Supplementary Material

A matter of minutes: Breccia dike paleomagnetism provides evidence for rapid crater modification

March 20, 2016

1 Data analysis associated with breccia dikes in the Slate Islands Impact Structure

This Jupyter notebook is provided as the data repository for a manuscript in review entitled **A matter of minutes: Breccia dike paleomagnetism provides evidence for rapid crater modification** by Luke M. Fairchild, Nicholas L. Swanson-Hysell and Sonia M. Tikoo.
The code that comprises this notebook and the associated data files are availible for download from this Github repository: https://github.com/Swanson-Hysell-Group/2016_Breccia_Dikes.
The notebooks can currently be viewed in these two statically rendered websites:
https://nbviewer.jupyter.org/github/swanson-hysell-group/2016_Breccia_Dikes/blob/master/Code/Breccia_Dike_Data.ipynb
https://nbviewer.jupyter.org/github/swanson-hysell-group/2016_Breccia_Dikes/blob/master/Code/dike_cooling_model.ipynb

2 Introduction

This notebook contains:

- Breccia dike paleomagnetic data
- Host rock paleomagnetic data
- Site means
- Demagnetization type comparison by site
- Clasts/Matrix comparison and calculation of overall mean
- Virtual Geomagnetic Pole (VGP) calculations:
  - Mean pole
  - Comparison to Laurentia APWP
  - Secular variation analysis

3 Import Functions

Here we import the functions necessary for our analyses. The first code block imports function modules that are part of standard scipy libary (http://www.scipy.org/) and normally come standard with distributions of Python. The second code block imports code from the PmagPy project (https://github.com/PmagPy/) for paleomagnetic data analysis.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from mpl_toolkits.basemap import Basemap
        %config InlineBackend.figure_formats = {'svg',}
        %matplotlib inline
```

```
In [2]: import pmagpy_3_4.pmag as pmag
        import pmagpy_3_4.pmagplotlib as pmagplotlib
        import pmagpy_3_4.ipmag as ipmag
```

4 Watson randomness test example

Conglomerate tests were performed on clast samples from sites PI16, PI22, PI24, and PI31.

To determine whether breccia dike clasts were remagnetized during their emplacement, we test for uniformity or randomness among their paleomagnetic directions. In the Watson test for randomness, if a resultant vector length (R) for a population of unit vectors exceeds a specified length (R_o) then the null hypothesis of randomness can be rejected. Watson (1953) shows that R_o can be calculated as: $R_o = \sqrt{(7.815 * N/3)}$. The function Watson_Ro(N) defined below calculates R_o.

```
In [3]: def Watson_Ro(N):
            Ro = np.sqrt(7.815*(N/3))
            return Ro
```

Here is an example of using this function in the case of N=30.

```
In [4]: Watson_Ro(30)

Out[4]: 8.84024886527523
```

A **conglomerate test** is when the Watson test for randomness is applied to clasts within a conglomerate or breccia. If magnetic remanence of clasts within a conglomerate predates the formation of the conglomerate, the directions of that magnetization should be randomly distributed and therefore R should be less than R_o (passing the conglomerate test). If magnetization was acquired following emplacement of the conglomerate/breccia, those directions should not be random and therefore R should be greater than R_o (failing the conglomerate test). Watson (1956) provides a statistical formula for determining confidence intervals of his test for randomness for a particular N. We import a set of calculated values below for use in our analyses. We then standardize our conglomerate test function in an additional function, cong_test, which also determines the 95% confidence of our analysis.

```
In [5]: #Create repository for conglomerate test results
        cong_test_all_data = pd.DataFrame(columns=['demag_type','n',
                                                   'R','Ro','result',
                                                   '95_confidence',
                                                   '99_confidence'])
        # Create dictionary of confidence intervals for Watson test of randomness,
        # organized by N value.
        # These can be found at
        # http://magician.ucsd.edu/essentials/WebBookse115.html#x136-237000C.2
        cong_conf_intervals = {5:{95:3.50,99:4.02},6:{95:3.85,99:4.48},
                               7:{95:4.18,99:4.89},8:{95:4.48,99:5.26},
                               9:{95:4.76,99:5.61},10:{95:5.03,99:5.94},
                               11:{95:5.29,99:6.25},12:{95:5.52,99:6.55},
                               13:{95:5.75,99:6.84},14:{95:5.98,99:7.11},
                               15:{95:6.19,99:7.36},16:{95:6.40,99:7.60},
                               17:{95:6.60,99:7.84},18:{95:6.79,99:8.08},
                               19:{95:6.98,99:8.33},20:{95:7.17,99:8.55},
                              22:{95:7.5,99:8.0}}

        def cong_test(mean_data,demag_type='Thermal'):
            cong_result = {}
            n = int(mean_data['n'])
```

```
        r0 = Watson_Ro(n)
        cong_result['n'] = n
        cong_result['R'] = mean_data['R']
        cong_result['Ro'] = r0
        cong_result['demag_type'] = str(demag_type)
        cong_result
        conf_95 = cong_conf_intervals[n][95]
        conf_99 = cong_conf_intervals[n][99]
        if mean_data['R'] <= r0:
            cong_result['result'] = 'PASS'
        elif int(mean_data['R']) > r0:
            cong_result['result'] = 'FAIL'
            if int(mean_data['R']) > conf_95:
                cong_result['95_confidence'] = 'YES'
            else:
                cong_result['95_confidence'] = 'NO'
            if int(mean_data['R']) > conf_99:
                cong_result['99_confidence'] = 'YES'
            else:
                cong_result['99_confidence'] = 'NO'
        return cong_result


    def add_cong_result(mean_data,site_name,demag_type='Thermal'):
        new_cong_data = pd.Series(cong_test(mean_data,demag_type),name=site_name)
        cong_test_all_data.loc[site_name] = new_cong_data
        return cong_test_all_data
```

5 Create site mean data frame

Here we create an empty dataframe to be populated with site mean directions.

```
In [6]: site_means = pd.DataFrame(columns=['site_type','site_lat','site_lon',
                                           'demag_type','dec','inc','a_95',
                                           'n','kappa','R','cong_test_result'])
```

Site indicates the site name designated in the field. Our names correspond to the particular island within the Slate Islands archipelago from which these samples were collected (i.e. PI=Patterson Island, DeI=Delaute Island) and the site number.

Site Type indicates whether samples consist of breccia clasts or breccia matrix.

Site Lat, Site Long are the WGS84 latitude/longitude coordinates of each site (used for VGP calculations).

Demag Type indicates the demagnetization procedure used for the particular dataset.

Dec, Inc are the mean declination and inclination values determined for the site. These values are in geographic (insitu) coordinates.

a_95 is the α_{95} error of the calculated site Fisher mean.

n is the number of samples used for the site mean.

kappa is the Fisher precision parameter of the site mean (high values represent a tight cluster, lower ones a lower precision (more scattered) distribution.)

R represents the sum length of the cumulate unit vectors (see above discussion on the conglomerate test).

Cong. Test Result is the result of the paleomagnetic conglomerate test (when appropriate). It is designated as either “pass” or “fail.”

6 Breccia Dike Paleomagnetic Analysis

Directional fits were made to paleomagnetic data using least-squares analysis (Kirschvink, 1980) using the software package PmagPy (https://github.com/PmagPy/). Raw data in both CIT and MagIC formats can be found in the 'Data' repository of the supplementary materials. Individual samples within the sites listed below can contain anywhere from a single to several directional components. For thermal demagnetization data, the abbreviations for each component (signifying their blocking temperatures) are:

- **HT** High temperature — 450 to 580°C
- **LT/PLF** Low temperature — NRM to 300-400°C
- **hem** Hematite — 580 to $\leq$ 680°C

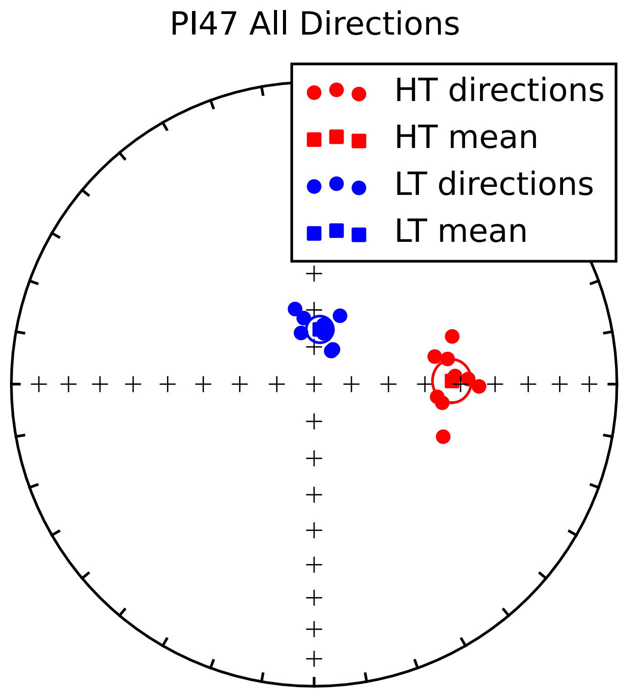
6.1 PI47 breccia dike

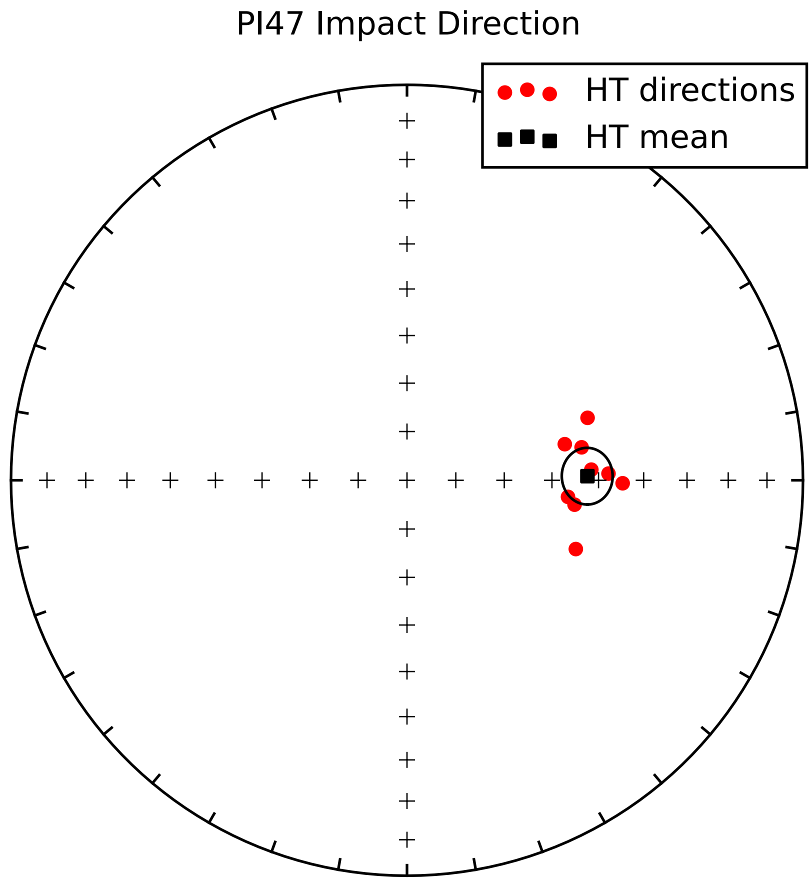
Site PI47 is a clast-poor breccia dike intruding Archean schist that is approximately 3-4 cm thick. The site PI47 sample collection comprises 9 samples of green-colored matrix. Core samples are 2.5 cm in diameter and therefore span most of the breccia dike's width as seen in the photo below. The parameters used in the breccia dike cooling model are from this site, as its minimal thickness is a useful boundary condition for determining the maximum requisite timeframe in which the breccia dike impact direction was recorded.

In [7]:
```
PI47 = ipmag.Site('PI47',
                  '../Data/magic_files/Thermal/PI47')
PI47.eq_plot_everything('PI47 All Directions', clrs=('r', 'b', 'y'), size=(4,4))
PI47.eq_plot('HT','PI47 Impact Direction', 'r')
PI47_mean_data = PI47.get_fisher_mean('HT')
```

```
        print 'Fisher mean: ', PI47_mean_data
        site_means.loc['PI47'] = PI47.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['HT', 'LT'] fits and can be accessed by <site_name>.<fit_name>
HT_mean
88.7 52.4
LT_mean
5.9 75.2
```






```
Fisher mean:  {'k': 90.0, 'n': 9.0, 'r': 8.9112, 'alpha95': 5.5, 'dec': 88.7, 'inc': 52.4}
```

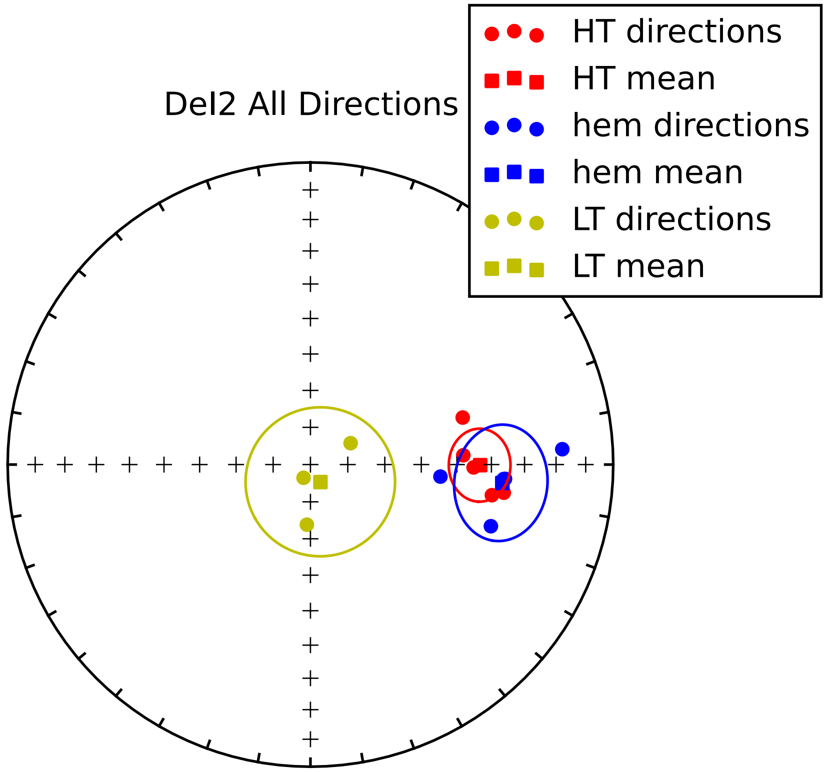
6.2 DeI2 breccia dike

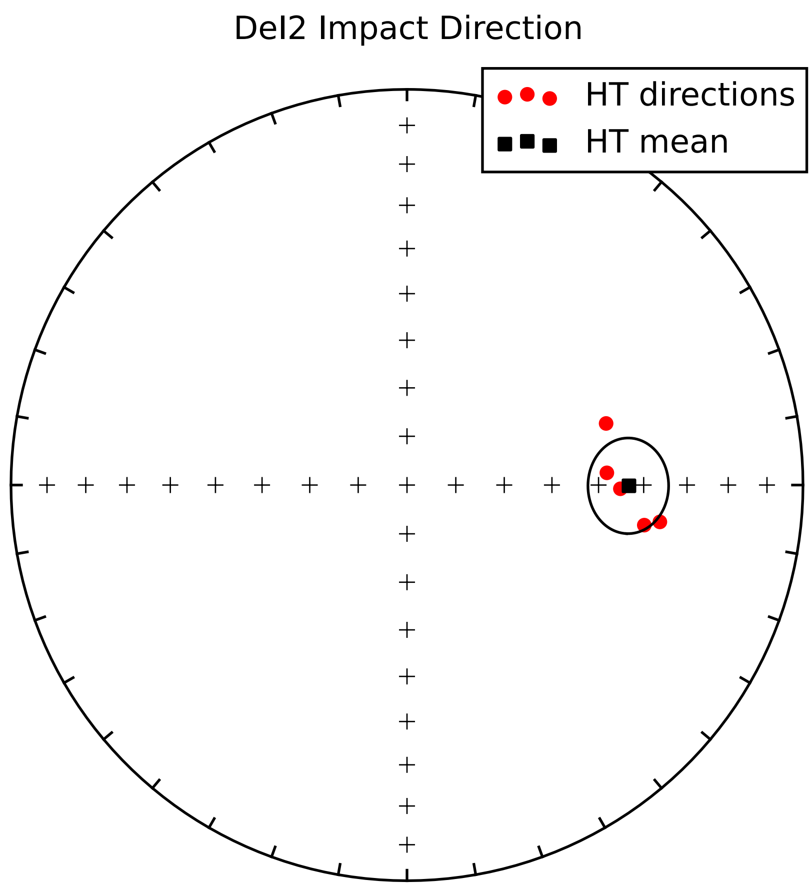
At site DeI2, the matrix of a 2 to 8 cm thick breccia dike was sampled. The matrix was composed of hematite-rich siltstone. Clasts were sub-angular to sub-rounded fine to very coarse grained sand grains, and consisted dominantly of quartz with the minor presence of red and gray lithics.

```
In [8]: DeI2 = ipmag.Site('DeI2',
                    '../Data/magic_files/Thermal/DeI2')
        DeI2.eq_plot_everything('DeI2 All Directions', clrs=('r', 'b', 'y'),
                                size=(4,4), loc=(0.75,0.75))
        DeI2.eq_plot('HT','DeI2 Impact Direction', 'r')
        DeI2_mean_data = DeI2.get_fisher_mean('HT')
        print 'Fisher mean: ', DeI2_mean_data
        site_means.loc['DeI2'] = DeI2.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['HT', 'hem', 'LT'] fits and can be accessed by <site_name>.<fit_name>
HT_mean
90.2 43.3
hem_mean
```

```
95.5 36.5
LT_mean
150.3 84.6
```






```
Fisher mean:  {'k': 73.0, 'n': 5.0, 'r': 4.9456, 'alpha95': 9.0, 'dec': 90.2, 'inc': 43.3}
```

6.3 PI2 breccia dike

Breccia dike PI2 contained clasts of amygdaloidal basalt as well as more massive mafic volcanics some with hematite alteration. The largest sampled clast was 17 x 14 cm. The matrix at this site was a deep red color, likely a consequence of interstitial hematite.

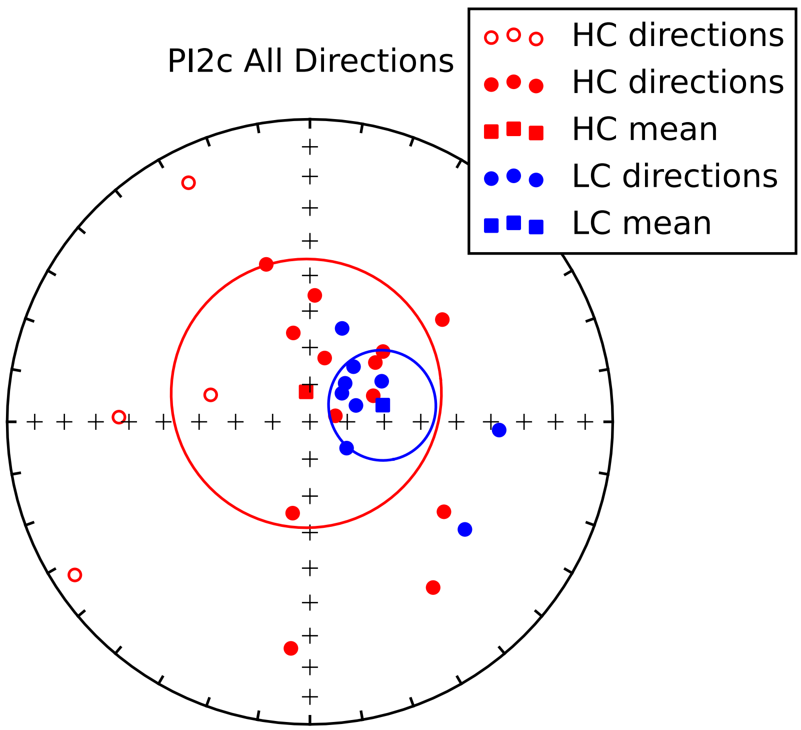
6.3.1 Clasts

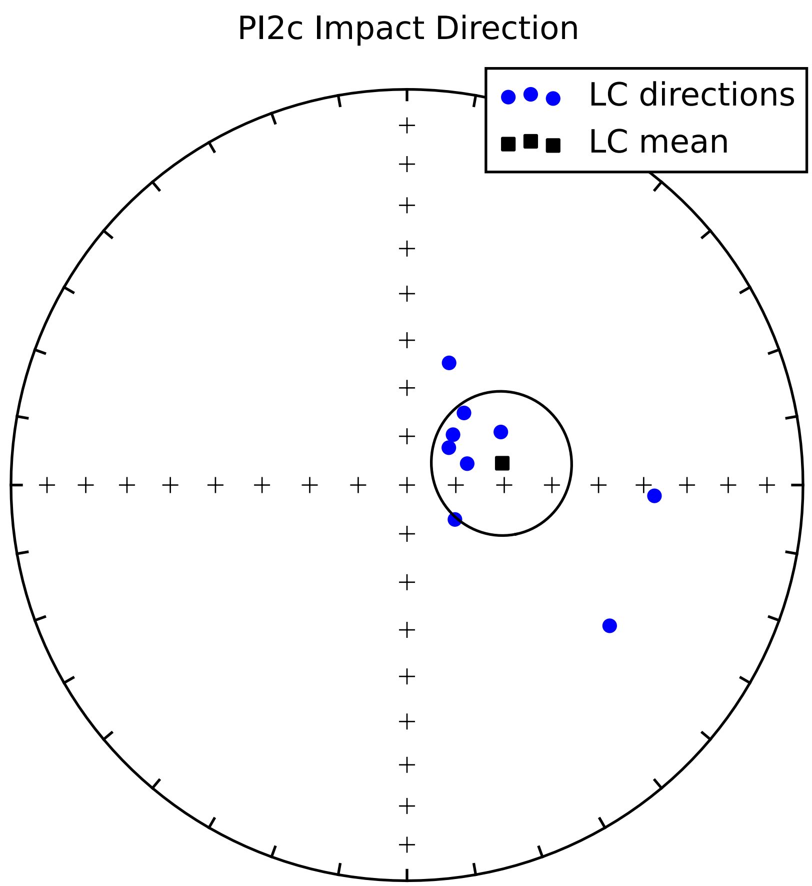
Paleomagnetic directions of clasts exhibit a low coercivity remanence that fails a conglomerate test and aligns well with the impact direction inferred from other breccia sites. The high coercivity components, on the other hand, are quite scattered and suggest that clasts at this site were not fully remagnetized. Unfortunately, these clast samples experienced intense gryoremanence during AF demagnetization, so a legitimate separate high coercivity component was not well isolated. Additionally, there was not enough remaining sample material for thermal demagnetization. We present the low coercivity data here as a likely partial TRM acquired during emplacement (if not a full TRM that was obscured by GRM during measurement).

```
In [9]: PI2c = ipmag.Site('PI2c',
                          '../Data/magic_files/AF/PI2c')
```

```
PI2c.eq_plot_everything('PI2c All Directions',clrs=('r', 'b', 'y'),
                         size=(4,4),loc=(0.75,0.75))
PI2c.eq_plot('LC','PI2c Impact Direction', 'b')
PI2c_mean_data = PI2c.get_fisher_mean('LC')
print 'Fisher mean: ', PI2c_mean_data
site_means.loc['PI2c'] = PI2c.get_site_data('breccia dike clasts','LC', demag_type='AF')
```

```
Data separated by  ['HC', 'LC'] fits and can be accessed by <site_name>.<fit_name>
HC_mean
352.7 81.9
LC_mean
77.1 69.9
```





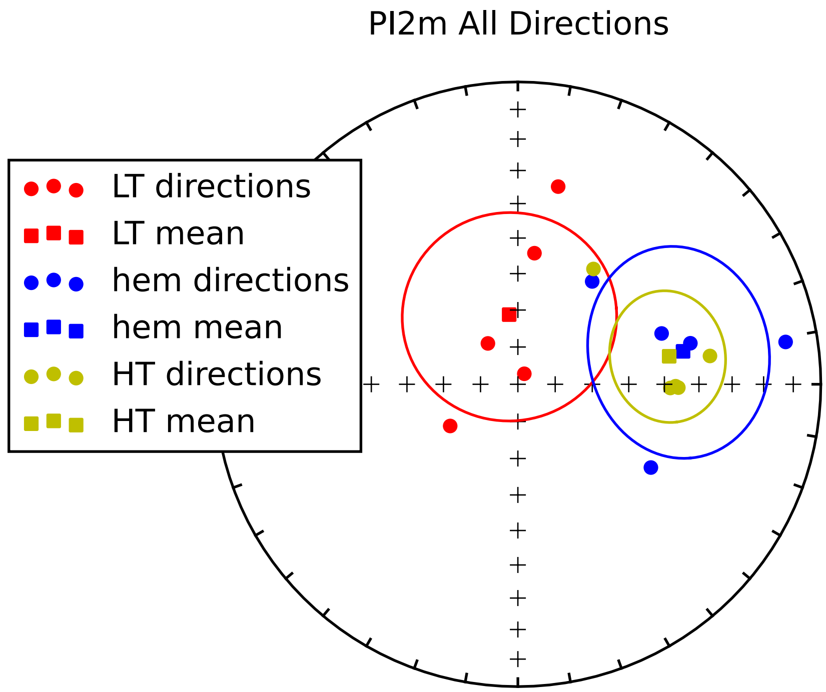

```
Fisher mean:  {'k': 13.0, 'n': 9.0, 'r': 8.3992, 'alpha95': 14.6, 'dec': 77.1, 'inc': 69.9}
```

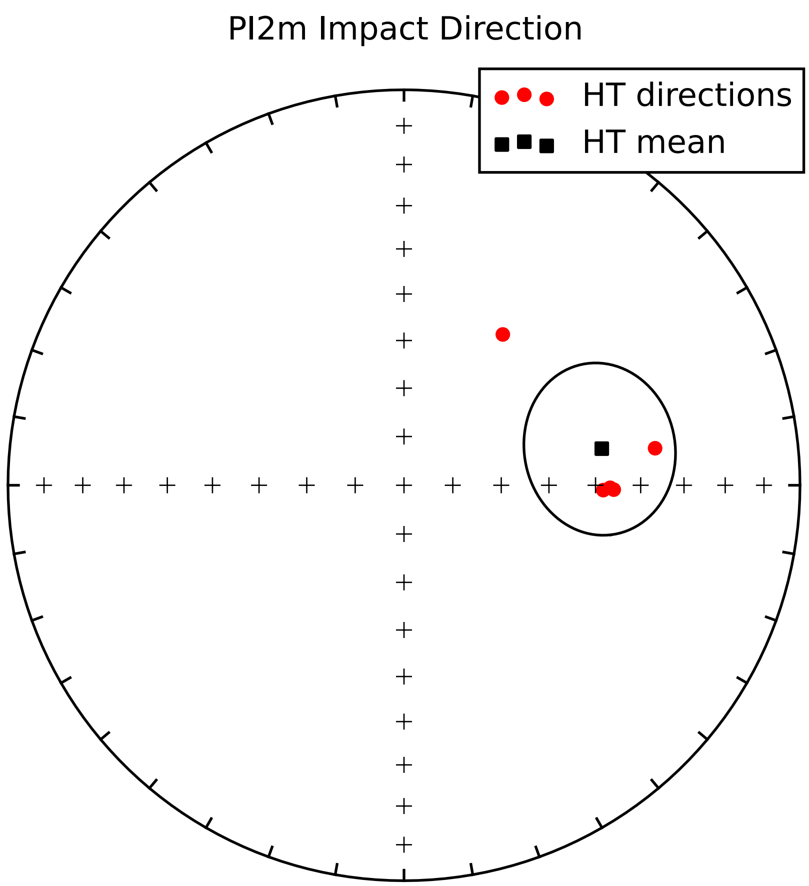
```
In [10]: add_cong_result(PI2c.get_site_data('breccia dike clasts','HC'),'PI2c',demag_type='AF')
```

6.3.2 Matrix

