Earth Substorm Updates

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1 Methodology

- Initial interest in the **Forsyth, Newell, and Ohtani** datasets was due to their recognizable temporal overlap between the years 1976 - 2023

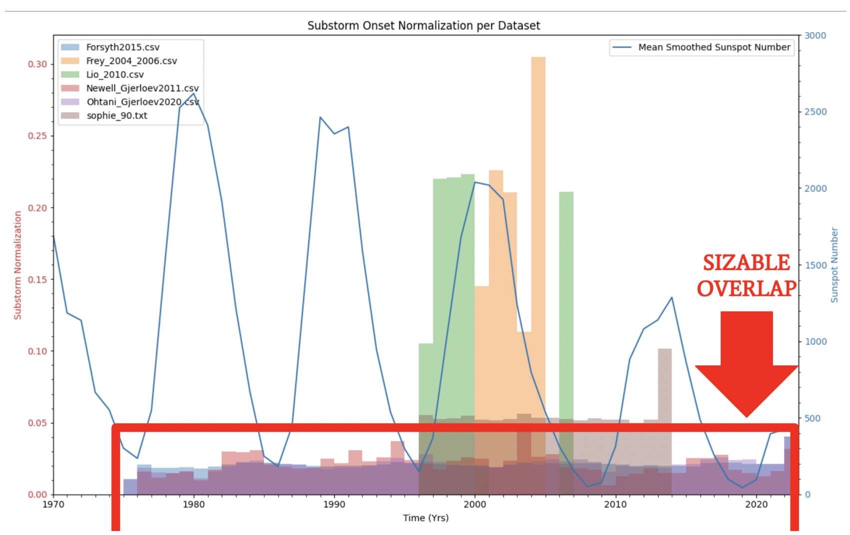

Figure 1: Substorm onset intialization across multiple datasets between 1976 and 2023. Substantial agreement in time range coverage between Forsyth, Newell, and Ohtani datasets. Solid blue line illustrates smoothed yearly solar sunspot variability. The Sun's 11 year cycle can be clearly made out from the periodic variability in sunspot count. This recurring fluctuation is independent of the substorm occurrence rate.

- **Binning Technique:** A dataframe was generated for each respective increment size (i.e. 10 minutes, 20 minutes, 30 minutes, 1 hour, etc.) with indices that corresponded to a particular hard coded time interval [See dual figure below]. Each classified substorm onset within each of the three datasets (Forsyth, Newell, and Ohtani) was iterated through and a count (+1) was added to the respective (row,column) combination in the Initialization DF which consisted of the lower bound of the increment bin the observed onset fell in. For example, if a substorm onset in Forsyth was found to have occurred on 2002-08-31 at 08:38:00, the counts in bin 2002-08-31 08:30:00 would increase by +1.

Figure 2:

	Forsyth	NG	Ohtani
1970-01-01 00:00:00	0	0	0
1970-01-01 00:10:00	0	0	0
1970-01-01 00:20:00	0	0	0
1970-01-01 00:30:00	0	0	0
1970-01-01 00:40:00	0	0	0
...	...	...	...
2023-12-31 23:20:00	0	0	0
2023-12-31 23:30:00	0	0	0
2023-12-31 23:40:00	0	0	0
2023-12-31 23:50:00	0	0	0
2024-01-01 00:00:00	0	0	0

2840113 rows × 3 columns

a) 10 Min Index Initalization Dataframe (IID)

	Forsyth	NG	Ohtani
1970-01-01 00:00:00	0	0	0
1970-01-01 01:00:00	0	0	0
1970-01-01 02:00:00	0	0	0
1970-01-01 03:00:00	0	0	0
1970-01-01 04:00:00	0	0	0
...	...	...	...
2023-12-31 20:00:00	0	0	0
2023-12-31 21:00:00	0	0	0
2023-12-31 22:00:00	0	0	0
2023-12-31 23:00:00	0	0	0
2024-01-01 00:00:00	0	0	0

473353 rows × 3 columns

b) 60 Min Index Initialization Dataframe (IID)

- Initally, we posed two leading questions: statistical probability of repeating a substorm (3 to 4 hours)

  1) Is there an optimal binning time that could be used as the standard when stating that a recorded substorm onset in one dataset was the same observed event across the subsequent datsets?

