Quantifying the sun's magnetic stress with the photospheric flows

***Authors**: Raphael Attié[1,2], Benoit Tremblay[3,4], Michael S. Kirk[1], Pete W. Schuck[1], W. Dean Pesnell[1], Lisa Upton[5]*

Co-signers: James A. Klimchuk[1], Nicholeen Viall[1], Barbara J. Thompson[1]

[1]NASA/GSFC, [2]George Mason University, [3]University of Colorado, [4]National Solar Observatory, [5]Southwest Research Institute

Synopsis:

We address the problem of constraining the mechanisms by which a massive amount of energy erupts from the sun at multiple scales, and how the corona is heated to high temperature. These mechanisms are highly dependent on how the magnetic field is stressed.

As recommended in Klimchuk et al. white paper, translational and rotational motions of the photospheric magnetic elements are important drivers of the coronal heating that must be accurately characterized. Yet despite an abundance of photospheric observations, many uncertainties remain in measuring these flows that entangle and twist the magnetic field.

This white paper states the current capacities for mapping the sun's photospheric flows, with an emphasis on how to quantify the magnetic stress that builds up free energy and heats the corona. It also provides research avenues on how to go beyond our current limitations, so that the sun's energy transport between the photosphere and the corona can be more accurately determined.

Introduction: The Sun is a differentially rotating sphere of magnetized fluid, presenting flow fields at multiple scales throughout its interior and atmosphere. By tracking and characterizing the magnetic flux flowing across the solar photosphere, we learn about fundamental properties of the solar plasma, including how plasma flows act on and react to strong magnetic fields. By converting kinetic energy into magnetic stress, the transport of solar plasma in the photosphere governs how our nearest star produces magnetic energy that is released during solar energetic events, such as solar flares and coronal mass ejections that put our technology-depended society at risk of space weather.

One of the means to measure that energy conversion mechanism is to measure the photospheric flux of magnetic helicity, which is a conservative quantity that describes how much the magnetic field wraps around itself; it is a metric of magnetic stress, which builds up energy in excess of the field's potential energy. The magnetic helicity flux depends on the magnetic flux transport velocity, which is subject to great uncertainties. Therefore, one requires to map the photospheric plasma flows at higher accuracy and higher resolution than what is currently possible, which implies also reliable error analyses.

Since the beginning of the SDO era in 2010, systematic full sun photospheric imagery has been readily available at a time and spatial resolution sufficient to track the sun's granulation flows over an entire solar cycle. Nonetheless, only the longitudinal component (in the direction of the line of sight) of the plasma flows can be imaged directly using Doppler effects, whereas the magnetic helicity flux requires knowledge of the magnetic flux transport vector parallel to sun's surface, accessible by tracking and mapping the "horizontal" plasma flows over the photosphere.

