

1 **Long Range Sea Ice Drift Model Verification**

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ABSTRACT

4 Integrated sea ice drift is predictable to about 16 days in the Arctic. This surprising result
5 is an extension from Grumbine (1998), where there was no apparent decline of skill through
6 the 6 days forecast lead at that time. Forecasts from 1998 to 2007 provide a further test of
7 that, and a continued search for good measures of model skill. Index of Agreement, used in
8 Grumbine (1998), turns out to be a poor skill measure for sea ice drift.

1. Introduction

The drift of sea ice is important for safety of navigation and fishing. A feature of particular importance is the motion of the ice edge. Since most vessels are not strengthened for working inside the ice pack, even low concentrations (15%) of thin (0.1 m) ice are a concern [Cavalieri et al. (1991)]. Alaska Region National Weather Service forecast offices, lead by Anchorage, have been making use of sea ice drift guidance models for a number of years (at least since 1978 [Crisci (1978)]) to assist in making these forecasts. The nature of these models has been to use 'virtual floes'. That is, if there were an ice floe at this location at the start of the model run, then it is predicted by the model to drift this distance in the following direction. The lead time of these models was 2 days in 1978 [Crisci (1978)], to 4 days some time before 1989, and to 6 days in 1989 [Grumbine, inspection of source code] where it remained until January 2001.

In 1997 a new drift model was implemented operationally [Grumbine (1998)], hereafter G1, which again went to day 6. The new model was superior to the old, measured by drift error radius. It was a sufficient improvement that Anchorage Weather Service Forecast Office soon thereafter requested that guidance be extended [Page, pers. comm, 1998] to day 10. Since the atmospheric model used by the drift model, the Global Forecast System (GFS), extends to day 16, the experiment was begun running the model to day 16. The experiment was successful, and the 16 day guidance became operational in January 2001.

A remarkable feature of the verification statistics for forecasts of up to 6 day lead in G1 was that there was no apparent decline in skill by any of the measures used – index of agreement, correlation, vector correlation. As noted in G1, this behavior could be expected in a case where the steadily increasing bias, from biased forcing, was offset by a decreasing random error component as positive errors are offset by negative errors. One of the interests for this paper is to determine how long that compensation could continue. We will see that that limit is 2-5 days, depending on skill measure.

The new model has been running as a parallel since 14 April 1993, and operationally

36 since September 1997, which gives us over 15 years worth of experience.

37 We have two main questions: Does the model have skill beyond day 6? and Is there
38 potential for a higher resolution model to improve on this one? The first can be tested in a
39 fairly straightforward manner. The second, we will examine by comparing the verification
40 statistics between buoys as a function of initial distance between buoy and forecast point. If
41 the model performs better for buoys closer to forecast points, then we have reason to believe
42 that we should go to a higher resolution model. This resolution test applies only to the
43 quantity tested – N-day integrated drift. This point is important to keep in mind as there
44 is reason to believe that more than averaged drift conditions are required in order to model
45 the sea ice thickness correctly [e.g. Geiger (1997)].

46 **2. Skill Assessment Methods and Results**

47 We will again use the International Arctic Buoy Program (IABP) observations of ice
48 motion for our verification, partly to ensure comparability with the G1 scores.

49 As in G1, we use several different assessors of skill. We use several because each will
50 penalize different types of errors. Also, we are seeking skill measures which provide insight to
51 how well the model is performing. We expand here from four assessors to ten. In considering
52 how well the model performs by each measure, we are simultaneously also examining how
53 informative each measure is. We will wind up concluding that only five are needed, and one
54 of the four (index of agreement) used in G1 is not useful for evaluating this model.

55 Since the GFS Hybrid [Lord et al. (2007)] implementation on 1 May 2007 the drift
56 model has actually been running with a regression tuned with only 2 weeks of model 10
57 meter winds, rather than geostrophic winds of G1 and prior models. For consistency as we
58 examine performance measures and model skill, only the 1998-2007 frame is used in this
59 paper. A subsequent paper will examine the 2007-present model. And will use 2 years of
60 observations for tuning.