  2) How can the method of sorting substorm onset intialization times into their respective IID (as a function of binning size) help in extracting a useful metric to help further the search for the "optimal" increment size?

- Be began with the second question - arguably the more qualitative one. Each potential increment was assigned its own IID whose contents could be visually represented by a corresponding Venn Diagram.

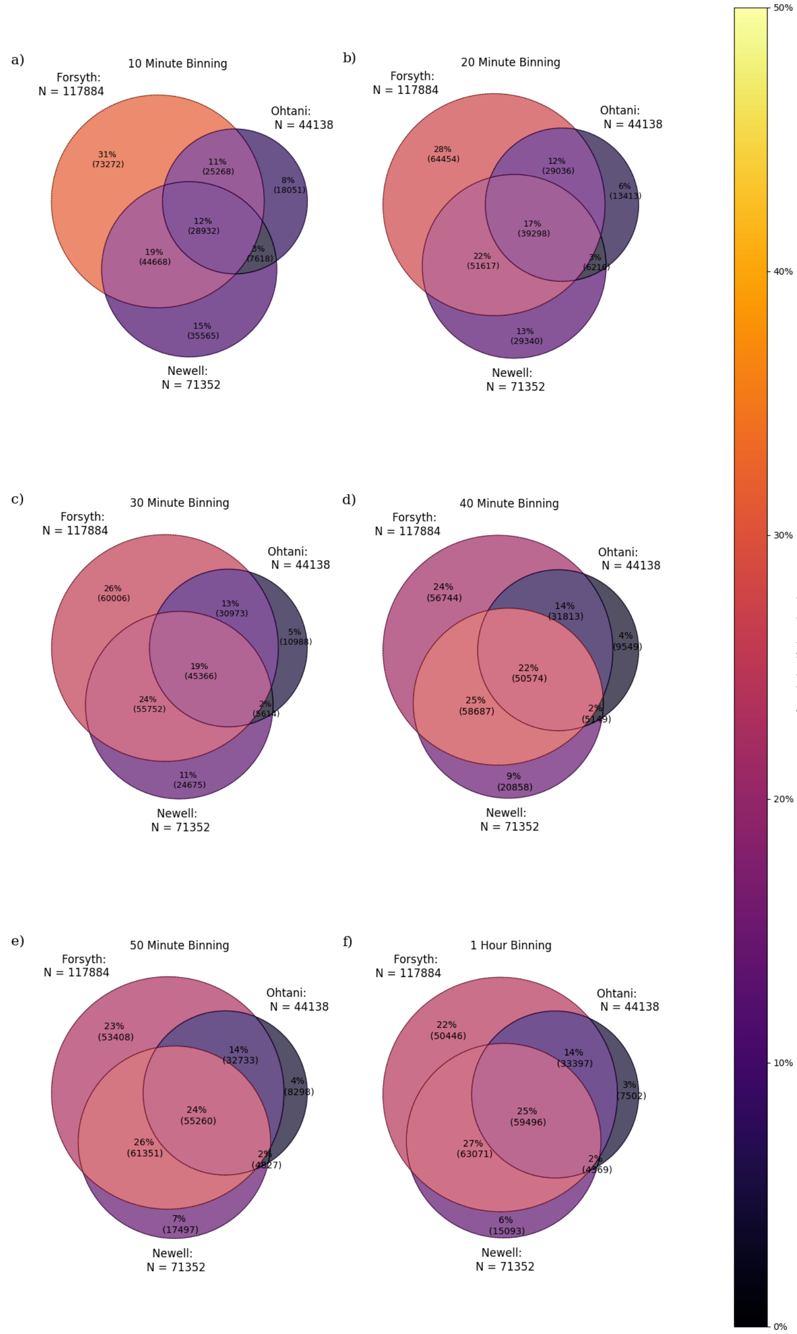

Figure 3: Six panel subplot illustrates the subdivision of joint events across the three datasets (Forsyth, Newell, and Ohtani) during 10-60 minute increments. Each component of the venn diagram includes both the number of substorm onsets that belong to the specific classification as well as the percentage of each category as a function of the three list's total summed events.

