the 42 dynamos database in red diamonds, and the same relation, but setting \( Rm_0 \) to zero in blue squares. The blue points gradually move away from a linear fit when \( Rm \) decreases, as expected (because the approximation \( Rm - Rm_0 \approx Rm \) worsens). Relation (28) can however then be applied to the 102 dynamos database, provided that the parameter \( Rm_0 \) is dropped (since it is only known for the 42 simulations of the reduced database). It is represented in Fig. 10(b). As in Fig. 10(a), the full numerical database appears to follow the proposed scaling law, except for low values of Rm for which \( Rm_0 \) cannot be neglected.

It is worth noting that relation (28) reveals a dependence of the magnetic field strength on viscosity, which is geophysically not realistic. To illustrate this, let us now try to apply this relation to the Earth’s core. We choose the common estimate value \( Rm = 10^3 \). The distance to the onset of dynamo action \( Rm - Rm_0 \) can be estimated by \( Rm \), which leads to an overestimated value of \( \Lambda \). We find \( \Lambda \sim 10^{-2} \), which is an upper bound because \( Rm_0 \) was not taken into account. It is yet much smaller than its estimated value for the Earth’s core, expected to be close to unity (Roberts 1988).

This indicates very clearly that available numerical models are not in the dynamical regime relevant to geodynamo. In other words, the Earth’s core would simply be out of the range of Fig. 10(a) (with \( Rm \approx 10^3 \), and \( \Lambda E^{1/3} \approx 10^0 \)).

The magnetic Reynolds number is however a measured quantity in the numerical database. In order to establish a predictive scaling for the magnetic field strength, it is thus necessary to express the flow amplitude as a function of control parameters. This is the purpose of the two next sections.

4.4 Predictive scaling law for the injected power

The definition of the output parameter \( \text{Ra}_g \) involves the efficiency with which heat is transferred by convection, measured by the Nusselt number \( Nu \) (see eq. 13). This is a subject of study in itself, many studies of heat transfer have been performed for rotating convection. Fig. 11 shows that the numerical data globally correspond to an intermediate regime between the rapidly rotating regime (\( Nu \sim \tilde{R}^{6/5} \), Aurnou 2007; King et al. 2009, 2010) and the weakly rotating regime (\( Nu \sim \text{Ra}^{2/7} \), see King et al. 2009). The simple relation \( Nu \sim \tilde{R} \) provides a good description of the database. Note that in Fig. 11, a dependence on Pr remains. This could be further investigated by seeking for a dependence on \( \text{Pr}/(1 + \text{Pr}) \) (instead of a power law dependence which would lack regularity in the limit \( \text{Pr} \to 0 \) or \( \text{Pr} \to +\infty \)). As we will however discuss later (see Section 4.6), the \( \text{Pr}/(1 + \text{Pr}) \) term can be omitted without significant loss of quality in describing the present database.

---

\(^1\) A direct numerical fit of \( \Lambda \) as a function of \( (Rm - Rm_0) \), E, Pn and Pr yields \( \Lambda \approx 0.30 (Rm - Rm_0)^{0.88} E^{0.12} Pm^{0.79} \text{Pr}^{-0.82}, \text{ with } \chi_{rel} = 0.301 \) (see Table 3 and Fig. 9a). The proposed dependence on Pr is not strongly constrained, since the estimation of the optimal exponent of Pr is only based on three simulations corresponding to \( \text{Pr} \neq 1 \) (and for all three, \( E = 1 \times 10^{-4}, Pm = 10, \text{Pr} = 10 \), see Table 1). The proposed dependence is therefore clearly not robust. The bias between E and Pn in the database probably accounts for the smaller exponent of E and the extra dependence on Pn in the above relation compared to (30).
In the available database, the bias $\text{Ra} \sim \text{Ra}_c$ (see Section 4.1) allows us to approximate $\text{Ra}$ by $(\bar{R} - 1) \text{Ra}_c$ in the definition (13) of $\text{Ra}^*_Q$. Injecting (24) and the above simple expression for $\text{Nu}$ (which is admittedly not based on solid physical considerations) yields

$$\text{Ra}^*_Q \sim (\bar{R} - 1)^2 E^{-5/3} \text{Pr}^{-2} \left( \frac{\text{Pr}}{1 + \text{Pr}} \right)^{4/3}. \tag{31}$$

The corresponding relative misfit when applied to the 102 dynamos database is $\chi_{\text{rel}} = 0.311$ and it is represented in Fig. 12(a). Note that the dependence on $\text{Pr}^{-2}$ in (31) comes from the definition (13) of $\text{Ra}^*_Q$, whereas that on $(\text{Pr}/(1 + \text{Pr}))^{4/3}$ results from the expression of $\text{Ra}_c$ (relation 24).

Relation (31) can be compared to an optimized empirical fit, which provides

$$\text{Ra}^*_Q \simeq 5.10 (\bar{R} - 1)^{1.78} E^{1.70} \text{Pr}^{-2.12} \left( \frac{\text{Pr}}{1 + \text{Pr}} \right)^{1.26}, \tag{32}$$

with $\chi_{\text{rel}} = 0.173$, \hspace{1cm} (95 per cent confidence intervals are given in Table 2). Relation (31) is therefore close to providing the best fit through the numerical database. \footnote{If the dependence on $\text{Pr}/(1 + \text{Pr})$ is omitted, it yields a larger misfit ($\chi_{\text{rel}} = 0.326$), and $\text{Ra}^*_Q \simeq 1.47 (\bar{R} - 1)^{1.77} E^{1.68} \text{Pr}^{-1.56}$. Both relations would not be modified if a dependence on $\text{Pm}$ was sought (see Table 2).}

The parameter $\text{Ra}^*_Q$ varies over six orders of magnitude, while none of the control parameters varies over such a wide range (see Appendix C2). Fig. 12(b) highlights the strong dependence of $\text{Ra}^*_Q$ on the Ekman number explicitied in (31). This explains the above range of variation. The control parameter $\bar{R} - 1$ covers a much more physically realistic range.

