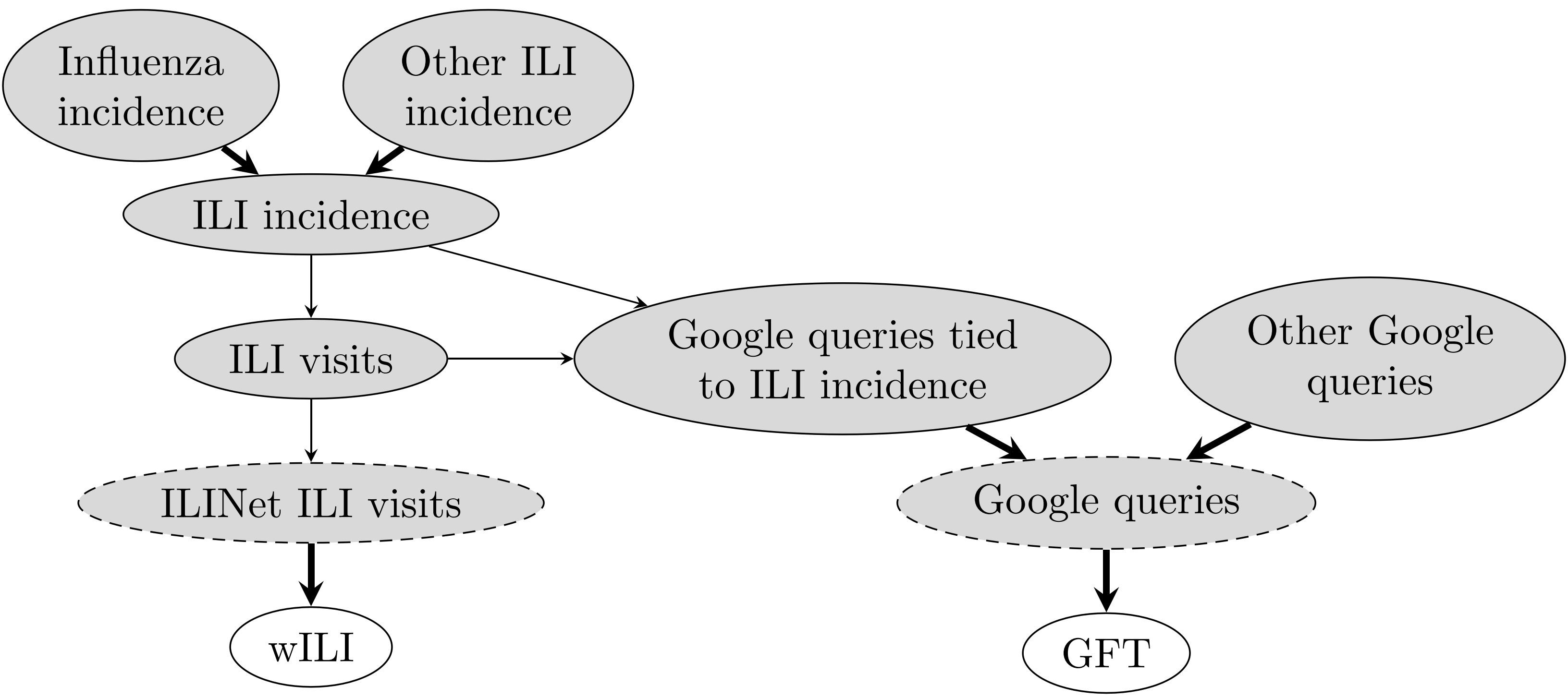
S6 Fig

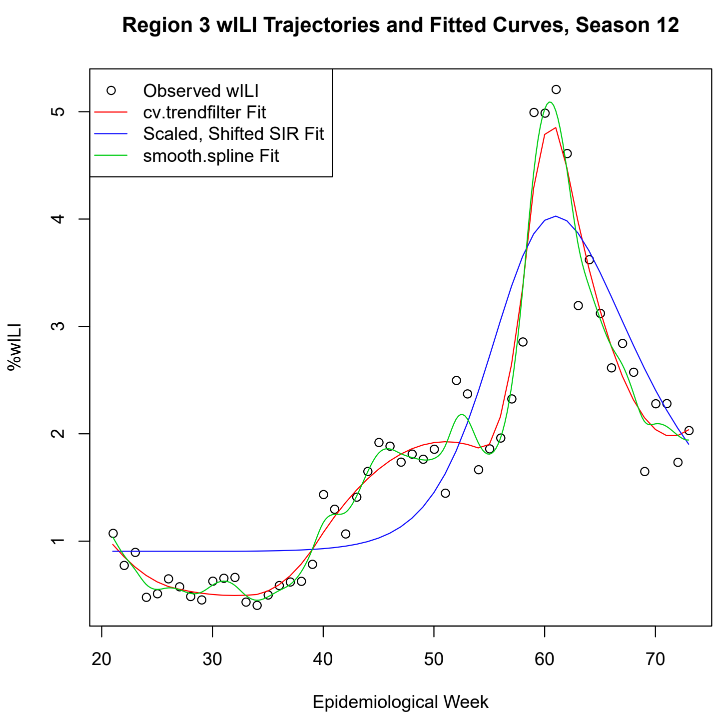
Diagram of the generation process for ILINet and GFT data. We are interested in influenza and other ILI incidence, but cannot observe them directly. Instead, we rely on wILI as a measure of flu prevalence, and sometimes use GFT to approximate wILI. Shaded nodes, unobserved quantities; shaded dashed nodes, proprietary data; unshaded nodes, publicly available data; thin arrows, dependencies; thick arrows, deterministic dependencies. (PDF.)