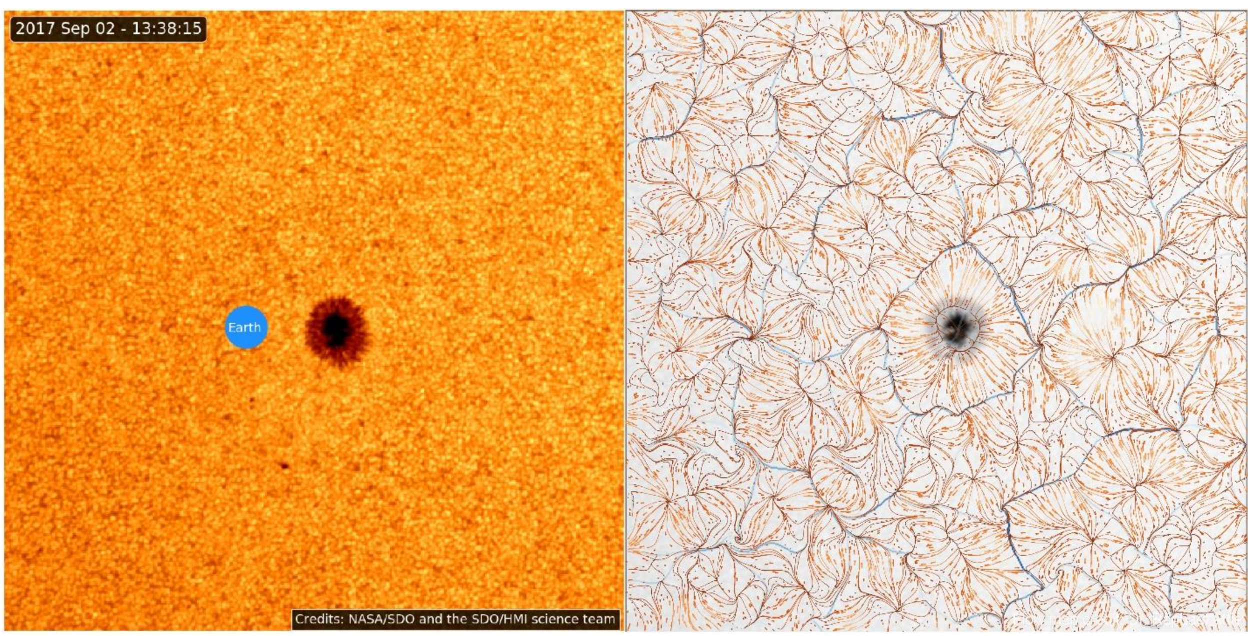

***Figure 1: Left**: Continuum image from SDO/HMI showing the Quiet Sun (granulation) and a sunspot. **Right**: Flow map processed with "Balltracking" using the continuum image series. The red-orange lines are the steramlines of the flows. The blue lanes outline the supergranular boundaries.*

Current capacities in mapping horizontal flows

In the last decade, photospheric flow maps (Figure 1) have been extremely valuable in advancing the characterization of the solar activity. For example, Toriumi et al. (2014) detected divergent flows prior to the emergence of active regions. Using SDO/HMI Dopplergrams, Hathaway et al. (2015) could accurately calculate the spectral components that reproduce the average photospheric convection spectrum down to granulation scales, thereby enabling realistic synthetic flow maps over nearly the entire solar disk. In general, mapping photospheric flows has been key in better understanding the sun's supergranulation (Rincon & Rieutord 2018), and the global circulation of the magnetic flux over the solar cycle (Upton & Hathaway 2014). By tracking both the granulation horizontal flow and magnetic flux, Attie et al. (2016) mapped out a compelling relationship between vortical flows and coronal heating in the Quiet Sun. Attie et al. (2018) detected disturbances of an active region moat flow prior to one of the most dramatic active region's flux emergence (Sun & Norton 2017), opening new research avenues for forecasting space weather events.

To measure the horizontal surface flows, one often relies on tracking the displacements of photospheric "tracers", such as Quiet-Sun granules in photospheric image series and moving magnetic features in series of magnetograms (Figure 3). Different methods exist to track these tracers. We categorize them into four main groups:

1. **Methods of optical flow:** The displacements of matching patterns are tracked, with no physical assumption (Figure 2). Different implementations exist but they all share the use of a metric of similarity in tracking areas between consecutive images, e.g., maximum local correlation or maximum overlap (DeRosa 2001, Fisher & Welsch 2008, DeForest et al. 2007). This method has been widely used in our community since the end of the 1980s, when a granulation-specific implementation known as "Local Correlation Tracking" (aka LCT) was introduced by November & Simon (1988). The main disadvantage of optical flow is the aperture problem, which refers to the ambiguity in determining the true motion vector using a local motion detector (like LCT). Another disadvantage is the use of tracking sub-windows that are necessary for better velocity estimations at great cost on the resolution of the flow field. If magnetic fragments are small enough and rotating around each other, thereby injecting so-called "mutual helicity", a tracking sub-window larger than the pair of rotating fragments will blur out that motion, which will not be seen as a rotation.

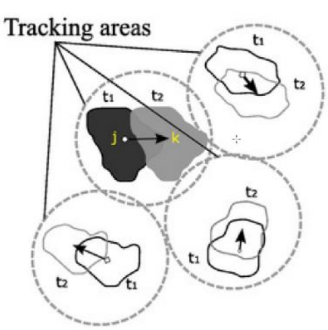

Figure 2: *Tracking areas (sub-windows) of optical flow methods define the widest possible search region where the moving parcels of fluid can move. If the sub-window is too wide, the algorithm may face ambiguous displacements, where the moving feature at time t_1 is mapped to the wrong feature at time t_2. If the tracking sub-window is too small, there may not be any solution at all.*

