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Research Article

Keywords:

Posted Date: October 29th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11353019/v1>

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Additional Declarations: No competing interests reported.

BT2PB: High-cadence polarized brightness of the solar corona from LASCO C2 total brightness observations using deep learning

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Abstract BT2PB is a convolutional neural network (CNN) that increases the effective cadence of calibrated polarized brightness (pB) observations of the Large Angle and Spectrometric Coronagraph (LASCO) C2 instrument aboard the Solar and Heliospheric Observatory (SOHO) from one or a few per day to the total brightness (B_t) cadence of tens of images per day, allowing new science and operations dependent on high time-resolution calibrated data. LASCO C2 has been observing the solar corona almost continuously for over three decades. The pB observations offer a measurement of the polarized K-corona with drastically reduced signal from the F-corona and stray light components that dominate the B_t images, thus are more useful for quantitative coronal science. In this work we aim to estimate pB directly from B_t images using a convolutional neural network (CNN) trained on thousands of pB and B_t observation pairs made over the past 25 years. The CNN operates on brightness profiles extracted at multiple heliocentric heights between 2.3 and 6.0 $R_\odot$, learning to predict $\log_{10}(pB/B_t)$ as a function of position angle. Observing geometry metadata including the spacecraft roll angle, spacecraft heliocentric distance, and heliographic latitude are provided as auxiliary inputs, allowing the network to account for time-varying instrumental and orbital effects. When evaluated on held-out test observations, the model achieves a mean absolute relative error of approximately 8-12% on the predicted pB across heliocentric heights from 2.3 to 6.0 $R_\odot$, with accuracy varying by a few percent as a function of solar cycle. We estimate the error arising solely from model prediction as ≈ 4 -8%. The approach enables high time-resolution studies of dynamic events including coronal mass ejections (CME), the potential for more reliable mass estimates of dynamic events, and improved time resolution for coronal density diagnostics including tomography. Furthermore,

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the quality of these results allow highly efficient observation strategies for current or future coronagraphs with the capability for measuring B_t and pB .

Keywords: Coronagraph, calibration; Polarized brightness, coronal density; Convolutional neural network

1. Introduction

It is difficult to overstate the contribution that the LASCO instruments (Brueckner et al. 1995) onboard SOHO (Domingo et al. 1995) have made to our understanding of the solar corona and CMEs. The dataset spans three decades and has contributed to many discoveries, catalogues of CMEs, motivated the development of new analysis methods, aided the interpretation of other datasets, and provided unique constraints for models. It has also allowed studies of near-Sun comets. As other instruments aboard SOHO reach their end of life, LASCO C2 (and C3) are allowed a larger proportion of telemetry, leading to more frequent observations. LASCO continues to contribute to scientific studies, and is crucial for operational space weather forecasting of CMEs.

In typical operations, LASCO C2 collects tens of total brightness (B_t) observations per day. These observations are without polarisation, and therefore the measured brightness is a combination of the K-coronal brightness (B_k), the F-corona brightness, background stars, planets (occasionally), and instrumental stray light. The B_t observations are of most value to studies of dynamic events including CMEs. Typically, time-differencing is applied, so that a pre-event image is subtracted from subsequent images, or each image has the previous image subtracted. This is an effective way of revealing dynamic phenomenon and allows measurements of their size, location, and dynamics. Unfortunately, such data are not reliable for density or mass analysis which is dependent on radiometric calibration and a careful subtraction of all components that are not coronal. LASCO C2 also makes polarized brightness (pB) observations. These are sequences of four observations which include polarisers at three angles separated by 60° , plus a ‘clear’ observation (no polarizer). Combined through inversion via a Mueller matrix, the three polarised images can be combined to give pB . The advantage of pB observations is that the coronal brightness B_k is highly polarized, while the other components are not. The F-corona does become increasingly polarised with increasing distance in the corona, but at the level of approximately 7% polarisation at distances of around $6R_\odot$ and further (e.g. Mann & MacQueen 1996; Morgan & Cook 2020; Lamy et al. 2022). Therefore the pB observations are, to first order, an isolated measurement of the coronal brightness, and can be inverted to estimate coronal densities. These type of studies include simple inversions invoking, for example, spherical symmetry (e.g. Quémerais & Lamy 2002; Morgan & Habbal 2007), or more sophisticated methods based on rotational tomography (e.g. Aschwanden 2011; Morgan 2019; Morgan & Cook 2020). Such calibrated pB data can in principle also be used to estimate CME masses (Vourlidas et al. 2010; Lamy et al. 2017). The main disadvantage of the pB observations are that, in general, they are made only

once or twice per day. This infrequent cadence does not allow high-resolution tomography and makes CME mass estimates difficult. Indeed, most CMEs will be missed by the pB observations. Over the LASCO lifetime, there have only been a few special observational periods when a far higher pB cadence was applied. Another disadvantage is the coarser spatial resolution of the pB observations: the B_t observations are 1024×1024 pixels, while the pB are 512×512 pixels over the same field of view.

There is considerable incentive therefore to find effective methods to extract B_k from the B_t observations, and this involves estimating the F-corona and stray light brightness in LASCO C2 so they can be subtracted in order to isolate B_k . Morgan (2015) calculated improved calibration factors using background stars, and using subtraction of long-term backgrounds formed from a comparison of the pB observations with the B_t , showed that the B_t observations could be converted to B_k (see also Morgan & Habbal (2007)). While the Morgan (2015) method works, it involves the expensive calculation of a background image over a long (~ 10 day) period surrounding the observation of interest. This becomes particularly cumbersome during periods of spacecraft roll, when SOHO rotates by 180° , since different backgrounds are needed before and after roll manoeuvres. Lamy et al. (2020) and Llebaria et al. (2021) present the most thorough analytical approach on restoring the B_k and F-corona components from LASCO-C2 B_t observations. Their procedure isolates B_k , F-corona brightness, and instrumental stray light through a complex multi-stage process. Burtovoi et al. (2022) presented a correlation method for deriving the F-corona brightness based on the evolution of B_t and pB in LASCO C2 observations, exploiting the fact that in high-correlation regions the F-corona does not vary significantly on a timescale of one month. In principle, this F-corona brightness can then be subtracted from the B_t bringing one closer to B_k .