Influenza incidence
Other ILI incidence
ILI incidence
ILI visits
Google queries tied to ILI incidence
Other Google queries
ILINet ILI visits
Google queries
wILI
GFT

S7 Fig

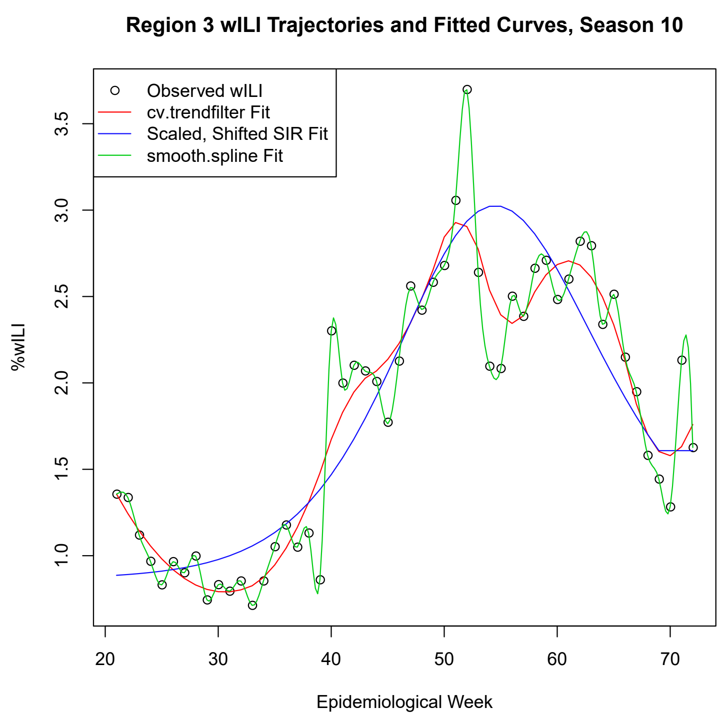
Trend filtering, SIR, and smoothing spline fits for HHS region 3 for two seasons. The quadratic trend filtering fit was performed with the `cv.trendfilter` [40] method, which automatically selects a level of smoothness to use. The cubic natural smoothing spline fit was produced by `smooth.spline` [48], which also automatically selects a level of smoothness, but by different criteria. (a) 2008–2009 season: trend filtering and smoothing splines both smooth out the holiday effects. The smoothing spline appears to overfit to noise in the preseason and early flu season. (b) 2006–2007 season: in addition to holiday effects, there is a large jump in wILI at week 40, which coincides with the beginning of the influenza season and a large jump in the number of reporting providers (from about 30 to over 100). The trend filtering procedure has trouble matching the beginning-of-season and holiday effects, attributing most of these effects to noise and smoothing them out. The `smooth.spline` procedure selects a level of smoothness that essentially duplicates the observed wILI and would produce a noise estimate near 0, which does not seem appropriate. Alternative methods of selecting a level of smoothness may produce looser fits and avoid these near-0 noise estimates, though.

Beginning-of-season and holiday effects can be incorporated in both of the smoothing procedures, and would likely improve the resulting fits. Regional wILI dynamics are generally not tightly fit by the described SIR model. (PDF.)



Region 3 wILI Trajectories and Fitted Curves, Season 12
Observed wILI
cv.trendfilter Fit
Scaled, Shifted SIR Fit
smooth.spline Fit
%wILI
Epidemiological Week

(a)