62 One measure is simply the linear correlation between the forecast distance of drift and
 63 the observed distance. This is a statistic most are familiar with, and with well-known
 64 weaknesses. One is that it will consider a 50 km drift forecast correct even if the drift is
 65 southward rather than northward. The other is that the magnitude of drift error is considered
 66 equally significant regardless of how large the observed drift is. That is, if the forecast is 22
 67 km, and the observed drift is 2 km, this will be penalized the same (in a least squares linear
 68 regression) as a forecast of 40 km versus an observation of 20 km. Both are 20 km wrong,
 69 but the relative error is very different.

70 The distance correlation between forecast and observed for each forecast lead (averaging
 71 period in this model) is shown in figure 1. The peak is at 3 days, with it not declining below
 72 the 1 day lead's score until day 8.

$$slope = (\Sigma xy - n * \bar{x} * \bar{y}) / (\Sigma xx - n * \bar{x} * \bar{x}) \quad (1)$$

$$intercept = \bar{y} - b * \bar{x} \quad (2)$$

$$correlation = (\Sigma xy - n * \bar{x} * \bar{y}) / \sqrt{(\Sigma xx - n * \bar{x} * \bar{x})} / \sqrt{(\Sigma yy - n * \bar{y} * \bar{y})} \quad (3)$$

$$(4)$$

73 *Slope of Regression*

74 The slope of the regression line between forecast and observed distances provides infor-
 75 mation beyond the correlation itself. If the model were perfect, this slope would be 1, as
 76 would correlation. But one can have a perfect correlation with a model that is continually
 77 wrong by a factor of 2. This parameter will show that situation. As we see in figure 1, the
 78 model consistently under-predicts the drift of ice, at most about 65% of the observed. Given
 79 this model's linear nature, an *a posteriori* fix could be made to the model's output. As we

80 will see in discussion of the intercept (below), part of this is systematic bias in the model's
 81 guidance.

82 This skill measure peaks for 2-3 days, and declines below the 1 day forecast, slightly,
 83 at day 4. Of the figure 1 skill measures, it shows the shortest period to peak skill, and for
 84 sustaining day 1 skill in to the future.

85 *Regression Intercept*

86 In making the linear regression for the slope, above, we also find the optimal intercept
 87 for the line. This is the bias in forecast drift distances. Regression intercept is displayed in
 88 figure 2, where we see it increase to about 45 km at 16 day forecast lead.

89 *Vector Correlation*

90 Vector correlation [Crosby et al. (1993)] will penalize directional errors as well, although
 91 it is still subject to the usual problems of correlation scores. Figure 1 shows this score as
 92 well. A perfect score is 2 (2 dimensional vectors). This score peaks at 4 days lead/averaging,
 93 and does not decline below the 1 day lead's skill until 11 days. This vector correlation's
 94 definition for a sample is:

$$r^2 = Tr[\Sigma_{11}^{-1}\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}] \quad (5)$$

95 where Tr denotes the trace of the matrix and Σ_{ij} is:

$$s(u_i, u_j) \quad s(u_i, v_j) \quad (6)$$

$$s(v_i, u_j) \quad s(v_i, v_j) \quad (7)$$

96 $s()$ is the sample covariance, and $i, j = 1$ represent the observations and $i, j = 2$ are the
 97 forecasts.

99 Index of Agreement [Wilmott et al. (1985)] ignores direction, as does correlation, but
 100 does include a sense of how large the error is relative to the forecast. Figure 1 shows this
 101 as well, this skill having little trend, whether to rise or fall in time. Given the behavior
 102 of all other measures, this is inconsistent, and the score shows little ability to distinguish
 103 better from worse. As such, it should not be used as a skill measure for integrated ice drift
 104 distances.

$$d_2 = 1 - [\sum \omega_j |\mathbf{e}_j|^2] / [\sum \omega_j (|\mathbf{p}_j - \bar{\mathbf{o}}| + |\mathbf{o}_j - \bar{\mathbf{o}}|)^2] \quad (8)$$

105 where d_2 is the index of agreement, summations are from 1 to N (the number of observations),
 106 ω are weights to correct \mathbf{e}_j for being over- or underrepresentative, \mathbf{e}_j is the error in the j th
 107 forecast, \mathbf{p} is the prediction, \mathbf{o} is the observation, and $\bar{\mathbf{o}}$ is the mean of the observations
 108 weighted by ω . In our case, the weights are taken to be unity. The index of agreement will
 109 be largest when the numerator is smallest (forecasts agree with observations), and when the
 110 denominator is largest (large natural variability - the \mathbf{o}_j vary greatly from $\bar{\mathbf{o}}$).