```
In [11]: PI2m = ipmag.Site('PI2m',
                     '../Data/magic_files/Thermal/PI2m')
         PI2m.eq_plot_everything('PI2m All Directions', clrs=('r', 'b', 'y'),
                                 loc=(-0.3,0.4), size=(4,4))
         PI2m.eq_plot('HT','PI2m Impact Direction', 'r')
         PI2m_mean_data = PI2m.get_fisher_mean('HT')
         print 'Fisher mean: ', PI2m_mean_data
         site_means.loc['PI2m'] = PI2m.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['LT', 'hem', 'HT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
352.9 71.1
hem_mean
78.7 43.7
HT_mean
79.5 47.9
```


PI2m All Directions
LT directions
LT mean
hem directions
hem mean
HT directions
HT mean


PI2m Impact Direction
HT directions
HT mean

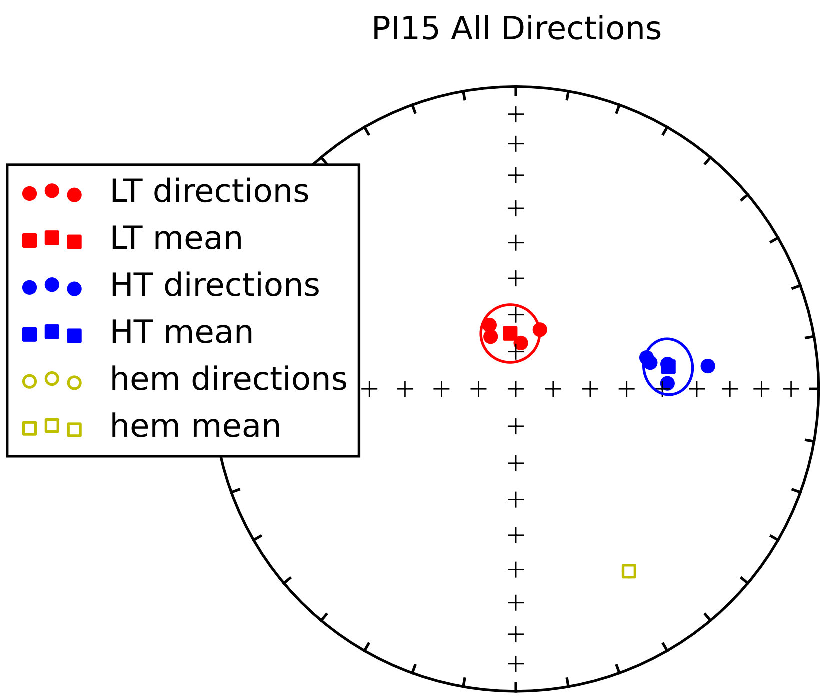
```
Fisher mean:  {'k': 22.0, 'n': 5.0, 'r': 4.8202, 'alpha95': 16.6, 'dec': 79.5, 'inc': 47.9}
```

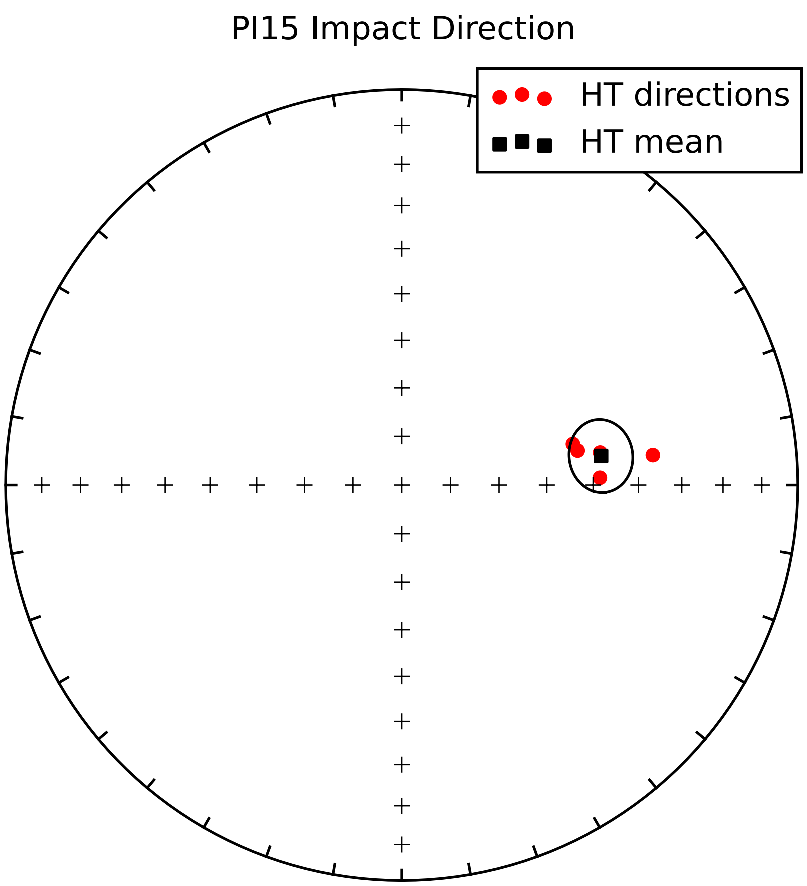
6.4 PI15 breccia dike

At site PI15, the matrix of a 20 cm thick breccia dike was sampled. The matrix is green/grey and contains small (mm scale) clasts.

```
In [12]: PI15 = ipmag.Site('PI15',
                         '../Data/magic_files/Thermal/PI15')
         PI15.eq_plot_everything('PI15 All Directions', clrs=('r', 'b', 'y'),
                                 size=(4,4),loc=(-0.3,0.4))
         PI15.eq_plot('HT','PI15 Impact Direction' ,'r')
         PI15_mean_data = PI15.get_fisher_mean('HT')
         print 'Fisher mean: ', PI15_mean_data
         site_means.loc['PI15'] = PI15.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['LT', 'HT', 'hem'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
354.2 75.0
HT_mean
81.7 47.8
hem_mean
148.2 -29.8
```





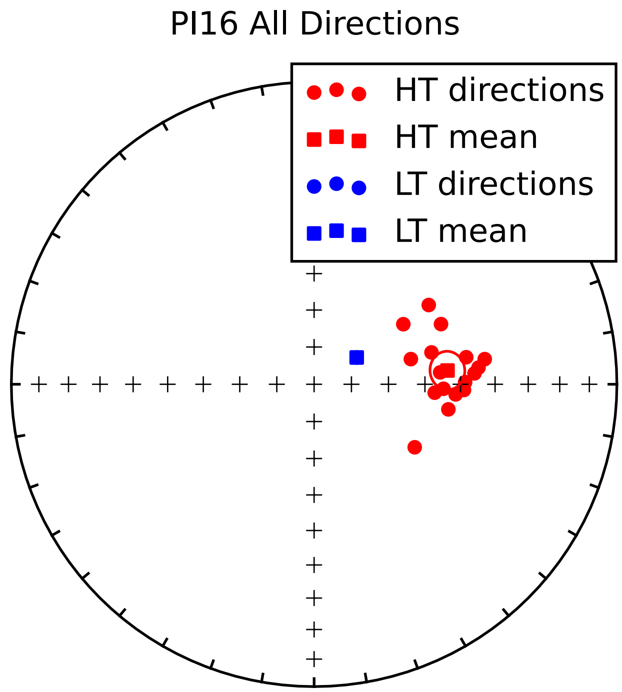

```
Fisher mean:  {'k': 119.0, 'n': 5.0, 'r': 4.9664, 'alpha95': 7.0, 'dec': 81.7, 'inc': 47.8}
```

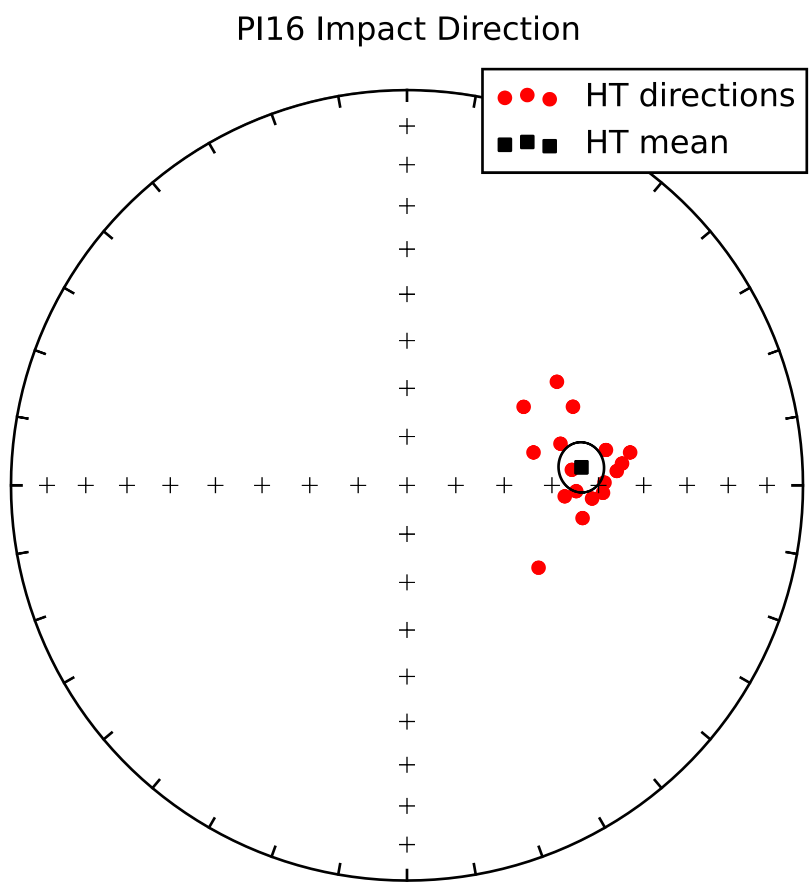
6.5 PI16 breccia dike

At site PI16, 25 clasts of Archean schist were sampled within an up to 80 cm thick breccia dike.

```
In [13]: PI16 = ipmag.Site('PI16',
                     '../Data/magic_files/Thermal/PI16')
         PI16.eq_plot_everything('PI16 All Directions', clrs=('r', 'b', 'y'),size=(4,4))
         PI16.eq_plot('HT','PI16 Impact Direction','r')
         PI16_mean_data = PI16.get_fisher_mean('HT')
         print 'Fisher mean: ', PI16_mean_data
         site_means.loc['PI16'] = PI16.get_site_data('breccia dike clasts','HT')
```

```
Data separated by  ['HT', 'LT'] fits and can be accessed by <site_name>.<fit_name>
HT_mean
84.1 53.5
LT_mean
57.8 76.5
```


PI16 All Directions
HT directions
HT mean
LT directions
LT mean


PI16 Impact Direction
HT directions
HT mean

```
Fisher mean:  {'k': 55.0, 'n': 17.0, 'r': 16.7069, 'alpha95': 4.9, 'dec': 84.1, 'inc': 53.5}
```

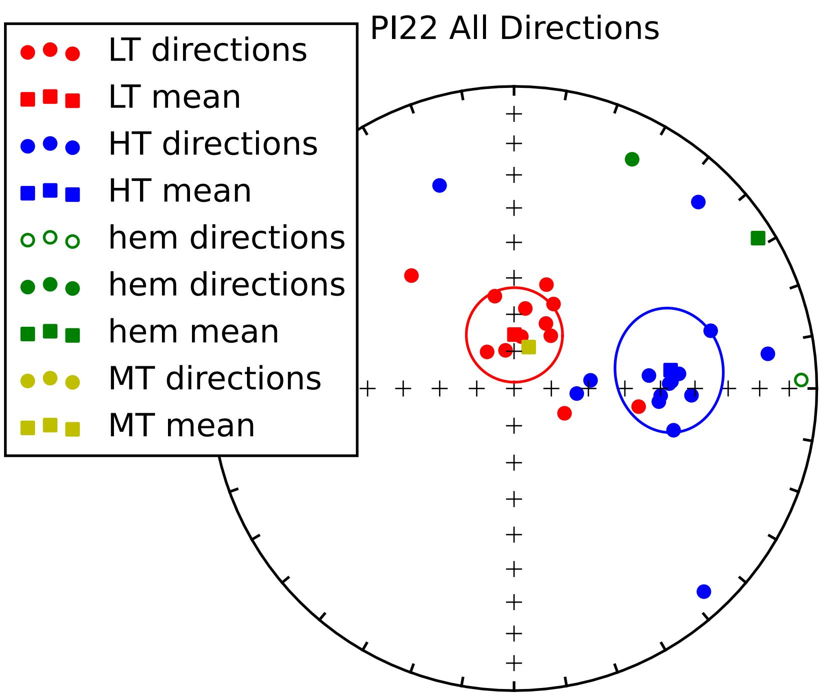
```
In [14]: add_cong_result(PI16.get_site_data('clasts','HT'),'PI16')
```

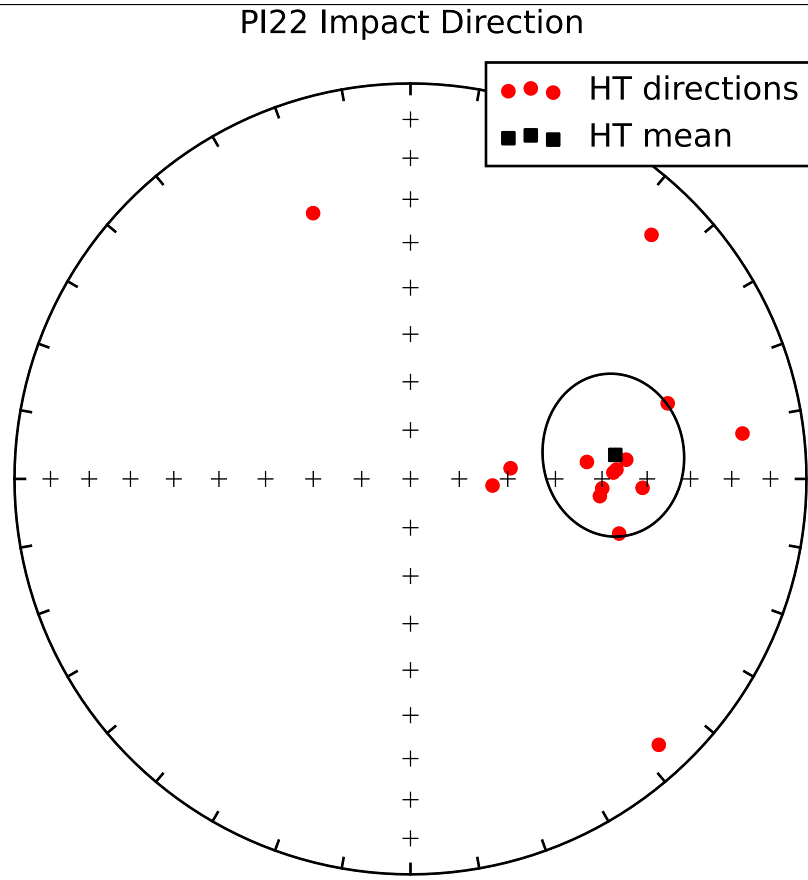
6.6 PI22 breccia dike

At site PI22, 15 clasts comprised of felsic porphyry (with the exception of samples PI22-1 and PI22-2 [felsic metamorphic schists] and PI22-3 [intermediate metavolcanic]) were sampled within an ~10 m thick breccia dike. Clasts are subangular, and sampled clasts range in size from 9 to 40 cm in diameter.

```
In [15]: PI22 = ipmag.Site('PI22',
                        '../Data/magic_files/Thermal/PI22')
         PI22.eq_plot_everything('PI22 All Directions', clrs=('r', 'b', 'g','y'),
                                 loc=(-0.3,0.4),size=(4,4))
         PI22.eq_plot('HT','PI22 Impact Direction', 'r')
         PI22_mean_data = PI22.get_fisher_mean('HT')
         print 'Fisher mean: ', PI22_mean_data
         site_means.loc['PI22'] = PI22.get_site_data('breccia dike clasts','HT')
```

```
Data separated by  ['LT', 'HT', 'hem', 'MT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
0.4 75.5
HT_mean
83.3 46.8
hem_mean
58.3 5.9
MT_mean
19.4 78.2
```






```
Fisher mean:  {'k': 7.0, 'n': 15.0, 'r': 12.9965, 'alpha95': 15.6, 'dec': 83.3, 'inc': 46.8}
```

```
In [16]: add_cong_result(PI22.get_site_data('breccia dike clasts','HT'),'PI22')
```

6.7 PI24 breccia dike

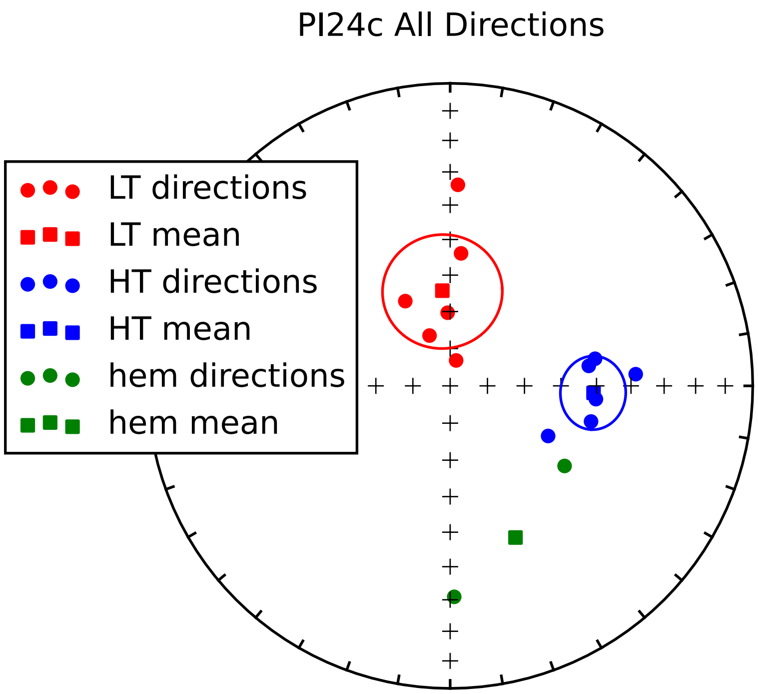
At site PI24, 8 clasts comprised of Archean felsic intrusive rock (PI24c-1 through PI24c-8) were sampled from a 1.4 m wide breccia dike. Clasts are subangular and range from granule size to 50 cm in length. Multiple clasts contain shatter cones, indicating emplacement subsequent to the passing of the shock wave. The breccia matrix is gray/green. PI24m-9 through PI24m-14 are matrix samples.

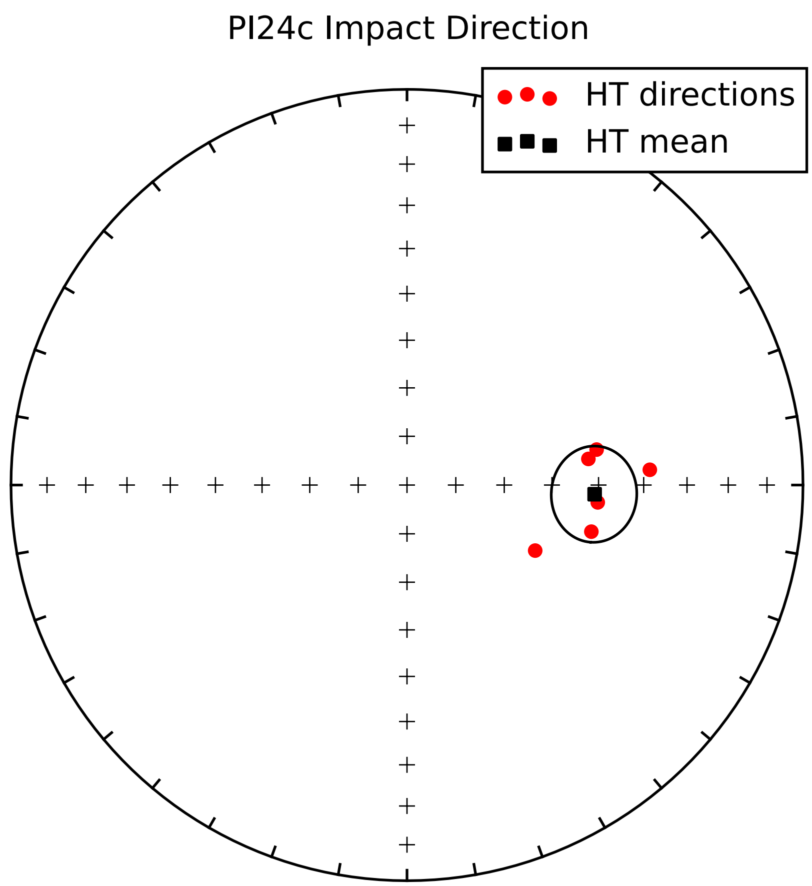
6.7.1 Clasts

```
In [17]: PI24c = ipmag.Site('PI24c',
                   '../Data/magic_files/Thermal/PI24c')
         PI24c.eq_plot_everything('PI24c All Directions', clrs=('r', 'b', 'g'),
                                 loc=(-0.2,0.4), size=(4,4))
         PI24c.eq_plot('HT','PI24c Impact Direction', 'r')
         PI24c_mean_data = PI24c.get_fisher_mean('HT')
         print 'Fisher mean: ', PI24c_mean_data
         site_means.loc['PI24c'] = PI24c.get_site_data('breccia dike clasts','HT')
```

```
Data separated by  ['LT', 'HT', 'hem'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
```

```
355.3 64.2
HT_mean
92.8 50.8
hem_mean
156.7 44.6
```






```
Fisher mean:  {'k': 53.0, 'n': 6.0, 'r': 5.9056, 'alpha95': 9.3, 'dec': 92.8, 'inc': 50.8}
```

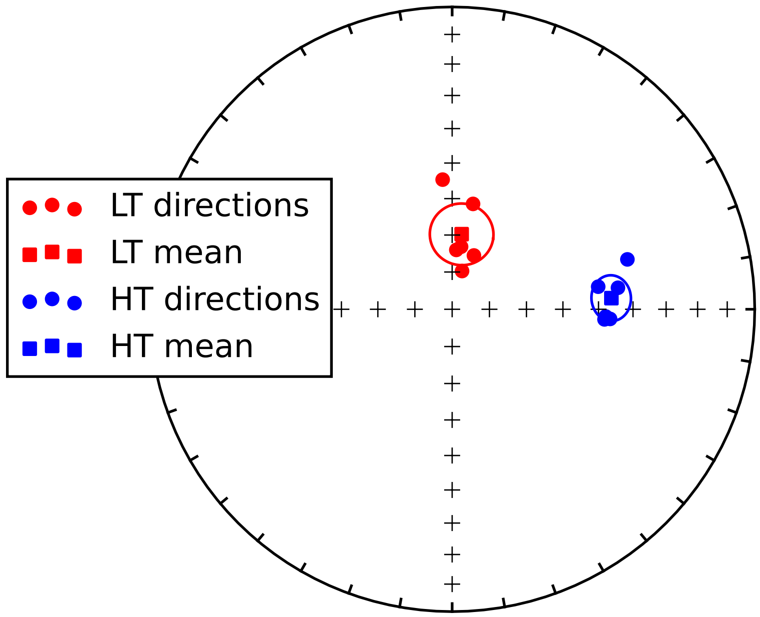
```
In [18]: add_cong_result(PI24c.get_site_data('breccia dike clasts','HT'),'PI24c')
```

6.7.2 Matrix

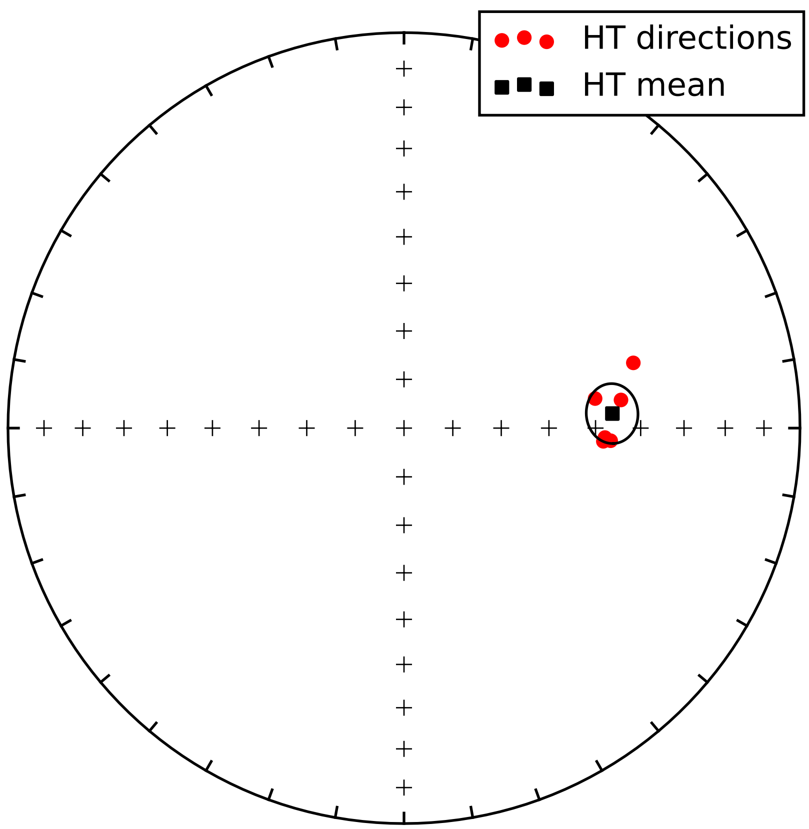
```
In [19]: PI24m = ipmag.Site('PI24m',
                    '../Data/magic_files/Thermal/PI24m')
         PI24m.eq_plot_everything('PI24m All Directions', clrs=('r', 'b', 'g'),
                                  loc=(-0.2,0.4), size=(4,4))
         PI24m.eq_plot('HT','PI24m Impact Direction', 'r')
         PI24m_mean_data = PI24m.get_fisher_mean('HT')
         print 'Fisher mean: ', PI24m_mean_data
         site_means.loc['PI24m'] = PI24m.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['LT', 'HT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
7.2 69.6
HT_mean
86.0 46.2
```

PI24m All Directions



PI24m Impact Direction



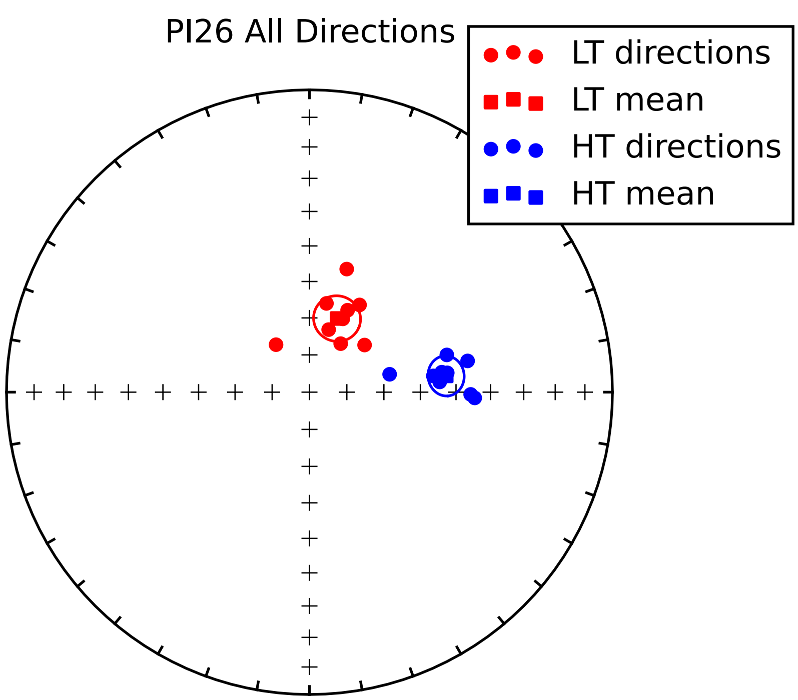
```
Fisher mean:  {'k': 140.0, 'n': 6.0, 'r': 5.9644, 'alpha95': 5.7, 'dec': 86.0, 'inc': 46.2}
```

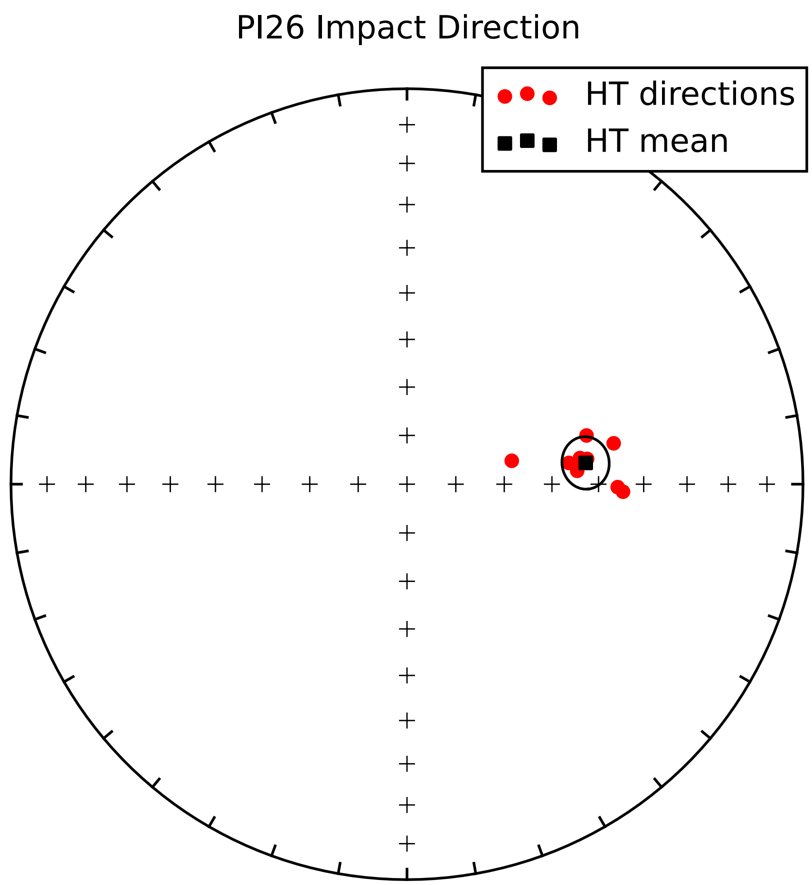
6.8 PI26 breccia dike

At site PI26, 8 samples of matrix were collected from a breccia dike network intruding felsic Archean schist. The multiple diverging branches of the breccia dike are up to 40 cm thick. Branches thin to mm-scale thickness farther away from the locus of the breccia network. The breccia dike is clast-rich, but matrix-supported. Clasts are angular to subangular, granule to pebble size, and are comprised of a variety of metamorphic lithologies and some diabase. Some clasts are of the same lithology as the adjacent host rock, but others are not from the immediate locale. The breccia dike matrix is fine to very fine grained and its dark red coloration due to the presence of interstitial hematite.