### 4.5 Predictive scaling laws for the flow amplitude

Several scaling laws based on different forces balances have been proposed in the literature concerning the flow amplitude (detailed in King & Buffett 2013). For simulations near the onset of dynamo action, the Lorentz force can be expected to be small. Then, balancing the curl of the buoyancy term with that of the Coriolis force yields

$$u^* \sim \bar{L} = \frac{1}{\bar{\eta}} \frac{\text{Pr}}{1 + \text{Pr}} \frac{1}{\text{Pr}}. \tag{33}$$

which can be rewritten, using relation (12), as

$$\text{Ro} \sim \frac{1}{\bar{\eta}} \frac{\text{Pr}}{1 + \text{Pr}} \text{Ra}^*_Q^{1/2}. \tag{34}$$

Combining (34) and (27) leads to the Viscous–Archimedean–Coriolis (VAC) scaling proposed by King & Buffett (2013)

$$\text{Ro} \sim \text{Ra}^*_Q^{1/2} E^{-1/6}. \tag{35}$$

Its application to the 102 dynamos database is represented in Fig. 13(a), with a relative misfit $\chi_{\text{rel}} = 0.201$. It can be compared to the inertial Ro-scalings $\text{Ro} \sim \text{Ra}^*_Q^{2/5}$ (derived from the IAC balance, see Aubert \textit{et al.} 2001; Jones 2011) and $\text{Ro} \sim \text{Ra}^*_Q^{1/3}$ (resulting from mixing length theory, see Christensen 2010) (see Fig. 13b). These three scaling laws provide descriptions of the database of comparable quality. The scaling law (27) for the length scale $\bar{L}$ however indicates that the VAC scaling (35) is more relevant to the present study than inertial scaling laws.

The direct multiple linear approach provides the following optimal scaling law expressing Ro as a function of $\text{Ra}^*_Q$ and $E$.

---

**Figure 8.** Scaling laws for the magnetic field strength as a function of the flow amplitude as measured by $\text{Rm} - \text{Rm}_d$: (a) relation (26), (b) relation (28) and (c) relation (29). This figure relies on the 42 dynamos database.

**Table 2.** Optimal scaling laws obtained by the multiple linear regression method, for $\text{Ra}_c$, $\text{Ra}^*_Q$ (relation (32) and relation given in the footnote 2), $\text{Ro}$ (relation (36) and relation given in the footnote 3) and $\text{Rm}$ (relation given in the footnote 4 and relation (38)) (95 per cent confidence intervals). Crosses indicate that the corresponding parameter is chosen not to enter the fit. The dashes indicate that the contribution of the corresponding parameter has been found negligible.

<table>
<thead>
<tr>
<th>Pre-factor</th>
<th>$\text{Ra}^*_Q$</th>
<th>$\bar{R} - 1$</th>
<th>$\text{E}$</th>
<th>$\text{Pm}$</th>
<th>$\text{Pr}$</th>
<th>$\text{Pr}/(1 + \text{Pr})$</th>
<th>$\chi_{\text{rel}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Ra}_c$</td>
<td>17.779 ± 1.468</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>0.579 ± 0.030</td>
</tr>
<tr>
<td>$\text{Ra}^*_Q$</td>
<td>1.470 ± 0.517</td>
<td>×</td>
<td>1.774 ± 0.064</td>
<td>1.675 ± 0.032</td>
<td>×</td>
<td>×</td>
<td>0.517 ± 0.036</td>
</tr>
<tr>
<td>$\text{Ro}$</td>
<td>5.103 ± 1.550</td>
<td>×</td>
<td>1.775 ± 0.041</td>
<td>1.703 ± 0.021</td>
<td>×</td>
<td>×</td>
<td>0.137 ± 0.015</td>
</tr>
<tr>
<td>$\text{Ro}$</td>
<td>0.589 ± 0.133</td>
<td>×</td>
<td>0.466 ± 0.018</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>0.184 ± 0.010</td>
</tr>
<tr>
<td>$\text{Ro}$</td>
<td>1.103 ± 0.094</td>
<td>0.433 ± 0.006</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>0.100 ± 0.010</td>
</tr>
<tr>
<td>$\text{Rm}$</td>
<td>1.535 ± 0.371</td>
<td>×</td>
<td>0.749 ± 0.036</td>
<td>–</td>
<td>0.264 ± 0.020</td>
<td>0.843 ± 0.030</td>
<td>0.656 ± 0.035</td>
</tr>
<tr>
<td>$\text{Rm}$</td>
<td>2.421 ± 0.547</td>
<td>×</td>
<td>0.757 ± 0.029</td>
<td>–</td>
<td>0.257 ± 0.016</td>
<td>0.857 ± 0.024</td>
<td>0.901 ± 0.070</td>
</tr>
</tbody>
</table>


timal scaling law expressing $\text{Ro}$ as a function of $\text{Ra}^*_Q$ and $E$.
The term Pr is represented in Fig. 14, with a relative misfit only intermediate steps in the reasoning. Besides, the dependence of \( R_m \) yields a simple power law dependence (e.g. Schütter et al. 1996).

\[ \tilde{R} = \left( \tilde{R} - 1 \right)^{1.07} \left( \frac{E}{1 + Pr} \right)^{0.80} P_m^{-1.49} P_r^{-1.49}, \]

\[ \tilde{R} = \left( \tilde{R} - 1 \right)^{0.75} \left( \frac{E}{1 + Pr} \right)^{0.80} P_m^{-0.66} P_r^{-0.66}, \]

This relation is essential in order to establish a predictive scaling law (relation 40). Squares correspond to the 102 dynamos database, black points to the 42 runs of the reduced database.

Finally, note that relation (37) can be compared to the optimized fit to the available data. A direct numerical fit provides

\[ R_m \approx 2.42 \left( \tilde{R} - 1 \right)^{0.76} E^{-0.26} P_m^{0.86} P_r^{-0.90} \left( \frac{Pr}{1 + Pr} \right)^{0.53}, \]

with \( x_{rel} = 0.108 \).