In this work, we present a CNN-based method for the conversion and calibration of LASCO C2 B_t observations to pB , which we call BT2PB. The method, including data selection, preparation, and the CNN architecture and training, is presented in Section 2. Results and discussion are presented in Section 3, including case studies for solar minimum and maximum in Subsection 3.1, a more statistical analysis of performance over two solar cycles in Subsection 3.2, a discussion of certain factors that effect the performance in Subsection 3.3, the effect of metadata in Subsection 3.4, and an example application for coronal tomography in Subsection 3.5. Conclusions are given in Section 4

2. Method

2.1. Data selection and preparation

We search for all pB sequences made by LASCO C2 between 2000 January 1 and 2025 March 13 with the orange filter and of image size 512×512 pixels. This is the most common configuration for the LASCO C2 pB sequences. There are certain special periods when LASCO C2 collects many more pB observations per day. In these cases we limit the number of pB sequences to a maximum of

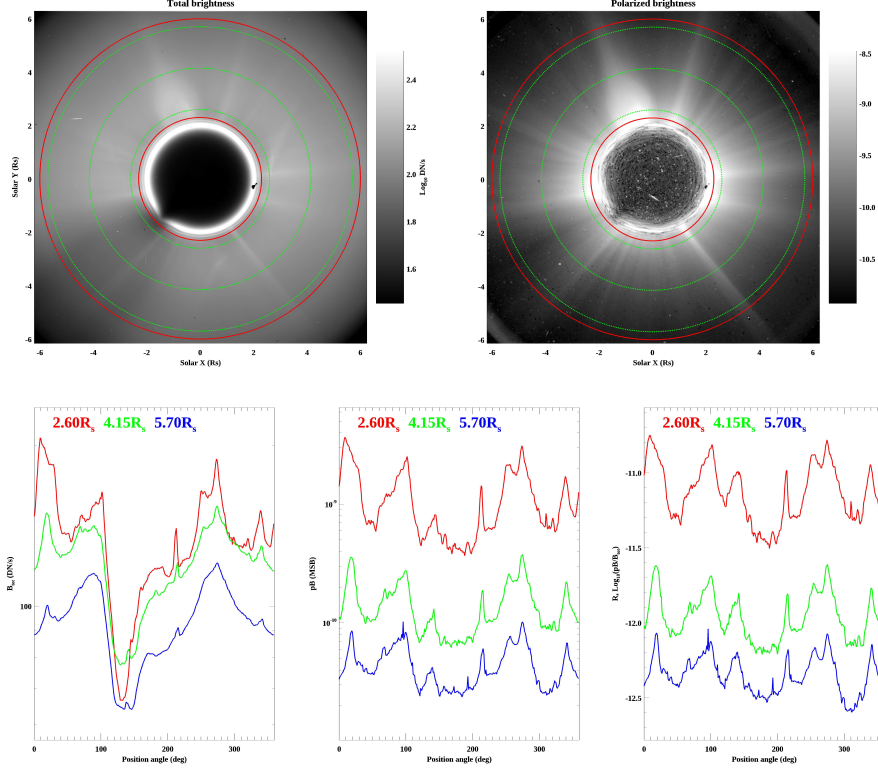


Figure 1. Example of a B_t and pB data pair used for training. The top left panel shows a LASCO C2 B_t image for date 2012 February 29 21:12UT in $\log_{10}(DN/s)$. The two red circles show constant heliocentric distances of 2.3 and $6.0R_{\odot}$, which are the limits we define for a reliable FOV. The three green dashed circles are at distances 2.60 , 4.15 , and $5.70R_{\odot}$ where we extract brightness values to display in the lower panels. The top right panel shows the same for a pB image in units of $\log_{10}(MSB)$ calculated from a pB sequence taken at 2012 February 29 21:08UT. The bottom left panel shows the B_t profiles from the circular slices at the three selected distances, with position angle measured counter-clockwise from north. The bottom middle panel shows the same for pB . The bottom right panel shows R , or the $\log_{10}$ of the ratio pB/B_t . The model’s aim is to predict R given an input B_t . For training, we extract brightness profiles at 30 distances between the limits of the FOV as defined by the red circles in the top panel images.

four, approximately equally spaced throughout the day. For each pB sequence we search for the B_t observation made closest in time to the mid-time of each sequence. We require that the B_t observations are made with the orange filter and are of size 1024×1024 pixels, being the most common configuration of B_t observations. Another criteria for selection is that the B_t image is made within half an hour to the mid-time of the pB sequence. If valid, we download the paired pB sequence and B_t image as level 0.5 fits data. Over the period there are 24,161 valid pairs. An example of a training observation pair is shown in Figure 1.

Each pB sequence contains three images labelled with polarizer states -60° , 0° , and $+60^\circ$. The main calibration steps applied to the pB sequence images

individually are division by the exposure time, application of a calibration factor, and correcting for vignetting. The final pB image is then gained from inversion of the separate polarizer images using the Mueller formulation (e.g. Lamy et al. 2020). For this calibration pipeline we use the standard LASCO routine `c2.calibrate.pro` included in the Solarsoft library with a few modifications: (i) a modified calibration factor, (ii) a point filter, and (iii) a modified polarizer factor:

- (i) *Calibration factor*. The dashed black line plotted in Figure 2 shows the overall LASCO C2 calibration factor which we apply to the pB sequence images separately (along with the ‘polarizer factor’ described below). This factor converts the DN/s units of a LASCO C2 image to mean solar brightness (MSB). The factor shows an overall increase over time as instrumental components lose efficiency. The green line in Figure 2 shows the estimate of Lamy et al. (2020), extracted from their Figure 9. It’s clear that their profile closely follows the estimate reported by Gardès et al. (2013) prior to around year 2010, and follows the estimate of Colaninno & Howard (2015) from around year 2011 until 2019. For this work therefore, we use the calibration factor of Gardès et al. (2013) for any observations made in year 2010 or earlier, and Colaninno & Howard (2015) otherwise. Any future studies using our model that look at observations near date 2010 December 31 23:59UT, or are perhaps studying time changes that span this date, should be aware of this rapid change in calibration factor near this date.
- (ii) *Point filter*. Each separate polarizer angle image has a two-dimensional point filter applied. This filter iteratively identifies local outlying pixel values, and replaces them with a value closer to the local mean.
- (ii) *Polarizer factor*. For the -60° , 0° , $+60^\circ$ polarizer angles, we multiply by factors of 4.00, 3.83, and 3.94 respectively, estimated by Morgan (2015) through an analysis of thousands of stars spanning many years. These are modified from the pre-flight value of 3.95 used for all three states.