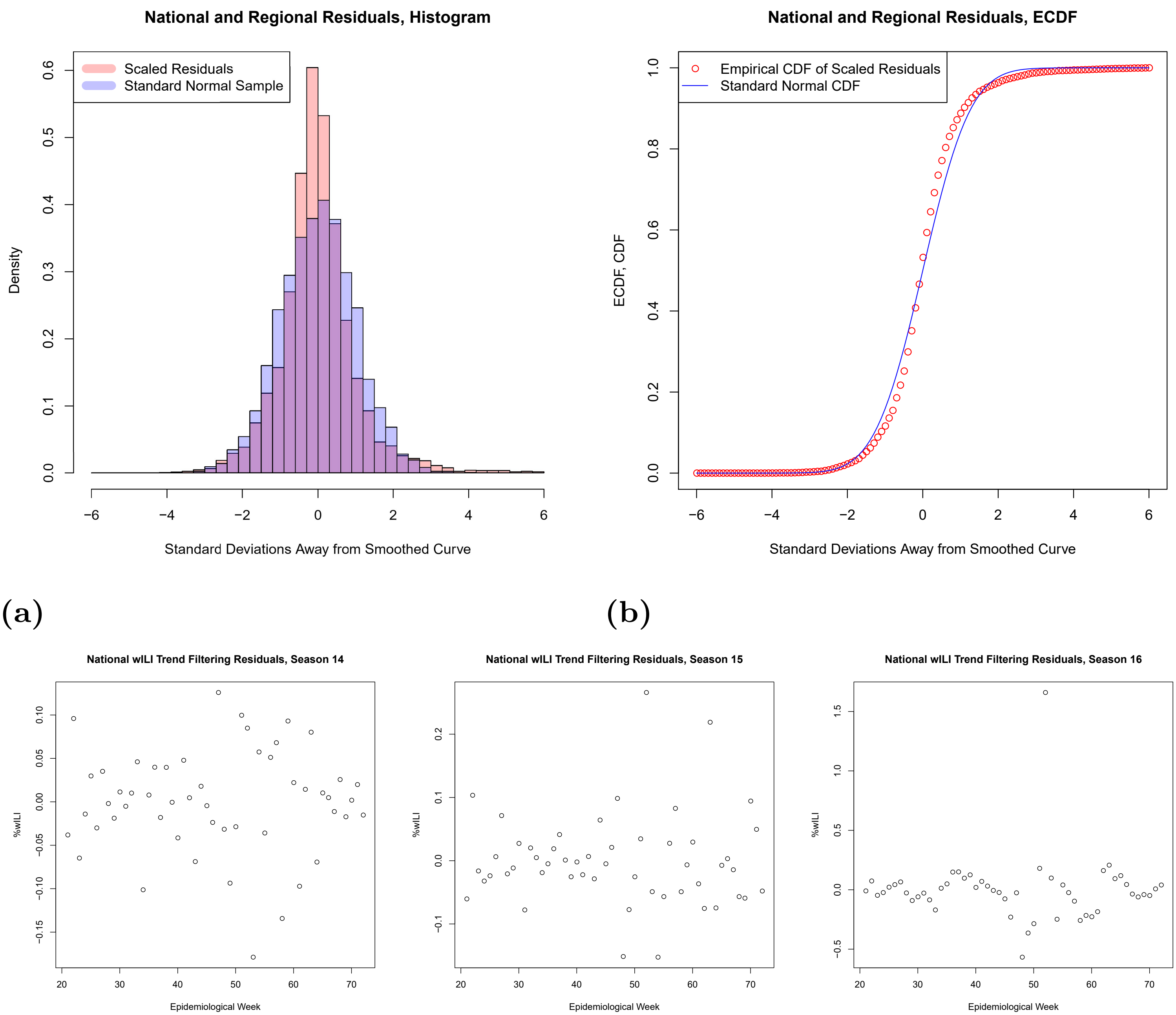


Region 3 wILI Trajectories and Fitted Curves, Season 10
Observed wILI
cv.trendfilter Fit
Scaled, Shifted SIR Fit
smooth.spline Fit
%wILI
Epidemiological Week

(b)

S8 Fig

National and regional residuals after trend-filtering fit. We took the difference between the observed wILI and trend-filtered fit for each historical season and region, and put them on the same scale by dividing by the standard deviation of residuals in the corresponding season and region (giving a z-score). (a) A histogram of the scaled residuals, together with a histogram for a standard normal random sample of the same size. (b) The empirical cumulative distribution function of the residuals, together with the cumulative distribution function of a standard normal random variable. (c,d,e) The (unscaled) residuals for the trends filtering fits to the national data for the (c) 2010–2011, (d) 2011–2012, and (e) 2012–2013 seasons. The trend filtering fits corresponding to (c), (d), and (e) are shown in Fig. S5. The winter holiday effect is unusually pronounced in (e), while (c) and (d) show more typical residual patterns. The trend-filtering residuals do not look exactly normally distributed; deviations from normality may be due to holiday effects, autocorrelation between residuals, and/or non-normality of wILI measurements. (PDF.)


National and Regional Residuals, Histogram
Scaled Residuals
Standard Normal Sample
Density
Standard Deviations Away from Smoothed Curve
(a)
National and Regional Residuals, ECDF
Empirical CDF of Scaled Residuals
Standard Normal CDF
ECDF, CDF
Standard Deviations Away from Smoothed Curve
(b)
National wILI Trend Filtering Residuals, Season 14
%wILI
Epidemiological Week
(c)
National wILI Trend Filtering Residuals, Season 15
%wILI
Epidemiological Week
(d)
National wILI Trend Filtering Residuals, Season 16
%wILI
Epidemiological Week
(e)

S9 Table

Leave-one-out cross-validated bias and variance estimates, aligned by epidemiological week. Most years are assigned 52 epidemiological weeks, but a few are assigned 53; we examine prediction error at weeks 39–52 and 1–20 when the first year of a season has 52 weeks, and weeks 39–53 and 1–19 when the first year has 53 weeks. Predictors are assigned the following abbreviations: "bl", baseline (mean of other seasons); "splice", pinned baseline (mean of other seasons, conditioned on current season to date); "eb", empirical Bayes framework, using other seasons' wili curves; "per", pointwise percentile method; "knn", k-nearest neighbors method; "ebsir", empirical Bayes framework, modified to use SIR curves. All units of measurement are omitted. (PDF.)

