Unification of Babcock-Leighton Dynamo models with Surface Flux Transport Models

Gopal Hazra & Mark Miesch

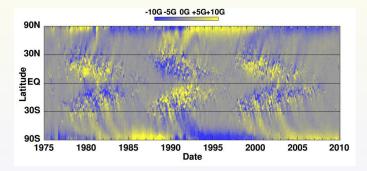
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Nov 6, 2015 APSPM15, Seoul National University

Photospheric Magnetic Field

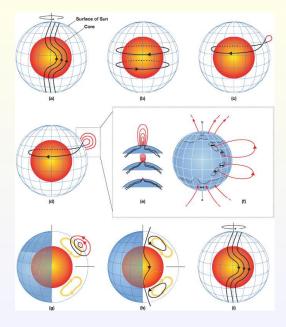
Importance of studying evolution of large scale surface magnetic field:

- Sets the structure of the heliospheric magnetic field
- Only observable part of the Babcock-Leighton Dynamo



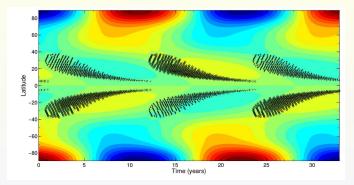
[Hathaway et. al (2010)]

Babcock-Leighton Dynamo Models



Babcock-Leighton Dynamo Models

a.k.a Flux Transport Dynamo Model (Axisymmetric Model!!)



[Thesis (2012), B B karak]

- Successfully model the 11-year solar cycle and its irregularities
- Structure of the surface magnetic field is not captured.

Surface Flux Transport Models

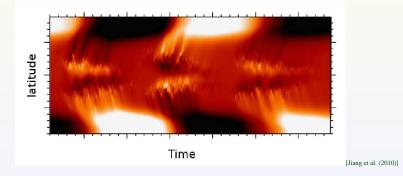
Solves induction equation on the surface of the sun with $v_r = 0$ & $\frac{\partial}{\partial r} = 0$

$$\frac{\partial B_r}{\partial t} = \frac{1}{\sin\theta} \frac{\partial}{\partial \theta} \left[\sin\theta \left(-u(\theta) B_r + D \frac{\partial B_r}{\partial \theta} \right) \right] - \Omega(\theta) \frac{\partial B_r}{\partial \phi} + \frac{D}{\sin^2\theta} \frac{\partial^2 B_r}{\partial \phi^2} + \frac{S(\theta, \phi, t)}{S(\theta, \phi, t)}$$

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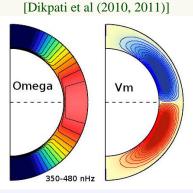
Simulates the surface magnetic field quite well!

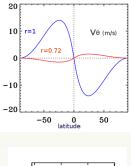
Develop a model which will simulate the surface magnetic field from the dynamo generated field self consistently and captures the 11 year solar cycle.

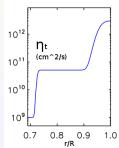
Unified 3D Babcock-Leighton Model

Solve 3D kinematic induction equation (Non-Axisymmetric !!!)

$$\frac{\partial B}{\partial t} = \nabla \times (v \times B - \eta_t \nabla \times B)$$





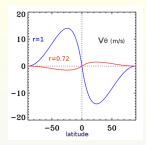


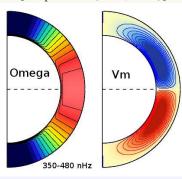
Unified 3D Babcock-Leighton Model

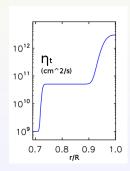
Solve 3D kinematic induction equation (Non-Axisymmetric !!!)

$$\frac{\partial B}{\partial t} = \nabla \times (\nu \times B - \eta_t \nabla \times B) + S(\theta, \phi)$$









Spot Making Algorithm

- Introduce spots sporadically and systematically, based on dynamo generated field.
- Let them evolve naturally, under the influence of mean flows and η_t

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Where ?

Spot producing field:

$$B_{\phi}(\theta.\phi,t) = \int_{r_a}^{r_b} h(r) B_{\phi}(r,\theta,\phi) dr$$

where $h(r) = h_0(r - r_a)(r_b - r), r_a = 0.71 R_{\odot}, r_b = 0.70 R_{\odot}$

if $B^*(\theta,\phi,t) = g(\theta)|B_{\phi}(\theta,\phi,t)| > B_t$ place spots on the surface

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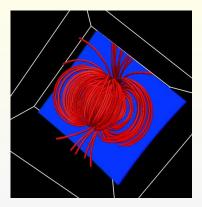
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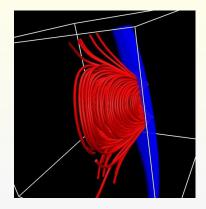
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When ?

Introduced some time delay and randomness!! [Miesch & Dikpati (2014)] Bipolar Spots are localized to the surface layers only.

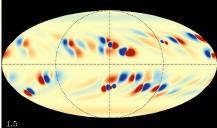




Spots quickly decouple from deep roots [Longcope & Choudhuri 2002, Schüssler & Rempel 2005]

Results: sunspots

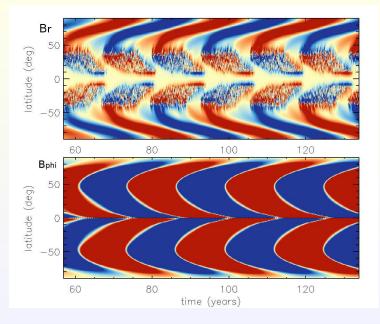




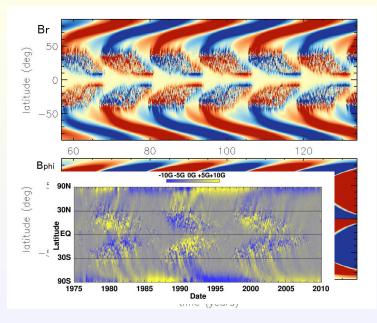
Self sustained 3D dynamo model which has sunspots and sunspots play very essential role in operation of dynamo

This is not the first. See Yeats & Muñoz – Jaramillo, A. (2013).