The associated B_t fits file is opened and divided by its exposure time, giving units of $DN s^{-1}$. No further processing or calibration is applied. For both the pB and B_t images, we extract circular profiles of signal at 30 heliocentric distances spaced evenly in logarithmic space between 2.3 and $6.0R_\odot$. For each distance r , all pixels lying within $\pm\Delta r$ are identified, and their position angles and values extracted. $\pm\Delta r$ increases linearly from $0.04R_\odot$ at $2.3R_\odot$ to $0.10R_\odot$ at $6.0R_\odot$. For a regular position angle binning of 1° we calculate the mean value at each bin, as well as the standard deviation. Our final array is of shape 360 position angle $\times$ 30 distance. There are four such arrays for each training pair - the means and standard deviations of values for both B_t and pB .

Examples of $B_t(PA, r)$ and $pB(PA, r)$ are shown for three selected r in the left and middle panels respectively of the bottom row of Figure 1. The external occulter pylon of LASCO leads to a significant reduction in B_t signal for a broad region centered at position angle 135° . During times of spacecraft roll, this feature moves to PA 315° . In general, the drop in signal with distance is

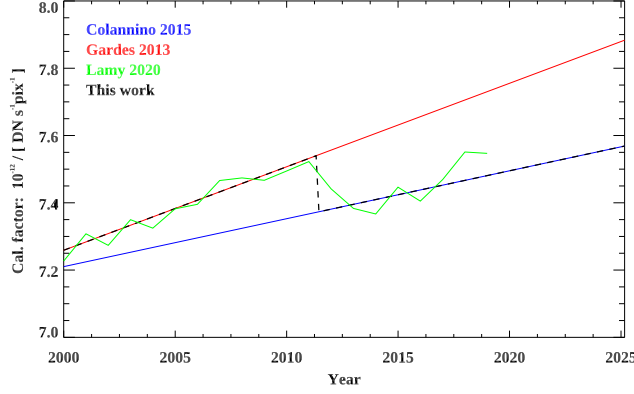


Figure 2. The LASCO C2 calibration factor used for this work (dashed black line) is shown as a function of time from year 2000 to 2025. The estimated calibration factor of Lamy et al. (2020), extracted from their Figure 9, is shown as the green line. The calibration factor of Colaninno & Howard (2015) is $(3.9 \times 10^{-5} M + 5.2) \times 10^{-12}$, where M is the modified Julian day number; shown as the blue line. The Gardès et al. (2013) calibration factor is the red line, and is $(6.794 \times 10^{-5} M + 3.757) \times 10^{-12}$.

small between 2.60 and $4.15R_{\odot}$ compared to between 4.15 and $5.70R_{\odot}$. This is due to the stray light component, and no vignetting has been applied to this data. Whilst coronal features can be seen, they are faint compared to smoother non-coronal features, and they become relatively more faint with distance so that the B_t profile becomes increasingly smooth. There are also some distinct instrumental stray light artifacts such as the close-to-vertical streak near the west equator.

In comparison, the pB profiles (bottom middle panel, Figure 1) are dominated by coronal structures and maintain a similar shape across all distances (showing the overwhelmingly radial structure of the K corona at these distances). As well as more clearly showing the higher-frequency coronal structure, the pB images are noisier than B_t for two main reasons: (i) they have significantly less signal than B_t , and (ii) they are the combination of three separate observations so subject to noise amplification. This is an important point raised again in Section 3. The pB images are calibrated (including vignetting) and any decrease in signal due to the pylon is absent. Furthermore, stray light artifacts (such as the west equator streak) are absent due to their lack of polarized signal. There may be a weak component of the F-corona in the pB signal at the outer limit of the FOV, but only at the level of a few percent of the total signal. This is a difficult value to quantify (e.g. Mann & MacQueen 1996; Morgan & Habbal 2007; Morgan 2019).

We calculate the ratio of the pB standard deviation over the pB mean at each PA, r bin, and similarly the same ratio for B_t . Any bins which have a pB ratio greater than 0.25 , or B_t ratio greater than 0.035 , are defined as a ‘bad’ bin, and set to not-a-number (NaN). To clarify - a position-angle/height bin here contains values from multiple image pixels, from which we calculate a mean and standard deviation. A large standard deviation to mean ratio means that that portion of the image is probably not dependable for training. For example, one

or more of the pixels may contain a spuriously high value due to a cosmic ray hit, or a planet, or is at the boundary of a bright dynamic event. Over all our training data, around 6% of bins are labelled as bad. Along with the B_t and pB arrays, we also record certain metadata: date, r (30 values), Δr (30 values), position angle (360 values), spacecraft roll, x_0 (or `crpix1`; the pixel location of sun center along the B_t image x -axis), y_0 (`crpix2`; the same along the y -axis), the B_t exposure time, and the original data filenames. Several of these metadata are used during training, as described in later sections.

Information is extracted and saved for all 24,161 datasets. These data are concatenated, with the metadata forming vectors of length 24,461 time steps and the pB and B_t arrays (mean and standard deviation arrays) forming three-dimensional datacubes of size $360 \times 30 \times 24,461$ (position angle, distance, time steps).

2.2. Data preprocessing and the target quantity

As described in the previous subsection, the main training data are the arrays $B_t(\text{PA}, r)$ and $pB(\text{PA}, r)$, where PA is position angle sampled at 360 uniformly-spaced bins and r is the heliocentric distance at 30 locations evenly spaced in logarithmic distance. Rather than training the network to predict pB directly, we instead define the target quantity

$$R(\text{PA}, r) = \log_{10} \left(\frac{pB(\text{PA}, r)}{B_t(\text{PA}, r)} \right), \quad (1)$$

which is the logarithm of the ratio of polarized to total brightness at each position angle and distance. This value is shown in the bottom right panel of Figure 1. This logarithmic formulation offers stability since B_t and pB span a wide dynamic range, particularly over distance. The network can reconstruct pB at inference time via $pB = 10^{\log_{10}(B_t) + R}$, meaning any errors in B_t are exactly propagated into the prediction, and only errors in R are attributable to the network.