	Onset		Peak Week		Peak Height		Duration	
Week, Predictor	Bias	Variance	Bias	Variance	Bias	Variance	Bias	Variance
All weeks, bl	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW39, splice	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW40, splice	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW41, splice	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW42, splice	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW43, splice	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW44, splice	-0.0042	16.1846	0.0000	13.9567	0.0000	3.0419	0.0042	13.4184
EW45, splice	0.0583	16.1232	-0.0750	13.2787	0.0002	3.0407	-0.0583	13.4921
EW46, splice	0.3750	15.2059	-0.0708	13.3117	0.0014	3.0334	-0.2667	13.4690
EW47, splice	0.1042	12.9831	-0.3000	12.7040	0.0111	2.9768	-0.1833	14.2889
EW48, splice	0.0167	11.1950	-0.3542	12.5930	0.0321	2.8631	-0.2000	13.7908
EW49, splice	-0.1417	9.1792	-0.4875	11.3924	0.0669	2.7065	-0.1167	13.2145
EW50, splice	-0.3125	6.7732	-0.7042	11.0477	0.1778	2.4180	-0.0833	13.5535
EW51, splice	-0.4375	4.1043	-1.0958	8.1914	0.2727	2.1471	0.0375	12.5635
EW52, splice	-0.5833	3.3964	-1.3375	5.8000	0.2563	1.7092	0.1417	12.1315
EW53/EW01, splice	-0.5485	2.2196	-1.1854	5.5341	0.1162	1.5391	0.1083	10.9410
EW01/EW02, splice	-0.3214	1.0898	-1.0137	5.1310	0.0216	1.4677	-0.0167	10.6889
EW02/EW03, splice	-0.2040	0.5769	-0.6836	5.1085	0.0925	1.0961	-0.0417	10.4035
EW03/EW04, splice	-0.0975	0.2635	-0.7700	4.9601	0.1232	0.9194	-0.0458	9.2704
EW04/EW05, splice	-0.0529	0.0653	-0.2064	3.5087	0.2847	0.4214	-0.0125	8.2372
EW05/EW06, splice	0.0000	0.0000	0.0740	2.5109	0.3343	0.1870	-0.0417	6.5167
EW06/EW07, splice	0.0000	0.0000	0.4177	1.8649	0.2576	0.0897	-0.0583	5.0044
EW07/EW08, splice	0.0000	0.0000	0.2958	0.9375	0.1218	0.0318	-0.0583	4.1161
EW08/EW09, splice	0.0000	0.0000	0.1667	0.5422	0.0586	0.0130	-0.0375	2.9920
EW09/EW10, splice	0.0000	0.0000	0.0708	0.0880	0.0212	0.0029	-0.2292	1.1893
EW10/EW11, splice	0.0000	0.0000	0.0458	0.0336	0.0057	0.0005	-0.3250	0.3786
EW11/EW12, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	-0.1167	0.1799
EW12/EW13, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	0.0000	0.0000
EW13/EW14, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	0.0000	0.0000
EW14/EW15, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	0.0000	0.0000
EW15/EW16, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	0.0000	0.0000
EW16/EW17, splice	0.0000	0.0000	0.0292	0.0136	0.0015	0.0000	0.0000	0.0000
EW17/EW18, splice	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW18/EW19, splice	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW19/EW20, splice	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW39, eb	-1.3683	14.6834	-0.7048	12.3395	0.0581	2.6886	0.3120	12.9559
EW40, eb	-0.2359	17.0516	0.0637	14.8989	0.0478	2.6831	0.0681	12.5243
EW41, eb	-0.4482	17.4568	-0.0523	13.8363	0.0453	2.6277	0.2372	13.2797
EW42, eb	-0.5753	15.1804	-0.1636	12.7525	0.0386	2.6204	0.3461	13.7412
EW43, eb	-0.4303	15.9185	-0.0642	12.2951	0.0306	2.6084	0.4400	15.6307
EW44, eb	-0.8199	15.0793	-0.2945	13.8429	0.0438	2.5040	0.6382	14.9225
EW45, eb	-0.6538	10.5027	-0.2341	12.9821	0.0384	2.5454	0.5527	14.1195
EW46, eb	-0.6646	9.3439	-0.3130	12.2822	0.0479	2.5291	0.6044	13.7023
EW47, eb	-1.0978	8.7012	-0.6728	11.9278	0.1777	2.4366	0.5568	13.8698
EW48, eb	-0.5716	7.3771	-0.1990	8.3687	-0.0667	3.1534	0.0094	12.6947
EW49, eb	-0.2231	6.7093	0.0997	8.1231	-0.2105	3.0043	-0.0905	13.9767
EW50, eb	-0.3324	5.8932	-0.1981	9.1617	-0.1204	3.4127	-0.0765	18.0436
EW51, eb	-0.5213	3.4601	-0.4280	8.7569	0.0205	3.2622	0.1592	17.1434
EW52, eb	-0.7488	2.9597	-0.2013	8.0907	0.5062	1.2562	1.0584	11.9685
EW53/EW01, eb	-0.6605	2.2068	-0.0668	11.3573	0.2562	2.2659	0.8288	14.5039