Butterfly Diagrams

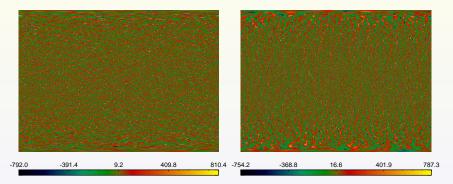


Butterfly Diagrams



Convective flow fields

Simulated flow fields $(V_{\theta} \& V_{\phi})$ from Doppler Velocity data (SDO)



[Upton & Hathaway, 2014a,b]

Incorporating Data in Simulation

Assumption:

1. Mass flux is divergence less

$$\nabla .\rho \mathbf{v} = 0 \tag{1}$$

2. Convection in upper CZ is completely poloidal

$$\rho \mathbf{v} = \nabla \times \nabla \times W \hat{r} \tag{2}$$

Obtaining 3D Convective Flows:

From Observation we have measurement of horizontal flows (V_h) Eqn(1) \Rightarrow

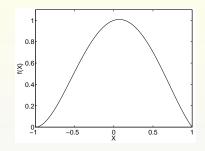
$$\nabla_{h} \cdot (\rho V_{h}) = -\frac{1}{r^{2}} \frac{\partial}{\partial r} (r^{2} \rho V_{r}) = -\frac{l(l+1)}{r^{2}} \frac{\partial W}{\partial r}$$
(3)

Now since $W(r, \theta, \phi) = f(r)g(\theta, \phi)$ so Eqn(3) $\Rightarrow g(\theta, \phi) = \frac{r^2 \nabla_{h} \cdot (\rho V_h)}{l(l+1)\frac{\partial F}{\partial r}}$

Extrapolation downward:

So we need F(r) and $\frac{\partial F}{\partial r}$

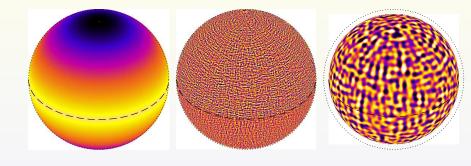
- $f(x) = a + bx + cx^2 + dx^3 + ex^4$, where $x = \frac{r - r_w}{r - r_p}$
- Have chosen f(r) so that $f(r) = 0, r = R_{\odot} \& r = r_p$ and $f(r) = 1, r = r_w$ where, $r_w = R_{\odot}(1 - \pi/l)$ and $r_p = R_{\odot}(1 - 2\pi/l)$

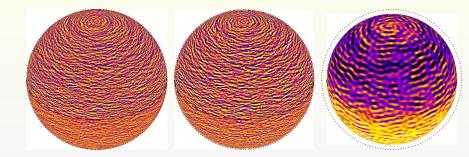


Hence we can calulate $W(r, \theta, \phi) = f(r)g(\theta, \phi)$ and then all three velocity component

Extrapolated Convective velocity fields

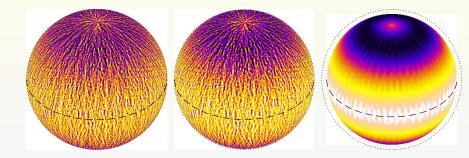
Vr





Vtheta

-9.0e+02 m/s	1.1e+03	-5.9e+02 m/s	6.4e+02	-18. m/s	18.

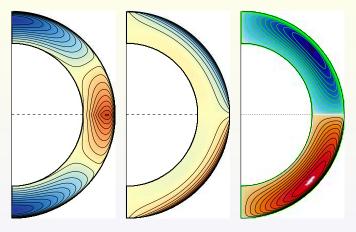


Vphi

-7.6e+02 m/s

7.2e+02	-5.1e+02 m	n/s 5.4e+02	-1.3e+02 m/s	1.4e+02

Axisymmetric flow

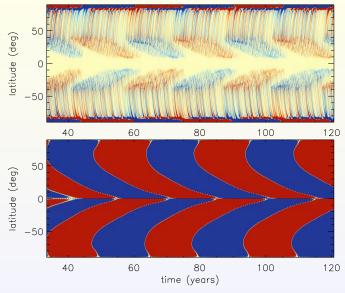


Vr (cm/s), Vtheta (cm/s), Psi

[-1.6E+02, 1.6E+02], [-2.6E+03, 2.6E+03]

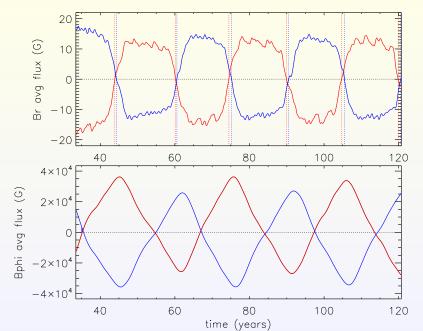
[Chatterjee et al. 2004]

Simulated magnetic field



[Hazra & Miesch (2015) in Prep.]

Poloidal Fields and Toroidal Fields



Summary

- Spot algorithm is used for better treatment of surface flux transport.
- Realistic convective flow from observation is incorporated in simulation.
- Evolution of photospheric magnetic field is captured well.
- Unification of this two model is already done but in future we want to incorporate time varying flow fields from observation also