The B_t and pB profiles are resampled from 360 to 128 position angle bins using linear interpolation before being passed to the network. 128 anchor points reduces computational cost, and is sufficient to characterise the correction field R since R is subsequently interpolated back to the required B_t image resolution. The criteria for bad bins are described in Section 2.1. Bad bins are set to NaN and recovered by a two-pass linear interpolation: first along the position angle axis within each height row, then along the height axis at each PA bin using the remaining valid heights as anchor points. A height row in which more than 60% of PA bins remain NaN (i.e. too heavily contaminated to interpolate reliably) is blanked entirely before the height-axis pass, allowing it to be filled from neighbouring heights. Any observation in which more than 30% of heights are so affected is rejected outright. After quality filtering, 22,797 training pairs remain from an initial sample of 24,161, corresponding to a rejection rate of 5.6%.

2.3. CNN architecture

The network is a one-dimensional (1D) CNN that takes as input the full multi-height $\log_{10}[B_t(\text{PA}, r)]$ array and predicts $R(\text{PA}, r)$ at all 30 heights simultaneously. The architecture, illustrated in Figure 3, comprises four components.

Encoder. The input tensor of shape $(N_h \times 128)$ is passed through two successive 1-D convolutional layers. The first uses a kernel size of 7 with zero-padding of 3, mapping from N_h input channels to $C/2$ feature channels; the second uses a kernel size of 5 with zero-padding of 2, mapping to C channels. Each convolution is followed by a Gaussian Error Linear Unit (GELU) activation, and batch normalisation is applied after the second convolution. Standard zero-padding is used throughout; circular padding at the $0^\circ/360^\circ$ position-angle boundary is not employed in the network. Instead, the periodicity of the PA coordinate is handled at the data-preparation stage: profiles are extracted on two grids offset by 180° , $R(\text{PA}, r)$ is computed independently on each, and the two estimates are blended with a cosine taper in the overlap region before the final per-pixel pB map is assembled.

Residual blocks. Four ResBlock1D modules refine the encoded representation. Each block contains two Conv1D layers with batch normalisation, GELU activations, and a dropout rate of 0.1, connected by a residual skip connection followed by a final GELU activation. The 128-point PA dimension is preserved throughout.

Metadata injection. Observational metadata (described in Section 2.4) is projected from 8 scalars into $C = 64$ channels via a three-layer multi-layer perceptron (MLP; $\text{Lin} \rightarrow \text{GELU} \rightarrow \text{Lin} \rightarrow \text{GELU} \rightarrow \text{Lin}$) and added to the main feature tensor after the residual blocks. A second, separate MLP maps the N_h normalised height values fixed at log-spaced intervals between 2.3 and $6 R_\odot$ into C channels, providing the model with a learned positional encoding of the height grid. Both projections are broadcast across the 128 PA bins and added to the feature tensor. Additive injection is used rather than concatenation so that the spatial (PA) structure of the main pathway is preserved without a change in tensor dimensions.

Decoder. Two further ResBlock1D modules followed by two Conv1D layers project the feature maps back to the output shape $(N_h \times 128)$, producing the predicted $R(\text{PA}, r)$ at all heights and position angles. A physics-informed penalty term is added to the training loss to suppress unphysical positive values of R . The penalty is $\lambda \langle \max(R, 0)^2 \rangle$, where the mean is taken over all height and PA bins in the batch and $\lambda = 0.1$. Because $R = \log_{10}(pB/B_t)$, a positive value would imply $pB > B_t$, which is not physically possible for Thomson-scattered coronal emission. The penalty softly penalises any such predictions during training without enforcing a hard constraint and is applied to the unnormalised (physical-unit) output R before comparison with the target. The total number of trainable parameters is approximately 285,000.

2.4. Metadata

Each observation is accompanied by an 8-element metadata vector that provides the network with observational context directly, rather than requiring it to re-

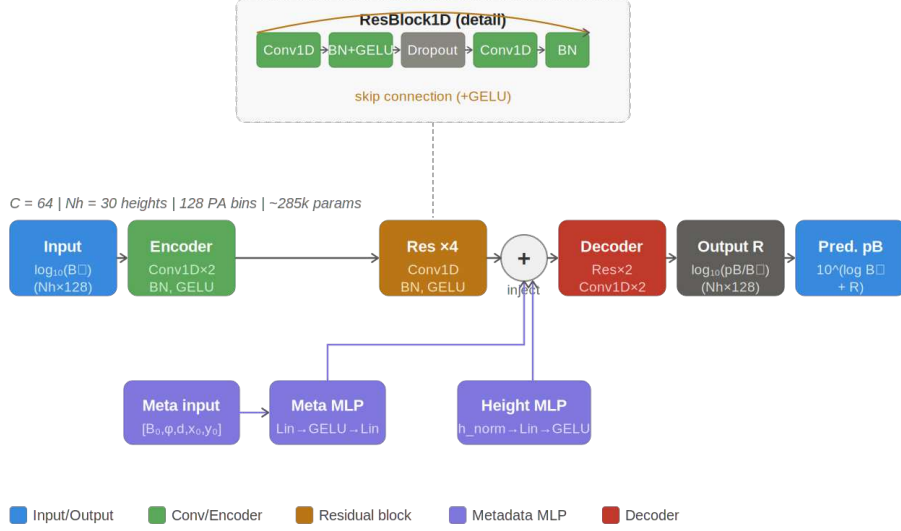


Figure 3. Architecture of the PBPredictorMultiHt network. The main pipeline (top) processes the multi-height B_t profile stack through an encoder, four residual blocks, and a decoder. Scalar metadata and the normalised height vector are projected by separate MLPs and injected additively into the bottleneck feature map. The inset shows the internal structure of a single residual block. $C = 64$ denotes the number of base channels; BN = batch normalisation; DO = dropout.

cover such information from the B_t profiles themselves. The full metadata vector is $[B_0, \sin \phi, \cos \phi, d, x_0, y_0, t_{\text{year}}, t_{\text{exp}}]$, where B_0 is the heliographic latitude of the Sun’s central meridian (degrees), ϕ is the spacecraft roll angle encoded as the pair $(\sin \phi, \cos \phi)$ rather than as a scalar (following standard practice for circular inputs to neural networks), d is the SOHO–Sun distance (AU), x_0 and y_0 are the image pixel coordinates of solar disk centre (`crpix1`, `crpix2`), t_{year} is the decimal year of observation, and t_{exp} is the B_t exposure time in seconds. All scalars are normalised to zero mean and unit variance using training set statistics before being passed to the metadata MLP; the sin/cos components, which are already bounded to $[-1, +1]$, are normalised by the same procedure for consistency. After training, an ablation analysis is applied to the held-out test set in order to quantify the relative importance of each metadata value, described in Section 3.4.