```
In [20]: PI26 = ipmag.Site('PI26',
                      '../Data/magic_files/Thermal/PI26')
         PI26.eq_plot_everything('PI26 All Directions', clrs=('r', 'b', 'g'),
                                 loc=(0.75,0.75), size=(4,4))
         PI26.eq_plot('HT','PI26 Impact Direction','r')
         PI26_mean_data = PI26.get_fisher_mean('HT')
         print 'Fisher mean: ', PI26_mean_data
         site_means.loc['PI26'] = PI26.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['LT', 'HT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
20.5 68.8
HT_mean
83.2 52.5
```






```
Fisher mean:  {'k': 103.0, 'n': 9.0, 'r': 8.922, 'alpha95': 5.1, 'dec': 83.2, 'inc': 52.5}
```

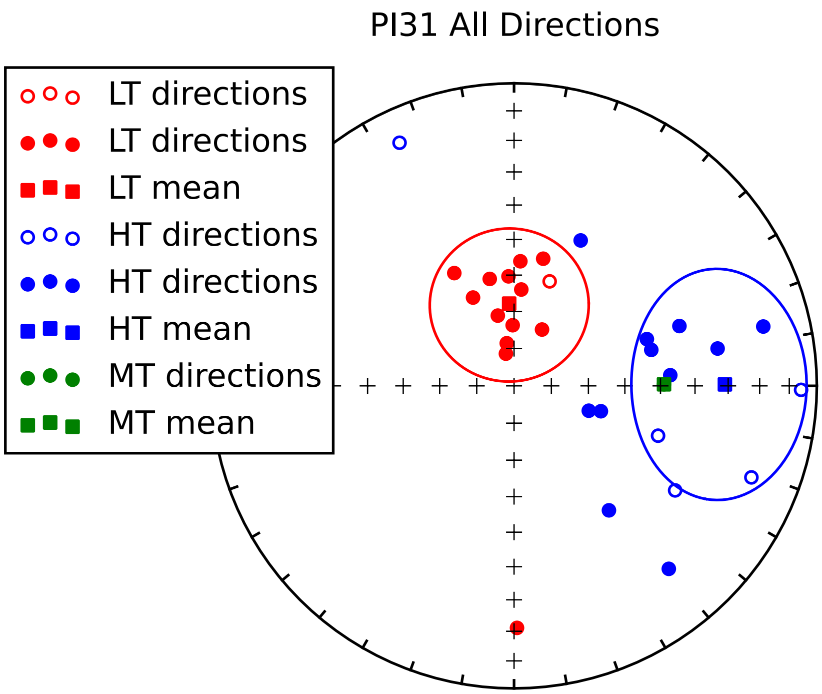
6.9 PI31 breccia dike

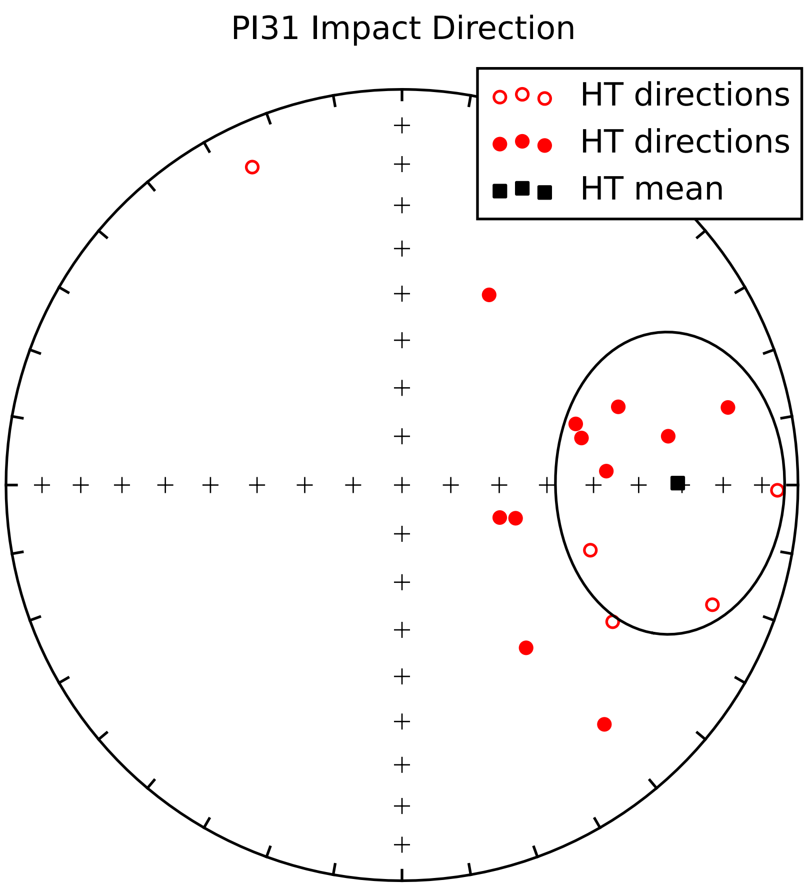
At the site PI31 breccia dike, 20 clasts comprised of felsic, mafic, and K-feldspar porphyry schist were sampled from a >3 m breccia dike. The matrix of the breccia is a deep red color.

```
In [21]: PI31 = ipmag.Site('PI31',
                         '../Data/magic_files/Thermal/PI31')
         PI31.eq_plot_everything('PI31 All Directions',clrs=('r', 'b', 'g'),
                                        loc=(-0.3,0.4),size=(4,4))
         PI31.eq_plot('HT','PI31 Impact Direction','r')
         PI31_mean_data = PI31.get_fisher_mean('HT')
         print 'Fisher mean: ', PI31_mean_data
         site_means.loc['PI31'] = PI31.get_site_data('breccia dike clasts','HT')
```

```
Data separated by  ['LT', 'HT', 'MT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
```

```
356.6 67.8
HT_mean
89.6 31.0
MT_mean
89.4 49.0
```






```
Fisher mean:  {'k': 3.0, 'n': 16.0, 'r': 10.6733, 'alpha95': 27.2, 'dec': 89.6, 'inc': 31.0}
```

```
In [22]: add_cong_result(PI31.get_site_data('breccia dike clasts','HT'),'PI31')
```

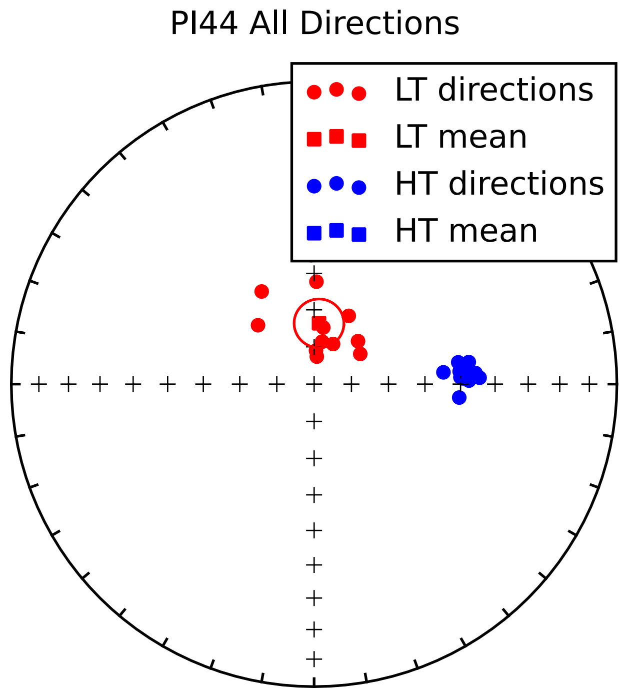
6.10 PI44 breccia dike

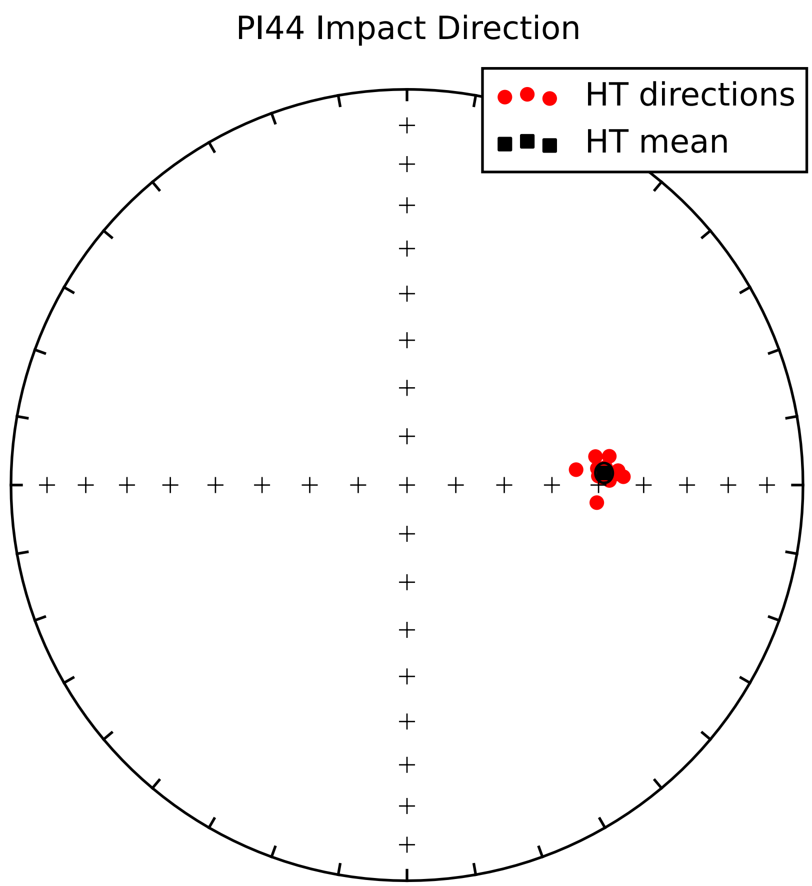
At site PI44, 13 samples of matrix were collected from a ~10-40 cm thick breccia dike. The breccia cross-cuts a Keweenawan diabase dike and an Archean meta-intrusive (?) schist. Clasts are dominantly pebble size, but can be as large as 25 cm in length. Breccia matrix is fine-grained and the collected specimens include small, granule-sized clasts.

```
In [23]: PI44 = ipmag.Site('PI44',
                   '../Data/magic_files/Thermal/PI44')
         PI44.eq_plot_everything('PI44 All Directions',clrs=('r', 'b', 'g'),size=(4,4))
         PI44.eq_plot('HT','PI44 Impact Direction','r')
         PI44_mean_data = PI44.get_fisher_mean('HT')
         print 'Fisher mean: ', PI44_mean_data
         site_means.loc['PI44'] = PI44.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['LT', 'HT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
```

4.6 73.6
HT_mean
86.5 48.7





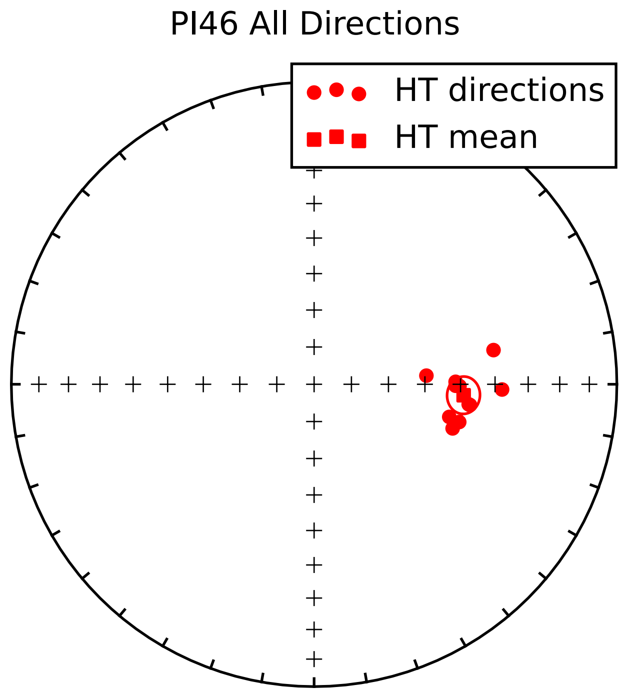

```
Fisher mean:  {'k': 499.0, 'n': 12.0, 'r': 11.978, 'alpha95': 1.9, 'dec': 86.5, 'inc': 48.7}
```

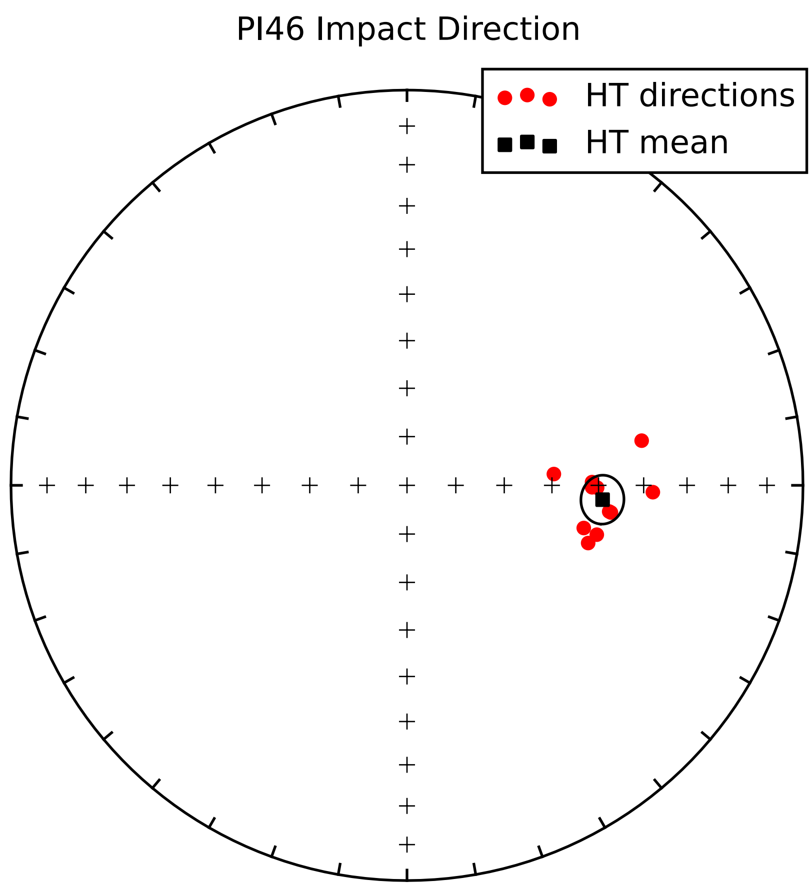
6.11 PI46 breccia dike

At site PI46, 11 samples of matrix were collected from a 25 cm thick breccia dike. The breccia dike contains granule to small-sized clasts (the largest clast is 15 cm across, although the majority are smaller). Breccia matrix is green/gray and very fine-grained.

```
In [24]: PI46 = ipmag.Site('PI46',
                     '../Data/magic_files/Thermal/PI46')
         PI46.eq_plot_everything('PI46 All Directions',clrs=('r', 'b', 'g'), size=(4,4))
         PI46.eq_plot('HT','PI46 Impact Direction','r')
         PI46_mean_data = PI46.get_fisher_mean('HT')
         print 'Fisher mean: ', PI46_mean_data
         site_means.loc['PI46'] = PI46.get_site_data('breccia dike matrix','HT')
```

```
Data separated by  ['HT'] fits and can be accessed by <site_name>.<fit_name>
HT_mean
94.2 49.0
```


PI46 All Directions
HT directions
HT mean


PI46 Impact Direction
HT directions
HT mean

```
Fisher mean:  {'k': 96.0, 'n': 11.0, 'r': 10.8956, 'alpha95': 4.7, 'dec': 94.2, 'inc': 49.0}
```

7 Breccia dike host rock

Here we present the results of baked contact tests for one breccia dike intrusion into a stack of basalt flows (host rock sites PI32, PI33, PI34) and three breccia dike intrusions into Archean schist (host rock sites PI16, PI22, PI24). These results support the hypothesis that breccia dikes were emplaced at high temperatures, which imparted partial overprints to host rock removed at lower (higher) temperatures at greater (lesser) distance from the nearest breccia dike contact. Moreover, the general observation of partial overprinting of host rock (pTRM) contrasts with the full overprinting of daughter clasts of similar lithology within breccia dikes and therefore supports the hypothesis that breccia dike clasts record a TRM.

The maximum unblocking temperatures of magnetic components have been compiled for both breccia dike clasts and host rock data. These can be found in the Data repository and are uploaded below.

```
In [25]: # upload unblocking temperature data for host rock
         host_bct = pd.read_csv('../Data/baked_contact_analysis/baked_contact.csv')
         host_bct.to_latex('latex_tables/host_bct.txt')
         # upload unblocking temperature data for breccia dike clasts
         breccia_bct = pd.read_csv('../Data/baked_contact_analysis/clasts_max_temp.csv')
         breccia_bct.to_latex('latex_tables/breccia_bct.txt')
         breccia_bct.head()
```

Breccia clasts:

sample	max temp (°C)	fit
PI16-10	560	HT
PI16-11	580	HT
PI16-12	525	HT
PI16-13	550	HT
PI16-14	570	HT
PI16-16	580	HT
PI16-17	525	HT
PI16-19	550	HT
PI16-1	550	HT
PI16-20	580	HT
PI16-23	525	HT
PI16-2	550	HT
PI16-3	580	HT
PI16-4	575	HT
PI16-6	560	HT
PI16-7	575	HT
PI16-9	580	HT
PI22-10	560	HT
PI22-11	475	HT
PI22-12	520	HT
PI22-13	580	HT
PI22-14	580	HT
PI22-15	580	HT
PI22-1	580	HT
PI22-2	500	HT
PI22-3	580	HT
PI22-4	550	HT
PI22-5	550	HT
PI22-6	475	HT
PI22-7	580	HT
PI22-8	580	HT
PI22-9	580	HT
PI24-10	580	HT
PI24-1	550	HT
PI24-2	580	HT
PI24-3	580	HT
PI24-4	580	HT
PI24-7	580	HT
PI31-10	580	HT
PI31-12	580	HT
PI31-13	580	HT
PI31-14	580	HT
PI31-16	580	HT
PI31-17	500	HT
PI31-18	580	HT
PI31-19	500	HT
PI31-1	450	HT
PI31-20	580	HT
PI31-2	425	HT
PI31-4	580	HT
PI31-5	450	HT
PI31-6	580	HT
PI31-8	570	HT
PI31-9	580	HT

```
In [26]: host_bct.head()
```

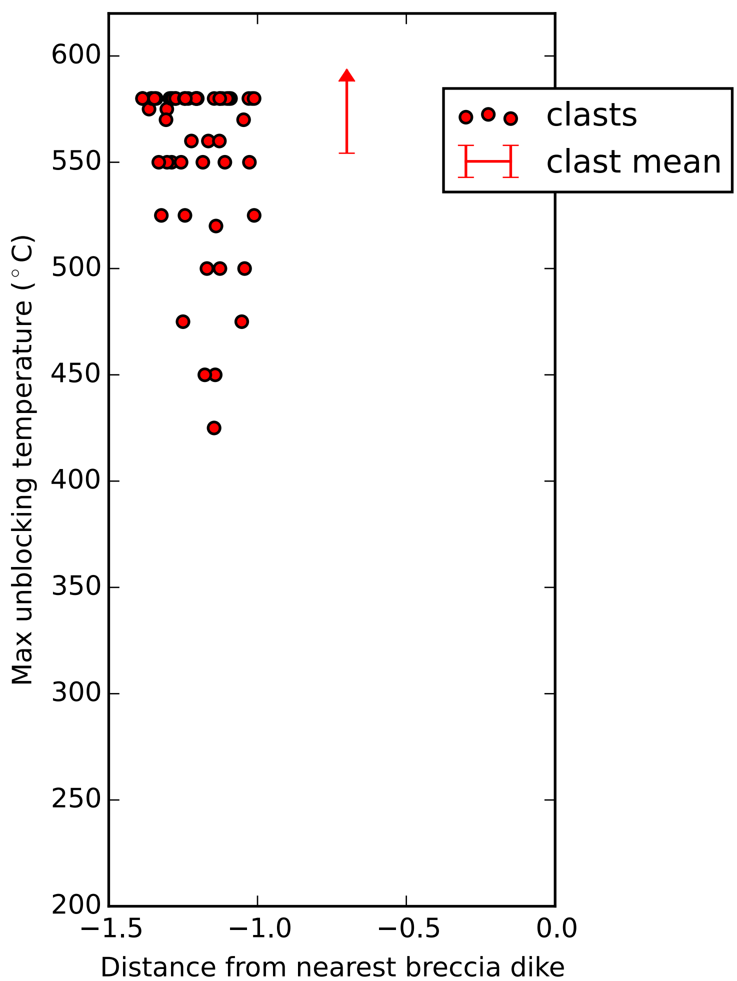
Host rock:

sample	max temp (°C)	fit	distance (m)	distance (normalized to breccia thickness)
PI24-16a	375	MT	0.860000	0.330769
PI24-17a	400	MT	1.130000	0.434615
PI24-18a	500	MT	0.560000	0.215385
PI24-20a	570	MT	0.060000	0.023077
PI24-21a	560	MT	0.500000	0.192308
PI24-23a	570	MT	0.040000	0.015385
PI24-24a	375	MT	0.030000	0.011538
PI24-26a	300	MT	4.400000	2.200000
PI24-27a	400	MT	4.450000	2.225000
PI24-28a	577	MT	5.130000	2.565000
PI24-29a	275	MT	5.330000	2.665000
PI24-31a	475	MT	2.450000	1.225000
PI22-16	450	MT	0.040000	0.057143
PI22-17	525	MT	0.050000	0.071429
PI22-18	550	MT	0.140000	0.107692
PI22-19	525	MT	0.380000	0.292308
PI22-20	500	MT	0.730000	0.561538
PI22-21	475	MT	1.600000	1.230769
PI22-22	525	MT	2.080000	1.600000
PI22-23	525	MT	2.150000	1.653846
PI22-24	550	MT	3.110000	2.392308
PI22-25	525	MT	3.220000	2.476923
PI22-26	500	MT	3.350000	2.576923
PI22-27	550	MT	NaN	NaN
PI22-28	475	MT	NaN	NaN
PI22-29	500	MT	NaN	NaN
PI22-31	300	MT	NaN	NaN
PI22-32	525	MT	NaN	NaN
PI16-26	475	MT	8.000000	NaN
PI16-27	400	MT	8.000000	NaN
PI16-28	400	MT	8.000000	NaN
PI16-29	350	MT	8.000000	NaN
PI16-30	375	MT	8.000000	NaN
PI32-1	400	MT	20.924485	6.538902
PI32-2	350	MT	21.002272	6.563210
PI32-3	250	MT	21.313416	6.660443
PI32-4	250	MT	21.002272	6.563210
PI32-5	275	MT	21.002272	6.563210
PI32-6	325	MT	21.157844	6.611826
PI32-7	275	MT	22.091278	6.903524
PI32-8	250	MT	22.169065	6.927833
PI32-9	250	MT	22.246851	6.952141
PI33-1	325	MT	17.890824	5.590883
PI33-2	350	MT	16.801817	5.250568
PI33-3	350	MT	18.046396	5.639499
PI33-5	350	MT	17.735252	5.542266
PI33-6	300	MT	17.579679	5.493650
PI34-1	570	HT	7.934192	2.479435
PI34-2	570	HT	6.845185	2.139120
PI34-3	570	HT	8.089764	2.528051
PI34-4	570	HT	8.089764	2.528051
PI34-5	570	HT	7.778619	2.430818
PI34-6	570	HT	6.534040	2.041888
PI34-7	570	HT	5.133889	1.604340
PI34-8	570	HT	2.489158	0.777862

We first initialize the plot we will use to visualize the baked contact test and compare the unblocking temperatures to distance from the nearest breccia dike. We start by plotting the range of temperatures at which the full overprints in breccia dike clasts were removed from clasts throughout the sampled breccia dieks. This range will be used as a helpful visual comparison in the baked contact tests below. We generalize the following code within a function, **BCT**, below.