	Onset		Peak Week		Peak Height		Duration	
Week, Predictor	Bias	Variance	Bias	Variance	Bias	Variance	Bias	Variance
EW01/EW02, eb	-0.2155	0.6258	0.2150	12.1756	-0.0904	1.8285	-0.1356	13.3206
EW02/EW03, eb	-0.0854	0.3488	0.2218	9.4779	0.2062	1.6053	-0.0067	4.8841
EW03/EW04, eb	-0.0125	0.1358	0.1467	7.5909	0.0646	1.1971	-0.1118	4.1492
EW04/EW05, eb	-0.0022	0.0023	0.8216	7.5349	0.1764	0.4593	0.7434	6.2939
EW05/EW06, eb	0.0537	0.0461	0.4864	5.3437	0.1103	0.0768	0.5264	7.5699
EW06/EW07, eb	0.0394	0.0248	0.6616	4.7960	0.0870	0.0485	0.5145	5.6693
EW07/EW08, eb	0.0186	0.0055	0.4665	3.7520	0.0144	0.0029	0.3912	1.9780
EW08/EW09, eb	0.0000	0.0000	0.1027	0.6475	-0.0030	0.0006	0.4322	1.8886
EW09/EW10, eb	0.0000	0.0000	-0.0541	0.1199	-0.0063	0.0007	0.3807	1.7018
EW10/EW11, eb	0.0000	0.0000	0.0232	0.0074	0.0008	0.0000	0.4339	1.2235
EW11/EW12, eb	0.0000	0.0000	0.0164	0.0043	0.0004	0.0000	0.4265	0.9528
EW12/EW13, eb	0.0000	0.0000	0.0093	0.0014	0.0002	0.0000	0.1904	0.0852
EW13/EW14, eb	0.0000	0.0000	0.0055	0.0005	0.0001	0.0000	0.0212	0.0024
EW14/EW15, eb	0.0000	0.0000	0.0045	0.0003	0.0000	0.0000	0.0132	0.0012
EW15/EW16, eb	0.0000	0.0000	0.0034	0.0002	0.0000	0.0000	0.0054	0.0002
EW16/EW17, eb	0.0000	0.0000	0.0010	0.0000	0.0000	0.0000	0.0021	0.0000
EW17/EW18, eb	0.0000	0.0000	0.0011	0.0000	0.0000	0.0000	0.0050	0.0003
EW18/EW19, eb	0.0000	0.0000	0.0006	0.0000	0.0000	0.0000	0.0358	0.0205
EW19/EW20, eb	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW39, per	0.0000	16.2276	0.0000	13.9567	0.0000	3.0419	0.0000	13.4590
EW40, per	-2.0000	15.6923	-1.2857	18.9890	-0.7537	6.3261	0.8750	40.2500
EW41, per	-2.2143	16.7967	-1.0714	24.9945	-0.7164	5.6286	1.4375	45.5958
EW42, per	-0.9333	25.3524	-0.8667	20.1238	-0.7362	5.1276	1.4375	38.9292
EW43, per	-0.2500	25.9333	-0.8125	20.1625	-0.8528	5.5846	1.1875	30.5625
EW44, per	-0.3125	22.6292	-0.3125	19.6958	-0.9532	4.9736	1.1875	27.8958
EW45, per	-0.5625	16.5292	-1.2500	20.8667	-0.9848	4.6183	1.3750	23.9833
EW46, per	-0.3750	14.2500	-1.6250	23.1833	-1.0356	4.1186	1.3750	21.3167
EW47, per	-0.6875	10.4958	-2.0000	17.8667	-1.0913	2.9846	1.5000	20.1333
EW48, per	-0.6250	9.7167	-1.1875	19.2292	-1.0935	2.5043	1.5000	19.7333
EW49, per	-0.7500	7.1333	-1.3750	15.0500	-1.0778	2.1149	1.5625	20.3958
EW50, per	-0.6875	6.2292	-0.8750	17.1833	-0.9751	1.9669	1.5000	20.2667
EW51, per	-0.6667	3.6667	-0.3333	13.8095	-0.9442	1.8090	1.3125	18.7625
EW52, per	-0.6667	3.6667	-1.8000	8.7429	-0.7581	1.6013	1.3125	18.7625
EW53/EW01, per	-0.5333	2.1238	-1.7333	7.9238	-0.6948	1.5197	1.1875	17.7625
EW01/EW02, per	-0.2667	1.0667	-1.7333	7.9238	-0.7035	1.4696	0.8750	16.5167
EW02/EW03, per	-0.2000	0.6000	-1.4667	6.4095	-0.5849	1.0879	0.7500	16.3333
EW03/EW04, per	-0.1333	0.2667	-1.2667	5.7810	-0.5144	0.7225	0.6250	15.3167
EW04/EW05, per	-0.0667	0.0667	-0.3333	5.6667	-0.2567	0.2249	0.5625	14.2625
EW05/EW06, per	0.0000	0.0000	-0.1333	5.1238	-0.0390	0.0609	0.4375	12.3958
EW06/EW07, per	0.0000	0.0000	0.3125	4.7625	0.0145	0.0030	0.5625	8.2625
EW07/EW08, per	0.0000	0.0000	-0.1875	0.5625	-0.0093	0.0014	0.5625	6.1292
EW08/EW09, per	0.0000	0.0000	-0.1875	0.5625	-0.0093	0.0014	0.4375	4.3958
EW09/EW10, per	0.0000	0.0000	-0.1875	0.5625	-0.0093	0.0014	-0.4375	0.7958
EW10/EW11, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.3750	0.5167
EW11/EW12, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.1875	0.2958
EW12/EW13, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW13/EW14, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW14/EW15, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW15/EW16, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW16/EW17, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