(95 per cent confidence intervals given in Table 2) \(^3\):

\[ Ro \approx 0.59 R_\alpha^{0.47} E^{-0.10} \quad \text{with} \quad x_{rel} = 0.184. \]  

Replacing the parameter \( R_\alpha \) by its expression (31) in eq. (35) yields

\[ R_m \approx \left( \tilde{R} - 1 \right)^{1.091} \left( \frac{E}{1 + Pr} \right)^{0.516} \left( \frac{P_m}{1 + Pr} \right)^{0.144}. \]

The role of both terms \( Pr \) allows to correct the data corresponding to the full database, approximating the unknown \( R_\alpha \) dependence to unity.

Finally, Fig. 16(b) corresponds to the application of relation (39) to the reduced 42 dynamos database for which \( R_\alpha \) is approximately correct, the coefficients based on a direct numerical fit are therefore weakly constrained. In particular \( P_r \) does not vary much in this subsample. Despite of this, the agreement between both expressions is remarkably good, except for a larger exponent of \( P_m \) for the latter, which remains to be investigated.

The application of relation (39) to the 42 dynamos database is represented in Fig. 16(a) in red diamonds. The same expression approximating \( R_\alpha \) to unity is plotted using blue squares. As expected, the quality of the approximation decreases with \( \tilde{R} \).

### Table 3. Optimal scaling laws obtained by the multiple linear regression method, for \( \Lambda \) as a function of \( (R_m - R_{m,d}) \) (relation (30) and relation given in footnote 1) and \( (\tilde{R} - \tilde{R}_d) \) (relation 40) (95 per cent confidence intervals).

<table>
<thead>
<tr>
<th>Pre-factor</th>
<th>( R_m - R_{m,d} )</th>
<th>( \tilde{R} - \tilde{R}_d )</th>
<th>( E )</th>
<th>( P_m )</th>
<th>( Pr )</th>
<th>( x_{rel} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Lambda )</td>
<td>10.243 ± 8.619</td>
<td>1.091 ± 0.157</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>0.149 ± 0.698</td>
</tr>
<tr>
<td>( \Lambda )</td>
<td>0.305 ± 0.212</td>
<td>0.879 ± 0.087</td>
<td>×</td>
<td>0.119 ± 0.101</td>
<td>0.787 ± 0.141</td>
<td>0.196 ± 0.301</td>
</tr>
<tr>
<td>( \Lambda )</td>
<td>0.351 ± 0.210</td>
<td>0.796 ± 0.062</td>
<td>0.702 ± 0.071</td>
<td>1.496 ± 0.069</td>
<td>0.196 ± 0.233</td>
<td></td>
</tr>
</tbody>
</table>

(95 per cent confidence intervals are provided in Table 2) \(^3\): \( \tilde{R} = 0.147 \) and \( R_m \approx 1.54 \left( \tilde{R} - 1 \right)^{0.75} E^{-0.26} P_m^{0.84} P_r^{-0.66} \) (see Fig. 9b and Table 2).

### 4.6 Predictive scaling law for the magnetic field strength

Replacing the flow amplitude in relation (28) by its expression (37) yields the following predictive scaling law

\[ \tilde{R} \approx 0.35 \left( \tilde{R} - 1 \right)^{0.30} E^{-0.07} P_m^{1.49} P_r^{-1.49}, \]

\[ \tilde{R} \approx 0.35 \left( \tilde{R} - 1 \right)^{0.30} E^{-0.07} P_m^{1.49} P_r^{-1.49}, \]

with \( x_{rel} = 0.233 \),

(see Fig. 9c and Table 3 for 95 per cent confidence intervals). The dependence on the Ekman number is here negligible. Besides, we used here the reduced 42 dynamos database for which \( R_\alpha \) can be estimated, the coefficients based on a direct numerical fit are therefore weakly constrained. In particular \( P_r \) does not vary much in this subsample. Despite of this, the agreement between both expressions is remarkably good, except for a larger exponent of \( P_m \) for the latter, which remains to be investigated.

The application of relation (39) to the 42 dynamos database is represented in Fig. 16(a) in red diamonds. The same expression approximating \( R_\alpha \) to unity is plotted using blue squares. As expected, the quality of the approximation decreases with \( \tilde{R} \). Finally, Fig. 16(b) corresponds to the application of relation (39) to the full database, approximating the unknown \( R_\alpha \) contribution to unity.

Finally, in order to assess the role of the two terms \( Pr^{-1} \) and \( [Pr/(1 + Pr)]^{2/3} \) in relation (39), we compare in Fig. 17 the improvements obtained by each contribution of \( Pr \). It highlights the important role of the \( Pr^{-1} \) term. The role of the \( Pr/(1 + Pr) \) term in the description of the available numerical database is marginal (compare Figs 16b and 17b).
Thus, instead of the power based scaling law proposed by Christensen (2010), which can be rewritten as
\[ \Lambda \sim f_{\text{ohm}} \text{Ra}^{2/3} \chi_{\text{rel}} E^{-1} \text{Pm}, \quad \text{with } \chi_{\text{rel}} = 0.452, \quad (41) \]
and which involves measured quantities \( f_{\text{ohm}} \) and \( \text{Ra} \), we propose the simple relation (39), which can be reformulated as
\[ \Lambda \sim (\tilde{R} - \tilde{R}_d) q \left( \frac{\text{Pr}}{1 + \text{Pr}} \right)^{2/3}, \quad \text{with } \chi_{\text{rel}} = 0.516. \quad (42) \]
The \( \text{Pr}/(1 + \text{Pr}) \) dependence comes from the asymptotic expression of the critical Rayleigh number at the onset of convection (24). The moderate variation of \( \text{Pr} \) in the database implies that it can be omitted without significant loss in the quality of the fit (see Fig. 17b). This provides an even simpler scaling law, valid for the available range of \( \text{Pr} \)
\[ \Lambda \sim (\tilde{R} - \tilde{R}_d) q, \quad \text{with } \chi_{\text{rel}} = 0.512. \quad (43) \]
It involves input parameters only, and its derivation was guided by physical arguments. Besides, it is worth noting that (43) as well as (42) imply a dependence of the magnetic field amplitude on the rotation rate \( \Omega \). This contradicts earlier claims of saturation values independent on the rotation rate.