111 *RMS Distance Error*

112 The root mean square of the distance error prevents under-forecast drifts from compen-
 113 sating for over-forecast drifts. In the limit of an unbiased model, this becomes the standard
 114 deviation of the errors. As for the regression intercept, figure 2 shows this monotonically
 115 increasing in time. It is always greater than the intercept, increasing to about 52 km at 16
 116 day forecast lead.

117 *Error Radius*

118 The error radius is the difference between the position of the drifter (ice floe) at the end
 119 of N days versus the forecast location. This is a very natural figure in terms of visualization.

120 It is also shown in figure 2. The mean shows monotonic increase, to about 35 km at 16 days.
121 The root mean square of this error also shows monotonic (aside from a curious decline at 16
122 day lead, likely artefactual) increase to about 60 km at 16 day lead.

123 The preceding 4 measures are all distances, all of which increase monotonically with time.
124 One can equate them, then, to a speed, which ranges from 2-5 cm/s.

125 *RMS Direction Error*

126 Figure 4 shows the root mean square of the direction error. We see it decline to about
127 71 degrees at 5 day forecast lead. It remains superior to the day 1 forecast through 9 days.
128 Errors increase from the minimum at day 5, though only slightly.

129 We can compare this measure to the result of a random guess for direction, given in
130 equation 1. Uniformly random selection of direction would have an rms error of 103 degrees.
131 At 16 days, the directional error is still less than this. Actually, as shown in figure 4, the
132 rms direction error at day 16 is only slightly larger (85 degrees versus 71 degrees) than at
133 day 5.

$$\sqrt{\frac{1}{180} \int_0^{180} \theta^2 d\theta} = 103^\circ \quad (9)$$

134 *Mean Distance Error*

135 Figure 3 shows the mean distance error, allowing underforecasts to compensate for over-
136 forecasts. This shows an increase through time much like the measures above which do not
137 permit compensation. This confirms the impression from the slope of the regression line that
138 the model is systematically biased.

140 The mean direction error, also shown in figure 4, is consistently small, untrended, and
 141 of the same sign – a magnitude of -5 to -10 degrees. While small, it is the same order of
 142 magnitude as the drift rotation in the first place (8 degrees in G1).

143 **3. Implications for Resolution of Velocity grid**

144 The mean error radius is given in table 1 with respect to matchup radius. That is, for
 145 the given radius, buoys which were this close to the Skiles point (the set of points used by
 146 ? were treated as drifting in the same distance and direction as a buoy which really was at
 147 the Skiles point. Table 1 also gives the error radius for only those matchups which were in
 148 the annulus between the given matchup radius and the next smaller matchup radius. Thus,
 149 in the row for 55 km (the matchup radius used in G1), values for the matchups are given
 150 both for initial distance between forecast point and buoy being between 0 and 55 km, and
 151 between 38.9 and 55 km. Figure 5 helps illustrate this.

152 The mesh of Skiles points is a 381 km polar stereographic grid. This rectangular mesh
 153 does not translate uniquely to a representation based on radius from a point. There are
 154 three obvious methods of translation:

155 1) Tile the plane with circles inscribed inside the rectangles (leading to radius = $dx / 2$,
 156 where we let dx be the 381 km spacing). This leaves gaps between the circles, especially
 157 along the diagonals between grid points.

158 2) Tile the plane with circles having the same area as the squares, (giving radius = $dx /$
 159 $\sqrt{\pi}$). This gives both some gaps along the diagonals, and some overlap perpendicular to
 160 them.

161 3) Tile the plane with circles circumscribed around the squares. This gives radius = $dx /$
 162 $\sqrt{(2)}$, and no gaps, but much more overlap.

163 As compromise among the three, I will take the circles having the same area as the

164 squares. In this case, the matchup radius of 55 km, for instance, corresponds to a grid
165 spacing of just about 100 km (97.5), much finer than the model’s actual grid spacing of 381
166 km. Table 1 also lists this equivalent grid spacing.