2.5. Training

The 22,797 paired observations are divided into training (75%), validation (15%), and test (10%) subsets by random permutation with a fixed seed yielding 17,099 training pairs, 3,419 validation pairs, and 2,279 test pairs. Since at most four LASCO C2 observations are used per day, consecutive samples in the dataset are typically separated by several hours to a full day, making leakage between subsets negligible. The network is trained to minimise a composite loss function. The primary term is the mean squared error (MSE) on the predicted R . The

target R values are standardised to zero mean and unit variance across the training set before training, and the network output is normalised similarly. The secondary term is a physics penalty applied after denormalising the predictions back to physical R : a penalty $\lambda \langle \max(R, 0)^2 \rangle$ (with $\lambda = 0.1$) suppresses any predictions for which $R > 0$.

Training uses the AdamW optimiser (Loshchilov & Hutter 2019) with an initial learning rate of 10^{-3} , weight decay of 10^{-4} , and a cosine annealing schedule that decays the learning rate to 10^{-5} over 150 epochs. Early stopping with a patience of 20 epochs is applied on the validation loss, with a batch size of 64. All training is performed on CPU on a standard desktop computer, which takes a few minutes. The model converged at epoch 73 with a best validation loss of 0.01905.

3. Results and Discussion

3.1. Case studies

Figure 4 shows the result of applying the trained model to a B_t observation made during solar maximum, at 2012 August 15 21:12UT. Five minutes prior to this time, at 21:07UT, LASCO C2 made a pB observation and this figure compares the predicted pB to the observed. These data were not used for training. Visually, as seen in the top middle and right panels, the predicted and observed pB are very similar, with the shape and main features of the corona matching closely. The observed pB appears more noisy than the predicted, and contains a spurious white streak near pixel location $x, y = 60, 195$. The bottom left panel compares profiles of pB as a function of position angle for circular slices at 5 heights between 2.3 and $6R_\odot$. The worst agreement is at $2.3R_\odot$, where the predicted pB is overestimated across broad sections. The agreement is generally excellent at other heights, although the observed pB shows more high-frequency variability. The bright artifact, or streak, seen in the observed pB image can be seen in the profile for $4.76R_\odot$ as an isolated very high value near position angle 100° . The percentage relative error map shown in the bottom middle panel shows an excellent MAE of 9.1%. The innermost FOV shows the greatest overestimated error (as seen also in the circular profile of the left plot). The broad low-signal region at position angles 120 to 190° shows overestimation at the 15 to 25% level. The bottom right plot shows a log-log scatter plot. The distribution follows the equality line closely, with only a small fraction of outliers.

Figure 5 shows a prediction and comparison for solar minimum, at date 2008 September 14 21:30UT. Similar to the solar maximum case, the predicted pB gives excellent general agreement to the observed, with a MAE of 12.5%. The circular cuts shown in the lower left panel show good agreement except for the north polar region at $2.3R_\odot$. In the polar regions in particular there are more spatial small-scale structures present in the observed pB , and the predicted pB is considerably smoother. The relative error map (lower middle panel) shows that the high brightness streamers near the equator suffer from an underestimated prediction, whilst the low brightness polar regions contain a mix of over- and

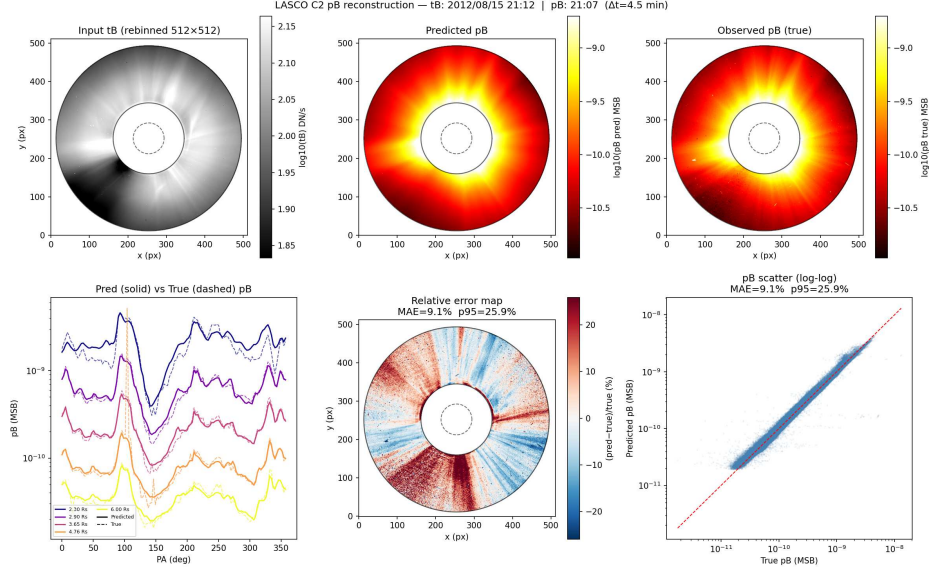


Figure 4. Top left: a LASCO C2 B_t observation made at 2012 August 15 21:12UT, with no processing other than division by the exposure time (units DN s^{-1}) and masking of the field of view to distances between 2.3 and $6R_{\odot}$. Top middle: the predicted pB gained from the B_t using our trained model. This data is now in units of MSB. Top right: a pB observation made 5 minutes prior to the B_t observation at 21:07UT, also in MSB units. Bottom left: comparison of the predicted (solid) and true (dashed) pB for five circular profiles at distances between 2.3 and $6R_{\odot}$. Bottom middle: the percentage relative error between the observed and predicted pB . The mean absolute error is 9.1%. Bottom right: log-log scatter plot of the predicted pB vs. the true pB . The red line shows equality.

underestimated values. The scatter plot is symmetric on the line of equality at all distances with only a small fraction of outliers.