Relations (41) and (43) are applied to a reduced 33 dynamos database (for which all quantities involved in both relations are available) and represented in Fig. 18. The relative misfits given in (41), (42) and (43) are computed on the basis of this reduced database.

Note that the power based relation (41) does not involve any distance to the onset of dynamo action. Indeed, the parameter \( f_{\text{ohm}} \) does not vanish at the onset of dynamo action [it vanishes at the onset of convection, see eq. (13)]. The parameter \( f_{\text{ohm}} \) however corrects this issue, as it tends to zero at the onset of dynamo action.

5 CONCLUSION

In this study, we combine a numerical approach, which consists in establishing scaling laws for quantities of interest thanks to a multiple linear regression method applied to numerical data under the approximation of power laws, and a physical approach based either on energetics or on forces balances. Our numerical approach is based on a 102 dynamos database (U. Christensen) corresponding to Boussinesq fully convecting (\( \text{Nu} > 2 \)) and dipolar dynamo models.

In a first phase, we focus our attention on scaling laws for the magnetic field strength as a function of the injected power by buoyancy forces, quantified by the flux-based Rayleigh number \( \text{Ra} \). We show that the scaling laws previously obtained in the literature mainly correspond to the simple writing of the energy balance between production and dissipation, which is necessarily valid for any dynamo in statistical equilibrium. Such power based scaling laws are thus very general and applicable to any dynamo in statistical equilibrium irrelevantly of the dynamo mechanism (e.g. Schrinner et al. 2012).

The description of the magnetic dissipation length scale \( \ell_B \) determines the quality of the approximation. Assuming a constant value for \( \ell_B \) already provides a very good description of the numerical database. Improved fits can be obtained based on finer assumptions for \( \ell_B \). However, none of the proposed scaling laws corresponds to a realistic physically based relation to describe the numerical database (see Section 3.4).
Predictive scaling laws for rotating dynamos

Figure 12. (a) Validation of relation (31) expressing the flux-based Rayleigh number as a function of the normalized distance to the onset of dynamo. (b) The flux-based Rayleigh number versus the normalized distance to the onset of convection. The Ekman number is indicated by using different symbols (as in Fig. 5d). This figure is based on the full 102 dynamos database.

Figure 13. (a) The Rossby number as a function of the flux-based Rayleigh number (a) based on the VAC scaling (relation 35) (b) on the IAC scaling (dotted line, $\chi_{rel} = 0.237$) and on the scaling resulting from mixing length theory (dashed line, $\chi_{rel} = 0.431$). Both graphs rely on the full 102 dynamos database.

Figure 14. The resulting predictive scaling law for the magnetic Reynolds number as a function of the normalized distance to the onset of convection (relation 37). This figure relies on the full 102 dynamos database.

The second part of our study aims at establishing predictive scaling laws (i.e. as a function of input parameters only) for the magnetic field strength. Our reasoning is guided by physical arguments such as forces balances, and the numerical database is only used to validate the proposed relations. Indeed, we have shown that scaling laws obtained through a direct numerical fit can be biased by the numerical sample. It is in particular the case for the Ekman and magnetic Prandtl numbers, whose ranges are strongly correlated in the database. The flux-based Rayleigh number $Ra_\star$, which is a measured quantity, is replaced either by the normalized distance of the Rayleigh number to the onset of convection (denoted as $\tilde{R} - 1$) or by the normalized distance to the onset of dynamo action (measured by $\tilde{R} - \tilde{R}_d$). This last quantity is unfortunately only available for a subset of the numerical database.

Our four control parameters are the Ekman number, the Prandtl number, the magnetic Prandtl number and the relative distance to the onset of convection (resp. dynamo action). Our reasoning follows four steps.

The first step of the reasoning provides a scaling law for the magnetic field strength as a function of the distance to the onset of dynamo in term of flow amplitude, which is $\Lambda \sim (Rm - Rm_d)E^{1/3}$ and which matches numerical data. It is deduced from the balance...
Figure 15. Simplified expressions for Rm testing the Pr dependence. The magnetic Reynolds number as a function of the normalized distance to the onset of convection, eq. (37) (a) with no correction on Pr and Pr/(1 + Pr) (b) with the correction on Pr$^{-1}$ only. Both graphs rely on the 102 dynamos database.

Figure 16. Physically derived predictive scaling law for the magnetic field strength as a function of $\tilde{R} - \tilde{R}_d$. (a) Relation (39) (red diamonds), and the same relation but approximating $\tilde{R}_d$ to unity (blue squares), both applied to the 42 dynamos database. (b) Relation (39) approximating the unknown $\tilde{R}_d$ contribution to unity, applied to the full (blacks points) and reduced (blue squares) database. The dashed line corresponds to relation (39).

Figure 17. Test of the Pr dependence in the predictive scaling law (39) applied to the 102 dynamos database approximating the unknown $\tilde{R}_d$ contribution to unity (a) with no correction on Pr and Pr/(1 + Pr) (b) with the correction on Pr$^{-1}$ only. The dashed line in (a) and (b) corresponds to the scaling law (39).
between the Lorentz force and the viscous force associated to the flow distortion (Fauve & Petrelis 2007).

The second one consists in establishing the link between the injected power (measured by $\text{Ra}_D$) and $\tilde{R}$ = 1, by using the definition of $\text{Ra}_D$, the relation between Nu and $\tilde{R}$ (e.g. King et al. 2010) and previously established dependences of the critical Rayleigh number at the onset of convection on the Ekman and Prandtl numbers (Busse previously established dependences of the critical Rayleigh number visous effects.