2. **The Balltracking methods**: A displacement of a pattern is tracked, but without the use of any similarity metric. Local trackers assume the presence of "plasma blobs" characterized by local extrema in the distribution of brightness. Considering a line-of-sight magnetogram as a photospheric cut across vertically oriented magnetic flux tubes, the center of the magnetic fragments (Figure 3, right) appear as local extrema in the magnetogram. By rescaling the intensity of the image, the image turns into a data surface where all the local extrema map to local minima (Figure 3, left). Local trackers are then modeled as "balls" that are "pushed" in those blobs using a numerical Newton's law that makes them settle down into the local minima. A moving blob will push the balls around. By differentiating and averaging the positions of the balls, we map out the velocity of the blobs. Damping forces in the Newton's law add more resilience to noisy data which makes the algorithm very robust. The main advantage of this algorithm is that it tracks the flux at the native resolution of the instrument. The "Balltracking" and "Magnetic Balltracking" algorithms implement this paradigm (Potts, 2004, Attie & Innes, 2015, Attie et al. 2018 – Figure 1 and Figure 3).

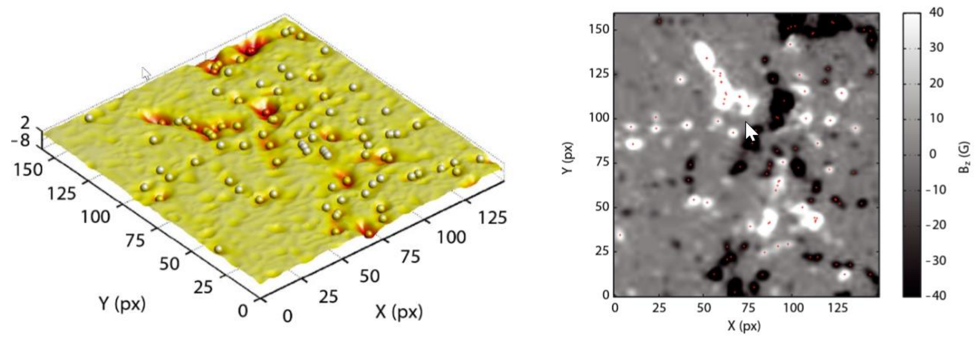

***Figure 3**: (Left) Magnetic Balltracking tracking the unsigned flux of magnetic elements in magnetograms (right) converted into a data surface. The downward bumps on the left map to areas of stronger flux in the magnetogram. The red dots are the center of the balls (left). Sometimes there can be multiple local extrema within the same magnetic fragment due to noise, non-vertical field orientation or poorly resolved magnetic fragments that appear coalescent as one single magnetic patch, which is why more than one ball may be involved in tracking the patch.*

3. **Physics-based methods:** Methods 1) and 2) are often considered "naive", as they only rely on the displacement of brightness patterns. When tracking magnetic elements, these methods track only the apparent velocity of the magnetic fragment that is thought to be different from the true horizontal flux transport velocity defined in MHD (Schuck 2008). Thus physics-based methods add further MHD constraints to the optical flow solution (method 1). One of the most recent methods that targets the helicity rates is DAVE4VM (Schuck 2008, Figure 4). MHD simulations showed that this method can reconstruct helicity rates more accurately than the methods based solely on optical flow. DAVE4VM has set itself as the benchmark algorithm for measuring flux transport vectors. Nonetheless, despite being more accurate than optical flow methods,

DAVE4VM inherits some of their limitations, such as the use of tracking sub-windows at the cost of resolution.

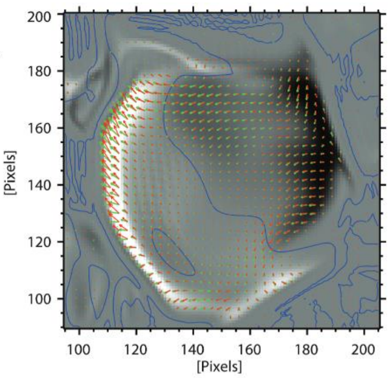

***Figure 4**: Illustration of the physics-based method DAVE4VM. The gray-scale background image is the vertical magnetic field **B_z** scaled within +/-3kG. The blue contours indicate smoothed neutral lines. The red arrows show the flux transport velocity, and the green arrows are the "ground truth" inductive velocity of the MHD simulation.*

4. **Neural Networks:** Through supervised learning (i.e., learning from existing examples of the inputs and the "ground truth" solutions), a neural network can emulate a numerical simulation of the solar photosphere and atmosphere. For example, the DeepVel neural network (Asensio Ramos et al., 2017) was trained in conjunction with realistic numerical simulations of the solar atmosphere to recover the depth-dependent velocity vector from surface quantities that relate to observational data. In reality, the neural network is only capable of generating an approximative mapping function between its input and output quantities. This approximation of the synthetic flows is model-dependent per the supervised training process which propagates biases existing in the model. Improvements in the neural network architecture have given more robust models and made them able to resolve flows at scales not achievable by traditional flow tracking methods (Tremblay & Attie 2020).