167 In order to test for statistically significant differences in the difference between the means
168 of two populations having unknown variance, the test statistic is [e.g. p 283 Devore (1982)]

$$t = \frac{(\text{mean}(x_1) - \text{mean}(x_2))}{\sqrt{\left(\frac{s_1^2}{m} + \frac{s_2^2}{n}\right)}} \quad (10)$$

169 where n = number of observations from population 1, m is the number from population 2,
170 x is the variable of interest, subscripts referring to which population was sampled, and s^2 is
171 the sample variance. This is also given in table 1, for annulus versus succeeding annulus. By
172 comparing annuli, we have independent samples. There these are t statistics, with $(n+m-2)$
173 degrees of freedom. A two tail t test for $p = 0.95$ has critical value of 1.97 for N tending to
174 infinity.

175 So, considering first the annulus from 165 to 190 km, representing the outer area of the
176 model’s grid, we find no (statistically) significant improvement until the matchup radius 55
177 km (annulus 38.9-55 km). The next improvement is with the matchup radius of 27.5 km
178 (annulus 19.5 to 27.5 km). By this point, the annuli have far fewer observations, down to
179 about 500 from the outermost annulus’ 13,000.

180 In terms of grid spacing, this suggests that there is no particular reason – in terms of
181 modeling N day integrated sea ice drift – for a model’s grid spacing to be reduced from
182 381 km until it can be reduced to about 100 km. And no need for spacing to be reduced
183 from 100 km until it can be reduced to about 50 km. Given modern computing this is of
184 mostly historical interest for stand-alone sea ice models, but is relevant for coupled air-sea-ice
185 models, where, for instance, the most recent Climate Forecast System [Saha et al. (2011)]
186 includes a half degree, about 50 km grid spacing, ocean and ice model. The point is worth
187 examining with a denser model and observational data set, and for other model types where
188 it may be prohibitive to perform full testing at the higher resolution.

189 4. Conclusions

190 Our first question, whether the model shows skill beyond 6 days' lead is answered yes.
191 It is clearly at least better than guessing random directions for ice floe drift. The second
192 question, whether the skill can be improved by increasing model resolution, is also answered
193 yes. Approximately a 25 km grid spacing is supported by this analysis, and such a model
194 was submitted for NCEP operational implementation 21 May 2012. This model will also
195 produce kml [Consortium (2012)] output for geographic inspection.

196 Skill does indeed, eventually, decline. Depending on the measure used, peak skill is some
197 time from day 2 to 5, with 4 days being a compromise lead between the different measures.
198 Also, insofar as forecasters consider the model to be useful/skilled at 1 day lead, it shows at
199 least equal skill for forecast leads of 4-10 days. How long, exactly, depends on the measure
200 used.

201 We also see that Index of Agreement, mean direction error, and mean distance error are
202 not useful skill measures for sea ice drift as they vary so little that we cannot distinguish
203 between day 1 and day 16 forecasts, even though the model, according to the other measures,
204 clearly does vary in skill with respect for forecast lead. The magnitude of the mean direction
205 error suggests, however, that the model could be improved markedly by correct tuning of
206 the angle difference between geostrophic winds and ice drift.

207 Five of the measures essentially repeat each other, so do not shed additional light on
208 the model's behavior. These are the mean distance error, the rms distance error, the error
209 radius, and the regression intercept. Of these, error radius has some advantages for physical
210 interpretation.

211 There are four additional measures which provide unique information with respect to each
212 other and the error radius regarding sea ice drift model. These are the vector correlation,
213 distance correlation, the slope of the regression between forecast and observed drift distance,
214 and the rms direction error. So I suggest that sea ice drift model verification use 5 measures
215 – error radius, vector correlation, distance correlation, the slope of the regression between

216 forecast and observed drift distance, and the rms direction error.

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249 **List of Tables**

250 1 Error radius skills, for 16 day lead/averaging period, for matchup radii and
251 annuli; all distances in km 15

TABLE 1. Error radius skills, for 16 day lead/averaging period, for matchup radii and annuli; all distances in km

Matchup Radius	N	Mean error radius	s	dx equiv	N annulus	mean error radius annulus	t vs. previous	t vs. 190 km
19.5	488	32.2	39.7	34.6	488	32.2	-0.44	3.11
27.5	948	31.4	38.5	48.7	460	30.55	2.14	3.62
38.9	2119	34.7	46.6	69.0	1171	37.37	-0.42	1.77
55	4247	35.6	44.6	97.5	2128	36.5	1.87	2.96
77.8	8000	37.4	50.0	137.9	3753	39.44	0.17	0.99
110	15806	38.5	57.9	195.0	7806	39.63	0.47	1.05
155	29451	39.2	52.4	274.7	13645	40.01	0.68	0.68
190	42663	39.6	52.9	336.8	13212	40.49		