	Onset		Peak Week		Peak Height		Duration	
Week, Predictor	Bias	Variance	Bias	Variance	Bias	Variance	Bias	Variance
EW17/EW18, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW18/EW19, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW19/EW20, per	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW39, knn	-8.7120	13.8254	-10.9061	11.7477	-0.9117	2.8697	-4.1993	13.1550
EW40, knn	-10.4419	340.7679	-13.0872	352.4695	-1.2717	3.0460	-5.2232	20.7891
EW41, knn	-5.9967	118.3835	-7.2394	160.5568	-0.8421	4.0008	-2.4171	31.3419
EW42, knn	-3.3464	76.4803	-4.3017	111.8005	-0.6601	3.4380	-0.7567	29.3526
EW43, knn	-4.0971	145.0482	-5.1159	209.1143	-0.7264	3.5555	-0.4598	37.4966
EW44, knn	-0.3767	21.9166	-0.6958	21.9734	-0.6100	2.5889	0.4250	13.2386
EW45, knn	-0.7228	24.4833	-1.2457	26.6108	-0.5867	2.8380	0.3250	14.7753
EW46, knn	0.0228	14.1718	-0.4382	16.4066	-0.5359	2.8201	0.5946	16.1227
EW47, knn	-0.5367	9.2108	-0.9316	16.4781	-0.4399	3.1306	1.4297	14.5795
EW48, knn	-0.4158	6.6991	-0.6438	11.3774	-0.5132	3.3047	1.2676	16.8824
EW49, knn	-0.1716	6.1779	-0.4374	11.3338	-0.5436	3.2523	0.8126	20.5279
EW50, knn	-0.1185	5.0167	-0.6101	11.1436	-0.4573	3.6018	0.7415	23.9303
EW51, knn	-0.4462	5.6742	-0.8098	12.4346	-0.2724	2.4047	0.4500	17.9509
EW52, knn	-0.4984	3.5604	-1.0436	7.2930	0.1844	1.8262	1.0139	14.7664
EW53/EW01, knn	-0.5372	1.8718	-0.5462	6.6876	0.2313	2.0593	1.2877	14.4750
EW01/EW02, knn	-1.2646	19.4290	-1.6671	28.6025	-0.0855	1.5659	-0.0092	15.1151
EW02/EW03, knn	-0.8065	8.8553	-1.1175	18.5054	-0.0595	1.0623	-0.1121	11.4868
EW03/EW04, knn	-0.0063	0.0381	0.1679	4.5836	0.2228	0.9637	0.6256	7.8051
EW04/EW05, knn	0.0470	0.0171	0.5739	2.3217	0.2542	0.4810	0.6314	9.4912
EW05/EW06, knn	0.0921	0.1358	0.9400	1.8391	0.3936	0.3304	0.8940	10.3003
EW06/EW07, knn	0.0875	0.1226	0.9911	1.3874	0.4205	0.3237	0.9215	8.6460
EW07/EW08, knn	0.0404	0.0261	0.8891	1.5903	0.2952	0.2536	1.0343	6.8323
EW08/EW09, knn	-0.0000	0.0000	0.5718	1.3998	0.1799	0.2542	0.8621	6.7936
EW09/EW10, knn	0.0000	0.0000	0.4486	1.2254	0.1655	0.3569	0.8039	6.2430
EW10/EW11, knn	0.0000	0.0000	0.2817	1.2694	0.1754	0.4921	0.8469	4.9164
EW11/EW12, knn	0.0000	0.0000	0.3736	2.2338	0.1775	0.5039	0.9994	3.8841
EW12/EW13, knn	-0.0000	0.0000	0.4450	3.1680	0.1300	0.2703	0.5614	2.3919
EW13/EW14, knn	0.0000	0.0000	0.5086	4.1396	0.1072	0.1840	0.3264	1.2971
EW14/EW15, knn	0.0000	0.0000	0.4404	3.1034	0.0778	0.0969	0.1615	0.3353
EW15/EW16, knn	-0.0000	0.0000	0.1853	0.5493	0.0170	0.0046	0.0182	0.0053
EW16/EW17, knn	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000
EW17/EW18, knn	-0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
EW18/EW19, knn	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
EW19/EW20, knn	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000	0.0000
EW39, ebsir	-1.1954	14.5300	-1.6592	12.8341	-0.0627	2.9642	-0.5128	12.7544
EW40, ebsir	-0.7879	14.8024	-1.2641	13.7480	-0.0136	3.1515	-0.2290	11.1240
EW41, ebsir	-0.7453	16.6270	-1.1423	13.9564	0.0105	3.1475	0.2646	12.0290
EW42, ebsir	-0.6646	16.6953	-0.9911	13.7084	-0.0165	2.9851	0.6496	11.8704
EW43, ebsir	-0.3889	17.8120	-0.7142	14.3086	-0.0141	2.9573	0.7551	12.4100
EW44, ebsir	-0.8981	14.8169	-0.9798	14.2250	-0.0868	2.8470	1.4706	12.0126
EW45, ebsir	-0.5976	12.5010	-0.6744	13.1333	-0.1762	2.7527	1.4364	12.0954
EW46, ebsir	-0.7782	9.2146	-0.5740	11.2982	-0.3448	2.6660	2.1586	9.2101
EW47, ebsir	-1.1744	7.4824	-0.9366	11.9738	-0.4561	2.7483	2.2627	8.1528
EW48, ebsir	-0.6911	4.7284	-0.1093	8.3044	-0.7590	2.6897	2.6478	7.2520
EW49, ebsir	-0.0864	3.7140	0.7469	6.7075	-0.6428	3.1156	2.5966	6.5997
EW50, ebsir	0.3163	5.2890	0.9557	6.9338	-0.6230	3.3632	1.9161	8.0719
EW51, ebsir	-0.2200	3.6021	-0.0408	5.7004	-0.2286	3.0851	1.9464	9.4071