A fundamental limitation shared by all the above methods is their inability to track the rotation of magnetic patches around their own axis when the distribution of flux is axisymmetric around that axis. It makes it impossible to measure the twisting of field lines (Figure 5). We do not expect actual structures to be perfectly axisymmetric. Existing methods will work with varying accuracy depending on the amount of deviation from axisymmetry, but at best one would be measuring the velocity of a rotating wave-like pattern that does not correspond to the flux transport at play.

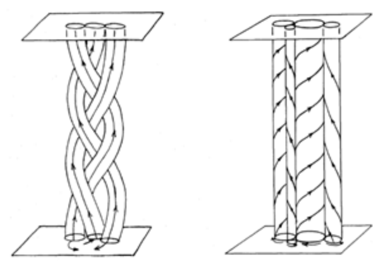

Figure 5: tangled field (left) and twisted field (right)

Another proxy for the magnetic stress is the "tangling efficiency" (see Klimchuk et al. white paper), defined as "the ratio of the random walk step size to the separation between nearby elements". Together with twisting motions, they define the fundamental ways to generate the magnetic stress that builds up free energy, and the current sheets that dissipate it. Because twisting flows may play an essential role in heating the corona, **quantifying rotational, stressing flows is a fundamental research area that needs further investigations and investments.**

Summary on limitations and proposed improvements:

Recent advances in tracking photospheric tracers such as the granulation show that this paradigm is accurate after averaging the output flows over mesogranular scales and above. In particular, using MHD simulation of the photospheric granulation (Rempel & Cheung 2014; Stein & Nordlund 2012), it has been established that to produce one flow map with a correlation above 0.9 between the measured velocity and the ground truth velocity of the MHD simulation, one needs to time-space average the flows over least 30 minutes and at least 2.5 Mm (Tremblay et al. 2018; Rieutord et al. 2007). Because much of the magnetic fragments covering the solar surface can be orders of magnitude smaller than 2.5 Mm, it is imperative to resolve the flux transport vector at much smaller scales by tracking these magnetic fragments at higher resolution.

As a matter of fact, at the center of vortical flows (Brandt et al., 1988, Attie et al., 2009), relatively small magnetic fragments are observed to rotate around each other, and possibly around their own center axis due to the increased vorticity (Figure 6). Resolving injection of helicity into the magnetic field over a statistically significant area of the photosphere requires the tracking at high-resolution of the magnetic tracers that are ubiquitous in the photosphere, so that one can reveal rotating motions over small areas: below the granulation scale of 1 Mm and lifetimes of 5-10 min. It is important to note that such magnetic tracers of the flux transport velocity would be the magnetic elements transporting weak field, i.e., below 10G, which are also small in area and close to each other, which often falls below the noise level and separating power of typical magnetograms (e.g., SDO/HMI resolution is 1 arcsec). In fact, if these observational constraints are not satisfied, any analysis of the magnetic stress of the sun using the horizontal flows would be highly biased, if not meaningless. So, **to accurately quantify the magnetic stress with current instruments (SDO/HMI, DKIST), more investments should be dedicated to track the smallest observable magnetic tracers (<= 1 arcsec).**

Current simulations of the photospheric convection do not include a large enough spectrum to include the supergranulation, whose effect on the transport of magnetic flux is not fully understood. While supergranular cells are ubiquitous within Quiet Sun flows, they are still lacking in current simulations of the Quiet Sun. In addition, simulations of active regions currently rely on artificial boundary conditions which may not be representative of all observed sunspot configurations (Rempel, 2012).Thus, it is not possible to reliably evaluate the capacity of the tracking methods to reconstruct the supergranulation flows and the flow of moving magnetic features in active regions.

Finally, neural networks built with supervised learning will propagate any bias of the simulation into the inferred flows, thus they cannot guarantee that the flows output by the model, when it is applied to real observations, is physical despite being presented physical examples during training (Tremblay et al., 2020, Figure 7).