The third step deals with the derivation of a scaling law for the flow amplitude. The Viscous–Archimedean–Coriolis scaling (King & Buffett 2013) matches the numerical data. Especially, the characteristic velocity length scale of the flow depends on $E^{2/3}$ in numerical simulations, which proves that viscous effects play a non-negligible role in the bulk of the flow. The role of inertia is shown to be negligible on this length scale for dipolar dynamos compared to that of viscous effects.

Finally, in a fourth step, the combination of the aforesaid results leads to a surprisingly simple predictive scaling law, that is $\Lambda \sim (\tilde{R} - \tilde{R}_D) q [\text{Pr}/(1 + \text{Pr})]^{2/3}$, which involves input parameters only, contrary to previous published scaling laws, and which properly describes available numerical data (as stressed in the text, the Pr dependence is not tested by the database and can be omitted here without loss). This scaling law relies on the dominant forces balance in the numerical dynamos. Contrary to power based scaling laws, it is applicable in the parameter range covered by this study, but will not be satisfied in general (e.g. if inertial forces become significant). Besides its predictive power, it also provides information on the underlying forces balance at work in the dynamo simulations.

Introducing predictive scaling laws, based on control parameters only, allows to underline two important ideas. First, the present numerical models do not operate in a dominant forces balance relevant for the geodynamo. Indeed, viscous effects are shown to be essential and extrapolation to geophysically relevant parameters produces strongly underestimated amplitudes for the magnetic field. Secondly, it allows to demonstrate the clear dependence of the magnetic field strength on the rotation rate $\Omega$.

**ACKNOWLEDGEMENTS**

The authors want to acknowledge stimulating discussion with Peter Davidson and gratefully thank Uli Christensen for sharing his numerical database.

**REFERENCES**


In the following, $\log(Y)$ is replaced by $\tilde{Y}$ and $\log(X_j)$ by $\tilde{X}_j$ for clarity. The system of $n$ equations (A2) can be represented in matrix notation as
\begin{equation}
\tilde{Y} = \tilde{X} \beta + \epsilon,
\end{equation}
where $\tilde{X}$ is referred to as the design matrix $[\tilde{X}_1 \ldots \tilde{X}_p]$ and $\beta$ is a $(p + 1)$-dimensional vector containing the whole set of regression coefficients. The vector $\beta$ can be estimated using least square estimates. The misfit $\epsilon$ is assumed to follow a Gaussian centred distribution with a variance $\sigma$ which is assumed to be a constant. The corresponding fitted model is
\begin{equation}
\hat{Y} = \hat{X} \hat{\beta}.
\end{equation}
where
\begin{equation}
\hat{\beta} = (\tilde{X}^T \cdot \tilde{X})^{-1} \cdot \tilde{X}^T \cdot \hat{Y}.
\end{equation}

The variance $\sigma$ can be estimated by the unbiased estimator $\hat{\sigma}$ defined as
\begin{equation}
\hat{\sigma}^2 = \frac{1}{n - p - 1} \|\hat{\epsilon}\|^2, \quad \text{where} \quad \hat{\epsilon} = Y - \hat{Y}.
\end{equation}
As a measure of misfit between data and fitted values, we use as in Christensen & Aubert (2006) the mean relative misfit to the original data $y_i [i \in (1, n)]$, defined as
\begin{equation}
\chi_{rel} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i}\right)^2}.
\end{equation}
The estimator $\hat{\beta}$ is unbiased and its covariance matrix can be estimated by
\begin{equation}
\hat{\sigma}^2 = \hat{\sigma}^2 (\tilde{X}^T \cdot \tilde{X})^{-1},
\end{equation}
which is a $(p + 1) \times (p + 1)$ matrix. An estimation of the variance $\hat{\sigma}_j$ of the $\hat{\beta}_j$ exponent $\{j \in (0, p)\}$ is
\begin{equation}
\hat{\sigma}_j = \hat{\sigma} \sqrt{(\tilde{X}^T \cdot \tilde{X})^{-1}}_{jj},
\end{equation}
and the estimator $(\hat{\beta}_j - \beta_j)/\hat{\sigma}_j$ follows a Student distribution (Student 1908; Fisher 1925) with $(n - p - 1)$ degrees of freedom. For the analysis performed in this paper, $(n - p - 1) \approx 100$. In that case, the coefficient $\beta_j$ is comprised in the 95 per cent confidence interval
\begin{equation}
\beta_j = \hat{\beta}_j \pm 2 \hat{\sigma}_j.
\end{equation}
This method provides the following power law for $y$
\begin{equation}
y = \exp(\hat{\beta}_0 \pm 2 \hat{\sigma}_0) \prod_{j=1}^{p} x_j^{\hat{\beta}_j \pm 2 \hat{\sigma}_j},
\end{equation}
which can be rewritten as
\begin{equation}
y = \left[\exp(\hat{\beta}_0) \cosh(2 \hat{\sigma}_0) \pm \exp(\hat{\beta}_0) \sinh(2 \hat{\sigma}_0)\right] \prod_{j=1}^{p} x_j^{\hat{\beta}_j \pm 2 \hat{\sigma}_j}.
\end{equation}
In this paper, the confidence intervals are provided in separate tables.

In a geometric interpretation where the essential quantity is reported in ordinate and the optimal combination of fitting parameters...
APPENDIX B: ROLE OF THE FRACTION OF OHMIC DISSIPATION $f_{\text{ohm}}$ IN EMPIRICAL SCALING LAWS FOR THE MAGNETIC FIELD STRENGTH

We stress here the pitfalls of direct numerical fits, free from physical insight, by showing that different a priori hypothesis on $f_{\text{ohm}}$ yield contradictory results.

B1 Power based scaling laws derived from multiple linear regressions

As noted in Section 3.1, $f_{\text{ohm}}$ is not at all a trivial parameter, as it involves both controlled and measured quantities. Indeed with our notations, eq. (5) can be rewritten as

$$f_{\text{ohm}} = \left(1 + \frac{\text{Ra}}{\text{Lo}} \ell_u^2 \ell_{\text{gas}}^2 \text{Pm} \right)^{-1}. \quad (B1)$$

where we introduced a kinematic dissipation length scale $\ell_u$ ($\ell_u = \ell_u/L$), defined using time averaged quantities as

$$\ell_u^2 = \frac{\int u^2 \, dV}{\int (\nabla \times u)^2 \, dV} = 2 \nu \frac{E_{\text{kin}}}{D_u}. \quad (B2)$$

The main distinction between the scaling laws (18) and (23) respectively proposed by Christensen & Aubert (2006) and Davidson (2013) relies on the different exponent of $f_{\text{ohm}}$.