	Onset		Peak Week		Peak Height		Duration	
Week, Predictor	Bias	Variance	Bias	Variance	Bias	Variance	Bias	Variance
EW52, ebsir	-0.7124	3.0373	-0.4725	4.5852	-0.0652	1.8135	2.6739	8.4739
EW53/EW01, ebsir	-0.5237	1.8475	-0.2601	4.4875	-0.3084	1.7382	2.1696	10.2676
EW01/EW02, ebsir	0.0759	0.8087	0.1234	5.1736	-0.6142	1.2898	1.1904	6.9612
EW02/EW03, ebsir	-0.0246	0.4197	-0.4973	7.4017	-0.4369	1.5237	0.1789	11.7250
EW03/EW04, ebsir	0.0342	0.1005	-0.4478	4.8013	-0.3379	0.8846	0.7796	13.5534
EW04/EW05, ebsir	0.0970	0.1024	0.2626	1.4561	-0.1285	0.3395	1.4625	11.7869
EW05/EW06, ebsir	0.0689	0.0645	0.6088	1.1083	0.0682	0.0728	2.4003	10.4557
EW06/EW07, ebsir	0.0568	0.0516	0.8223	1.5552	0.1440	0.0563	2.4456	14.5140
EW07/EW08, ebsir	0.0148	0.0035	1.1156	2.3491	0.1313	0.0553	2.8339	11.2242
EW08/EW09, ebsir	0.0000	0.0000	0.8199	1.3911	0.0640	0.0161	2.2715	8.0125
EW09/EW10, ebsir	0.0000	0.0000	0.5975	2.1884	0.0420	0.0150	1.8930	6.5177
EW10/EW11, ebsir	0.0000	0.0000	0.2578	0.2479	0.0118	0.0009	1.2423	2.8229
EW11/EW12, ebsir	0.0000	0.0000	0.1878	0.3904	0.0089	0.0011	0.8815	0.6077
EW12/EW13, ebsir	0.0000	0.0000	0.1129	0.1425	0.0046	0.0003	0.4862	0.5783
EW13/EW14, ebsir	0.0000	0.0000	0.2448	0.8573	0.0107	0.0018	0.2145	0.1951
EW14/EW15, ebsir	0.0000	0.0000	0.0291	0.0122	0.0007	0.0000	0.0568	0.0104
EW15/EW16, ebsir	0.0000	0.0000	0.0154	0.0037	0.0003	0.0000	0.0077	0.0004
EW16/EW17, ebsir	0.0000	0.0000	0.0022	0.0001	0.0000	0.0000	0.0023	0.0000
EW17/EW18, ebsir	0.0000	0.0000	0.0028	0.0001	0.0000	0.0000	0.0038	0.0001
EW18/EW19, ebsir	0.0000	0.0000	0.0007	0.0000	0.0000	0.0000	0.0269	0.0116
EW19/EW20, ebsir	0.0000	0.0000	0.0003	0.0000	0.0000	0.0000	0.0000	0.0000

S10 Text

Importance sampling algorithm. Pseudocode for one algorithm used to build a collection of possible futures for the current season. (PDF.)

Data: $y^{r,\,s_{\text{curr}}}$, the wILI observations so far; $z^{r,s_{\text{curr}}}$, a version of $y^{r,\,s_{\text{curr}}}$ with two extra points estimated from GFT; prior distributions of wILI curves, noise levels, and transformations
Result: weighted collection of curves
Let $\phi(x;\mu,\sigma)$ be the normal pdf;
for *a large number of times* **do**
  Randomly draw f^r, σ, ν, θ, and μ from the corresponding priors;
  Let $f^{r,\,s_{\text{curr}}}(i) = f_4^r(i) = b^r + \frac{\theta^r - b^r}{\max_j f^r(j) - b^r}\left[f^r\left(\frac{i-\mu^r}{\nu^r} + \arg\max_j f^r(j)\right) - b^r\right]$;
  Calculate weight $w = \prod_{i=1}^{\text{length}(z^{r,s_{\text{curr}}})} \phi(z; f^{r,\,s_{\text{curr}}}(i), \sigma)$;
  Let v be a 53-length vector, a possible curve for this season;
  for i *in* 1..length($y^{r,\,s_{\text{curr}}}$) **do**
    $v_i := y_i^{r,\,s_{\text{curr}}}$;
  end
  for i *in* (length($y^{r,\,s_{\text{curr}}}$) + 1)..53 **do**
    $v_i := f^{r,\,s_{\text{curr}}}(i)$;
  end
  Add curve v with weight w to the collection of possibilities for this season (the posterior estimate)
end