```
In [27]: def BCT(display_breccia=True, breccia_site = None, display_host=True,
                 host_name=None, one_error=False, error_x=5, figure_size = (8,6),
                 fillna=False, na_value=None, bin_number = 3, no_new_fig=False):

             if display_host==True:
                 criterion = host_bct['sample'].map(lambda x: x.startswith(host_name))
                 host = host_bct[criterion]
                 host.reset_index(inplace=True, drop=True)
                 if fillna==True:
                     host = host.fillna(na_value)
             if no_new_fig is False:
                 plt.figure(figsize=figure_size)

             if breccia_site is not None:
                 criterion = breccia_bct['er_sample_name'].map(lambda x: x.startswith(breccia_site))
                 breccia_data = breccia_bct[criterion]
                 breccia_data.reset_index(inplace=True, drop=True)
             else:
                 breccia_data = breccia_bct

             if display_breccia==True:
                 data_plt_x = []
                 data_plt_y = []
                 for i in range(len(breccia_data)):
                     rand_x = 0.4*np.random.random_sample()-1.4
                     data_plt_x.append(rand_x)
                     data_plt_y.append(breccia_data.measurement_step_max[i])
                     if i==0:
                         plt.scatter(rand_x,breccia_data.measurement_step_max[i],c='r',label="clasts")
                     else:
                         plt.scatter(rand_x,breccia_data.measurement_step_max[i],c='r')
                 breccia_mean_temp = np.mean(data_plt_y)
                 breccia_std = np.std(data_plt_y)
                 plt.errorbar(-0.7,breccia_mean_temp, yerr=breccia_std,label='clast mean', lolims=True,

             if display_host==True:
                 data_plt_x = []
                 data_plt_y = []

                 for i in range(len(host)):
                     data_plt_x.append(host.distance_m[i])
                     data_plt_y.append(host.max_temp[i])
                     if i==0:
                         plt.scatter(host.distance_m[i],host.max_temp[i],c='b',label="host")
                     else:
                         plt.scatter(host.distance_m[i],host.max_temp[i],c='b')
                 x = np.array(data_plt_x)
                 y = np.array(data_plt_y)
                 if one_error==False:
                     nbins = bin_number
                     n, a = np.histogram(x, bins=nbins)
                     sy, b = np.histogram(x, bins=nbins, weights=y)
                     sy2, c = np.histogram(x, bins=nbins, weights=y*y)
                     mean = sy / n
```

```
            std = np.sqrt(sy2/n - mean*mean)
            plt.errorbar((a[1:] + b[:-1])/2, mean, yerr=std, fmt='b-',label='host mean')
        else:
            plt.errorbar(error_x,np.mean(y), yerr=np.std(y), fmt='b-',label='host mean')

BCT(display_breccia=True, display_host=False, figure_size=(3,6))
plt.legend(loc=(0.75,0.8))
plt.xlim(-1.5, 0)
plt.ylim(200,620)
plt.xticks(np.arange(-1.5,0.5, .5))
plt.xlabel('Distance from nearest breccia dike')
plt.ylabel('Max unblocking temperature ($^\circ$C)')
plt.show()
```



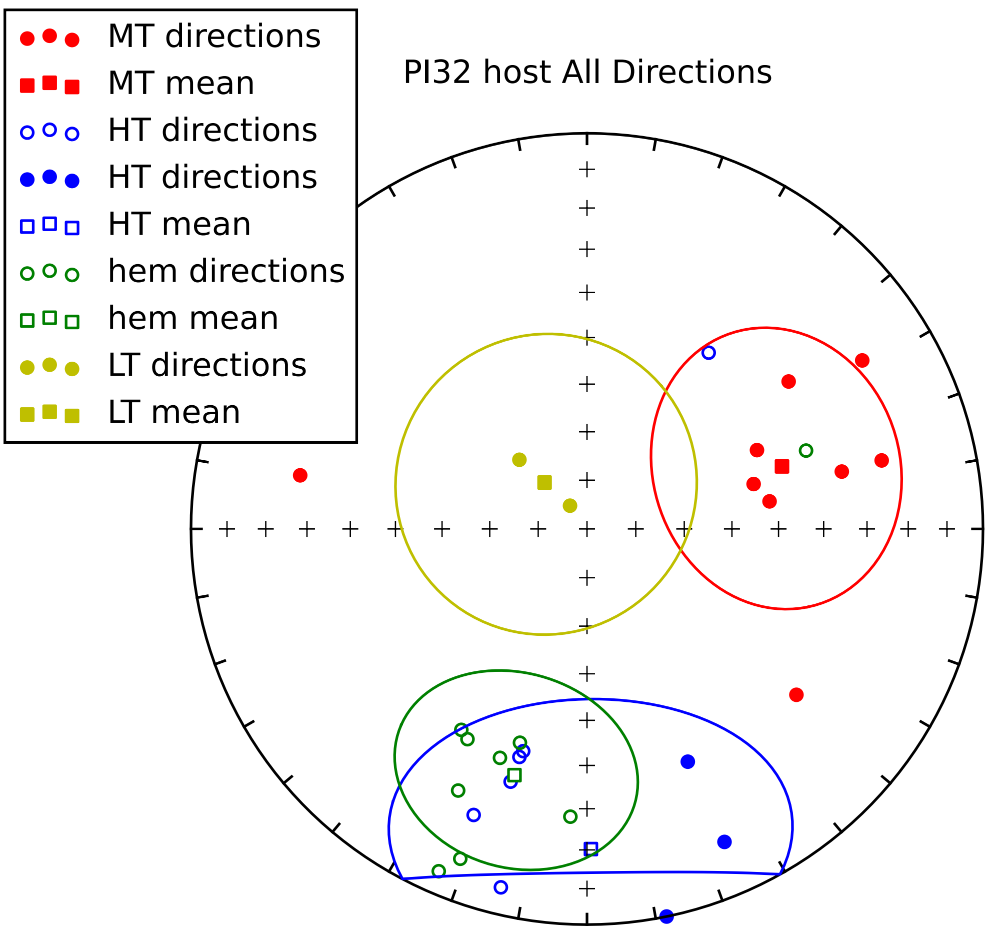
7.1 PI32, PI33 and PI34 host rock sites

In a stratigraphic section of Keweenawan lava flows, sites PI32 and PI33 are from flows that are ∼22 meters and ∼18 meters respectively away from a ∼5 meter thick breccia dike. PI34 is from the flow that is in contact with that ∼5 meter breccia dike with samples within a dike width's distance. PI32 and PI33 have partial impact direction overprints removed at ∼275°C while PI34 is fully overprinted in the impact direction. We interpret these PI34 results to indicate that the complete overprint of the samples is associated with localized heating due to emplacement of the hot breccia dike while the partial overprint on PI32 and PI33 is due to regionally elevated temperatures. These results constitute a positive test of the hypothesis that breccia dikes were emplaced hot into cooler rock and subsequently conductively cooled.

7.1.1 PI32

```
In [28]: PI32_host = ipmag.Site('PI32 host',
                        '../Data/magic_files/Thermal/Host_rock/PI32/')
         PI32_host.eq_plot_everything('PI32 host All Directions',clrs=('r','b','g','y'),loc=(-0.2,0.6))
```

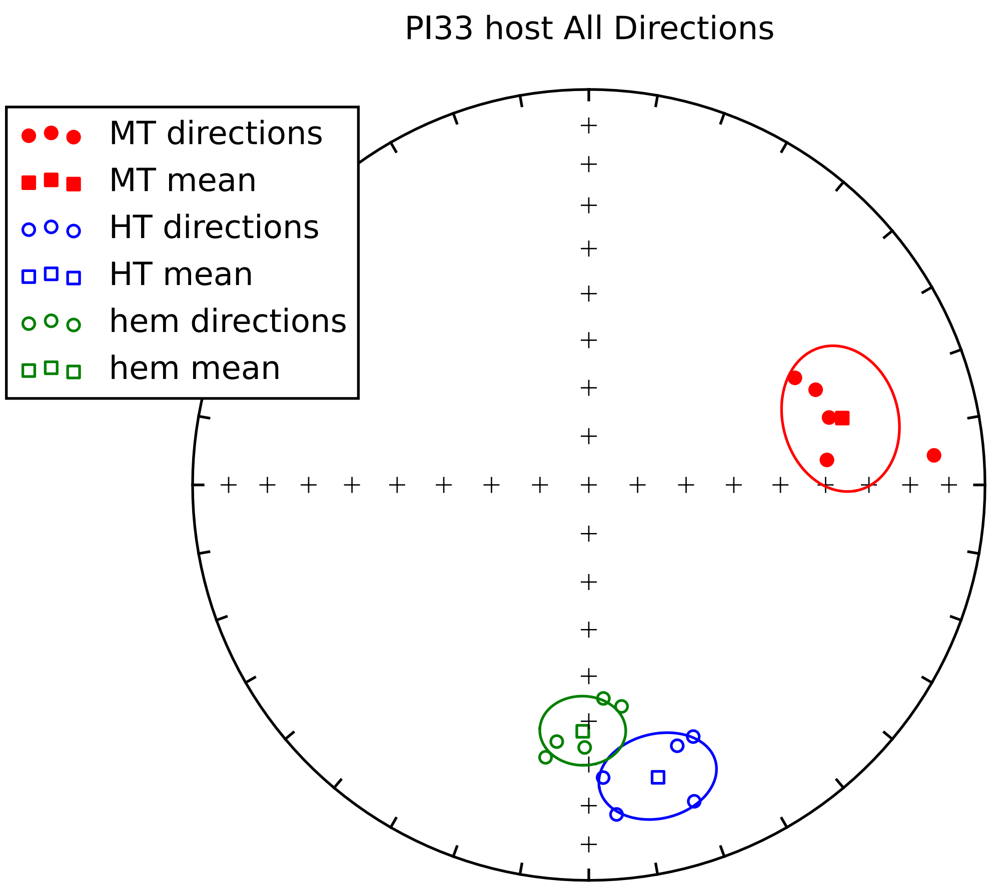
```
Data separated by  ['MT', 'HT', 'hem', 'LT'] fits and can be accessed by <site_name>.<fit_name>
MT_mean
72.2 47.1
HT_mean
179.3 -20.2
hem_mean
196.4 -35.4
LT_mean
317.6 77.1
```



7.1.2 PI33

```
In [29]: PI33_host = ipmag.Site('PI33 host',
                        '../Data/magic_files/Thermal/Host_rock/PI33/')
         PI33_host.eq_plot_everything('PI33 host All Directions',clrs=('r','b','g','y'),loc=(-0.2,0.6))
```

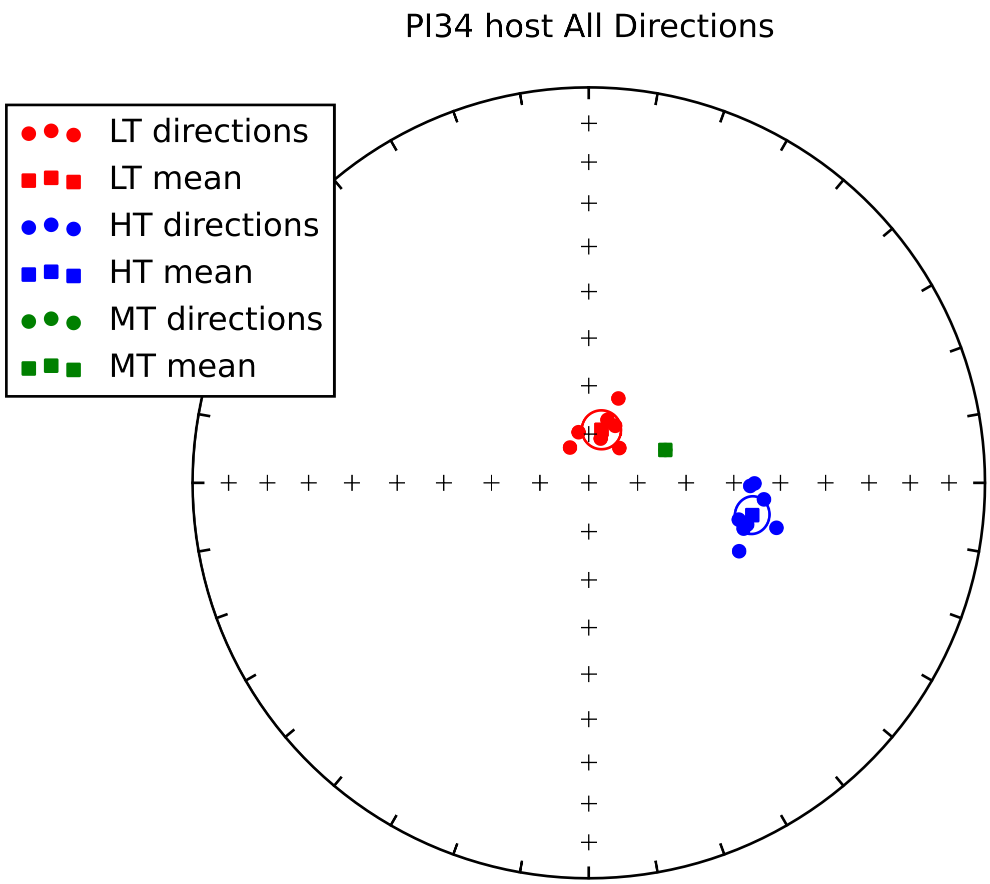
```
Data separated by  ['MT', 'HT', 'hem'] fits and can be accessed by <site_name>.<fit_name>
MT_mean
75.2 34.2
HT_mean
166.7 -25.0
hem_mean
181.4 -37.7
```



7.1.3 PI34

```
In [30]: PI34_host = ipmag.Site('PI34 host',
                        '../Data/magic_files/Thermal/Host_rock/PI34/')
         PI34_host.eq_plot_everything('PI34 host All Directions',clrs=('r','b','g','y'),loc=(-0.2,0.6))
```

```
Data separated by  ['LT', 'HT', 'MT'] fits and can be accessed by <site_name>.<fit_name>
LT_mean
13.4 78.8
HT_mean
101.2 55.4
MT_mean
66.7 72.9
```

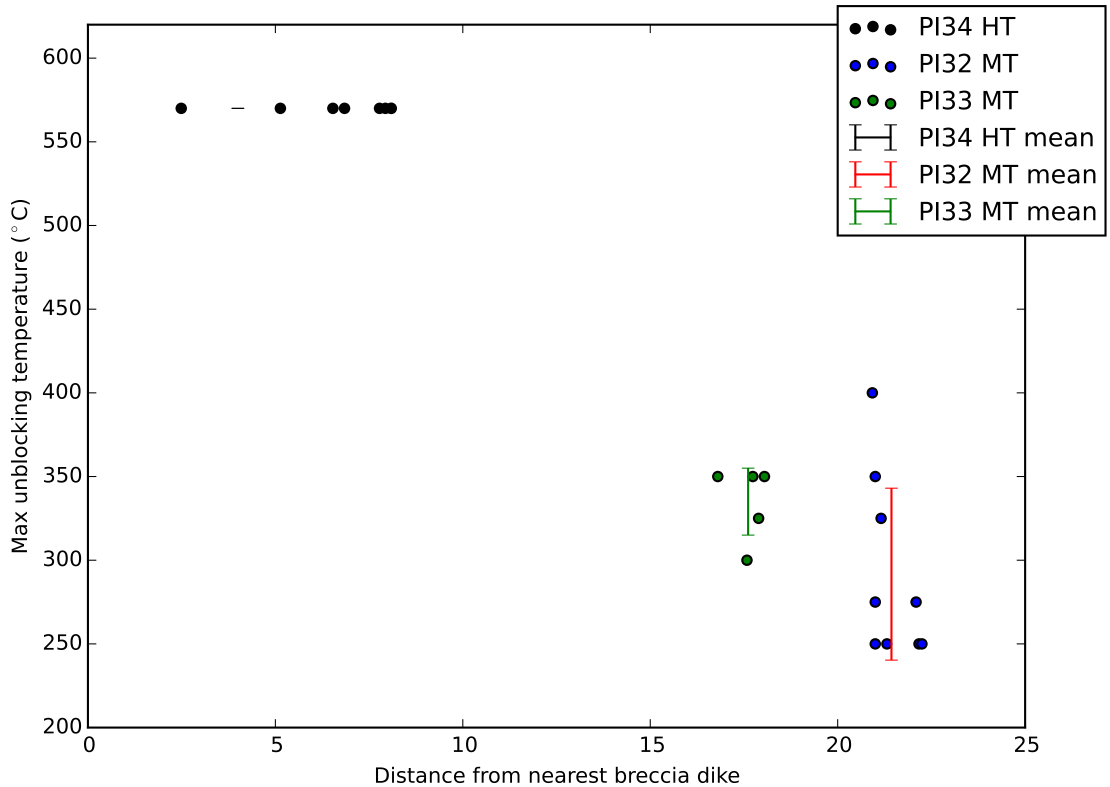


7.1.4 Baked contact test of basalt flow host rock

Below we plot the maximum unblocking temperature of impact-direction overprints within basalt host rock against distance from breccia dike which is within flow PI34.

```
In [31]: BCT(display_breccia=False, display_host=False)
         flow_clr_dict = {'PI32':('b','r-', 'PI32 MT'),
                          'PI33':('g', 'g-','PI33 MT'),
                          'PI34':('k', 'k-','PI34 HT')}
         for flow in flow_clr_dict.keys():
             j=0
             criterion = host_bct['sample'].map(lambda x: x.startswith(flow))
```

```
        host = host_bct[criterion]
        host.reset_index(inplace=True, drop=True)

        data_plt_x = []
        data_plt_y = []

        for i in range(len(host)):
            data_plt_x.append(host.distance_m[i])
            data_plt_y.append(host.max_temp[i])
            if j==0:
                plt.scatter(host.distance_m[i],host.max_temp[i],
                            c=flow_clr_dict[flow][0],
                            label=flow_clr_dict[flow][2])
            else:
                plt.scatter(host.distance_m[i],host.max_temp[i],
                            c=flow_clr_dict[flow][0])
            j=1
        x = np.array(data_plt_x)
        y = np.array(data_plt_y)
        if flow == 'PI34':
            plt.errorbar(4,np.mean(y), yerr=np.std(y),
                         fmt=flow_clr_dict[flow][1],
                         label=flow_clr_dict[flow][2]+' mean')
        else:
            plt.errorbar(np.mean(x),np.mean(y), yerr=np.std(y),
                         fmt=flow_clr_dict[flow][1],
                         label=flow_clr_dict[flow][2] +' mean')

    plt.legend(loc=(0.8,0.7))
    plt.ylim(200,620)
    plt.xlabel('Distance from nearest breccia dike')
    plt.ylabel('Max unblocking temperature ($^\circ$C)')
    plt.savefig('./Code_output/baked_contact_test_flows.pdf')
    plt.show()
```



7.2 Archean schist

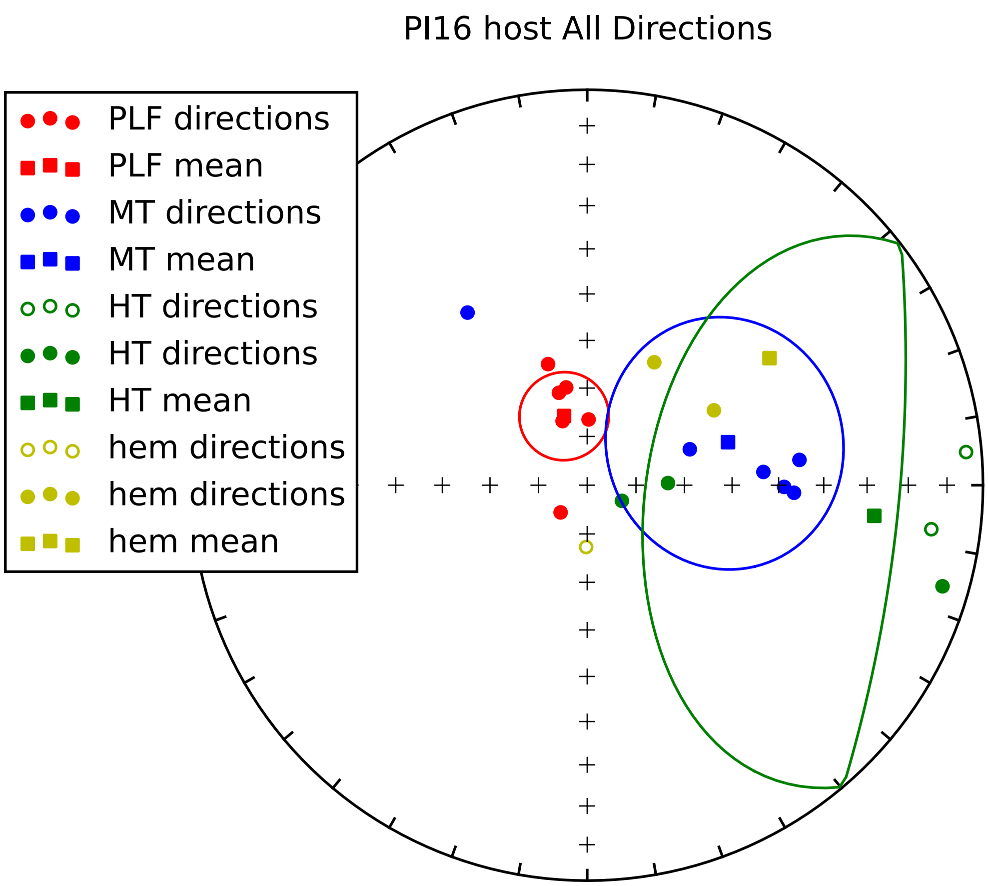
Here we present paleomagnetic data of breccia dike host rock (Archean schist) obtained from three breccia dike sample sites. In addition to Archean schist being poor magnetic recorders with the potential to have pTRM tails that cause remanence to be blocked at high temperatures than the rocks were heated and to have weak pre-impact remanence, the occasional high variability of unblocking temperatures may be due to the fact that the distance from the nearest breccia dike assigned to each data point is often unclear. Breccia dike networks are complicated and may extend closer to our host rock sampling sites than we are able to observe, or that initial breccia dike/host rock contacts have since been eroded. These factors are likely responsible for the outliers in the data shown below. Nevertheless, a relationship between the magnetizations of breccia dike clasts (plotted in red at a negative distance) and their parent (host) rocks can be established from the data. The impact direction magnetizations of host rock are consistently removed at temperatures below 580° C when sampled at appreciable distance from a breccia dike intrusion, indicating that the impact direction in host rocks is a partial thermal overprint (pTRM) as opposed to the full TRM acquired by breccia dike clasts.

7.2.1 PI16 host rock

At site PI16, 5 samples of mafic to intermediate Archean greenschist were collected at a minimum distance of 8 m from the nearest exposed breccia dike, which was approximately 0.4 meters thick. The demagnetization data reveal that these samples have a present local field overprint, a partial impact direction overprint and a poorly resolved direction held at unblocking temperatures above those that remove the impact direction. These results supports the interpretation that heating to temperatures >580°C was localized to the breccia dikes and their immediate vicinity.

```
In [32]: PI16_host = ipmag.Site('PI16',
                       '../Data/magic_files/Thermal/Host_rock/PI16H/')
         PI16_host.eq_plot_everything('PI16 host All Directions', clrs=('r','b','g','y'),
             loc=(-0.2,0.4))
```

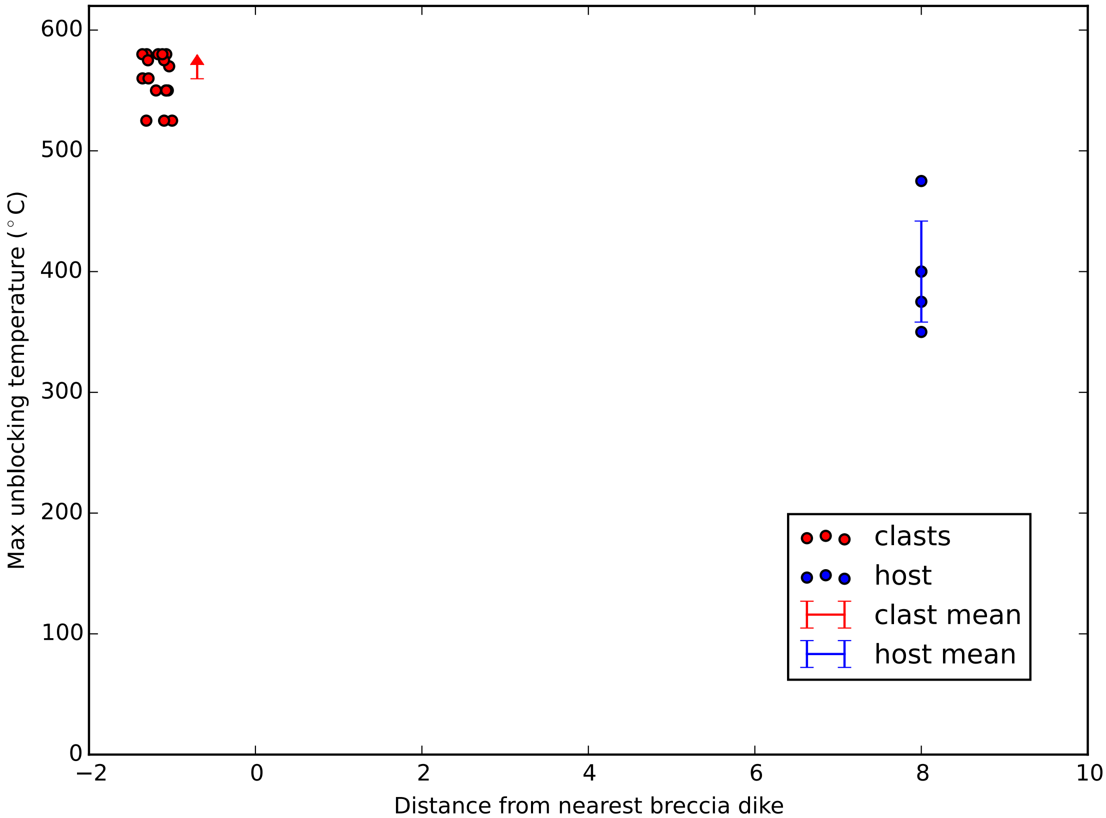
```
Data separated by  ['PLF', 'MT', 'HT', 'hem'] fits and can be accessed by <site_name>.<fit_name>
PLF_mean
341.5 75.0
MT_mean
73.0 59.5
HT_mean
96.1 27.9
hem_mean
55.1 43.2
```



Among the resolvable paleomagnetic directions of breccia dike host rock presented above, the component labeled **MT** (mid-temperatures) is most representative of the Slate Islands impact direction recorded in breccia dikes. Remanence is present after that overprint is removed, but the direction is poorly resolved.