First considering the best empirical scaling law for the magnetic field strength in our database, ignoring the $f_{\text{ohm}}$ parameter, we get

$$L_o \approx 0.16 \text{Ra}_g^{0.32} E^{-0.11} \text{Pr}_{m}^{0.30} \text{Pr}_{E}^{-0.18}, \quad \text{with } \chi_{\text{rel}} = 0.194, \quad (B3)$$

(see Fig. B1a). Note that in the above expression, the right-hand-side vanishes at the onset of convection and not at the onset of dynamo action. This expression is therefore obviously not valid close to the onset of dynamo action.

The balance between energy production and dissipation provides an exponent 1/2 for $f_{\text{ohm}}$ (see Section 3.1). The best power law approximation for $L_o$ as a function of $\text{Ra}_g$ obtained by setting the exponent of $f_{\text{ohm}}$ to 1/2 is then

$$L_o \approx 0.78 f_{\text{ohm}}^{1/2} \text{Ra}_g^{0.32}, \quad \text{with } \chi_{\text{rel}} = 0.256, \quad (B4)$$

whereas allowing for a dependence on $\text{Pm}$ leads to

$$L_o \approx 0.64 f_{\text{ohm}}^{1/2} \text{Ra}_g^{0.31} \text{Pr}_{m}^{0.17}, \quad \text{with } \chi_{\text{rel}} = 0.141. \quad (B5)$$

These two expressions correspond to the fits (18) and (19) of Christensen & Aubert (2006). The exponents do not exactly match because the numerical database used here is somewhat larger. However, the two latter relations are rigorously recovered if we apply our algorithm to the 65 dynamos numerical database of Christensen & Aubert (2006). This validates the multiple linear regression approach used in this paper. The role of the parameter $\text{Pr}$ is found to be negligible using the 65 dynamos numerical database of Christensen & Aubert (2006). But the 102 dynamos database used here contains more simulations corresponding to $\text{Pr} \neq 1$ than the earlier Christensen & Aubert (2006) database (32 versus 17). Considering an additional dependence on $\text{Pr}$ yields

$$L_o \approx 0.56 f_{\text{ohm}}^{1/2} \text{Ra}_g^{0.30} \text{Pr}_{m}^{0.20} \text{Pr}_{E}^{-0.11}, \quad \text{with } \chi_{\text{rel}} = 0.121, \quad (B6)$$

(see Fig. B1b), where the dependence on $\text{Pr}$ is not negligible. On the contrary, the contribution of the Ekman number appears negligible (taking E into account only provides a very minor improvement of $\chi_{\text{rel}}$ and a small power of E).

It is however natural in a fitting approach to let the exponent $f_{\text{ohm}}$ be determined by the multiple linear regression approach. Moreover, as noted above, the $f_{\text{ohm}}$ parameter is usually argued to be equal to unity in planetary dynamos. The best power law with the above parameters is

$$L_o \approx 0.66 f_{\text{ohm}}^{0.61} \text{Ra}_g^{0.31} \text{Pr}_{m}^{0.19} \text{Pr}_{E}^{-0.08}, \quad \text{with } \chi_{\text{rel}} = 0.117. \quad (B7)$$

(see Fig. B1c). The contribution of E is negligible, this last relation thus involves five non-dimensional parameters only, which corresponds to the maximum number of independent parameters in the problem (see Appendix A). Table B1 gathers the fitted values corresponding to equations (B3), (B4), (B5), (B6) and (B7) including their 95 per cent confidence interval. The exponents in relation (B7)
are not significantly different from those in relation (B6). In particular, the 95 per cent confidence interval associated to the optimized value 0.61 of the exponent of \( f_{\text{ohan}} \) in (B7) includes the value 1/2 provided by the energy balance.

The relative error on the exponents of \( Ra_{\Omega}^* \), \( Pm \) and \( f_{\text{ohan}} \) is in general moderate (less than 15 per cent). The error for the estimation of the exponent of \( Pr \) is more important (between 30 per cent and 50 per cent): the distribution of the control parameter \( Pr \) in our data set, although wider than in the data set used in Christensen & Aubert (2006), is indeed not wide enough to establish a clear dependence of 50 per cent for the corresponding exponent.

Finally, note that eqs (B3), (B6) and (B7) can be related by

\[
f_{\text{ohan}} \simeq 0.07 E^{-0.17} Pm^{0.18} Pr^{-0.18}, \quad \text{with } \chi_{\text{rel}} = 0.249, \tag{B8}
\]

where the contribution of \( Ra_{\Omega}^* \) is found to be negligible (95 per cent confidence intervals in Table B1). The high corresponding relative mif (25 per cent) reveals that the dependence of \( f_{\text{ohan}} \) on other parameters can not be reliably approximated by a simple power law.

#### B2 Extrapolation to natural dynamos

The results of Appendix B1 deserve careful analysis. Eq. (B7) may be indeed viewed as a minor improvement in the quality of the fit, resulting from the introduction of an additional degree of freedom in the problem. Besides, the \( f_{\text{ohan}} \) parameter involves most of the quantities we are trying to fit, that is to say Lo, Ro, \( \ell^*_f \) and \( \ell^*_\eta \) (see eq B1).