252 **List of Figures**

253	1	Skill versus forecast lead/averaging time for index of agreement, correlation	
254		of distance, vector correlation, slope of forecast vs. observed distance drifted	17
255	2	Skill versus forecast lead/averaging time for regression intercept, rms drift	
256		distance error, mean error radius, rms error radius	18
257	3	Skill versus forecast lead/averaging time for mean distance error	19
258	4	Skill versus forecast lead/averaging time for mean direction error and rms	
259		direction error	20
260	5	Illustration of annular matchup	21

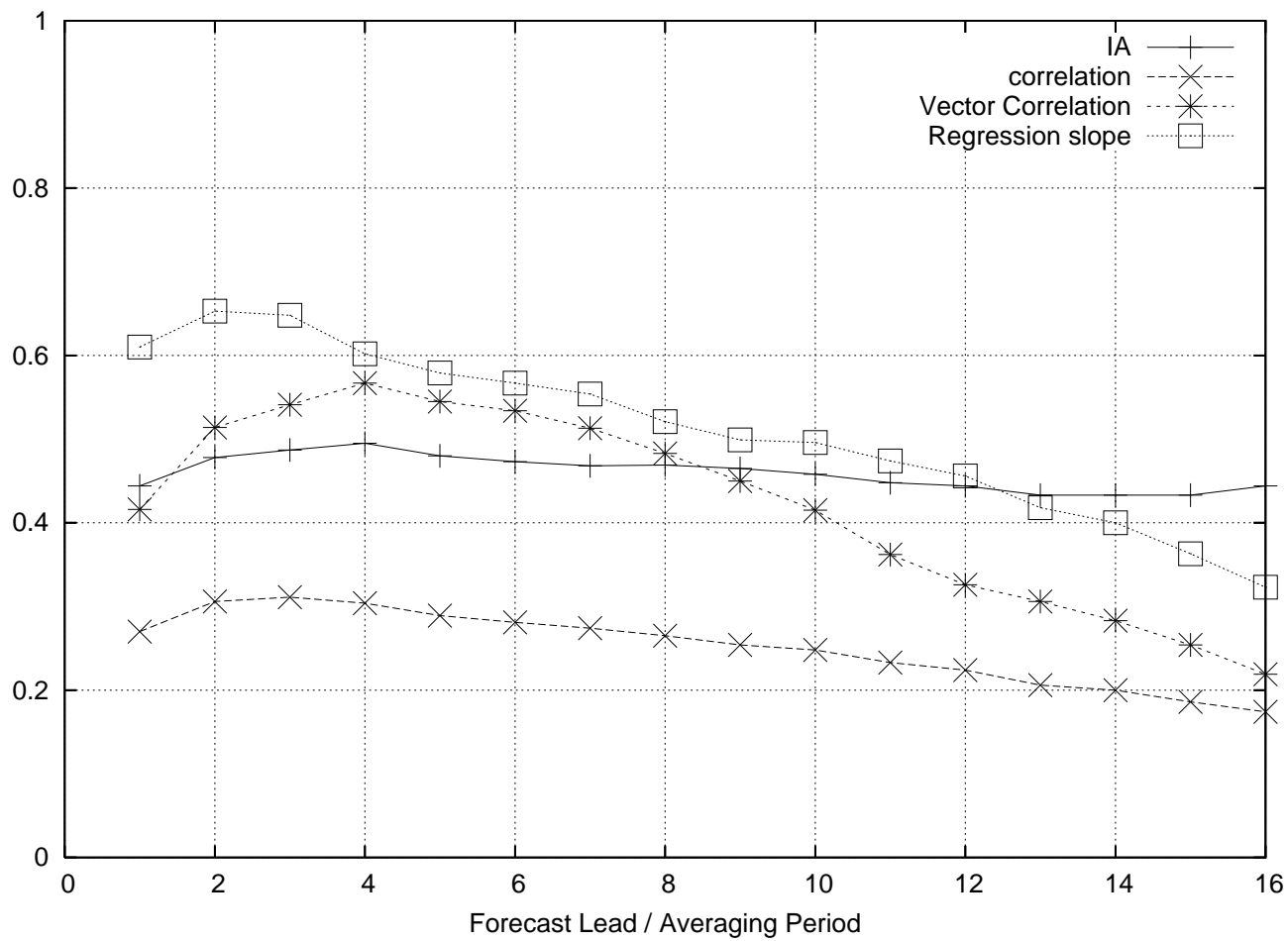


FIG. 1. Skill versus forecast lead/averaging time for index of agreement, correlation of distance, vector correlation, slope of forecast vs. observed distance drifted