3.2. Statistical performance over two solar cycles

Figure 6 shows a general overview of the performance of the model for 2,279 test pairs of data distributed over the 25 years. The top row shows the percentage relative error as a function of position angle and time for three distances. The left panel is for the innermost FOV at $2.3R_{\odot}$, where the MAE is worst at 9.6%. For 3.78 and $6.00R_{\odot}$, shown in the middle and right panels, the overall MAE is 7.5% and 7.7% respectively. The best comparison (smallest MAE) appear at the equatorial regions over periods of a few years centered on solar minimum. This is presumably due to the high brightness in these streamer-containing regions leading to reduced noise in both the predicted and observed pB . The highest MAE are consistently at the lower-signal polar regions, even at solar maximum when bright streamers appear at these position angles. The lower panels show the mean MAE as a function of time only. The solar cycle effect is clearly seen, particularly for the 3.78 and $6.00R_{\odot}$ distances, with mean MAE dropping during solar minimum and increasing to solar maximum. This effect is largely absent from the lowest FOV ($2.3R_{\odot}$) probably due to this distance being dominated

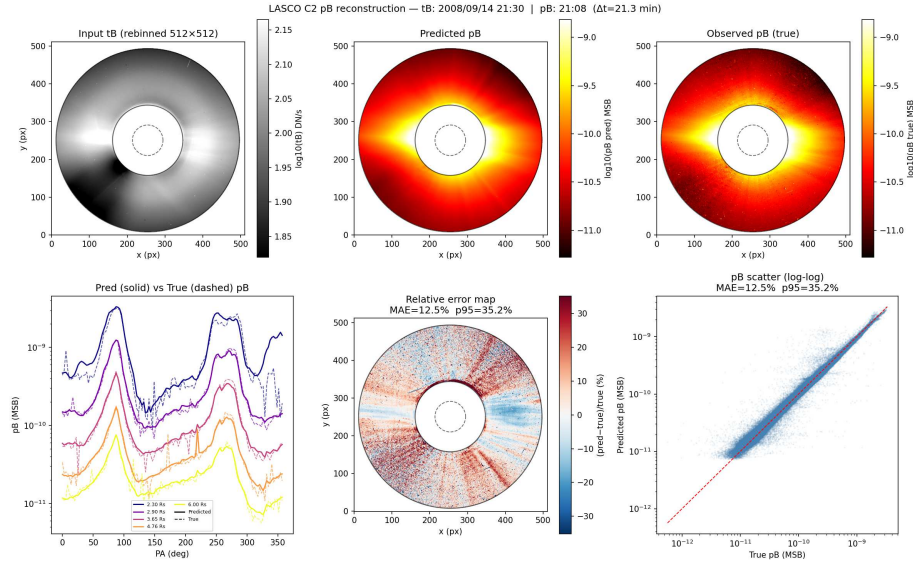


Figure 5. As Figure 4 but for solar minimum conditions at date 2008 September 14 21:30UT. The pB observation used for comparison is made 21 minutes earlier at 21:08UT.

by other errors. The blue regions in the lower panels show times when SOHO has been rolled to 180° . There is no clear correlation between roll state and MAE which shows that the model has very effectively learned to deal with roll, discussed further in Section 3.4.

3.3. Factors effecting the comparisons

An important point to these comparisons is that the MAE is dependent on factors other than the model calibration. One possible source of error is the MAE due to real changes in the corona between the time of the B_t and pB observations used in a comparison. In the solar maximum case in Section 3.1 the time difference is only five minutes; which in the absence of a CME is an interval too short to lead to any substantial contribution to the MAE. In the solar minimum case shown in Section 3.1 the time difference is 21 minutes and there may be more substantial real brightness differences, particularly at the boundaries of streamers due to solar rotation, and within current sheet streamers due to small-scale dynamic events. Figure 7 attempts to quantify this through relating the time difference between a B_t and pB observation and the mean MAE. This is investigated for all 2279 members of the training set used for testing (i.e. not used for training or validation). The right panel of Figure 7 shows a histogram of the time differences for this large number of test pairs, ranging from a minimum of 3 to a maximum of 26 minutes, and with very high populations at 6 and 14 minutes. For each bin, the mean and standard deviation of MAE is calculated, displayed in the left panel of Figure 7. Ignoring points without error bars (these are time difference bins with only one member), there

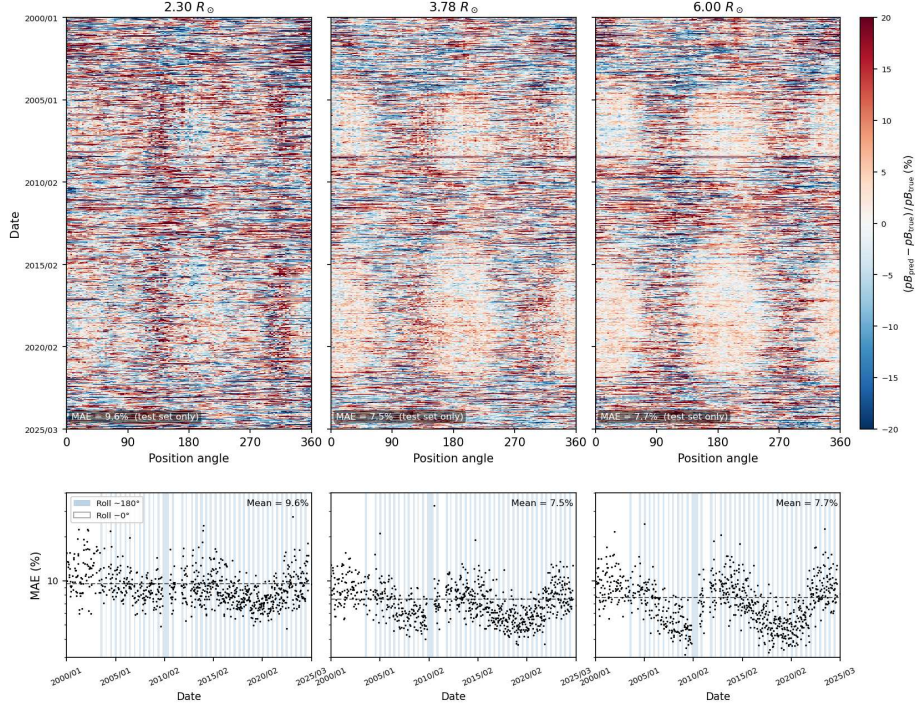


Figure 6. For 2,279 pB and B_t test pairs chosen at random over the 25 years of data (and not used for training), the top row shows the relative error as a function of position angle and time for heliocentric distances $2.30R_\odot$ (left), $3.78R_\odot$ (middle) and $6.00R_\odot$ (right). For display, the error values are saturated at $\pm 20\%$. The bottom row shows, for the same distances, the mean absolute relative error over time for the thousand cases. Blue shaded regions show times when the SOHO roll angle is at 180° .

is a small yet consistent trend for the MAE to increase with increasing time difference - from around 7% at $\Delta t = 4$ minutes to around 8% at 20 minutes. This shows that the mean contribution to MAE due to the time difference is less than 1%. For some cases this will be far larger, particularly if the corona contains large CMEs.