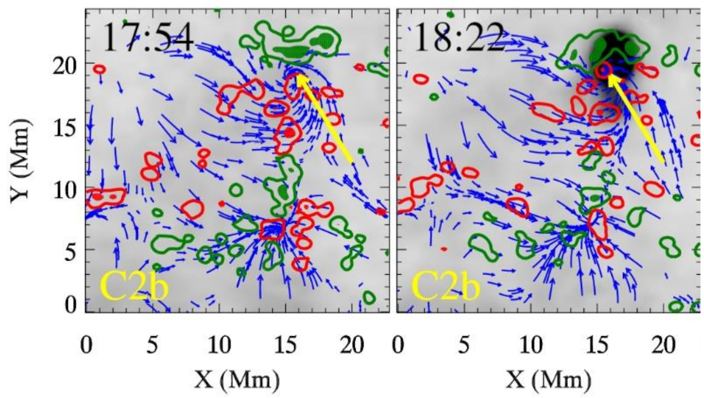

Figure 6: *Photospheric vortex flows at between supergranular boundaries, driving oppositive polarity magnetic flux (red and green) at the center of the vortex, where helicity can efficiently be injected. As an example of free energy built up by the vortical motions, a relatively intense energy is released as an x-ray brightening, seen as the black spot in the gray-scale.*

To summarize, **our ability to measure the sun's magnetic stress will plateau unless we improve (i) the simulations used to evaluate the performance of current flow tracking algorithms, (ii) the quality of the observations on which the tracking algorithms are applied, and (iii) the architecture of the tracking algorithms:**

Simulations: Current tracking methods rely on testing the reconstruction of the flow fields and the flux transport velocity using MHD simulations, by comparing the "ground truth" velocity of the simulation with the velocity inferred by the tracking method. **Due to the high impact of the photospheric drivers on the energetics of the sun, a high priority should be directed toward the determination of the accuracy of the flow tracking methods by using more realistic MHD simulations**. The closer the simulation is to the real sun, the more confident we will be on the accuracy of the algorithm applied to the real observations. We stress two avenues of improvements:

1) **Augmenting the capacity of the simulation to include (i) the physics and scales of supergranulation (30 Mm at least), and (ii) more realistic flows in and around sunspots will enable much more reliable error analysis of all the photospheric flow tracking methods** (Figure 7). We do realize this may be a "chicken and egg" problem as the results of the flow tracking methods are meant to be used to better constrain the models that we seek to improve. Nonetheless, through an iterative process, such improvement is very likely to happen.
2) In the more specific case of the physics-based methods (method 3), the induction equation is central to the inference of the flux transport velocity. But opacity effects of the photosphere can make the observations non-inductive. In addition, these effects can be scale-dependent, which reinforces the need to include larger convection scales in the simulations. Therefore, the simulations and the flow tracking methods must address **the problem of the non-ideal inductive nature of real photospheric observations.** Without such improvement, a simulation proving even perfect reconstruction of the photospheric flow field or the flux transport vector by induction-based methods will have limited value when applied to real observations.

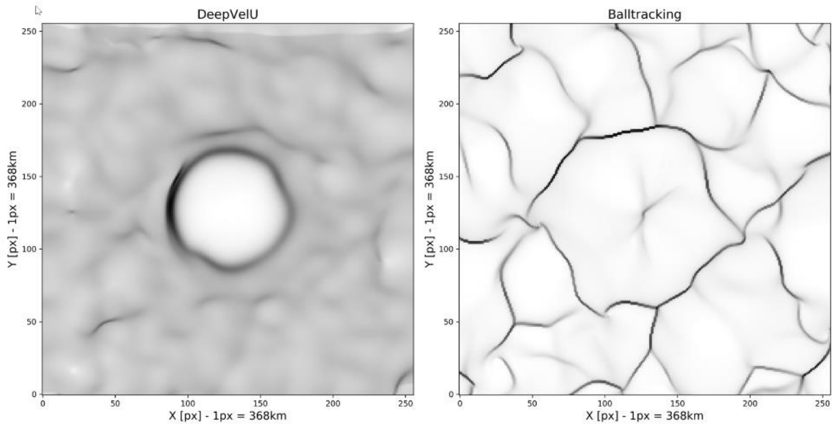

***Figure 7**: On the left, failed attempt at mapping the supergranular cells using the DeepVelU trained on an MHD simulation that lacks the supergranulation. On the right, using the same input data, supergranules revealed by the Balltracking algorithm.*

Flow tracking methods: Investments in deep learning are necessary to improve the neural networks' ability to infer velocity from real observations at higher resolution than what the other methods can achieve. In particular**, unsupervised physics-informed neural networks should be explored further to infer physical flows**. E.g., PINNs (Raissi et al., 2019) minimize the residuals of physical equations in their cost function (e.g., the Navier-Stokes equation in fluid mechanics: Jin et al., 2021). In the context of solar flows, PINNs could account for the continuity principle, or the vertical component of the magnetic induction equation as done by the Minimum Energy Fit (MEF: Longcope, 2004) or DAVE4VM (Schuck, 2008).