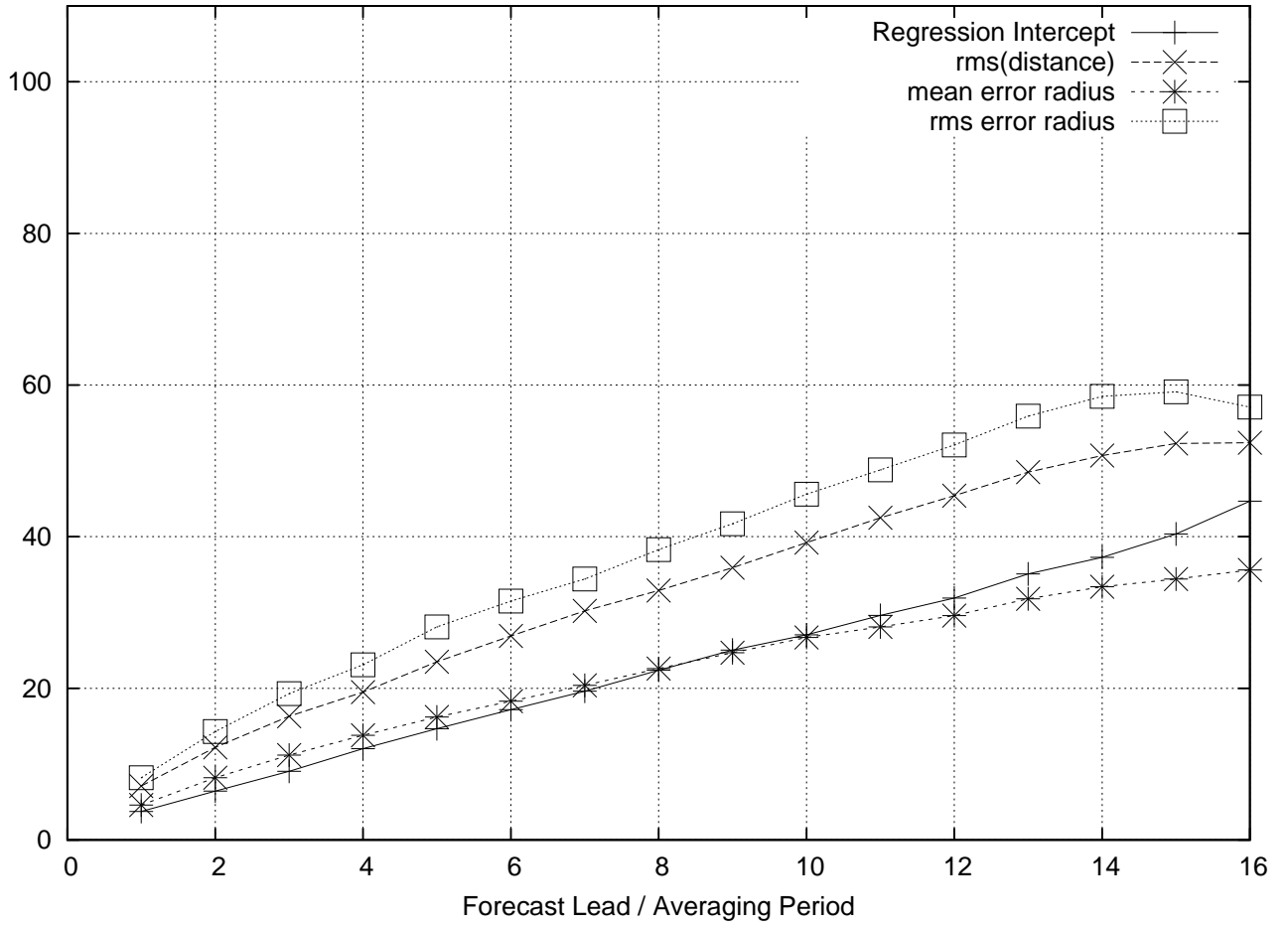


FIG. 2. Skill versus forecast lead/averaging time for regression intercept, rms drift distance error, mean error radius, rms error radius