```
In [33]: BCT(host_name = 'PI16', breccia_site='PI16', one_error=True,error_x=8)
         plt.legend(loc=(0.7,0.1))
```

```
plt.ylim(0,620)
plt.xlabel('Distance from nearest breccia dike')
plt.ylabel('Max unblocking temperature ($^\circ$C)')
plt.show()
```

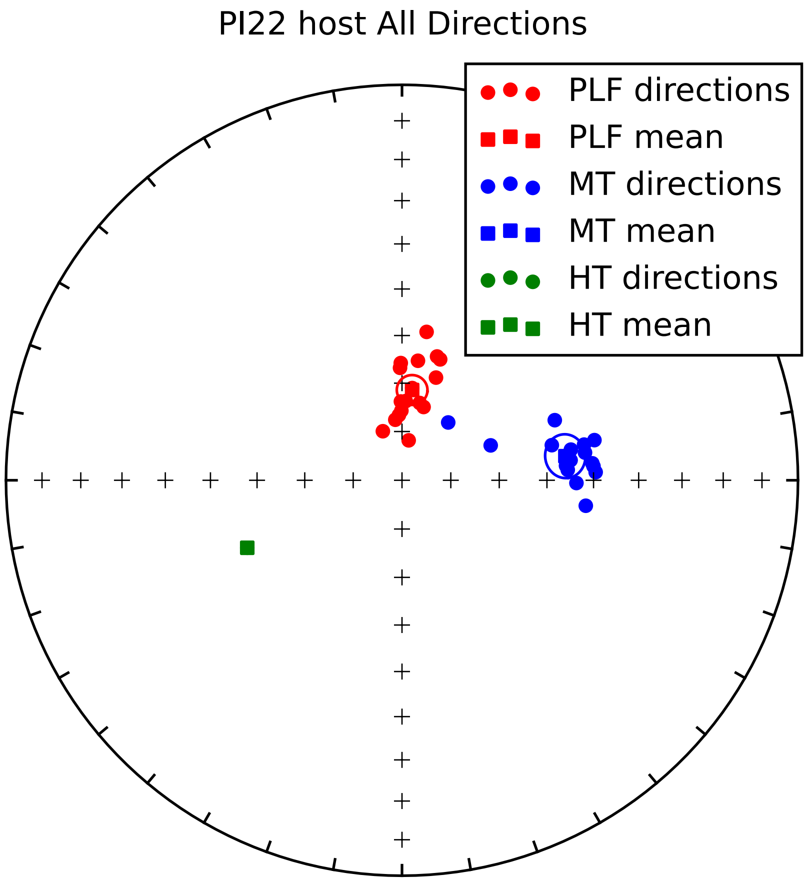


7.2.2 PI22 host rock

At breccia dike site PI22, 16 samples of Archean mafic schist host rock were collected at variable distances (3 cm to >5 m) from the nearest observable breccia dike contact. The thickness of breccia dike PI22 varied from 0.75 - 1.3 meters in the vicinity of the baked contact test.

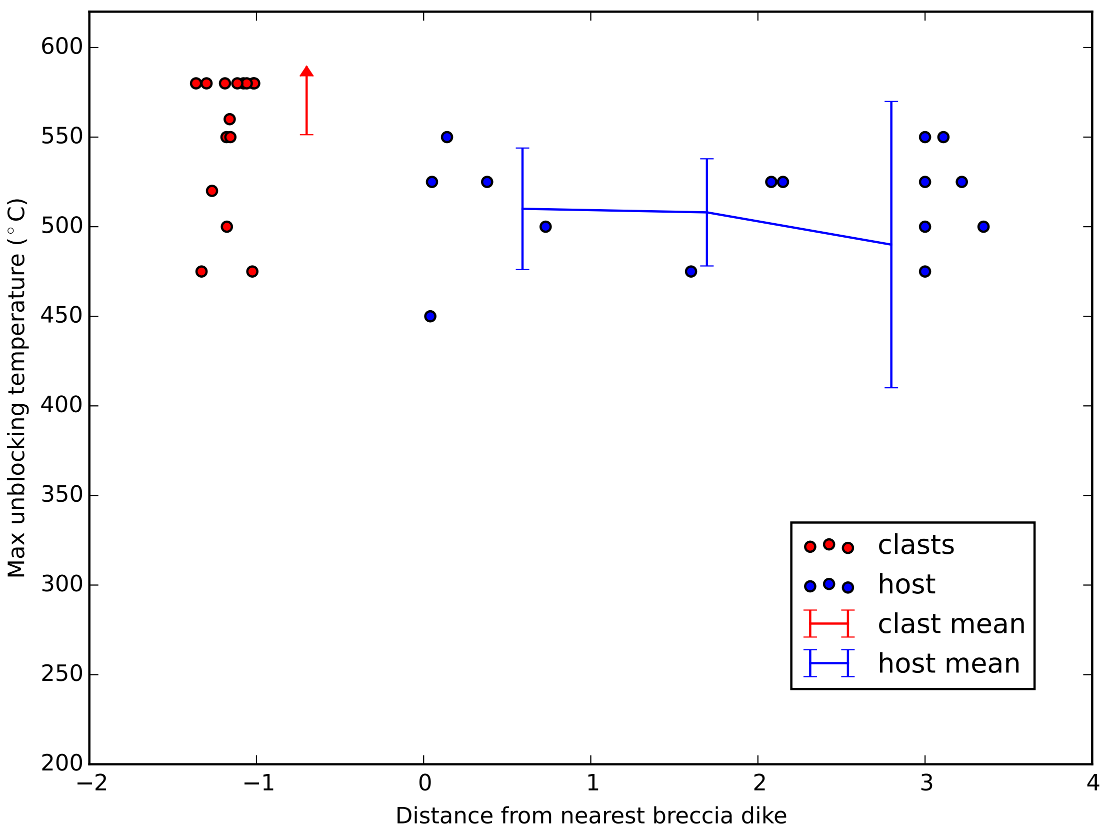
```
In [34]: PI22_host = ipmag.Site('PI22H',
                     '../Data/magic_files/Thermal/Host_rock/PI22H/')
         PI22_host.eq_plot_everything('PI22 host All Directions',clrs=('r','b','g','y'))
```

```
Data separated by  ['PLF', 'MT', 'HT'] fits and can be accessed by <site_name>.<fit_name>
PLF_mean
6.4 71.3
MT_mean
81.6 55.7
HT_mean
246.4 54.9
```



Among the resolvable paleomagnetic directions of breccia dike host rock presented above, the component labeled **MT** (mid-temperatures) is most representative of the Slate Islands impact direction recorded in breccia dikes.

```
In [35]: BCT(host_name='PI22', breccia_site='PI22', fillna=True, na_value=3)
         plt.legend(loc=(0.7,0.1))
         plt.ylim(200,620)
         plt.xlabel('Distance from nearest breccia dike')
         plt.ylabel('Max unblocking temperature ($^\circ$C)')
         plt.show()
```

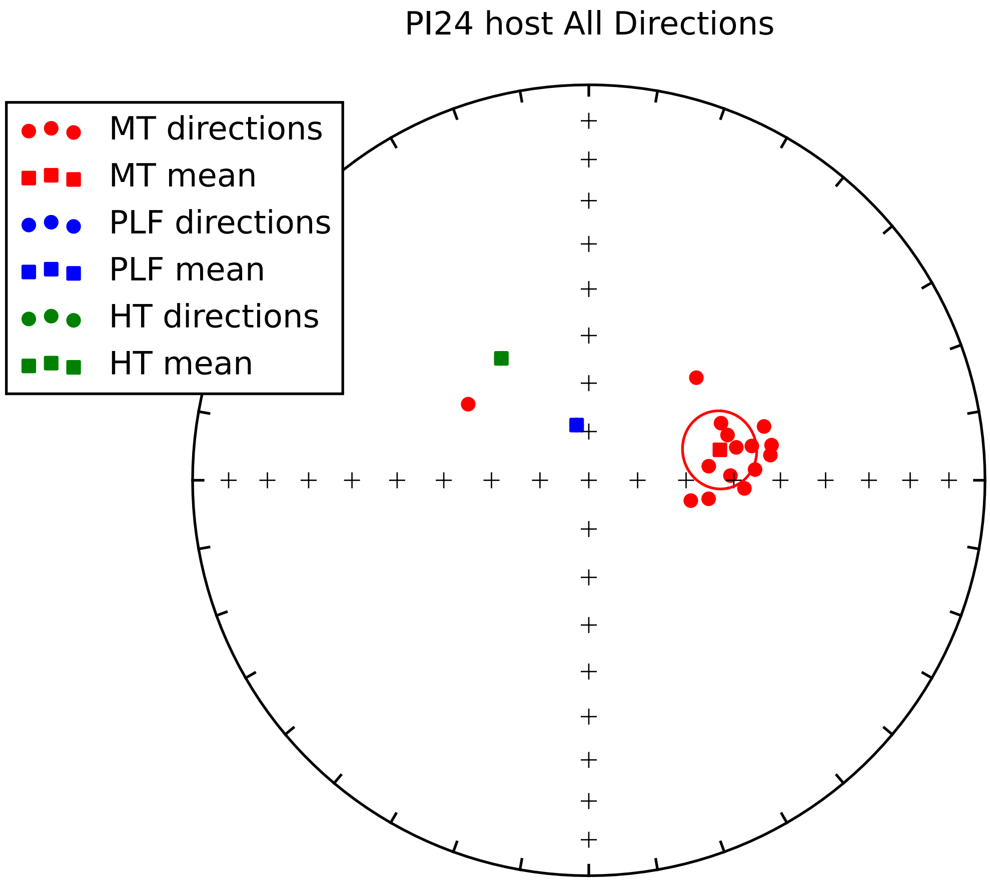


7.2.3 PI24 host rock

At breccia dike site PI24, 15 samples of K-feldspar porphyry host rock were sampled at variable distances (4 cm to >3 m) from the closest observable breccia dike contact. The photo below shows the sharp contact (outlined in yellow) of the breccia dike intrusion (top) with the host rock (bottom) that was amenable to a baked contact test. The thickness of breccia dike PI24 varied from 2.2–2.6 meters in the vicinity of the baked contact test.

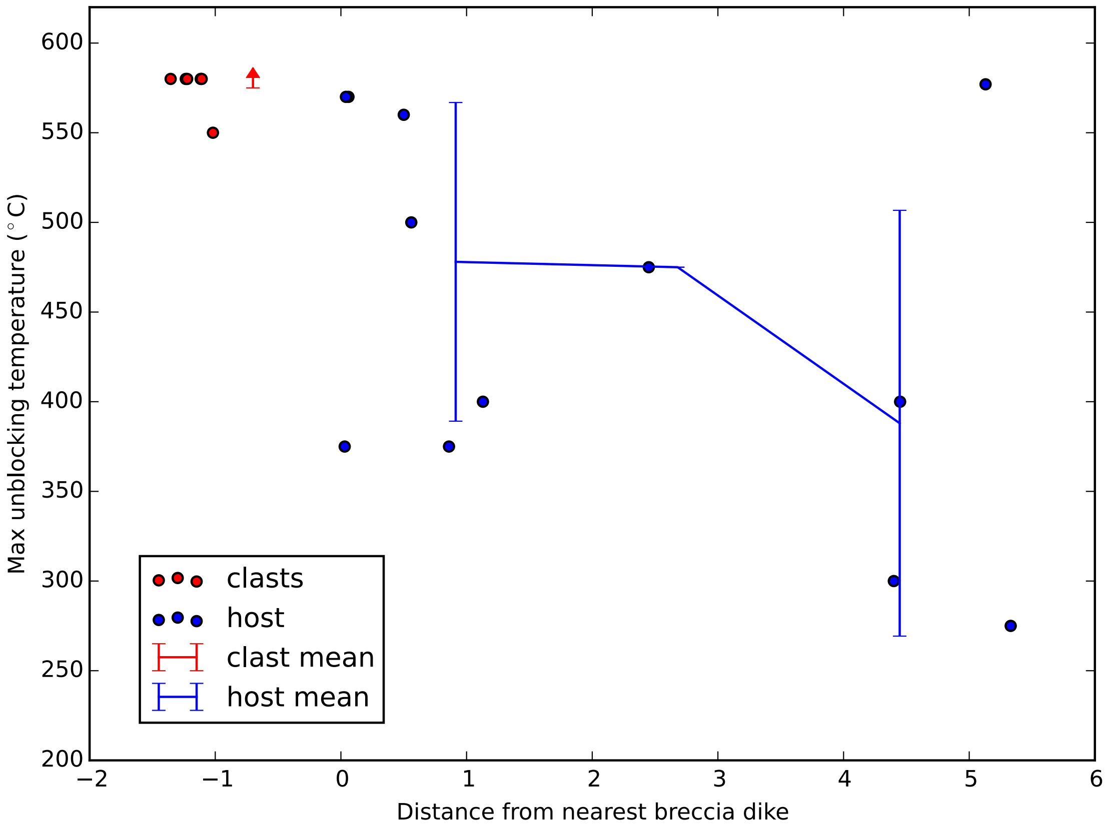
```
In [36]: PI24_host = ipmag.Site('PI24 host',
                         '../Data/magic_files/Thermal/Host_rock/PI24H/')
         PI24_host.eq_plot_everything('PI24 host All Directions',clrs=('r','b','g','y'),loc=(-0.2,0.6))
```

```
Data separated by  ['MT', 'PLF', 'HT'] fits and can be accessed by <site_name>.<fit_name>
MT_mean
76.9 62.2
PLF_mean
347.6 78.4
HT_mean
324.4 58.9
```



Among the resolvable paleomagnetic directions of breccia dike host rock presented above, the component labeled **MT** (mid-temperatures) is most representative of the Slate Islands impact direction recorded in breccia dikes.

```
In [37]: BCT(host_name='PI24', breccia_site='PI24')
         plt.legend(loc=(0.05,0.05))
         plt.ylim(200,620)
         plt.xlabel('Distance from nearest breccia dike')
         plt.ylabel('Max unblocking temperature ($^\circ$C)')
         plt.show()
```



8 Conglomerate Test Results

All breccia dike sites where clasts were sampled failed a paleomagnetic conglomerate test at the 99% confidence level (see table below).

```
In [38]: cong_test_all_data
```

	demag_type	n	R	Ro	result	95_confidence	99_confidence
PI2c	AF	17	8.6718	6.251000	FAIL	YES	YES
PI16	Thermal	17	16.7069	6.251000	FAIL	YES	YES
PI22	Thermal	15	12.9965	6.251000	FAIL	YES	YES
PI24c	Thermal	6	5.9056	3.953479	FAIL	YES	YES
PI31	Thermal	16	10.6733	6.251000	FAIL	YES	YES

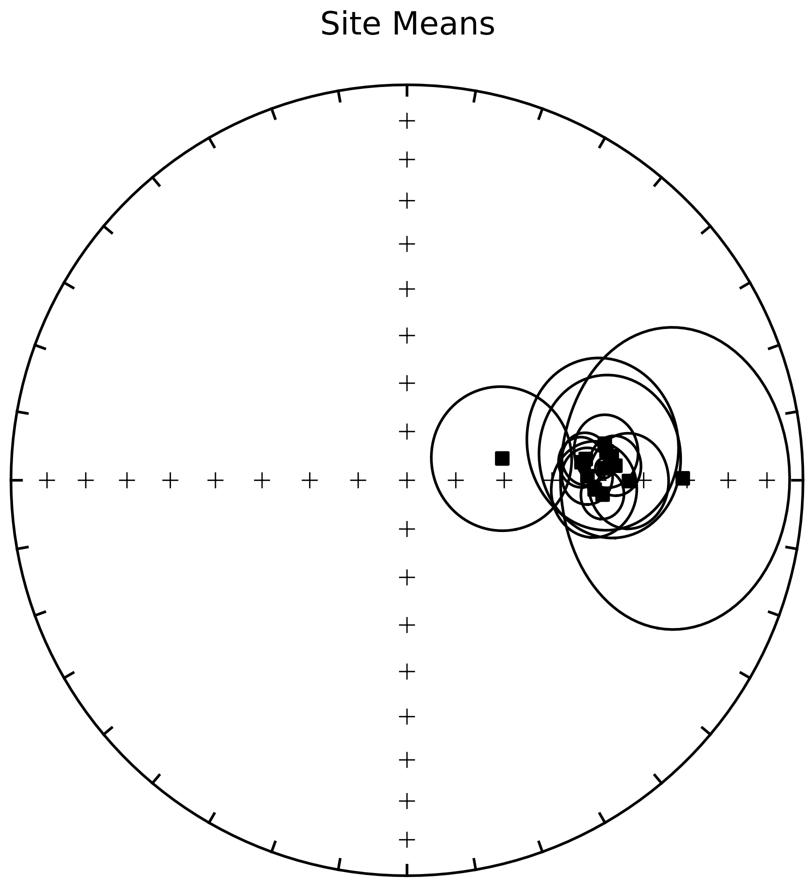
9 Site Means

```
In [39]: site_means
```

	site_type	site_lat	site_lon	demag_type	dec	inc	a_95	n	kappa	R
PI47	breccia dike matrix	48.7	-87.0	Thermal	88.7	52.4	5.5	9	90	8.9112
DeI2	breccia dike matrix	48.7	273.0	Thermal	90.2	43.3	9.0	5	73	4.9456
PI2c	breccia dike clasts	48.6	272.9	AF	77.1	69.9	14.6	9	13	8.3992
PI2m	breccia dike matrix	48.6	272.9	Thermal	79.5	47.9	16.6	5	22	4.8202
PI15	breccia dike matrix	48.6	273.0	Thermal	81.7	47.8	7.0	5	119	4.9664
PI16	breccia dike clasts	48.7	273.0	Thermal	84.1	53.5	4.9	17	55	16.7069
PI22	breccia dike clasts	48.7	273.0	Thermal	83.3	46.8	15.6	15	7	12.9965
PI24c	breccia dike clasts	48.7	273.0	Thermal	92.8	50.8	9.3	6	53	5.9056
PI24m	breccia dike matrix	48.7	273.0	Thermal	86.0	46.2	5.7	6	140	5.9644
PI26	breccia dike matrix	48.6	273.0	Thermal	83.2	52.5	5.1	9	103	8.9220
PI31	breccia dike clasts	48.6	273.0	Thermal	89.6	31.0	27.2	16	3	10.6733
PI44	breccia dike matrix	48.7	272.9	Thermal	86.5	48.7	1.9	12	499	11.9780
PI46	breccia dike matrix	48.7	273.0	Thermal	94.2	49.0	4.7	11	96	10.8956

In [40]:
```
site_means.to_csv('Code_Output/site_means.csv')
```

In [41]:
```
fignum = 10
plt.figure(num=fignum,figsize=(5,5),dpi=200)
ipmag.plot_net(fignum)
for n in range(0,len(site_means)):
    ipmag.plot_di_mean(site_means['dec'][n],
                       site_means['inc'][n],
                       site_means['a_95'][n],
                       color='k',marker='s')
plt.title('Site Means')
plt.savefig('Code_Output/site_means_equal-area_no_outliers.svg')
plt.show()
```



A couple of the site means have quite large α_{95} uncertainities and although they correspond with the mean population, we consider it best to filter them out of the calculation of an overall mean of the sites. Let's only include sites with α_{95}<16 in the calculation of the overall mean.

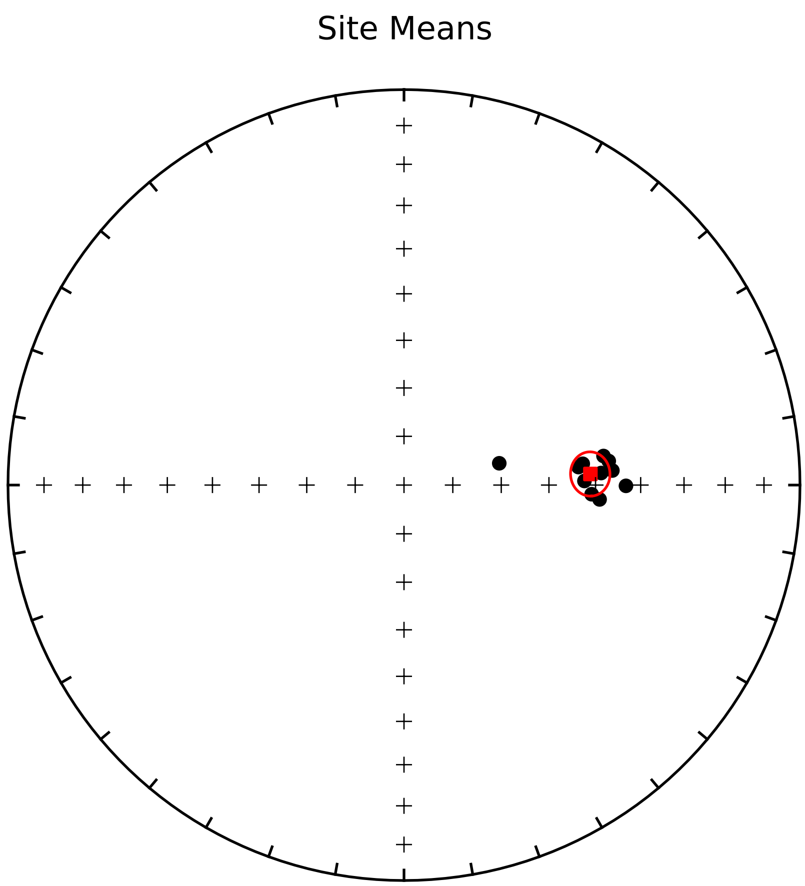
In [42]:
```
site_means_dec=[]
site_means_inc=[]
site_means_directions=[]

for n in list(site_means.index):
    if site_means.loc[n]['a_95'] < 16.0:
        dec = site_means.loc[n]['dec']
        inc = site_means.loc[n]['inc']
        site_means_dec.append(dec)
        site_means_inc.append(inc)
        site_means_directions.append([dec,inc,1.])

site_means_mean = pmag.fisher_mean(site_means_directions)
site_means_mean
```

Out[42]:
```
{'alpha95': 4.2789496500181077,
 'csd': 7.5590170029636949,
```

```
 'dec': 86.592742644284016,
 'inc': 51.049573957404384,
 'k': 114.82577711347182,
 'n': 11,
 'r': 10.912911540845764}
```

The sites (without their α_{95} errors) and the overall mean of the sites with its α_{95} error ellipse are plotted below.

```
In [43]: fignum = 11
         plt.figure(num=fignum,figsize=(5,5),dpi=200)
         ipmag.plot_net(fignum)
         ipmag.plot_di(site_means_dec, site_means_inc)
         ipmag.plot_di_mean(site_means_mean['dec'],
                            site_means_mean['inc'],
                            site_means_mean["alpha95"],
                            color='r',marker='s')
         plt.title('Site Means')
         plt.savefig('Code_Output/site_means_equal-area.svg')
         plt.show()
```



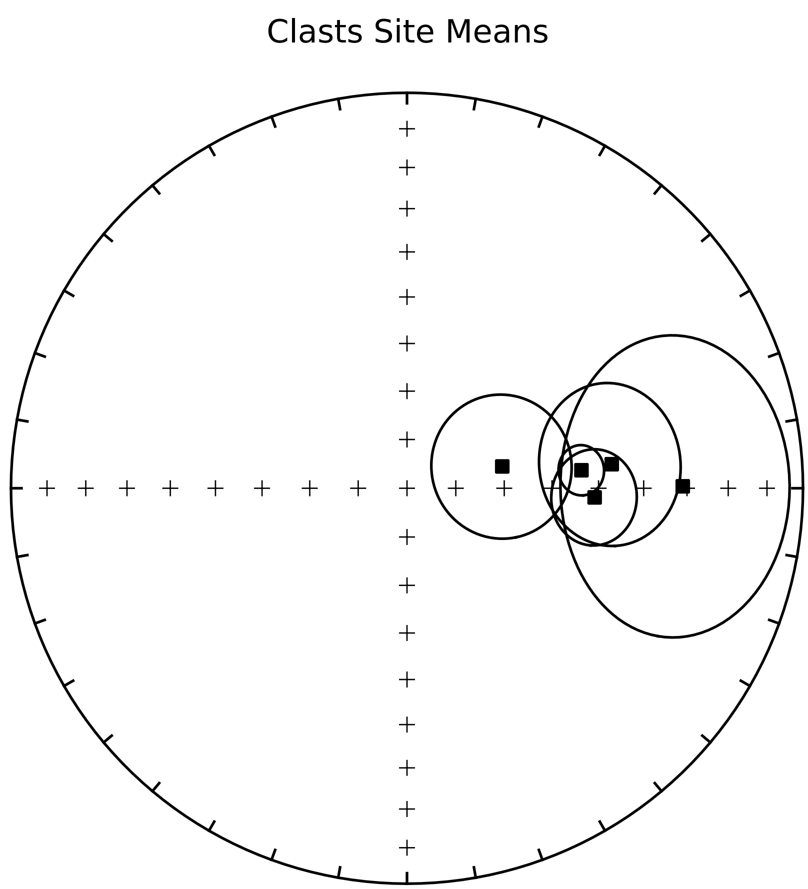
10 Clasts/Matrix Comparison and Calculation of Overall Mean

Here we compile the means of both clast and matrix sample sites and show that they share a common mean.

10.1 Site Means (clasts only)

```
In [44]: site_means_clasts = site_means[(site_means['site_type'] == 'breccia dike clasts')]
         site_means_clasts.to_latex('latex_tables/site_means_clasts.txt')
         site_means_clasts
```

```
In [45]: fignum = 13
         plt.figure(num=fignum,figsize=(5,5),dpi=200)
         ipmag.plot_net(fignum)
         for n in list(site_means_clasts.index):
             ipmag.plot_di_mean(site_means_clasts.loc[n]['dec'],
                                site_means_clasts.loc[n]['inc'],
                                site_means_clasts.loc[n]['a_95'],
                                color='k',marker='s')
         plt.title('Clasts Site Means')
         plt.savefig('Code_Output/site_means_clasts_equal-area_no_outliers.svg')
         plt.show()
```

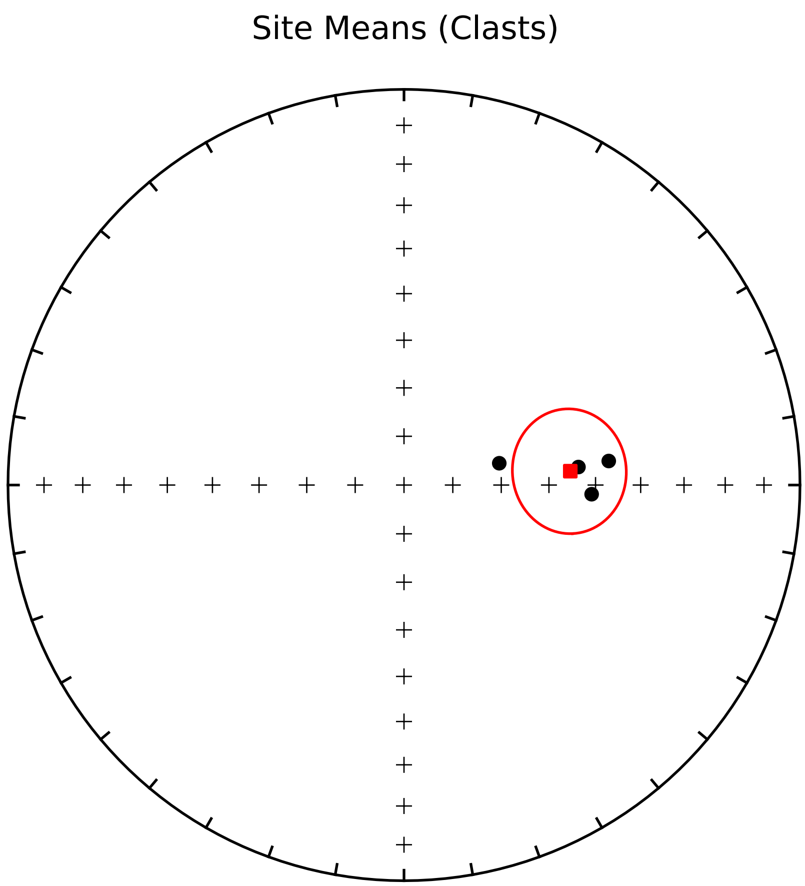


Let's restrict the calculation of the overall mean to sites with α_{95}<16.

In [46]:
```
site_means_clasts_dec=[]
site_means_clasts_inc=[]
site_means_clasts_directions=[]

for n in list(site_means_clasts.index):
    if site_means_clasts.loc[n]['a_95']<16:
        dec = site_means_clasts.loc[n]['dec']
        inc = site_means_clasts.loc[n]['inc']
        site_means_clasts_dec.append(dec)
        site_means_clasts_inc.append(inc)
        site_means_clasts_directions.append([dec,inc,1.])