Another source of uncertainty in the reported MAE is the large noise level in the observed pB . As stated in Section 2, the pB is composed of three observations that are generally low-signal due to the low transmission of the polarizers, and therefore have significantly less signal than B_t . Furthermore, in combining these three separate observations to calculate pB , noise is amplified. This can be seen in Figure 5, particularly in the lower left panel showing the circular profiles. The observed pB has considerable pixel-to-pixel noise compared to the predicted (although some of these high-frequency features may be due to real structure e.g. plumes in the coronal holes). Nevertheless, a major component of the MAE is due to noise in the observed pB , and not due to any error with the model. Figure 8 attempts to quantify this by applying increasingly wide median-smoothing boxcar windows to the observed pB , and assessing the subsequent decrease in MAE. The MAE drops rapidly from 12.53% to 8.01% with only a 3×3 boxcar

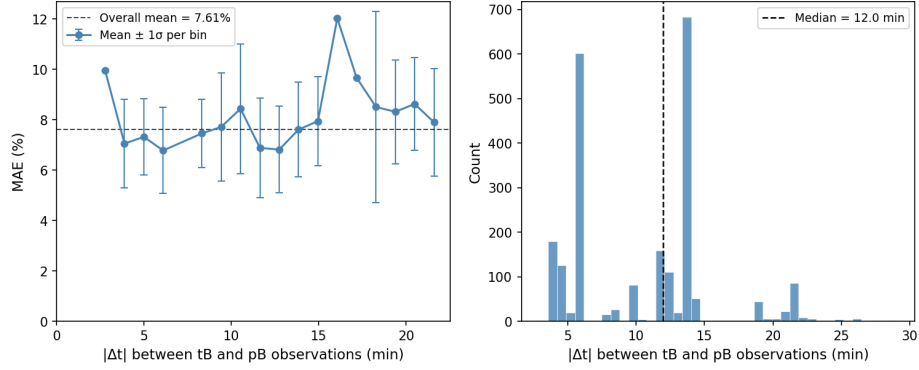


Figure 7. Left: the dependence of mean MAE on the time difference between the B_t and pB observations, with the error bars showing the standard deviation from the mean. Points without error bars indicate time bins where there is only one observation pair. The mean MAE shows only a small increase of around 1% with increasing time difference. Right: histogram of the absolute time difference between the B_t and pB observations.

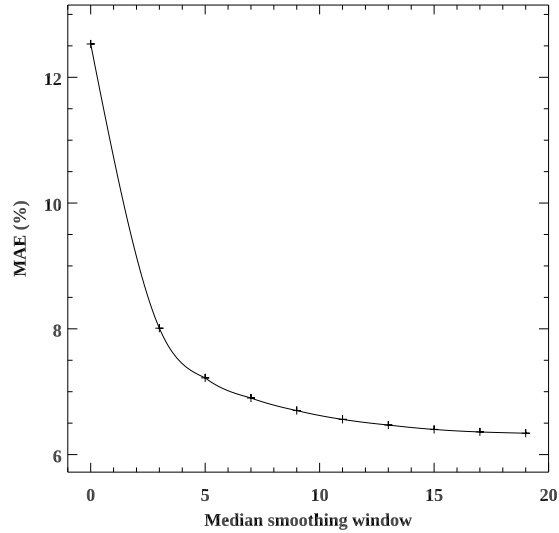


Figure 8. The dependence of the observed and predicted pB MAE on the degree of median smoothing applied to the observed pB . A value of zero means no median smoothing. A value of 3 means a median smoothing window of size 3×3 pixels.

median smoothing. With increasing boxcar width (more smoothing), the MAE drops but with decreasing intervals, with a minimum possible MAE of 6.3% with very wide smoothing. This analysis is not conclusive since as we increase the smoothing width the real high-frequency coronal features get increasingly damped (e.g. polar plumes). However, the large decrease of MAE from 12.5% to 8% as we introduce a narrow smoothing window suggests that the component of the MAE due to noise in the observed pB is on the order of 4%. The convergence of the curve to 6.3% suggests that the MAE due to noise does not exceed 6%.

In summary, we conclude that the mean MAE values reported in Sections 3.1 and 3.2, on the order of 8-12%, contain components that are not due to the model calibration. Assuming from our non-rigorous estimates above that these components contribute at least 4% to the MAE, the MAE values due to calibration uncertainties are therefore around 4-8%. This is not the radiometric calibration error, but the additional uncertainty introduced by the BT2PB procedure.

3.4. Effect of metadata

Table 1 quantifies the importance of the various metadata supplied to the network during prediction. The ablation values are obtained by taking the trained model and evaluating it on the held-out test set under two conditions: first with all metadata scalars set to their true values (the baseline), then with each scalar individually replaced by its training-set mean — which is equivalent to removing that scalar’s information content, since the model then receives no useful signal from that input. The resulting increase in MAE factor relative to the baseline quantifies each scalar’s contribution to prediction accuracy.

The SOHO–Sun distance is by far the most important metadata ($\Delta\text{MAE} = +7.25\%$ when removed), followed by the decimal year ($+1.42\%$), which likely acts as a proxy for the slow change in calibration factor (see Figure 2 and related text). The disk-centre coordinates and B_0 contribute at the sub-percent level. Most surprisingly, the spacecraft roll angle contributes only $+0.18\%$. This shows that the model has learnt the roll state implicitly from the asymmetry of the instrumental stray-light pattern in the B_t profiles, which makes the metadata redundant. The exposure time contributes negligibly ($+0.03\%$).