- **Sanity Check:** Let's take the Venn Diagram representing the distribution of onset events shared across 10 minute increments (Figure 3a) . If we look at the count of events which lie in the intersection between the Forsyth and Newell datasets, we see a value of 44,668 or 19 %. This can be interpreted as the percentage of events across all recorded onset data in Forsyth, Newell, and Ohtani where at least 1 substorm onset was recorded in the same 10 minute increment within ONLY the Forsyth and Newell catalogues - with no recorded events in Ohtani.
- **Analysis of Figure 3** suggests that we see substantially better agreement between the three lists as we increase the binning size. Naturally, we wanted to test the extrema increment sizes to understand whether our intuition (i.e. all events will contained within the central circle) would be proven. This check is illustrated in Figure 4.

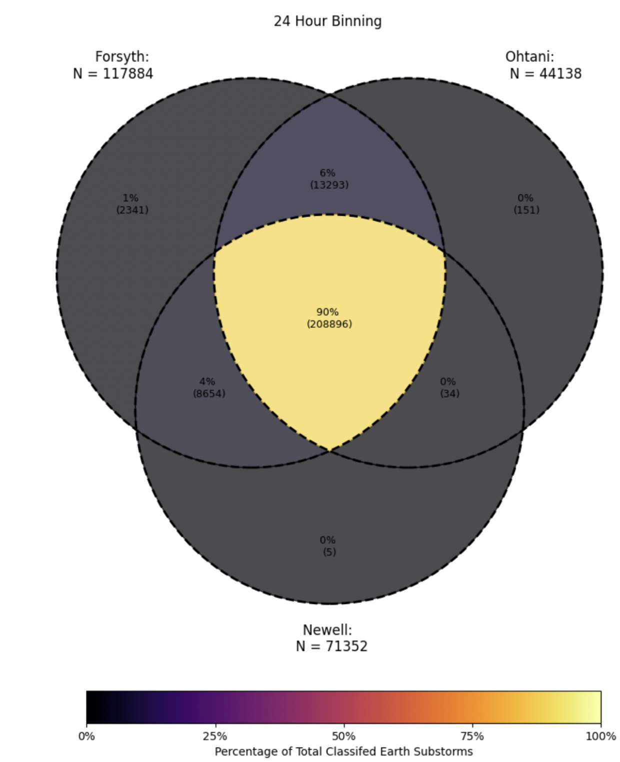

Figure 4: Substorm onset subdivision across Forsyth, Newell, and Ohtani datasets using a 24 hour window. The saturated results of the extreme time increment imply that choosing too large of a binning interval provides little useful information for differentiating between the same (or different) substorm events across the datasets. The 90 % signifies that among the recorded substorm onsets, in 90 % of the events there was at least 1 substorm onset observed in the SAME 24 increment across the three datasets.

- Initial analysis of the contents of the Venn Diagrams suggests our optimal bin increment will be **between 10 minutes to 24 hours.** Anything less and we risk missing substorm events due to bias in the calibration of each instrument when reading out onset initialization. Anything more and we lose our ability to differentiate any substorm onsets from one another, and effectively state that all substorm onsets found by Forsyth, Newell, and Ohtani have been captured and recorded across the three datasets.
- As per the suggestion from the initial Substorm Meeting, we were curious to plot the percentages of overlap as a function of binning period. This was to decipher potential turn-off locations that could prove best when capturing dataset agreeableness. Figure 5 illustrates overlap count as a function of binning time, with a maximum binning increment at approximately 5 hours.