site_means_clasts_mean = pmag.fisher_mean(site_means_clasts_directions)
site_means_clasts_mean
```

Out[46]:
```
{'alpha95': 12.227681675928041,
 'csd': 10.688665779374091,
 'dec': 85.226853841210229,
 'inc': 55.331533387344237,
 'k': 57.427914197308326,
 'n': 4,
 'r': 3.9477605961851108}
```

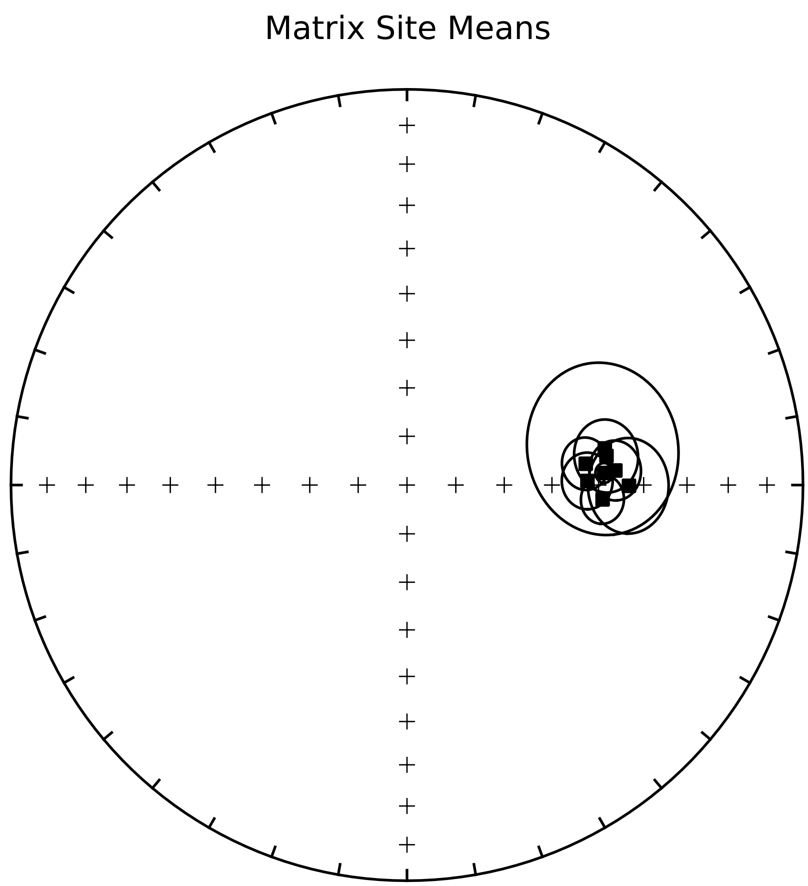
In [47]:
```
fignum = 14
plt.figure(num=fignum,figsize=(5,5),dpi=200)
ipmag.plot_net(fignum)
ipmag.plot_di(site_means_clasts_dec, site_means_clasts_inc)
ipmag.plot_di_mean(site_means_clasts_mean['dec'],
                   site_means_clasts_mean['inc'],
                   site_means_clasts_mean["alpha95"],
                   color='r',marker='s')
plt.title('Site Means (Clasts)')
plt.savefig('Code_Output/site_means_clasts_equal-area.svg')
plt.show()
```



10.2 Site Means (matrix only)

In [48]:
```
site_means_matrix = site_means[(site_means['site_type'] == 'breccia dike matrix')]
site_means_matrix
```

In [49]:
```
fignum = 13
plt.figure(num=fignum,figsize=(5,5),dpi=200)
ipmag.plot_net(fignum)
for n in list(site_means_matrix.index):
    ipmag.plot_di_mean(site_means_matrix.loc[n]['dec'],
                       site_means_matrix.loc[n]['inc'],
                       site_means_matrix.loc[n]['a_95'],
                       color='k',marker='s')
plt.title('Matrix Site Means')
plt.savefig('Code_Output/site_means_matrix_equal-area_no_outliers.svg')
plt.show()
```



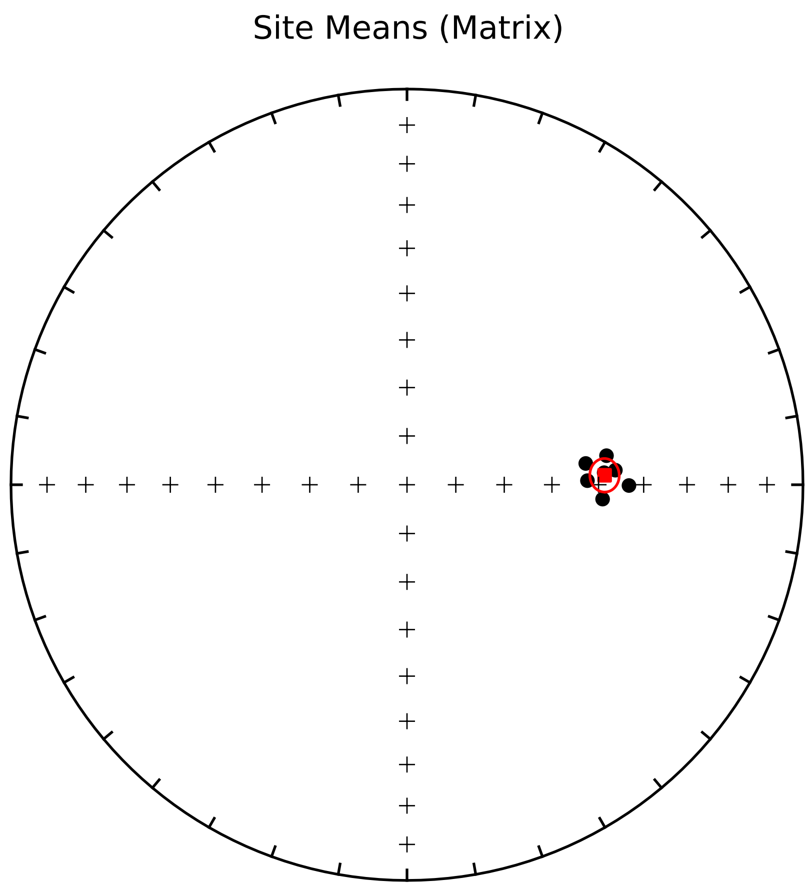
Once again, let's restrict the calculation of the overall mean to sites with α_{95}<16.

```
In [50]: site_means_matrix_dec=[]
         site_means_matrix_inc=[]
         site_means_matrix_directions=[]

         for n in list(site_means_matrix.index):
             if site_means_matrix.loc[n]['a_95']<16:
                 dec = site_means_matrix.loc[n]['dec']
                 inc = site_means_matrix.loc[n]['inc']
                 site_means_matrix_dec.append(dec)
                 site_means_matrix_inc.append(inc)
                 site_means_matrix_directions.append([dec,inc,1.])

         site_means_matrix_mean = pmag.fisher_mean(site_means_matrix_directions)
         site_means_matrix_mean
```

```
Out[50]: {'alpha95': 3.2155705333618667,
          'csd': 4.3088183805335873,
          'dec': 87.257210905039727,
          'inc': 48.624300303943357,
```

```
 'k': 353.38951537893479,
 'n': 7,
 'r': 6.9830215675935765}
```

```
In [51]: fignum = 14
         plt.figure(num=fignum,figsize=(5,5),dpi=200)
         ipmag.plot_net(fignum)
         ipmag.plot_di(site_means_matrix_dec, site_means_matrix_inc)
         ipmag.plot_di_mean(site_means_matrix_mean['dec'],
                            site_means_matrix_mean['inc'],
                            site_means_matrix_mean["alpha95"],
                            color='r',marker='s')
         plt.title('Site Means (Matrix)')
         plt.savefig('Code_Output/site_means_matrix_equal-area.svg')
         plt.show()
```



Now let's see if both clasts and matrix yield a common mean. We exclude clast sites **PI2c** and **PI31** from our analysis given the irregularity of the AF data and large α_{95}, respectively.

```
In [52]: Slate_breccia_dec_clasts=[]
         Slate_breccia_inc_clasts=[]
```

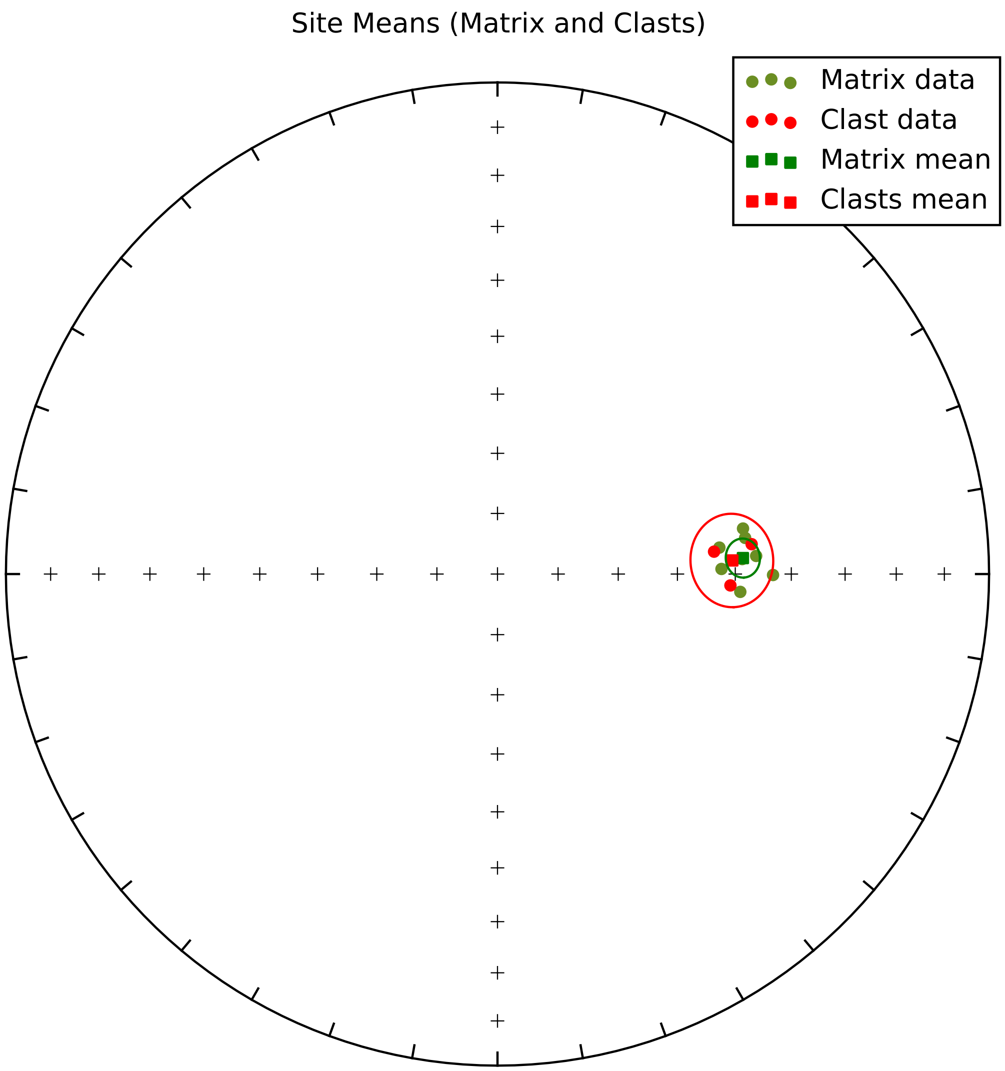
```
        Slate_breccia_DI_clasts=[]

        for n in ('PI16','PI22','PI24c'):
            Slate_breccia_dec_clasts.append(site_means_clasts.loc[n]['dec'])
            Slate_breccia_inc_clasts.append(site_means_clasts.loc[n]['inc'])
            Slate_breccia_DI_clasts.append([site_means_clasts.loc[n]['dec'],
                                            site_means_clasts.loc[n]['inc']])
```

and matrix:

```
In [53]: Slate_breccia_dec_matrix=[]
         Slate_breccia_inc_matrix=[]
         Slate_breccia_DI_matrix=[]

         for n in ('PI2m','PI15','DeI2','PI24m','PI26','PI44','PI46','PI47'):
             Slate_breccia_dec_matrix.append(site_means_matrix.loc[n]['dec'])
             Slate_breccia_inc_matrix.append(site_means_matrix.loc[n]['inc'])
             Slate_breccia_DI_matrix.append([site_means_matrix.loc[n]['dec'],
                                             site_means_matrix.loc[n]['inc']])
```

From this, we can calculate the means for both clasts and matrix for comparison:

```
In [54]: matrix_selected_sites_mean = pmag.fisher_mean(Slate_breccia_DI_matrix)
         clasts_selected_sites_mean = pmag.fisher_mean(Slate_breccia_DI_clasts)

         fignum = 14
         plt.figure(num=fignum,figsize=(7,7),dpi=200)
         ipmag.plot_net(fignum)
         ipmag.plot_di(Slate_breccia_dec_matrix, Slate_breccia_inc_matrix, color='OliveDrab', label = 'I
         ipmag.plot_di(Slate_breccia_dec_clasts, Slate_breccia_inc_clasts, color='Red', label = 'Clast c
         ipmag.plot_di_mean(matrix_selected_sites_mean['dec'],
                            matrix_selected_sites_mean['inc'],
                            matrix_selected_sites_mean["alpha95"],
                            color='Green',marker='s', label = 'Matrix mean')
         ipmag.plot_di_mean(clasts_selected_sites_mean['dec'],
                            clasts_selected_sites_mean['inc'],
                            clasts_selected_sites_mean["alpha95"],
                            color='Red',marker='s', label = 'Clasts mean')
         plt.title('Site Means (Matrix and Clasts)')
         plt.legend()
         plt.savefig('Code_Output/matrix_clasts_equal-area.svg')
         plt.show()
```

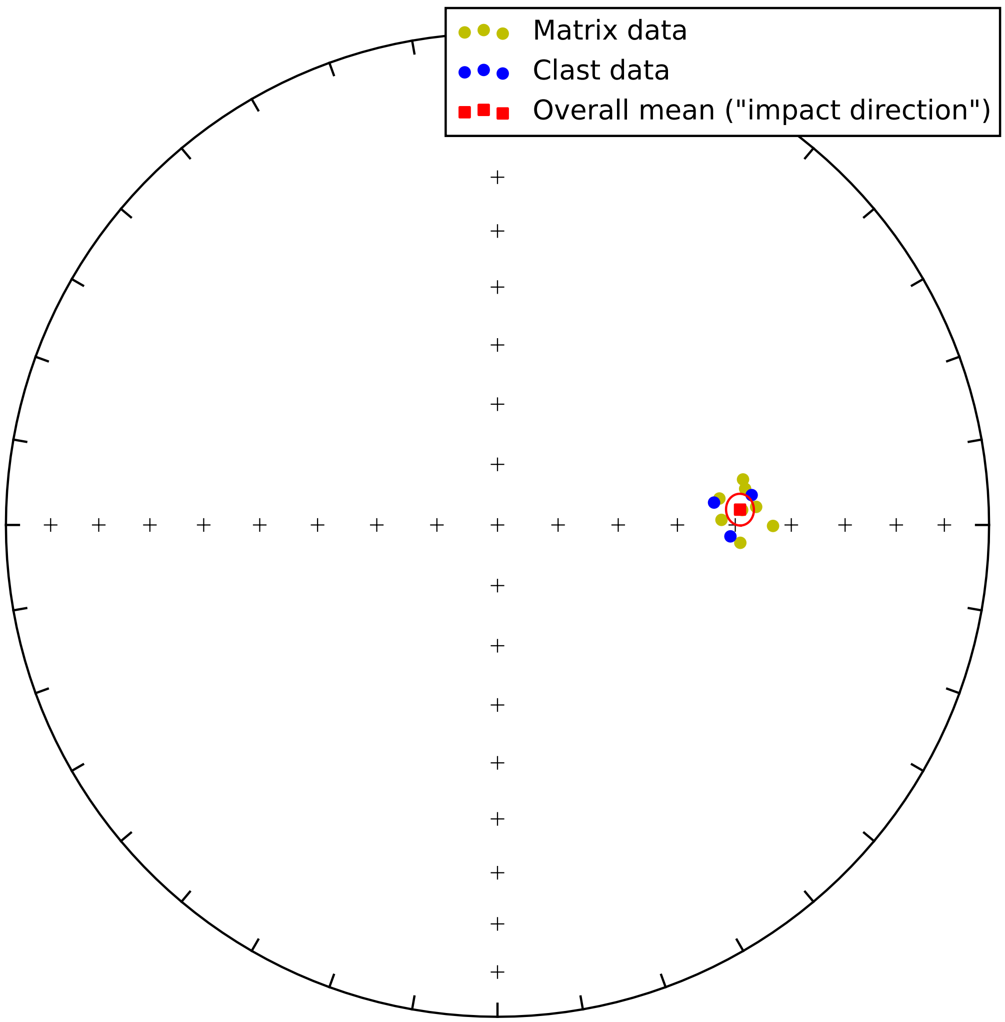


10.3 Overall Mean

We calculate an overall mean paleomagnetic direction for breccia dikes in the Slate Islands that combines the matrix and clast results. This direction can be considered to be the Slate Islands "impact direction."

```
In [55]: selected_sites_mean = pmag.fisher_mean(Slate_breccia_DI_matrix+Slate_breccia_DI_clasts)

In [56]: selected_sites_mean

Out[56]: {'alpha95': 2.4493063331415144,
          'csd': 4.3390825666803758,
          'dec': 86.384629275498114,
          'inc': 49.076457694734884,
          'k': 348.47707222251483,
          'n': 11,
          'r': 10.9713037074829}
```

```
In [57]: fignum = 30
         plt.figure(num=fignum,figsize=(7,7),dpi=200)
         ipmag.plot_net(fignum)
         #ipmag.plot_di(Slate_breccia_dec_matrix, Slate_breccia_inc_matrix, label='Site means')
         #ipmag.plot_di(Slate_breccia_dec_clasts, Slate_breccia_inc_clasts, label='Site means')
         ipmag.plot_di(Slate_breccia_dec_matrix, Slate_breccia_inc_matrix, color='y', label = 'Matrix da
         ipmag.plot_di(Slate_breccia_dec_clasts, Slate_breccia_inc_clasts, color='b', label = 'Clast dat
         ipmag.plot_di_mean(selected_sites_mean['dec'],
                            selected_sites_mean['inc'],
                            selected_sites_mean["alpha95"],
                            color='r',marker='s',label='Overall mean ("impact direction")')
         plt.legend()
         plt.savefig('Code_Output/equal-area_selected_overall_mean.svg')
         plt.show()
```



11 Virtual Geomagnetic Pole Calculations

11.1 VGP calculation with all data

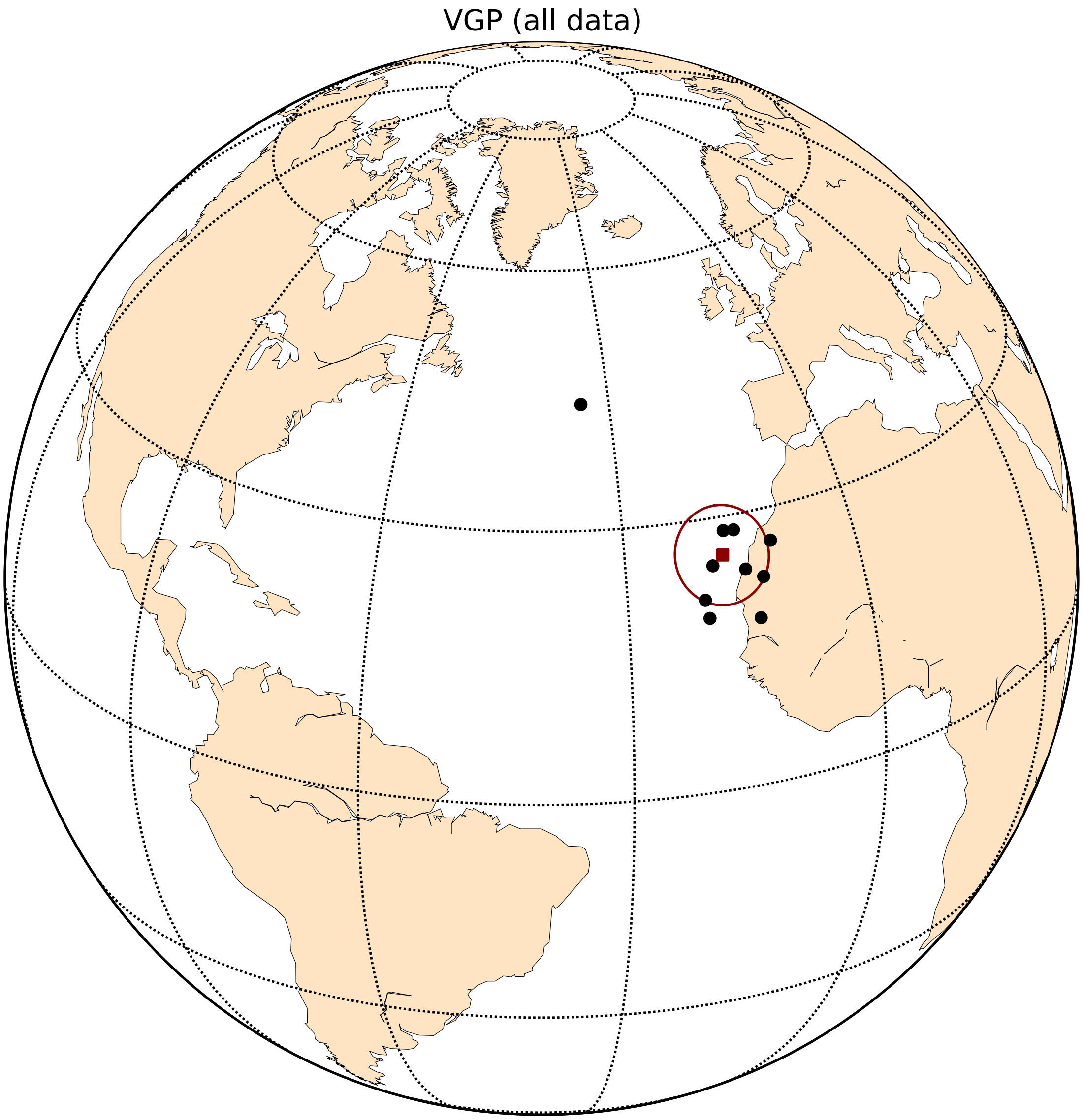
Here we calculate the virtual geomagnetic pole (VGP) of each site.

In [58]:
```
ipmag.vgp_calc(site_means, dec_tc='dec', inc_tc='inc')
site_means.to_latex('latex_tables/site_means_and_vgps.txt')
site_means
```

	site_type	paleolatitude	vgp_lat	vgp_lon	vgp_lat_rev	vgp_lon_rev
PI47	breccia dike matrix	32.994182	24.939599	340.629082	-24.939599	160.629082
DeI2	breccia dike matrix	25.228696	18.549815	345.588504	-18.549815	165.588504
PI2c	breccia dike clasts	53.799750	43.828671	325.841478	-43.828671	145.841478
PI2m	breccia dike matrix	28.958430	27.945514	349.775862	-27.945514	169.775862
PI15	breccia dike matrix	28.873360	26.475001	348.474455	-26.475001	168.474455
PI16	breccia dike clasts	34.047335	28.478517	342.659758	-28.478517	162.659758
PI22	breccia dike clasts	28.032887	24.900680	348.126813	-24.900680	168.126813
PI24c	breccia dike clasts	31.510820	21.417962	339.161877	-21.417962	159.161877
PI24m	breccia dike matrix	27.537319	22.839605	346.699576	-22.839605	166.699576
PI26	breccia dike matrix	33.088776	28.366994	343.989806	-28.366994	163.989806
PI31	breccia dike clasts	16.721861	12.723598	352.051585	-12.723598	172.051585
PI44	breccia dike matrix	29.645851	23.992766	344.617234	-23.992766	164.617234
PI46	breccia dike matrix	29.906833	19.431098	339.451746	-19.431098	159.451746

First, let's calculate a mean pole for all data:

In [59]:
```
Slate_breccia_VGPs=[]
Slate_breccia_Plong=[]
Slate_breccia_Plat=[]

for n in range(0,len(site_means)):
    if site_means['a_95'][n]<15:
        Plong,Plat=site_means['vgp_lon'][n],site_means['vgp_lat'][n]
        Slate_breccia_VGPs.append([Plong,Plat,1.])
        Slate_breccia_Plong.append(Plong)
        Slate_breccia_Plat.append(Plat)

Breccia_pole_mean=pmag.fisher_mean(Slate_breccia_VGPs)

plt.figure(figsize=(8, 8))
m = Basemap(projection='ortho',lat_0=25,lon_0=320,
            resolution='c',area_thresh=50000)
m.drawcoastlines(linewidth=0.25)
m.fillcontinents(color='bisque',lake_color='white',zorder=1)
m.drawmapboundary(fill_color='white')
m.drawmeridians(np.arange(0,360,30))
m.drawparallels(np.arange(-90,90,30))

ipmag.plot_vgp(m,Slate_breccia_Plong,Slate_breccia_Plat)
ipmag.plot_pole(m,Breccia_pole_mean['dec'],Breccia_pole_mean['inc'],
                Breccia_pole_mean['alpha95'],label='Slate breccia mean',
                marker='s',color='DarkRed')
plt.savefig('Code_output/VGP_all_data.pdf')
plt.title('VGP (all data)')
plt.show()
```




```
In [60]: ipmag.vgp_calc(site_means_clasts, dec_tc='dec', inc_tc='inc')
         site_means_clasts.to_latex('latex_tables/site_means_clasts.txt')
         site_means_clasts
```

From the clast sites above, we select sites **PI16**, **PI22**, and **PI24c** based on $\alpha_{95} < 16.0$ and reliability of demagnetization data (irregular AF demagnetization data of PI2c was rejected for the final analysis).

```
In [61]: Slate_breccia_VGPs_clasts=[]
         Slate_breccia_Plong_clasts=[]
         Slate_breccia_Plat_clasts=[]
         Slate_breccia_dec_clasts=[]
         Slate_breccia_inc_clasts=[]
         Slate_breccia_DI_clasts=[]

         #Using VGPs where DI_alpha95<16
```

```
#Use PI16 thermal, PI22 thermal, PI24 thermal
for n in ('PI16','PI22','PI24c'):
    Plong = site_means_clasts['vgp_lon'][n]
    Plat = site_means_clasts['vgp_lat'][n]
    Slate_breccia_VGPs_clasts.append([Plong,Plat,1.])
    Slate_breccia_Plong_clasts.append(Plong)
    Slate_breccia_Plat_clasts.append(Plat)
    Slate_breccia_dec_clasts.append(site_means_clasts['dec'][n])
    Slate_breccia_inc_clasts.append(site_means_clasts['inc'][n])
    Slate_breccia_DI_clasts.append([site_means_clasts['dec'][n],
                                    site_means_clasts['inc'][n]])

Breccia_pole_mean_clasts=pmag.fisher_mean(Slate_breccia_VGPs_clasts)
```

```
In [62]: ipmag.vgp_calc(site_means_matrix, dec_tc='dec', inc_tc='inc')
         site_means_matrix.to_latex('latex_tables/site_means_matrix.txt')
         site_means_matrix
```

All matrix sites above were selected for the final VGP analysis.

```
In [63]: Slate_breccia_VGPs_matrix=[]
         Slate_breccia_Plong_matrix=[]
         Slate_breccia_Plat_matrix=[]
         Slate_breccia_dec_matrix=[]
         Slate_breccia_inc_matrix=[]
         Slate_breccia_DI_matrix=[]

         #Using VGPs where DI_alpha95<10 and using either AF or thermal for single site
         #based on lower DI_alpha95

         for n in ('PI2m','PI15','DeI2','PI24m','PI26','PI44','PI46','PI47'):
             Plong,Plat=site_means_matrix['vgp_lon'][n],site_means_matrix['vgp_lat'][n]
             Slate_breccia_VGPs_matrix.append([Plong,Plat,1.])
             Slate_breccia_Plong_matrix.append(Plong)
             Slate_breccia_Plat_matrix.append(Plat)
             Slate_breccia_dec_matrix.append(site_means_matrix['dec'][n])
             Slate_breccia_inc_matrix.append(site_means_matrix['inc'][n])
             Slate_breccia_DI_matrix.append([site_means_matrix['dec'][n],
                                             site_means_matrix['inc'][n]])

         Breccia_pole_mean_matrix=pmag.fisher_mean(Slate_breccia_VGPs_matrix)
```

11.2 Mean Pole

Now let's calculate the final virtual geomagnetic pole for our selected data. Then, let's compare this VGP to the corresponding paleopole of the Laurentian APWP using data compiled by Torsvik (2012).