3.5. Application to coronal tomography

The left panel of Figure 9 shows the changing pB of the corona at a distance of $4R_\odot$ for a ~ 14 -day period on a position-angle vs. time plot. The original observations are the B_t images of LASCO C2, which are then converted to pB using the BT2PB model prediction. The ~ 14 -day period, centered on date 2008 March 02 12:00 UT, corresponds to half of a Carrington rotation, required to provide full coverage of the corona suitable for tomography.

We use the pB data as input to a CNN-based tomography module called CorTom-ML. CorTom-ML is trained on a large number of coronal density models and their corresponding pB synthetic observations, and learns to predict a density distribution given input pB in position-angle vs. time format. The middle panel of Figure 9 shows the density predicted by CorTom-ML using the LASCO C2 pB (predicted from the B_t observations). Electron densities vary from $1.6 \times 10^4 \text{ cm}^{-3}$ in the coronal holes to $2 \times 10^5 \text{ cm}^{-3}$ in the streamers, in agreement with non-tomographical inversions based on spherical symmetry, and with other tomographical methods (Morgan 2019). From this density distribution we create a synthetic observation with viewing geometry the same as the input real data, shown in the right panel of Figure 9. The large-scale distribution of synthetic pB agrees well with the input, giving confidence in the estimated density distribution. Tomography maps, such as shown here, are a

Table 1. Metadata ablation results for the final model evaluated on the held-out test set ($N = 2279$, overall MAE = $1.0808\times$). The MAE on $\log_{10}(pB)$ is reported both as a multiplicative factor (MAE, or 10^{MAE} , the typical ratio between predicted and true pB) and as a percentage increase relative to the baseline. The baseline uses all eight metadata scalars simultaneously. Each scalar (or scalar pair, in the case of roll) is then individually set to its training-set mean, equivalent to removing its information content from the input. The resulting change in the mean absolute error (MAE) factor on pB is reported. Rows are ordered by decreasing importance. The final row shows the combined degradation when all scalars are perturbed simultaneously.

	Metadata scalar	MAE factor	ΔMAE (%)
Baseline	All eight scalars	$1.0808\times$	—
Col. 3	SOHO–Sun distance d	$1.1592\times$	+7.25
Col. 6	Decimal year	$1.0962\times$	+1.42
Col. 5	Disk-centre y_0 (crpix2)	$1.0873\times$	+0.59
Col. 0	Heliographic latitude B_0	$1.0835\times$	+0.25
Cols. 1,2	Spacecraft roll $\sin \phi, \cos \phi$	$1.0828\times$	+0.18
Col. 4	Disk-centre x_0 (crpix1)	$1.0817\times$	+0.08
Col. 7	Exposure time t_{exp}	$1.0812\times$	+0.03
All	All eight scalars perturbed	$1.1836\times$	+9.51

Notes. The roll angle is encoded as a sine–cosine pair ($\sin \phi, \cos \phi$) rather than a scalar angle, following standard practice for circular inputs to neural networks.

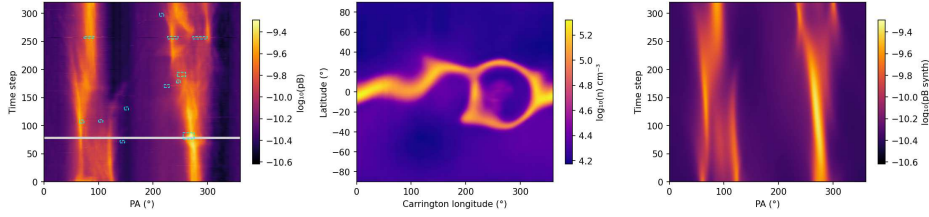


Figure 9. Left: Position angle-time plot of the polarized brightness, at a distance of $4R_{\odot}$, as gained from 320 LASCO C2 total brightness observations over a ~ 14 -day interval (half a Carrington rotation) centered on 2008 March 02 12:00 UT. The grey narrow horizontal band indicates a short data gap, and the cyan rectangles indicate localised periods/locations of brightness gradients which are treated as missing data. Middle: Electron density as predicted from the input data. Right: A synthetic position angle-time plot created from the predicted density with observing geometry corresponding to the real data.

unique valuable estimate of the coronal density structure which can be used for science directly (e.g. Morgan 2019, 2021; Edwards et al. 2022; Alzate et al. 2023), as observational constraints or checks on models (e.g. Edwards et al. 2025), and used to estimate outflow speeds for use in operational space weather forecasting (Bunting & Morgan 2022, 2023; Bunting et al. 2024).

The relevant point here is that during this period, LASCO C2 was only taking one pB observation sequence per day (14 observation sequences). These daily pB

observations give wholly inadequate temporal coverage to allow a mapping of the corona using tomography. Indeed, through most of the LASCO dataset, there are only a few periods during special observing campaigns where the cadence of pB observations allow high-resolution tomography. However, there are hundreds of B_t images taken within a 14-day period throughout most of the LASCO C2 dataset. In the example shown here, there are 320 images, and given the BT2PB prediction, there is more than adequate sampling for the tomography. This is one example of how BT2PB allows new capabilities of the LASCO C2 dataset.

4. Conclusions

BT2PB is a CNN-based framework that ingests a LASCO C2 B_t observation and predicts the corresponding pB . The mean absolute error is, on average, around 8-12%, although some proportion of this (on the order of 4%) is due to the greater noise and occasional defects that are present in the real pB observations that are used to evaluate the MAE. The agreement between predicted and true pB deteriorates at the inner field of view at distances of around $2.3R_\odot$.

BT2PB is a highly efficient approach for converting B_t images to pB , and does not require the calculation and archiving of a long-term F-corona background, or instrumental stray light model, for subtraction. We have deliberately implemented BT2PB so that it ingests level 0.5 B_t images for conversion to pB , and the calibration is therefore dependent on the calibration of the pB images that are used for training. Any future improvement or update to the LASCO C2 pB calibration factors requires a subsequent retraining of BT2PB. Training can be achieved using the CPU of a standard desktop computer in a few minutes, given availability of the training dataset.

BT2PB software and instructions are available at <https://zenodo.org/records/23321147>

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