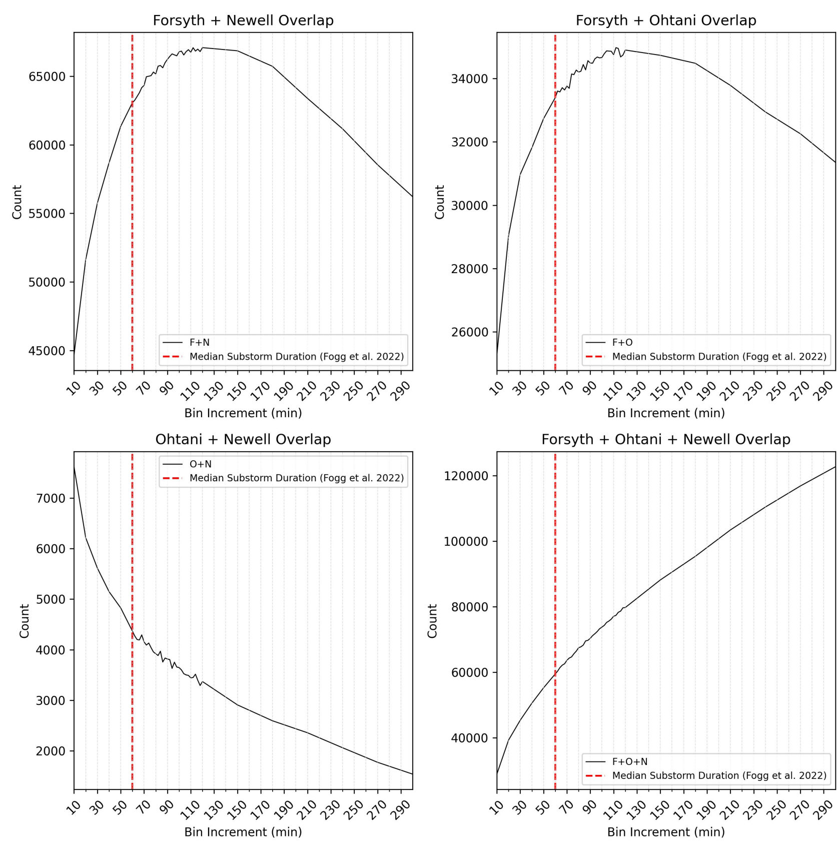

Figure 5: Count of overlapping substorm onsets across datasets as a function of bin interval in minutes. Light grey dotted lined are used to signify 10 minute increments, while the dotted red line at 60 minutes corresponds to the median substorm duration period found by Fogg et al. (2022)

- For this project, we decided to go with 60 minutes as the optimal increment for binning using evidence based in Fogg et al. (2022). However, in alignment with some of the methods presented during the discussion with our collaborators, we were intrigued by the possible effects associated with adding an additional offset to our 60 minute bin window. Figure 6 presents a visualization of event grouping based on providing an additional offset of 10 minutes to our initial indexed dataframe.