Nevertheless, the above study clearly indicates that different scaling laws can be proposed for Lo, depending on exponents considered for \( f_{\text{ohan}} \). If one adopts the usual assumption that \( f_{\text{ohan}} = 1 \) for planetary applications, the resulting relation for such applications will not depend on the exponent of \( f_{\text{ohan}} \). To illustrate this, we can write equations (B3), (B6) and (B7) in dimensional form assuming \( f_{\text{ohan}} = 1 \). These are, respectively,

\[
B \sim \mu^{1/2} P_{\text{Earth}}^{0.32} \, \Omega_{\text{Earth}}^{0.16} \, L^{-0.37} \, P_r^{0.18} \, \nu^{0.03} \, \eta^{0.38} \, \kappa^{0.18}, \quad \text{with } \chi_{\text{rel}} = 0.194, \tag{B9}
\]

with \( \chi_{\text{rel}} = 0.194 \).

#### Table B2. 95 per cent confidence intervals associated to exponents in the dimensional scaling laws for the magnetic field strength corresponding to relations (B9), (B10) and (B11).

<table>
<thead>
<tr>
<th>P</th>
<th>( \Omega )</th>
<th>L</th>
<th>( \rho )</th>
<th>( \nu )</th>
<th>( \eta )</th>
<th>( \kappa )</th>
<th>( \chi_{\text{rel}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>B/\mu^{1/2}</td>
<td>0.318 \pm 0.027</td>
<td>0.157 \pm 0.134</td>
<td>-0.368 \pm 0.241</td>
<td>0.182 \pm 0.027</td>
<td>0.008 \pm 0.142</td>
<td>-0.295 \pm 0.039</td>
<td>0.176 \pm 0.056</td>
</tr>
<tr>
<td>B/\mu^{1/2}</td>
<td>0.302 \pm 0.009</td>
<td>0.094 \pm 0.027</td>
<td>-0.510 \pm 0.045</td>
<td>0.198 \pm 0.009</td>
<td>0.091 \pm 0.054</td>
<td>-0.197 \pm 0.021</td>
<td>0.106 \pm 0.033</td>
</tr>
<tr>
<td>B/\mu^{1/2}</td>
<td>0.309 \pm 0.010</td>
<td>0.073 \pm 0.030</td>
<td>-0.545 \pm 0.050</td>
<td>0.191 \pm 0.010</td>
<td>0.106 \pm 0.062</td>
<td>-0.186 \pm 0.023</td>
<td>0.080 \pm 0.039</td>
</tr>
</tbody>
</table>

**APPENDIX C: THE MAGNETIC DISSIPATION LENGTH SCALE \( \ell_\eta \)**

#### C1 The \( \ell_\eta \) length scale as a function of the flow amplitude

We interpret here earlier scaling laws in terms of assumptions made on \( \ell^*_f \) and their implications for \( Ro \) and \( \ell^*_\eta \).

Christensen & Tilgner (2004) have empirically shown that \( \tau^*_\eta \sim Rm^{-1} \). Because \( \tau^*_\eta \sim \ell^*_\eta^2 \), this provides \( \ell^*_\eta \sim Rm^{-1/2} \) (see...
Predictive scaling laws for rotating dynamos

Figure C1. The magnetic dissipation length scale versus a combination of the magnetic Reynolds number, the Ekman number and the magnetic Prandtl number: (a) $\ell_B^* \sim \text{Rm}^{1/2}$ (b) $\ell_B^* \sim \text{Rm}^{-0.57} \text{Pm}^{0.08}$ (both derived from Christensen & Tilgner 2004) (c) $\ell_B^* \sim \text{Rm}^{-5/12} \text{E}^{1/12}$ (Christensen 2010) (d) $\ell_B^* \sim \text{Rm}^{-0.45} \text{E}^{0.05} \text{Pm}^{0.05}$ (Stelzer & Jackson 2013). These graphs rely on the full 102 dynamos database.

As expected, the relative misfit $\chi_{\text{rel}}$ decreases when the number of predictor variables increases. Moreover, note that fits in Fig. C1 are based on 102 numerical simulations extracted from the data sample provided by U. Christensen. Thus, the sample used in Fig. C1 is larger than the one originally used by Christensen & Tilgner (2004) and Christensen (2010), and slightly different from that used by Stelzer & Jackson 2013, also based on the 185 dynamos database of U. Christensen but including $\ell_B > 0.35$ dynamos.

Finally, whereas the simple scaling law used in Fig. C1(a) corresponds to a simple physical assumption on the length scale $\ell$, the three other laws, albeit more accurate, are simply based on empirical fits.

C2 The $\ell_B$ length scale as a function of the injected power

Whereas the four aforesaid scaling laws rely on the magnetic Reynolds number, scaling laws for the magnetic field amplitude based on a production/dissipation balance rely on the flux-based Rayleigh number $\text{Ra}_Q$ (see Sections 3.1 and 3.2). It is therefore natural to seek for relations between the dissipation length scale $\ell_B$ and $\text{Ra}_Q$.

Indeed, published scaling laws for the amplitude of the magnetic field, such as the empirical scaling laws of Christensen & Aubert (2006) (see our eqs (18) and (19)), can readily be translated in terms of scaling laws for $\ell_B$. Thus, using equations (10) and (12), the scaling laws (18) and (19), respectively imply $\ell_B^* \sim \text{Ra}_Q^{-0.16} \text{E}^{1/12}$, and $\ell_B^* \sim \text{Ra}_Q^{-0.18} \text{E}^{1/12} \text{Pm}^{-0.39}$. It is interesting to note that in the representations of relations (18) and (19) by Christensen & Aubert (2006), the $x$-coordinate varies over six orders of magnitude (see Figs 2a and b in this paper and figs 8–9 in Christensen & Aubert 2006) while none of the control parameters varies over such a wide range. Thus, Fig. 3 (i.e. the above two relations) offers a somewhat more challenging representation of the very same expressions (18) and (19) in so far as the axes vary on a smaller range.

The above scaling laws expressing $\ell_B^*$ as a function of $\text{Ra}_Q$ were deduced from (18) and (19). As $\ell_B^*$ is related to both $\ell^*$ and $\text{Ro}$, they also imply relations between these two parameters and $\text{Ra}_Q$.