Observations: To address the fundamental question of how inductive the sun is, imaging vector magnetograms with greater dynamic range and precision would significantly help. Although DKIST's high-resolution observations will help significantly, as mentioned earlier there is currently no algorithm able to measure the rotation of axisymmetric magnetic patches, regardless of the resolution of the observations, making the quantification of this fundamental source of magnetic stress (by twisting) inaccessible using current observations. In addition, stress-prone flows may be fundamentally different at the poles, where we have a highly foreshortened view of the magnetic field, an inescapable limitation when observed from Earth.

To break free from these observational barriers, **we recommend NASA to research on how magnetic fields move in the photosphere, and to research on stereoscopic (3D) spectropolarimeters to get simultaneous high-resolution Doppler measurements and vector magnetograms targeting the transport of the magnetic flux from different vantage points, including the polar view.** The motion of single magnetic patches will then be characterized by line shifts from different viewing angles, by which we can reconstruct the 3D motion vector of the magnetic flux**.** While this may take more than a decade to research, we also **recommend continued funding for SDO/HMI to fix current artifacts in the magnetograms to resolve the smallest possible sources of magnetic stress**, which will require **more investments in inversion techniques.**

References

Asensio Ramos, A., Requerey, I. S., and Vitas, N. (2017), A&A, 604:A11

Attie, R., Innes, D. E., Potts, H. E. (2009), A&A, 493, L13-L16

Attie, R., Kirk, M. S., Thompson, B. J.,Muglach, K., and Norton, A. (2018), Space Weather, 16

Attie, R., Innes, D. E., Solanki, S. K., Glassmeier, K. H. (2016), A&A, 596, A15

Brandt, P. N., Scharmer, G. B., Ferguson, S., Shine, R. A., Tarbell, T. D. (1988), Nat, 335, 238

DeForest, C.E., Hagenaar, H. J., Lamb, D. A., Parnell, C. E., and Welsch, B.T. (2007), ApJ, 666, 576

DeRosa, M. L. (2001), Ph.D. thesis, Univ. Colorado

Fisher, G. H., and Welsch, B. T. (2008), Volume 383 of Astronomical Society of the Pacific Conference Series, eds R. Howe, R. W. Komm, K. S. Balasubramaniam, and G. J. D. Petrie

Hathaway, D. H., Teil, T., Norton, A. A., Kitiashvili, I. (2015), ApJ, 811, 105

Longcope, D. W. (2004), ApJ, 612, 1181–1192

November, L. J., Simon, G. W. (1988), ApJ, 333, 427–442

Potts, H. E., Barett, R. K., and Diver, D. A. (2004), A&A, 424, 1

Raissi, M., Perdikaris, P., Karniadakis, G. E. (2019), Journal of Computational Physics, 378, 686-707

Rempel, M. (2012), ApJ, 750, 1

Rempel, M, Cheung, M. C. M. (2014), ApJ, 785, 2

Rieutord, M., Roudier, T., Ludwig, H.-G., Nordlund, Å., and Stein, R. (2001), A&A, 377, L14-L17

Rincon, F., Rieutord, M. (2018), Living Rev, Sol Phys, 15, 6

Schuck, P. W. (2008), ApJ, 683, 1134-1152

Stein, R. F., Nordlund, Å. (2012), ApJL, 753, 1

Toriumi, S., Hayashi, K., Yokoyama, T. (2014), ApJ, 794, 19

Tremblay, B., Roudier, T., Rieutord, M., and Vincent, A. (2018), Sol. Phys. 293:57

Upton, L. and Hathaway, D. H. (2014), *ApJ,* **792,** 142

Jin, X., Cai, S., Li, H., Karniadakis (2021), G. E., Journal of Computational Physics, 426, id. 109951

Xudong, S. & Norton, A., A. (2017), *Res. Notes, AAS,* 1, 24