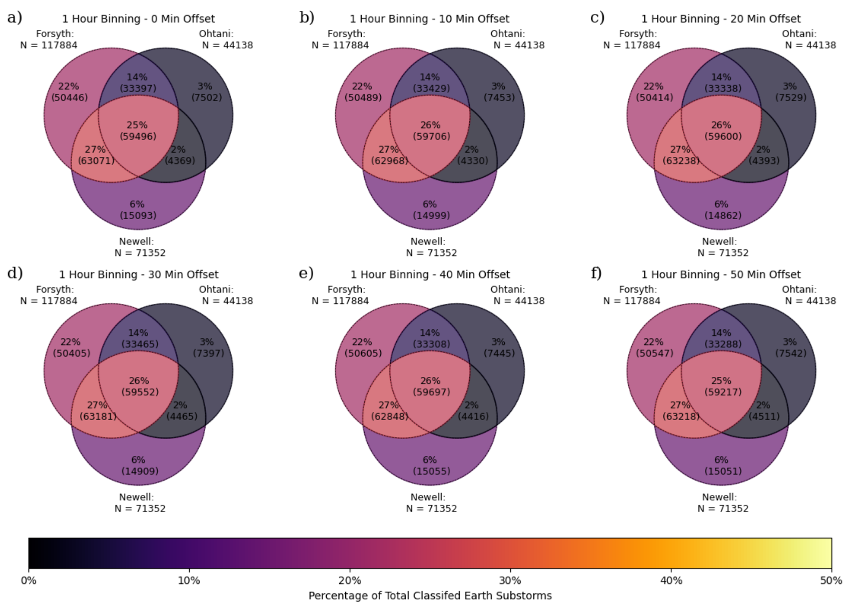

Figure 6: Six panel subplot that illustrates the effects of substorm onset subdivisions within 60 minute binning increments offset by 10 minutes.

- **Resulting Claim:** The substorm classification scheme cannot be as simple as hard-coding indexed bins and sorting substorm initialization times into their respective bin. We must turn to methods analogous to Christian's, where a type of "moving" bin increment captures percentage of overlap among substorm events within datasets constructed using different magnetometer data.

- **Addendum - Randomized Poisson Experiment:** Established baseline that the events recorded in each subset were related to one another.
  - If we assumed each of the three lists were random numbers defined by Poisson statistics, how would the overlap regions look like? What would the expected overlap be?
  - **Null Hypothesis:** Each substorm onset occurs independently across each list.

  Approach:

  1. Assume each list (L_i where i = 1, 2, 3) is generated from random Poisson process with λ_i. Each λ_i corresponds to the number of occurrence rate of substorms in a particular dataset (i.e. Forsyth, Ohtani, or Newell) over the total number of bins within a certain increment. For example, for i = 1 (Forsyth Dataset) within the 10 minute increment scheme, $\lambda_1 = \frac{117884}{bins_{10}}$. $bins_{10}$ is the number of rows in the 10 minute index initialization dataset (IID) defined above [Figure 2]. The numerator signifies the total number of onset events across all bins per dataset, while the denominator signifies the total number of bins per increment class.
  2. Compute the expected overlap under the null hypothesis. This is found through the calculation:

     $$EXPECTED_{OVERLAP} = \lambda_1 \times \lambda_2 \times \lambda_3 \times total_{bins}$$

  3. Calculate metric - such as the chi-squared value (and its respective p-value) - to check for statistically significant deviations from null hypothesis. All calculated expected overlap for 10, 20, 30, ... 60 minute increments was MUCH smaller than observed overlapping events. The chi-squared values were of order magnitude 1e3 with corresponding minuscule/trivial p-values. Setting $\alpha >= 0.001$, we were able to, without hesitation, reject the null hypothesis and accept the alternate hypothesis that the three lists are in fact correlated.

- **Future Direction:** Discuss here the method of matching the overlap percentages across datasets as opposed to hard-coding an indexed window where each event is tossed into its respective bin.

  - **Summary:** Instead of assigning each substorm onset to a trivial window, which is hard-coded to capture only a certain range of times, we look to quantify the percentage of overlap between two substorm events within a discretely selected time window.
  - Take for example EVENT A in Forsyth which occurs on 12-31-2002 at 11:08:00 and EVENT B in Ohtani which occurs on 12-31-2002 at 11:11:00. Instead of sorting the two onsets into bins 11:00:00 and 11:10:00, respectively, we calculate 1) whether the two events overlap in a 10 minute window containing the onset's start time, and if overlap occurs, 2) what percentage of the window is shared by all observed events across the datasets. **How do we define window for each respective increment? Possible options include:**
    1. A) 11:08:00 - 11:18:00 and B) 11:11:00 - 11:21:00 (+10 min)
    2. A) 11:03:00 - 11:13:00 and B) 11:06:00 - 11:16:00 (+/- 5 min)
    3. A) 10:58:00 - 11:18:00 and B) 11:01:00 - 11:21:00 (+/- 10 min)

FINAL THOUGHTS: Venn Diagram showing the optima and extremes bin increment values can be seen in Figure 7.