It is through these relations that the first of these scaling laws for the magnetic field strength was originally physically interpreted by

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Figure C1a, see also Roberts & King 2013). According to eq. (16), this scaling law corresponds to assuming that $\ell^* \sim 1$, that is, $\ell$ is the width of the spherical shell. It is reasonably consistent with the 102 dynamos database used in this paper, since $\text{Rm} \ell_B^2$ varies from 0.19 to 1.25, that is to say over about one order of magnitude. Moreover, note that some of the values are higher than unity: it is symptomatic of the role played by correlations between the norm and direction of $u$ and $B$. Christensen & Tilgner (2004) have empirically improved the above scaling law to $\ell_B^* \sim \text{Rm}^{-0.49} \text{Re}^{-0.08}$, where $\text{Re} = \text{Rm} \text{Pm}^{-1}$. This expression can be reformulated as $\ell_B^* \sim \text{Rm}^{-0.57} \text{Pm}^{0.08}$ (see Fig. C1b). Thanks to a larger numerical data sample, this last scaling law has been optimised by Christensen (2010) as $\ell_B^* \sim \text{Rm}^{-5/12} \text{E}^{1/12}$ (see Fig. C1c), and then by Stelzer & Jackson (2013) as $\ell_B^* \sim \text{Rm}^{-0.45} \text{E}^{0.05} \text{Pm}^{0.05}$ (see Fig. C1d).
Figure D1. The length scale $\ell_\star$ as a function of (a) $Rm\ell_B^2$ (relation D2) (b) $f_{\text{ohm}} Rm\ell_B^2$ (relation D3). These two graphs rely on the 102 dynamos database. This figure highlights that the hypothesis made by Davidson (2013), although well suited for planetary dynamos, are not met by numerical models.

APPENDIX D: LENGTH SCALES IN DAVIDSON’S (2013) DEMONSTRATION

The magnetic dissipation length scale denoted as $\ell_B$ in the present paper is referred to as $\ell_{\text{min}}$ in Davidson (2013). Besides, he carefully introduced two length scales $\ell_\parallel$ and $\ell_\perp$ (the integral length scales parallel and perpendicular to the rotation axis). The length scale $\ell_\parallel$ can be approximated by $L$, and the length scale $\ell_\perp$ corresponds to $\ell_u$ introduced in the present paper in Appendix B1. Davidson (2013) is interested in planetary dynamos, for which $f_{\text{ohm}} \approx 1$. We consider here the question of the applicability of his analytical results to the length scales computed from the numerical database.

Davidson’s dimensional analysis leading to relation (21) is based on the assumption that $\ell_B^2/\eta$ is independent on the rotation rate. This assumption, which was made in the limit relevant to planetary interiors, does not seem to extend to the parameter regime of numerical models. Indeed, using (9), the scaling law (B9) for the magnetic field strength implies

$$\frac{\ell_B^2}{\eta} \sim \Omega_{\text{pol}}^{0.314\pm0.268}, \quad (D1)$$

(95 percent confidence interval). Admittedly, the relative confidence interval is large, but the non-dependence of $\ell_B^2/\eta$ on the rotation rate, while sensible in the regime relevant to the geodynamo, is not relevant to the numerical data used here.

Besides, neglecting viscous effects, he considered the balance of the curl of the Coriolis force, the buoyancy force and the Lorentz force (the so-called MAC-balance, i.e. his eq. 10). Its combination with relation (21) provided by his dimensional analysis leads to $\ell_B^2 \approx \eta u^{-1} \ell_\star$, which can be rewritten in its non-dimensional form as

$$\ell_\perp^2 \approx Rm\ell_B^2. \quad (D2)$$

By comparison with eq. (16), that means that $\ell_\perp$ corresponds to our length scale $\ell$ defined in Section 3.3. The distinction between $\ell$ and $\ell_\perp$ is proved important in our study. Fig. D1(a) highlights that they should not be confused. The two assumptions, $f_{\text{ohm}} \approx 1$ and negligible viscous effects, are indeed not verified in numerical experiments.

If we use eq. (22) (eq. 9 in Davidson 2013) rather than (21) (eq. 6 in Davidson 2013) to take $f_{\text{ohm}}$ into account, we get $\ell_B^2 \sim \eta f_{\text{ohm}}^{-1} u^{-1} \ell_\perp$, which can be rewritten in its non-dimensional form as

$$\ell_\perp^2 \approx f_{\text{ohm}} Rm\ell_B^2. \quad (D3)$$

This expression corresponds to a modified form of relation (D2), adapted to $f_{\text{ohm}} < 1$ cases. Fig. D1(b) shows that even such an $f_{\text{ohm}}$ dependence does not provide a good description of the numerical data. This confirms that the assumption of negligible viscous effects, valid in the bulk of the Earth’s core, is not applicable to present numerical simulations. Davidson’s study therefore relies on assumptions relevant to the geodynamo, but not to present direct numerical simulations.

APPENDIX E: ESTIMATION OF THE ONSET OF DYNAMO ACTION

The critical values at the onset of dynamo action $Ra_d$ gathered in Table 1 have been estimated through a linear interpolation of the magnetic energy as a function of the Rayleigh number near the onset of dynamo action (see Section 4.1). As underlined by Morin & Dormy (2009), the dynamo bifurcation can be either supercritical or subcritical (or take the form of isola), the nature of the bifurcation depending on the parameters. The estimation of the critical Rayleigh number in the former case is represented in Fig. E1(a): the linear interpolation of data near the dynamo threshold provides $Ra_d$. In the case of subcritical bifurcations, the critical $Ra_d$ estimated by our method corresponds to the continuation of the subcritical branch, as shown in Fig. E1(b). A similar approach is used to determine $Rm_d$.  

Christensen & Aubert (2006), Christensen (2010) and Jones (2011) (see Section 3.4).
Figure E1. Schematic representation of the behaviour of the magnetic energy as a function of the Rayleigh number, for a (a) supercritical and (b) subcritical dynamo bifurcation. The solid (resp. dashed) lines indicate stable (resp. unstable) branches (see Morin & Dormy 2009). The linear interpolation (red solid line) associated to data (red points) provides the value of Ra_d in both cases.