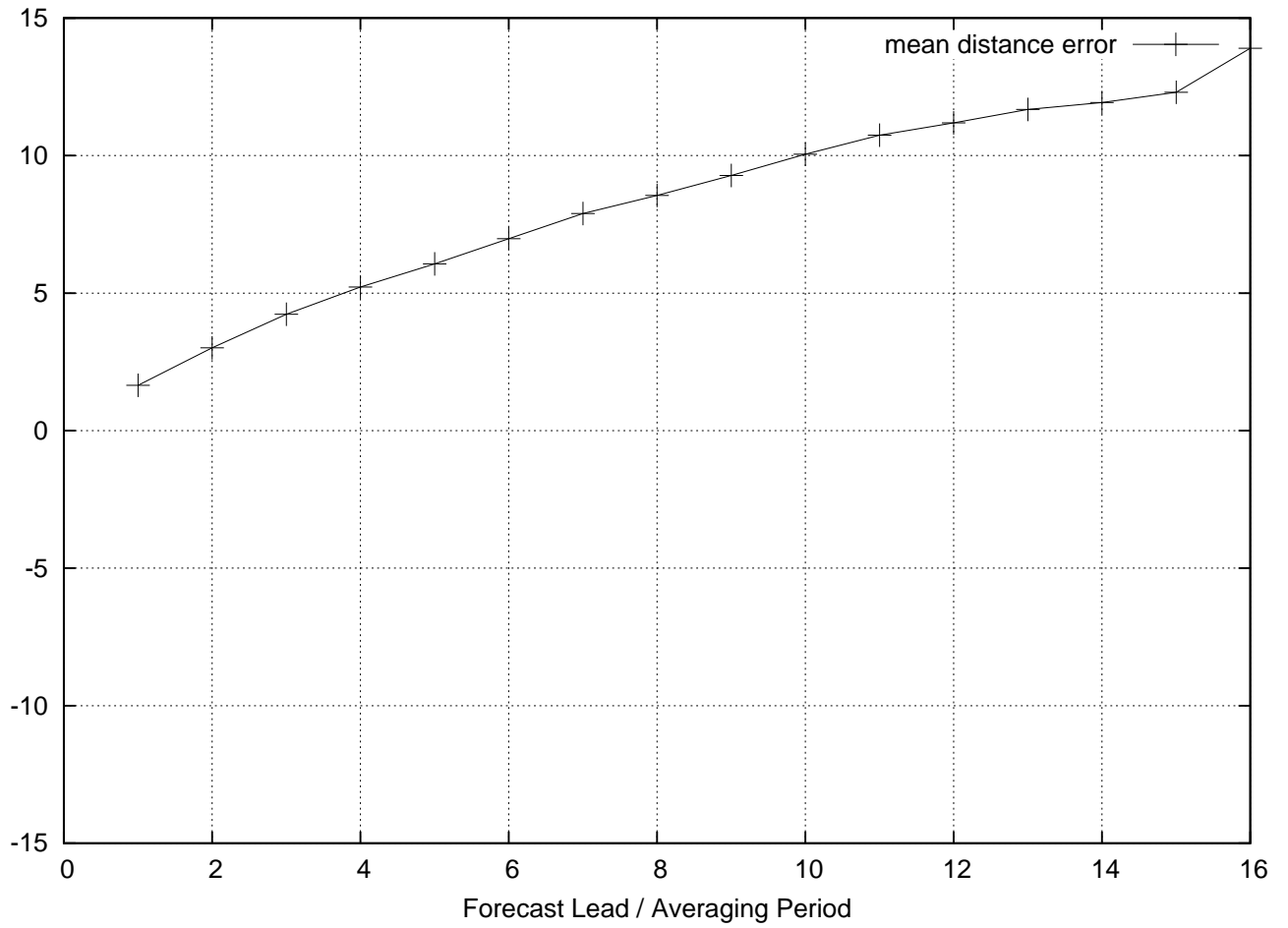


FIG. 3. Skill versus forecast lead/averaging time for mean distance error

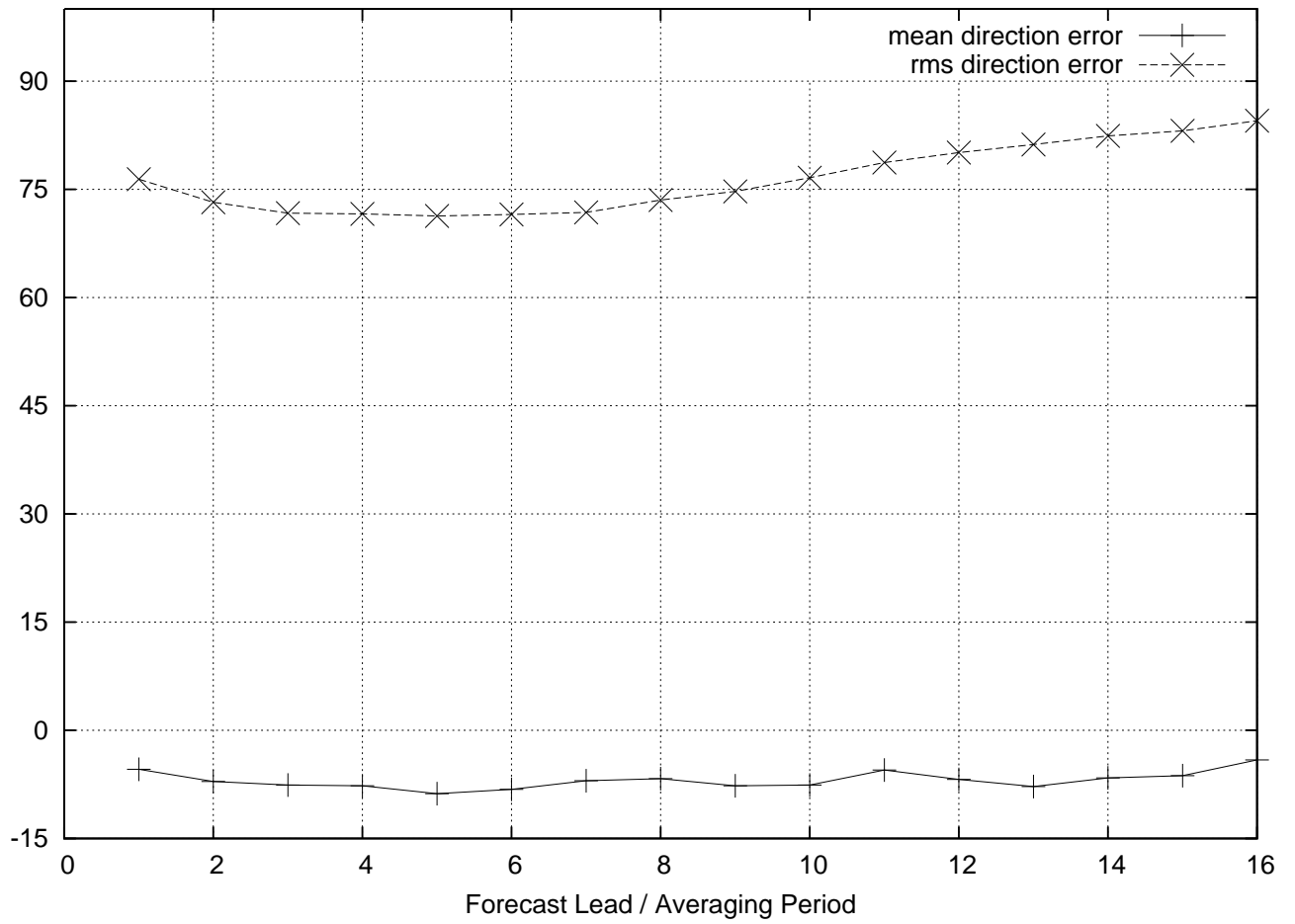


FIG. 4. Skill versus forecast lead/averaging time for mean direction error and rms direction error

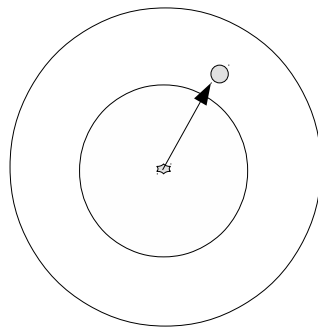


FIG. 5. Illustration of annular matchup