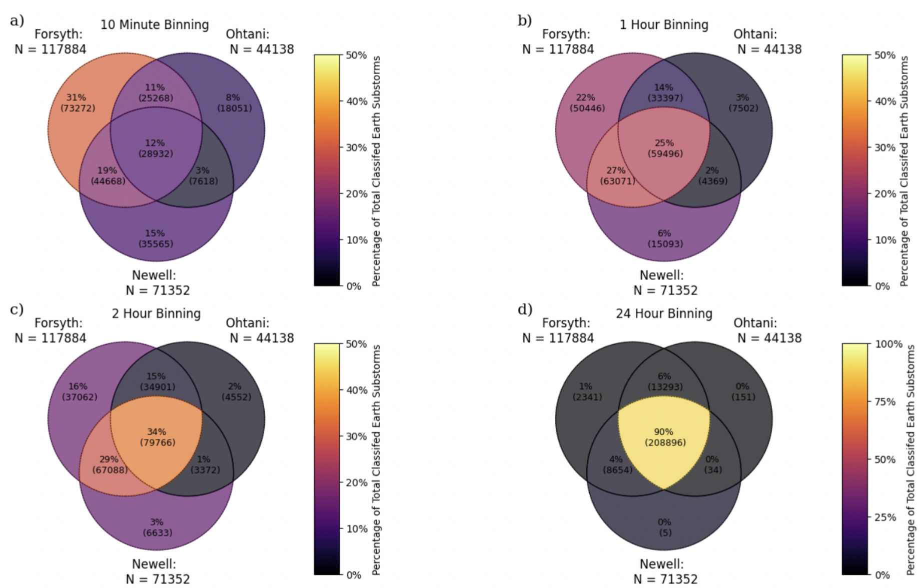

Figure 7: Venn diagram representing the subdivision of simultaneous substorm onsets across the Forsyth, Newell, and Ohtani datasets using a 10 minute, 1 hour, 2 hour, and 24 hour increment. Based on Fogg et al. (2022), the median duration of a substorm event is estimated to be 60 minutes. This assumption lays the foundation for the choice of our optimal bin - 1 hour - whose data overlap is visualized in 7b.

2 Future Directions/Ideas

Chat with Colin Forsyth (Alexandra 6/28):

- Percentages in each area are the percentages of events as a function of the three lists added together
- The three lists are using the same data, so in theory their detections of substom onsets should be uniform - so, the difference must be methology differences?
- **How will we determine which binning is the best?**

  Find metric for the **amplitude of the substorms located in the overlap regions** across differing datasets. Also consider overlap with Alexandra's AKR burst list.

  "Looks like the central bin is tapering off as we go to larger windows?" - If I'm interpreting the question correctly, I don't quite agree. The larger the window (i.e. 10min, 20 min, 30 min, etc.), the more events where there was at least 1 substorm onset classified in the SAME increment across the three datasets.

  note from ARF: I just edited the opening quote mark on bullet above, delete once you've seen this. In latex opening quotes require ' (look at the source code) so it's either 'single quote' or "double quote"

- When we incorporate other lists, derived from other datasets, as weel as methodology / visibility constraints, there might be science differences.

  For example, if a substorm is detected in SOPHIE, but not in AKR bursts - is this a case of substorm that isn't doing much to AKR? I'm imagining this is possible if there is particle precipitation but no density cavity? We might not be able to disentangle this from AKR visibility, at least not statistically.

References

Fogg, A. R., Jackman, C. M., Waters, J. E., et al. 2022, Journal of Geophysical Research: Space Physics, 127, e2021JA030209, doi: http://doi.org/https://doi.org/10.1029/2021JA030209https://doi.org/10.1029/2021JA030209