```
In [64]: Slate_breccia_VGPs_all = Slate_breccia_VGPs_clasts + Slate_breccia_VGPs_matrix
         Slate_breccia_Plong_all = Slate_breccia_Plong_matrix + Slate_breccia_Plong_clasts
         Slate_breccia_Plat_all = Slate_breccia_Plat_matrix + Slate_breccia_Plat_clasts
         Slate_breccia_VGPs_all_mean = pmag.fisher_mean(Slate_breccia_VGPs_all)
         Slate_breccia_VGPs_all_mean
```

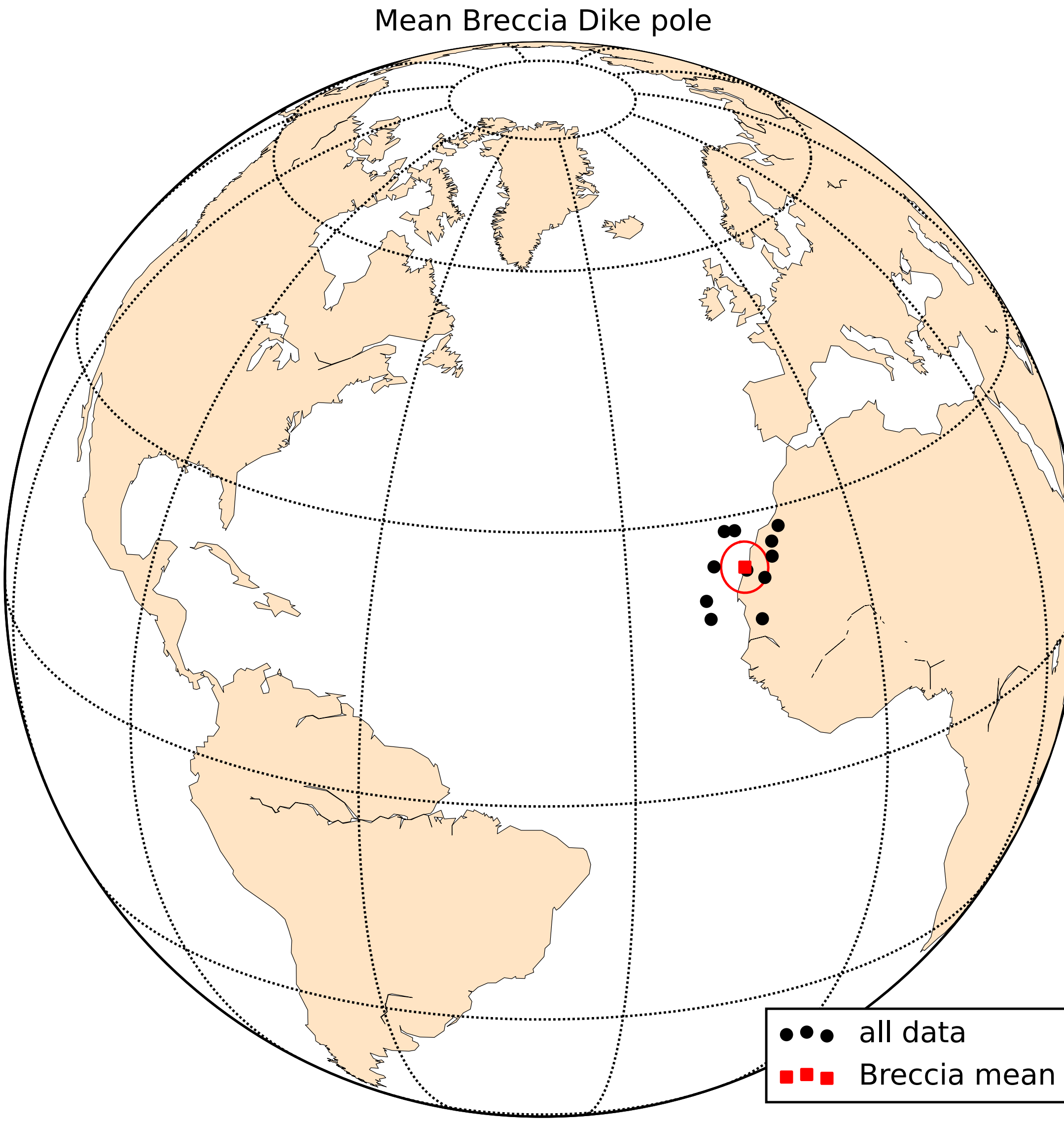
```
Out[64]: {'alpha95': 2.7221302583356581,
          'csd': 4.8208406069443672,
```

```
 'dec': 344.43709458172481,
 'inc': 24.344490277837423,
 'k': 282.30884990783176,
 'n': 11,
 'r': 10.964577801924152}
```

In [65]:
```
Slate_breccia_VGPs_all
```

Out[65]:
```
[[342.6597578995881, 28.478517393057071, 1.0],
 [348.12681294861392, 24.900679973982339, 1.0],
 [339.16187730323963, 21.41796247221362, 1.0],
 [349.77586230694658, 27.945513904950364, 1.0],
 [348.47445515872732, 26.47500062457603, 1.0],
 [345.58850397383299, 18.5498148685672, 1.0],
 [346.69957626235396, 22.839604966214189, 1.0],
 [343.98980574310781, 28.366994404340627, 1.0],
 [344.61723408807387, 23.9927664226059, 1.0],
 [339.45174629362003, 19.431097632218133, 1.0],
 [340.62908212720566, 24.939599070070557, 1.0]]
```

In [66]:
```
plt.figure(figsize=(8, 8))
m = Basemap(projection='ortho',lat_0=25,lon_0=320,
            resolution='c',area_thresh=50000)
m.drawcoastlines(linewidth=0.25)
m.fillcontinents(color='bisque',lake_color='white',zorder=1)
m.drawmapboundary(fill_color='white')
m.drawmeridians(np.arange(0,360,30))
m.drawparallels(np.arange(-90,90,30))

ipmag.plot_vgp(m,Slate_breccia_Plong_all,
              Slate_breccia_Plat_all,label='all data',color='Black')
ipmag.plot_pole(m,Slate_breccia_VGPs_all_mean['dec'],
               Slate_breccia_VGPs_all_mean['inc'],
               Slate_breccia_VGPs_all_mean['alpha95'],
               label='Breccia mean',marker='s',color='Red')
plt.legend(loc=4)
plt.savefig('Code_output/site_VGPs.pdf')
plt.title('Mean Breccia Dike pole')
plt.show()
```



11.3 Comparison to Laurentia APWP

First, let's compare our VGP to the Phanerozoic APWP compiled by Torsvik (2012).

```
In [67]: Laurentia_Pole_Compilation = pd.read_csv('APWP analysis/Laurentia_Pole_Compilation.csv')
         Laurentia_Pole_Compilation.to_latex('latex_tables/Laurentia_Pole_Compilation.txt')
         Laurentia_Pole_Compilation
```

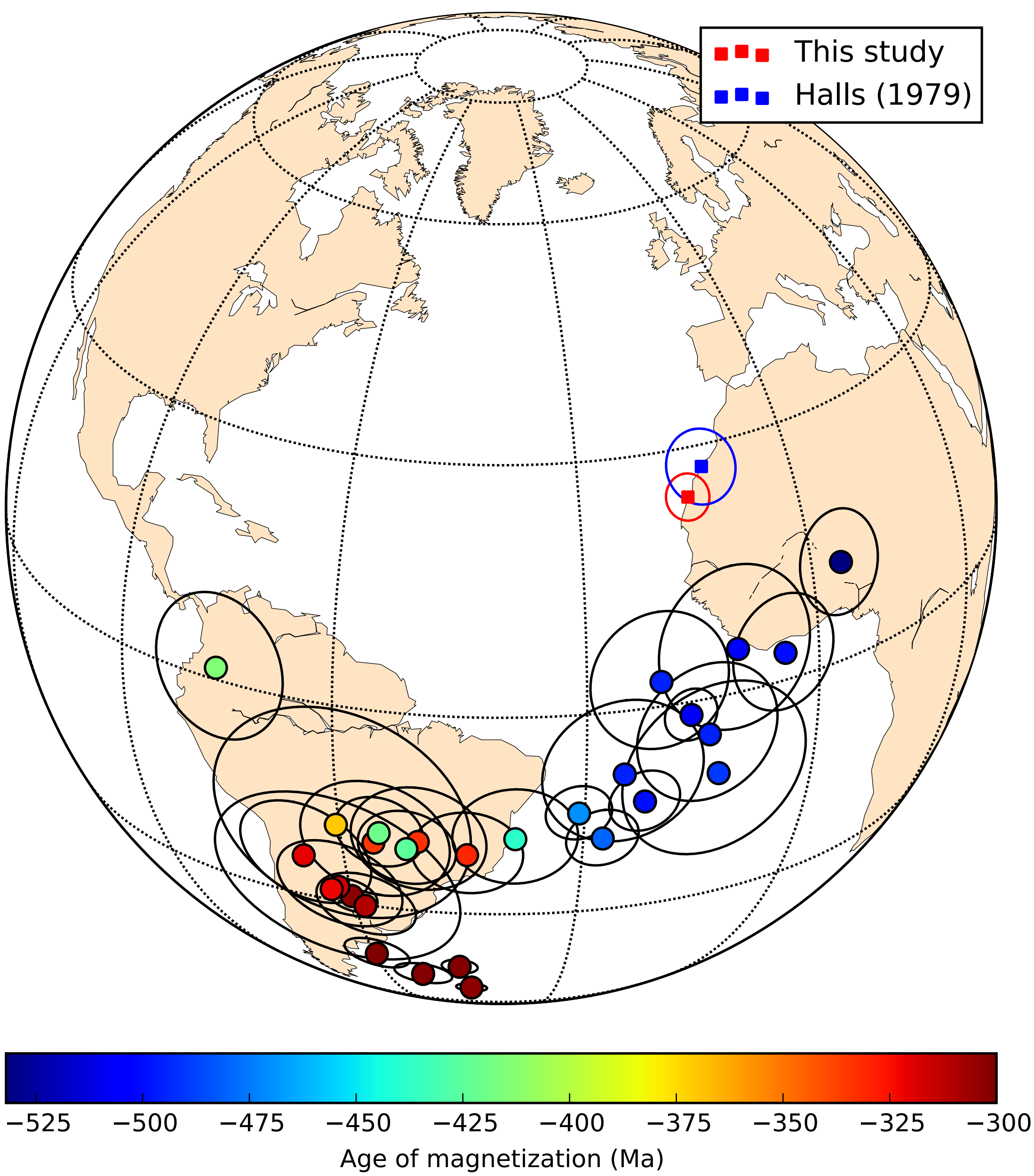
	Q	A95	Com	Formation	Lat	Lon	CLat	CLon
0	5	3.9	NaN	Dunkard Formation	-44.1	301.5	-41.5	300.4
1	5	2.1	NaN	Laborcita Formation	-42.1	312.1	-43.0	313.4
2	5	3.4	#	Wescogame Formation	-44.1	303.9	-46.3	306.8
3	6	3.1	I	Glenshaw Formation	-28.6	299.9	-28.6	299.9
4	5	1.8	NaN	Lower Casper Formation	-45.7	308.6	-50.5	314.6
5	5	6.0	NaN	Riversdale Group	-36.0	302.0	-30.2	301.5
6	7	7.7	I	Shepody Formation, Nova Scotia	-27.2	298.3	-27.2	298.3
7	6	8.3	I	Mauch Chunk	-22.6	294.4	-22.6	294.4
8	7	15.3	I	Maringouin Formation, Nova Scotia	-27.9	297.2	-27.9	297.2
9	4	6.5	NaN	New Brunswick volcanics I and redbeds	-19.5	315.8	-19.5	315.8
10	6	8.0	NaN	Jeffreys Village Member	-27.0	311.0	-17.8	309.8
11	7	9.0	I__	Deer Lake Formation	-18.6	304.2	-18.6	304.2
12	3	16.0	NaN	Catskill Formation South	-27.4	303.0	-16.6	299.6
13	4	9.0	NaN	Andreas red beds	-13.0	285.0	1.5	284.8
14	7	5.3	NaN	Wabash Reef	-17.0	305.0	-17.0	305.0
15	6	5.8	NaN	Rose Hill Formation	-19.1	308.3	-19.1	308.3
16	4	7.3	NaN	Ringgold Gap sediments	-24.0	326.6	-16.9	321.7
17	4	3.9	NaN	Tablehead Group limestone Mean	-13.4	329.3	-13.4	329.3
18	4	4.3	NaN	St. George Group limestone	-17.5	332.4	-17.5	332.4
19	6	11.9	NaN	Oneota Dolomite	-10.3	346.5	-10.3	346.5
20	5	8.5	NaN	Moore Hollow sediments	0.6	343.0	3.1	338.9
21	5	9.7	NaN	Morgan Creek	-10.6	338.0	-8.4	334.6
22	5	9.0	NaN	Point Peak	-5.2	345.8	-4.7	345.0
23	5	7.1	NaN	Taum Sauk limestone	3.4	355.1	3.4	355.1
24	6	4.3	NaN	Royer Dolomite	-12.6	337.3	-12.6	337.3
25	6	10.0	NaN	Florida Mountains	5.4	348.7	5.4	348.7
26	5	3.3	NaN	Tapeats Sandstone	-0.6	341.1	-1.7	342.6
27	5	6.2	NaN	Mont Rigaud and Chatham Grenville	11.9	4.5	11.9	4.5

	RLat	RLon	EULER	Age	GPDB RefNo/Reference
0	-38.0	43.0	(63.2/_ 13.9/79.9)	300	302, T
1	-32.7	52.9	(63.2/_ 13.9/79.9)	301	1311, T
2	-38.2	51.4	(63.2/_ 13.9/79.9)	301	1311, T
3	-28.6	32.4	(63.2/_ 13.9/79.9)	303	Kodama (2009)
4	-37.6	59.8	(63.2/_ 13.9/79.9)	303	1455, T
5	-29.0	34.8	(63.2/_ 13.9/79.9)	310	1110, T
6	-28.4	30.2	(63.2/_ 13.9/79.9)	317	Bilardello and Kodama (2010a)
7	-26.9	23.8	(63.2/_ 13.9/79.9)	320	Bilardello and Kodama (2010a)
8	-29.5	29.8	(63.2/_ 13.9/79.9)	322	Bilardello and Kodama (2010a)
9	-12.6	39.2	(63.2/_ 13.9/79.9)	330	Seguin et al. (1985)
10	NaN	NaN	NaN	333	1534, T
11	NaN	NaN	NaN	335	Bilardello and Kodama (2010b)
12	NaN	NaN	NaN	370	1693
13	NaN	NaN	NaN	415	1388, T96
14	NaN	NaN	NaN	420	1277, T96
15	NaN	NaN	NaN	425	1218
16	NaN	NaN	NaN	438	1689
17	NaN	NaN	NaN	470	2257, 1931, T96 (recalculated)
18	NaN	NaN	NaN	480	1928, T96
19	NaN	NaN	NaN	490	1283, T96
20	NaN	NaN	NaN	495	2383, T96
21	NaN	NaN	NaN	495	2376, T96
22	NaN	NaN	NaN	495	801, T96
23	NaN	NaN	NaN	500	1284, T96
24	NaN	NaN	NaN	500	2289, T96
25	NaN	NaN	NaN	503	2375, T96
26	NaN	NaN	NaN	508	1044, T96
27	NaN	NaN	NaN	532	McCausland et al., 2007

We use the actual paleopoles (no running mean) for this comparison. Then, let's add breccia dike data from Halls (1979) for comparison. We then add a color code to indicate the age of each paleopole. We are focused on comparision with ∼440 Ma paleopole, as this is the age of the Slate Islands impact inferred from Ar-Ar data (Dressler, 1999).

In [68]:
```
plt.figure(figsize=(8, 8))
pmap = Basemap(projection='ortho',lat_0=25,lon_0=320,
               resolution='c',area_thresh=50000)
pmap.drawcoastlines(linewidth=0.25)
pmap.fillcontinents(color='bisque',lake_color='white',zorder=1)
pmap.drawmapboundary(fill_color='white')
pmap.drawmeridians(np.arange(0,360,30))
pmap.drawparallels(np.arange(-90,90,30))

ipmag.plot_pole(pmap,Slate_breccia_VGPs_all_mean['dec'],
               Slate_breccia_VGPs_all_mean['inc'],
               Slate_breccia_VGPs_all_mean['alpha95'],
               label='This study',
               marker='s',color='Red')

#Halls data:
ipmag.plot_pole(pmap,347.1,27.5,4.4,label='Halls (1979)',
               marker='s',color='Blue')

for n in xrange (0, len(Laurentia_Pole_Compilation)):
```

```
        m = ipmag.plot_pole_colorbar(pmap, Laurentia_Pole_Compilation['CLon'][n],
                                     Laurentia_Pole_Compilation['CLat'][n],
                                     Laurentia_Pole_Compilation['A95'][n],
                                     -Laurentia_Pole_Compilation['Age'][n],
                                     -532,
                                     -300,
                                     markersize=80, color="k", alpha=1)

pmap.colorbar(m,location='bottom',pad="5%",label='Age of magnetization (Ma)')
plt.legend()
plt.savefig('Code_output/site_VGP_with_Laurentia_Pole_Compilation_colorbar.pdf')
plt.show()
```



```
In [69]: print "The distance between the Slate Island VGP and the ca. 490 Ma Oneota Dolomite pole is:"
         print pmag.angle([Slate_breccia_VGPs_all_mean['dec'],
                          Slate_breccia_VGPs_all_mean['inc']],
                     [Laurentia_Pole_Compilation['CLon'][19],
                                             Laurentia_Pole_Compilation['CLat'][19]])
         print "The distance between the Slate Island VGP and the ca. 438 Ma Ringgold Gap pole is:"
         print pmag.angle([Slate_breccia_VGPs_all_mean['dec'],
                          Slate_breccia_VGPs_all_mean['inc']],
                     [Laurentia_Pole_Compilation['CLon'][16],
                                             Laurentia_Pole_Compilation['CLat'][16]])
```

```
The distance between the Slate Island VGP and the ca. 490 Ma Oneota Dolomite pole is:
[ 34.7029994]
The distance between the Slate Island VGP and the ca. 438 Ma Ringgold Gap pole is:
[ 46.83051059]
```

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We see that there is an ˜47° difference between the Slate Islands VGP and the Silurian paleopole that most closely corresponds in age to the 440 Ma age assigned to the Slate Islands impact through Ar-Ar dating of pseudotachylite impact melt (Dressler et al., 1999). It is ˜35° from the ca. 490 Ma Oneota Dolomite pole.

Halls (1979) noted the similiarity of the Slate Islands VGP to the late Meso- to Neoproterozoic “Grenville Loop” of the Laurentia APWP. Given the quickly-acquired nature of magnetizations in the Slate Islands, this VGP cannot account for secular variation and therefore may correspond to a wide range of well-averaged paleopoles within the APWP. Additionally, the non-linear “loop” nature of this section of the APWP serves to cluster poles of a wide age range within a single location. Because of this, Halls (1979) uses the Slate Islands VGP to date the impact but can only do so within a very general timeframe of 500-900 Ma.

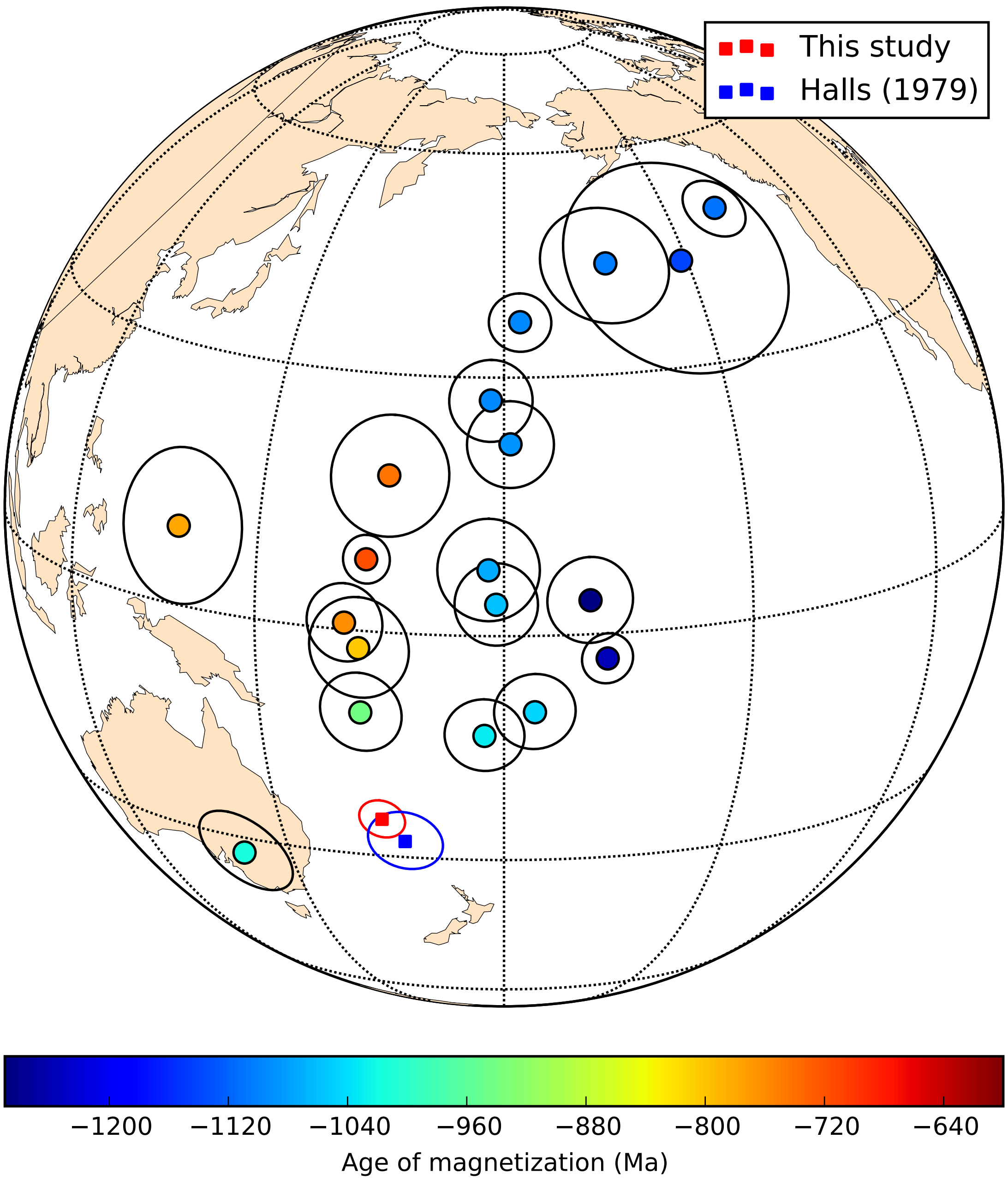
Here we compare the Slate Islands VGP (reversed polarity) to the Proterozoic APWP of Laurentia as compiled by Swanson-Hysell et al. (2012).

```
In [70]: Laurentia_Prot_poles = pd.read_csv('APWP analysis/Laurentia_Proterozoic_APWP.csv')
         Laurentia_Prot_poles_info = pd.read_csv('APWP analysis/Swanson-Hysell2012_Prot_APWP.csv')
         Laurentia_Prot_poles_info.to_latex('latex_tables/Laurentia_Prot_poles_info.txt')
         Laurentia_Prot_poles_info
```

	pole	abbr	Lat (N)	Long (E)	α_{95}	Age (Ma)	Reference
0	Mackenzie Dykes	L-MD	4.0	190.0	5.0	1267	Buchan and Halls (1990)
1	Sudbury Dykes	L-SD	-3.0	192.0	3.0	1235+7/-3	Palmer et al. (1977)
2	Abitibi Dykes	L-AD	43.0	209.0	14.0	1141	Ernst and Buchan (1993)
3	Logan sills	L-LS	49.0	220.0	4.0	1109	Buchan et al. (2000)
4	Osler Volcanics	L-OV	43.7	196.3	7.6	1105	Halls (1974)
5	North Shore Volcanic Group (upper)	L-NSVG	36.7	182.3	3.6	1098.4, 1096.6	Tauxe and Kodama (2009)
6	Portage Lake Volcanics	L-PL	27.3	178.3	4.8	1095	Hnat et al. (2006)
7	Lake Shore Traps	L-LST	22.2	180.8	5.0	1087	Diehl and Haig (1994)
8	Nonesuch Shale	L-NS	7.7	178.2	5.9	<1087	Henry et al. (1977)
9	Freda Sandstone	L-FS	3.7	179.1	4.8	<L-NS	Henry et al. (1977)
10	Jacobsville Sandstone	L-JS	-9.3	183.6	4.7	<L-FS	Roy and Robertson (1978)
11	Chequamegon Sandstone	L-CS	-12.3	177.7	4.6	<L-FS, upper L-JS	McCabe and Van der Voo (1983)
12	Haliburton Intrusives	L-HI	-32.6	141.9	6.3	1015	Warnock et al. (2000)
13	Nankoweap Formation	L-NF	-10.0	163.0	4.9	<942 Ma	Weil et al. (2003)
14	Gunbarrel dykes and sills	L-GB	9.2	138.7	9.0	782-776	Harlan et al. (2008)
15	Uinta Mountain Group	L-UM	0.8	161.3	4.6	780-742	Weil et al. (2006)
16	Galeros Formation	L-GF	-2.1	163.0	6.0	804	Weil et al. (2004)
17	Kwagunt Formation	L-KF	18.2	166.0	7.0	>742	Weil et al. (2004)
18	Franklin Event Grand Mean	L-FLIP	8.4	163.8	2.8	721-712	Denyszyn et al. (2009)
19	Long Range Dykes	L-LRD	19.0	355.3	17.4	615	Murthy et al. (1992)

In [71]:
```
plt.figure(figsize=(8, 8))
pmap = Basemap(projection='ortho',lat_0=15,lon_0=180,
               resolution='c',area_thresh=50000)
pmap.drawcoastlines(linewidth=0.25)
pmap.fillcontinents(color='bisque',lake_color='white',zorder=1)
pmap.drawmapboundary(fill_color='white')
pmap.drawmeridians(np.arange(0,360,30))
pmap.drawparallels(np.arange(-90,90,30))
```

```
ipmag.plot_pole(pmap,(Slate_breccia_VGPs_all_mean['dec']+180)%360,
               -Slate_breccia_VGPs_all_mean['inc'],
               Slate_breccia_VGPs_all_mean['alpha95'],
               label='This study',
               marker='s',color='Red')

#Halls data:
ipmag.plot_pole(pmap,347.1-180,-27.5,4.4,label='Halls (1979)',
               marker='s',color='Blue')

for n in xrange (0, len(Laurentia_Prot_poles)):
     m = ipmag.plot_pole_colorbar(pmap, Laurentia_Prot_poles['Plong'][n],
                                   Laurentia_Prot_poles['Plat'][n],
                                   Laurentia_Prot_poles['A95'][n],
                                   -Laurentia_Prot_poles['Age'][n],-1270,-600,
                                   markersize=80, color="k", alpha=1)

pmap.colorbar(m,location='bottom',pad="5%",label='Age of magnetization (Ma)')
plt.legend()
plt.show()
```



As seen above, the Slate Islands VGP accords better with the late Mesoproterozoic section of the Laurentia APWP than the Paleozoic (Silurian) section, despite radiometric evidence for a ∼440 Ma impact age (Dressler, 1999).

Next, we investigate the likelihood of the 50.6° geomagnetic excursion observed in our Slate Islands VGP/Paleozoic APWP comparison.

11.4 Probability of a large deviation from geomagnetic north by a VGP

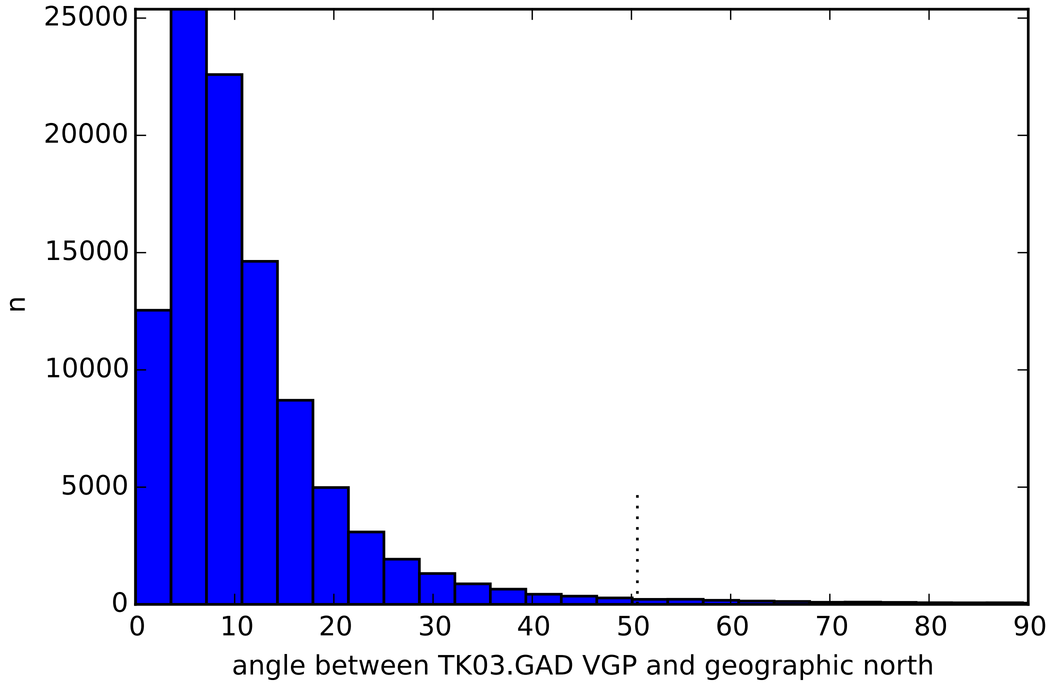
The statistical secular variation model TK03 can be used to simulate secular variation with random draws being taken from the model. The function is set up to return directions so they are then recalculated as poles. Using this model, we can estimate the probability of there being a single VGP that is as far from the APWP path as the Slate Islands pole is from the Silurian path.

Distance from the Slate Islands to the 438 Ma Rose Hill pole can be calculated (colatitude) and used to determine the paleolatitude of the Slate Islands as constrained by the Rose Hill pole. This paleolatitude is then used for the latitude at which the random draw from the TK03 model are taken.

In [72]:
```
Rose_Hill_Plat = -19.1
Rose_Hill_Plong = 308.3
Rose_Hill = (Rose_Hill_Plong, Rose_Hill_Plat)

Slate_Lat = 48.6
Slate_Long = -87.0
Slate = (Slate_Long, Slate_Lat)

plat = 90 - pmag.angle(Rose_Hill, Slate)
print plat[0]
```

```
15.3407768768
```

In [73]:
```
VGPs = ipmag.tk03(n=100000,lat=15) #set at 100,000 this takes a long time to run
VGP_dataframe = pd.DataFrame(VGPs,columns=['dec_tc','inc_tc','int'])
VGP_dataframe['site_lat'] = pd.Series(np.random.uniform(plat,plat,size=len(VGPs)))
VGP_dataframe['site_lon'] = pd.Series(np.random.uniform(0,0,size=len(VGPs)))

ipmag.vgp_calc(VGP_dataframe)

greater_10 = []
greater_20 = []
greater_30 = []
greater_40 = []
greater_50 = []
angles = []
for n in range(len(VGP_dataframe)):
    true_north = (0,90)
    vgp = (VGP_dataframe['vgp_lon'][n],VGP_dataframe['vgp_lat'][n])
    angle = pmag.angle(true_north,vgp)
    angles.append(angle[0])
    if angle > 10:
        greater_10.append(angle[0])
    if angle > 20:
        greater_20.append(angle[0])
    if angle > 30:
        greater_30.append(angle[0])
    if angle > 40:
        greater_40.append(angle[0])
    if angle > 50:
        greater_50.append(angle[0])

n, bins, patches = plt.hist(angles, bins=50)
plt.vlines(50.6,0,5000,linestyles='dotted')
plt.xlim(0,90)
plt.ylim(0,n.max())
plt.xlabel('angle between TK03.GAD VGP and geographic north')
plt.ylabel('n')
plt.show()
```




```
In [74]: percent_gt_30 = float(len(greater_30))/float(len(angles))*100
         percent_gt_40 = float(len(greater_40))/float(len(angles))*100
         print "The percent of VGPs >30° away from mean pole in the TK03 model is:"
         print percent_gt_30
         print "The percent of VGPs >40° away from mean pole in the TK03 model is:"
         print percent_gt_40
```

```
The percent of VGPs >30° away from mean pole in the TK03 model is:
5.586
The percent of VGPs >40° away from mean pole in the TK03 model is:
3.223
```

12 Breccia Dike Cooling Model

12.1 Heat transfer during dike cooling

We are interested in modeling heat transfer during the emplacement and subsequent cooling of breccia dikes. We are particularly interested in understanding the timescale for cooling within the dike itself. This problem was dealt with nicely in an article published by Paul T. Delaney of the US Geological Survey:

Delaney, P.T. 1987. Heat transfer during emplacement and cooling of mafic dykes In Mafic dyke swarms. Edited by H.C. Halls and W.F. Fahrig. Geological Association of Canada, Special Paper 34, pp. 31-46.

12.2 An analytical solution to transient heat conduction

Delaney (1987) formulates the problem by idealizing a dike as a tabular plane of infinite extent. Coordinates are based on the position of the dike wall with the X-direction being the direction orthogonal to the wall such that negative X values are within the dike and positive X values are in the host rock. The dike has a thickness T and an initial temperature Θ_{mi} (subscript stands for magma initial). The host rock has an initial temperature Θ_{hi} and a thermal diffusivity κ_h. > Conservation of energy for a motionless material undergoing one-dimensional heat transfer with no chemical reactions is (Carslaw and Jaeger, 1959, Ch. 1; Bird et al., 1960, Ch.10):

$$\rho C \frac{\partial \Theta}{\partial t} = \frac{\partial}{\partial X} k \frac{\partial \Theta}{\partial X} \tag{1}$$

This equation states that the heat conducted into a unit volume minus the heat conducted out is equal to the accumulation of heat within the volume. The right-hand side of equation 1 is the gradient in heat flux, which is given by Fourier's Law, $Q = -k\partial\Theta/\partial X$ where k is thermal conductivity; the left-hand side is the rate of accumulation of heat, where pC is heat capacity per unit volume. If k is constant, then:

$$\frac{\partial \Theta}{\partial t} = \kappa \frac{\partial^2 \Theta}{\partial X^2} \tag{2}$$

Thermal diffusivity, $\kappa = k/(pC)$, measures the ability of a material to conduct heat relative to its ability to accumulate heat.

> Generality and simplicity are gained by introducing non-dimensional temperature θ, distance x, and time τ:

$$\theta = (\Theta - \Theta_{hi})/(\Theta_{mi} - \Theta_{hi}) \tag{3}$$

$$x = X/(T/2) \tag{4}$$

$$\tau = t * \kappa_h/(T/2)^2 \tag{5}$$

Following this introduction, Delaney builds up to presenting the first and simplest whole-time solution. This solution neglects themal property contrasts between the host rock and dike (i.e. $\kappa_m/\kappa_h = 1$). These thermal property contrasts can affect the maximum temperatures reached in the host rock and early cooling rates, but the influence is rather small. This whole-time solution is:

$$\theta = \frac{1}{2}[erf(\frac{2+x}{\sqrt{4\tau}}) - erf(\frac{x}{\sqrt{4\tau}})] \tag{6}$$

Delaney also presents numerical solutions that incorporate the effects of the heat of crystallization, magma flow and the temperature dependance of thermal conductivity and diffusivity. In the application that we are exploring here, the cooling of a breccia dike emplaced within an impact crater neither the heat of crystallization nor magma flow apply and therefore the analytical solution using transient heat conduction theory will work well for our analysis.

12.3 Implementing the whole-time solution

12.3.1 Define the function dike_cooling()

A function can be defined that returns the temperature at a given time and distance from the contact (within or outside of the dike) for a given initial dike temperature, initial host rock temperature, dike width and thermal diffusivity. This function calculates non-dimensional distance and time and then solves for non-dimensional temperature using the whole-time solution detailed above. The temperature of interest can then be extracted from the non-dimensional temperature using the specified intial temperatures.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from matplotlib.patches import Polygon
```

```
from scipy import special
%config InlineBackend.figure_formats = {'svg',}
%matplotlib inline
```

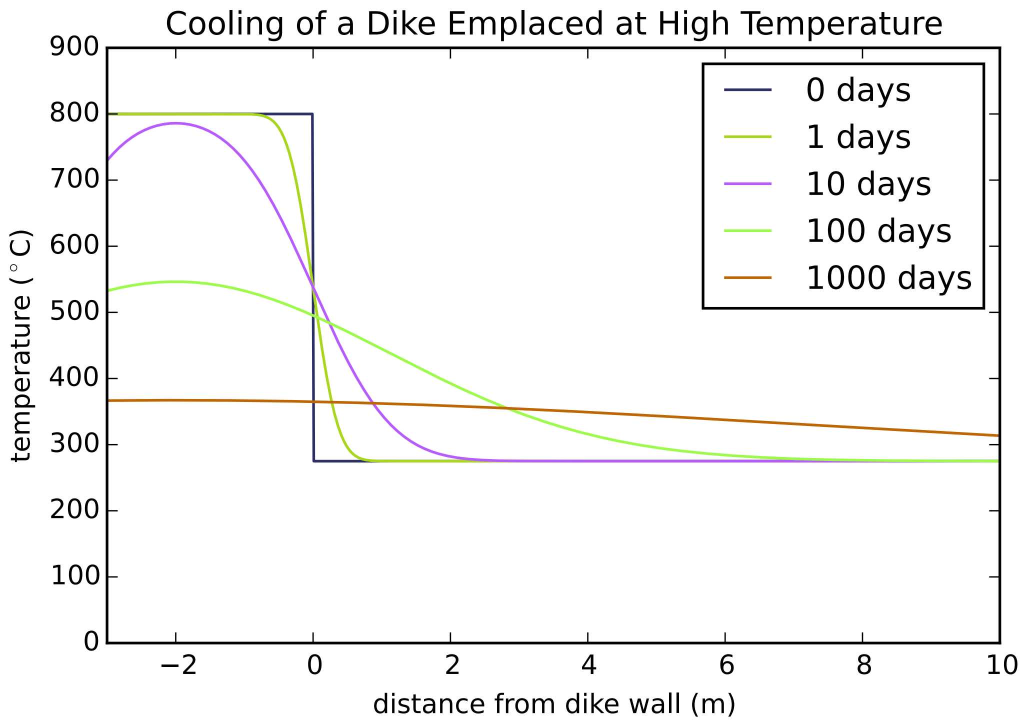
```
In [2]: def dike_cooling(t,distance_from_contact,temp_dike,temp_host,dike_width,kn):
            x_nd = distance_from_contact/(dike_width/2)
            tau_nd = t * kn/((dike_width/2.0)**2)
            temp_nd =  0.5 * (special.erf((2+x_nd)/np.sqrt(4*tau_nd)) - special.erf(x_nd/np.sqrt(4*tau_n
            temp = temp_nd*(temp_dike-temp_host) + temp_host
            return temp
```

12.3.2 Input parameters

```
In [3]: temp_dike = 800.0 #in Celcius
        temp_host = 275.0 #in Celcius
        dike_width = 5 #in meters
        kn = 7.35e-7 #thermal diffusivity (m^2/s)
```

12.3.3 Plot temperature vs distance at a number of times following dike emplacement

```
In [4]: for time in [1,1*60*60*24,10*60*60*24,100*60*60*24,1000*60*60*24]:

            temp = []
            distance = []

            for distance_from_contact in np.arange(-dike_width/2,
                                                   dike_width*2,0.01):
                temp_at_distance = dike_cooling(time,distance_from_contact,
                                                temp_dike,temp_host,
                                                dike_width,kn)
                temp.append(temp_at_distance)
                distance.append(distance_from_contact)
            plt.plot(distance,temp,c=np.random.rand(3),
                     label=str(time/60/60/24)+' days')

        plt.xlabel('distance from dike wall (m)')
        plt.ylabel('temperature ($^\circ$C)')
        plt.ylim((0,temp_dike+100))
        plt.xlim((-dike_width/2,dike_width*2))
        plt.legend()
        plt.title('Cooling of a Dike Emplaced at High Temperature')
        plt.savefig("Code_output/multitime_cooling.pdf")
        plt.show()
```



12.3.4 Temperature dependence of thermal diffusivity

The above analysis does not incorporate the temperature-dependence of thermal diffusivity explored by Delaney (1987) in some detail. Laser flash-analysis has enabled advances in measurements of thermal diffusivity at elevated temperature since the work of Delaney (1987). Estimated of thermal diffusivity from schist, granite and rhyolite were published by:

Whittington A. G., Hofmeister A. M., Nabelek P. I. (2009) Temperature-dependent thermal diffusivity of the Earth's crust and implications for magmatism. Nature 458:319–321

These data were similar between the three rock types and the following empirical fits were proposed by Whittington et al. (2009) for the temperature dependence of thermal diffusivity (in square millimetres per second) in the continental crust.

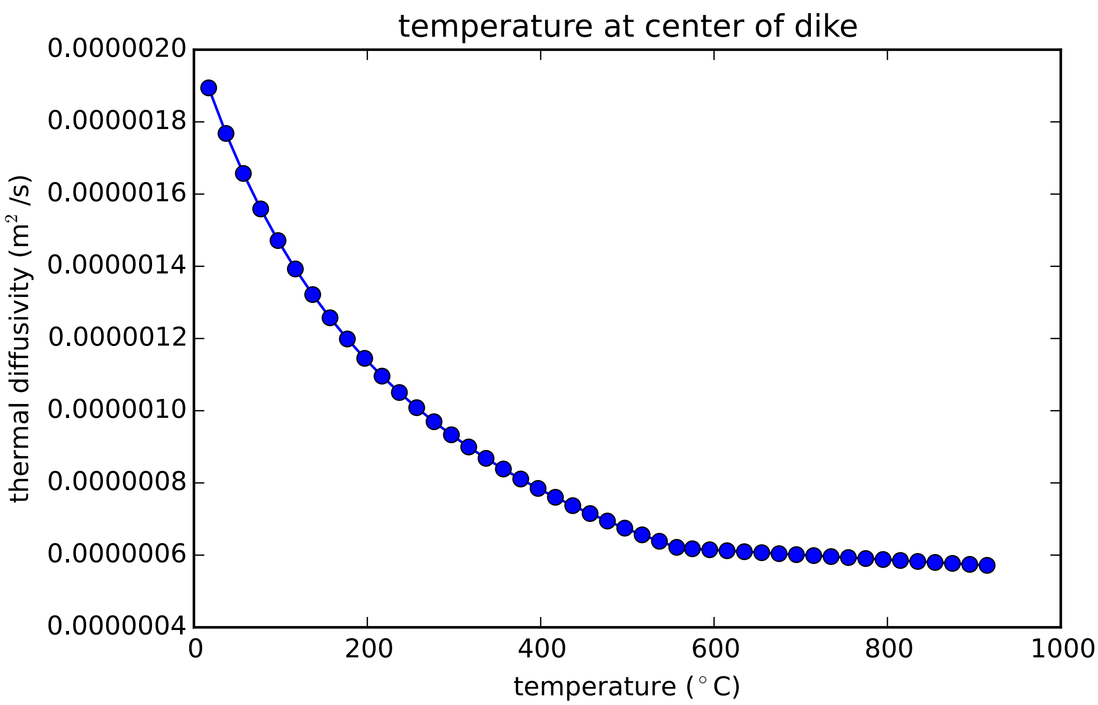
$$\kappa_{crust}(T < 846K) = 567.3/T - 0.062 \tag{7}$$

$$\kappa_{crust}(T > 846K) = 0.732 - 0.000135T \tag{8}$$

Our temperature range of interest is between the estimated emplacement temperature of 800°C and the interval over which the majority of magnetite remanence will be blocked (580°C to 400°C). There is minimal fluctuations of thermal diffusivity over this temperature range in the empirical fit of Whittington et al. (2009). The code below, plots the Whittington et al. (2009) empirical fit over a range of temperature and calculates an average value over the temperature range of 800°C to 400°C for use in the cooling model.

```
In [5]: T = []
        kappa = []

        for temp in range(290,845,20):
            k = 567.3/temp - 0.062
```

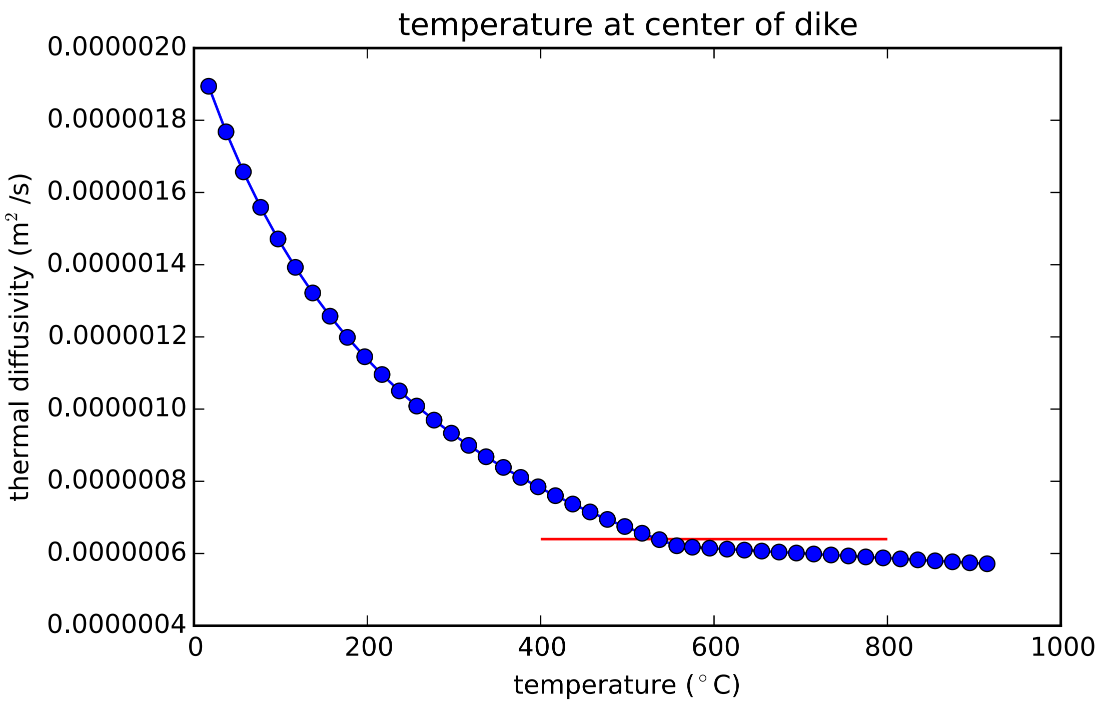
```
    kappa.append(k*10**-6)
    T.append(temp-273)
for temp in range(848,1200,20):
    k = 0.732 - 0.000135*temp
    kappa.append(k*10**-6)
    T.append(temp-273)

plt.plot(T,kappa,marker='o')
plt.ylabel('thermal diffusivity (m$^2$/s)')
plt.xlabel('temperature ($^\circ$C)')
plt.title('temperature at center of dike')
plt.show()
```




```
In [6]: T_for_avg = []
        kappa_for_avg = []

        for temp in range(400+273,800+273):
            if temp > 846:
                k = 0.732 - 0.000135*temp
                kappa_for_avg.append(k*10**-6)
                T_for_avg.append(temp-273)
            if temp < 846:
                k = 567.3/temp - 0.062
                kappa_for_avg.append(k*10**-6)
                T_for_avg.append(temp-273)
        average_kappa = np.average(kappa_for_avg)
        print "The average thermal diffusivity (m$^2$/s) over the range of 400 to 800 degrees C"
        print average_kappa
```

```
plt.plot(T,kappa,marker='o')
plt.hlines(average_kappa,400,800,color='r')
plt.ylabel('thermal diffusivity (m$^2$/s)')
plt.xlabel('temperature ($^\circ$C)')
plt.title('temperature at center of dike')
plt.show()
```

```
The average thermal diffusivity (m$^2$/s) over the range of 400 to 800 degrees C
6.39853102401e-07
```



From this fit we obtain an average thermal diffusivity of $\kappa = 6.4x10^{-7}\ m^2/s$ over the temperature range of interest that use for the model.

12.3.5 Implementing the Model

Here we input the new value we are using for thermal diffusivity. Other parameters such as emplacement temperature, host rock temperature, and dike width are explained above or within the main text.

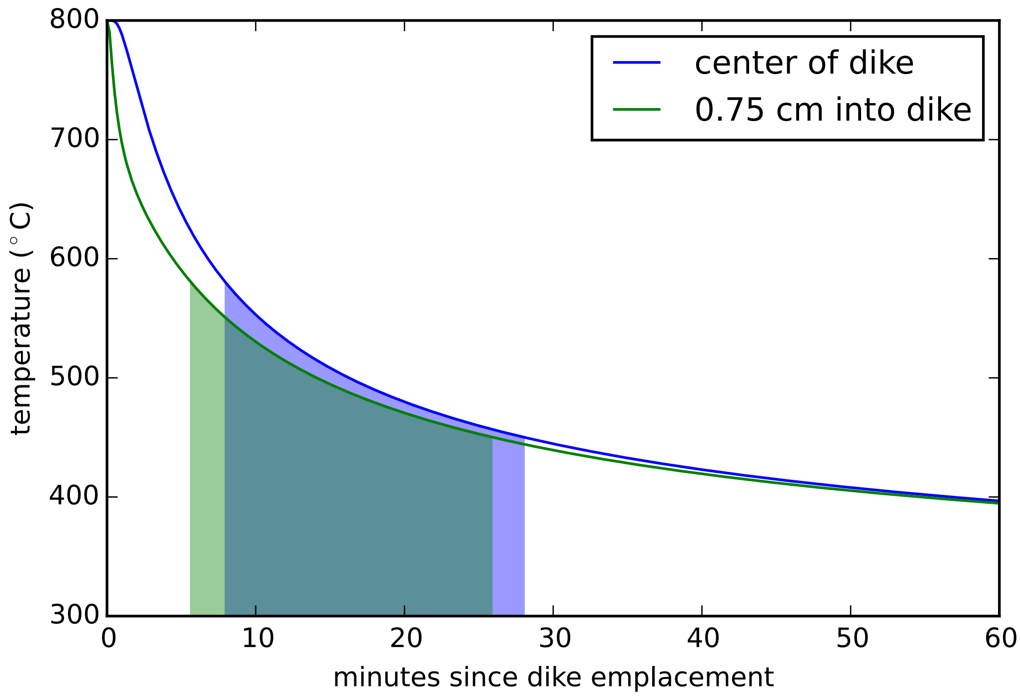
Because we would like to identify the minimum time over which the impact direction was acquired by a breccia dike after emplacement, we use the thinnest sampled breccia dike site (PI47; 4 cm thick) in the conductive cooling model. Paleomagnetic core samples from PI47 are 2.5 cm in diameter and therefore span most of the breccia dike's width as seen in the photo for the PI47 breccia dike in the paleomagnetic data analysis section. We therefore calculate characteristic cooling curves for both the center of the dike and 0.75 cm from the edge of the dike, since our paleomagnetic data encapsulates this range of positions within the PI47 breccia dike.

```
In [7]: #Input new parameters for PI47 dike (4.0 cm thick)
        temp_dike = 800.0 #in Celcius
        temp_host = 275.0 #in Celcius
```

```
dike_width = .04 #in meters
kn = 6.399e-7 #thermal diffusivity (m^2/s)
```

In [8]:
```
distance_from_contact = -dike_width/2.0 #center of dike in meters
time = []
time_hours = []
time_minutes = []
temp = []
temp_1cm = []

for t in range(0,15000,10):
    temp_at_t = dike_cooling(t,distance_from_contact,
                             temp_dike,temp_host,dike_width,kn)
    temp_at_1cm = dike_cooling(t,-0.0075,temp_dike,temp_host,dike_width,kn)
    temp_1cm.append(temp_at_1cm)
    temp.append(temp_at_t)
    time.append(t)
    time_hours.append(t/60.0/60.0)
    time_minutes.append(t/60.0)

def find_temp(temp_list, temp_target):
    for i in range(len(temp_list)):
        if temp_list[i] <= float(temp_target):
            return i

lvl_580 = find_temp(temp, 580)
lvl_450 = find_temp(temp, 450)

lvl_580_1cm = find_temp(temp_1cm, 580)
lvl_450_1cm = find_temp(temp_1cm, 450)

x_rng = time_minutes[lvl_580:lvl_450]
y_rng = temp[lvl_580:lvl_450]

x_rng_1cm = time_minutes[lvl_580_1cm:lvl_450_1cm]
y_rng_1cm = temp_1cm[lvl_580_1cm:lvl_450_1cm]

vertices_p1 = [(x_rng[0], 0)] + list(zip(x_rng, y_rng)) + [(x_rng[-1], 0)]
vertices_p2 = [(0,0)] + [(0,580)] + [(x_rng[0], y_rng[0])] + [(x_rng[0],0)]

vertices_p1_1cm = [(x_rng_1cm[0], 0)] + list(zip(x_rng_1cm, y_rng_1cm)) + [(x_rng_1cm[-1], 0)]
vertices_p2_1cm = [(0,0)] + [(0,580)] + [(x_rng_1cm[0], y_rng_1cm[0])] + [(x_rng_1cm[0],0)]


fig, ax = plt.subplots()
plt.plot(time_minutes,temp,label='center of dike')
plt.plot(time_minutes,temp_1cm,label='0.75 cm into dike')
poly1 = Polygon(vertices_p1, color = 'b', alpha = 0.4,ls=None)
poly_1cm = Polygon(vertices_p1_1cm, color = 'g', alpha = 0.4,ls=None)
#poly2 = Polygon(vertices_p2, color = 'g', alpha = 0.4)
plt.gca().add_patch(poly1)
plt.gca().add_patch(poly_1cm)
plt.xlabel('minutes since dike emplacement')
plt.ylabel('temperature ($^\circ$C)')
```

```
plt.xlim(0,60)
plt.gcf()
plt.legend()
plt.savefig('Code_output/breccia_temp_graph_hours.svg')
plt.show()

print "Center of dike cools to 580 in", time_minutes[lvl_580], "minutes"
print "0.75 cm into dike cools to 580 in",time_minutes[lvl_580_1cm], "minutes"
```




```
Center of dike cools to 580 in 8.0 minutes
0.75 cm into dike cools to 580 in 5.66666666667 minutes
```