Algorithm 1: Importance sampling procedure

Note that, since the GFT estimates are not exact, we weight $f^{r,\,s_{\text{curr}}}$ based on $z^{r,s_{\text{curr}}}$, using both ILINet wILI observations and GFT data, but we construct each possible curve v using $f^{r,\,s_{\text{curr}}}$ and $y^{r,\,s_{\text{curr}}}$, using no GFT. However, since ILINet data can undergo revisions, we have also considered versions that construct each v ignoring some of the more recent values in $y^{r,\,s_{\text{curr}}}$.

To improve computational efficiency, we also use a modified version of the code above that first divides up the possible values of f^r, σ, ν, θ, and μ into bins and estimates the average weight of $f^{r,\,s_{\text{curr}}}$'s in each bin. By sampling values of f^r, σ, ν, θ, and μ more frequently from the higher-weighted bins (and correcting for this decision in the weight calculation), we are able to construct a collection of curves with a high total weight more quickly than the version above.

S11 Text

Current limitations and future work

(PDF.)

Current limitations and future work

Our framework bases forecasts for a geographical unit based on the ILINet wILI for that area, sometimes with adjustments to recent wILI based on GFT data for that area. We are investigating ways to improve forecasts by incorporating additional sources of data, dependencies between geographical units, and more accurate models of reporting behavior.

In addition to GFT, other proxy data sources, such as Twitter activity and thermometer sales, can be used to estimate some underlying flu signal; wILI and proxy data can be modeled as noisy measurements of this signal. This measurement model can be incorporated into the weighting step of the framework, and used to refine the results of the smoothing procedure when forming the prior.

The framework can also be adjusted to incorporate lab testing data and spatial similarities and interaction, although the process is less straightforward. Lab test samples in the U.S. are not uniform random samples of ILI doctors' visits; they are collected from hospital visits, which are biased towards certain strains and age groups, and sent in from doctors on a non-random basis, with a goal of detecting novel strains. The mixture of test types and collection policies have also changed over time, and subtyping is not always performed, introducing additional complications. One basic approach to incorporating this data is to use wILI and lab data together to produce a signal for each subtype and for non-flu ILI, forecast each signal separately, then combine these forecasts to produce wILI predictions. Incorporating weather, vaccination coverage, and wILI data from other regions, is more involved. A simplistic approach is to make forecasts of weather, vaccination, and/or wILI in other regions alongside the wILI prediction for the target region, extending the transformations to shift the additional data alongside the corresponding wILI curve, and then to adjust the weighting step to incorporate the additional data, adding a score or log-likelihood term that favors transformed histories that more closely resemble the current season in terms of these additional data sources. However, conditioning on additional data sources in this way may exacerbate problems with latching onto a very small part of the prior.

Forecast accuracy can potentially be improved by a better model of wILI measurements. Modeling the inflation in wILI levels around holidays due to sharp drops in the number of non-ILI visits may improve forecasts by preventing "latching" of late-peaking seasons onto early ones, or seasons with a single real peak onto ones with secondary peaks like 2006-2007. As additional reports from ILINet providers are received and processed, wILI values for a particular week can be revised; revisions of wILI values after a few weeks tend to be slightly higher than the initial values, and are more stable. A model of the revision process can be incorporated into the weighting step of the framework and reduce errors in conditioning due to bias or increased noise in recent wILI measurements. Adjusting our wILI noise model may also yield improvements in the historical curve-fitting and importance sampling weighting steps. For example, one choice that incorporates the fact that wILI lies between 0% and 100% without requiring additional domain information would be to use betadistributed noise (with some constraints on the relationship of the parameters to make fitting and smoothing procedures well-defined, such as fixed dispersion). Considering various Box-Cox transformations [1] would add additional flexibility to the Gaussian noise model while maintaining generality. Tailoring a model to wILI specifically may also be an option, but is complicated by the fact that (a) ILINet providers can start or stop reporting on a weekly basis, differ in size and type, and potentially encourage or discourage visits for ILI (e.g., in phone calls before a visit is scheduled) in a way that can change from week to week and based on current patient load; (b) ILI visits can have trends based on the day of the week [2] and time of year; and (c) wILI is a weighted average of the ILI visit proportions for the states [3], and these proportions are not publicly available for all states for all seasons (nor is the data from the individual providers, nor is daily-level data for ILINet). Fig. S8 plots the trend-filtering residuals, which do not look exactly normally distributed; deviations from normality may be due to holiday effects, autocorrelation between residuals, and/or non-normality of wILI measurements.

References

[1] Sakia R. The Box-Cox transformation technique: a review. The Statistician. 1992;p. 169–178.

[2] Ong JBS, Chen MIC, Cook AR, Lee HC, Lee VJ, Lin RTP, et al. Real-time epidemic monitoring and forecasting of H1N1-2009 using influenza-like illness from general practice and family doctor clinics in Singapore. PLoS ONE. 2010 Jan;5(4):e10036. Available from: `http://www.plosone.org/article/info:doi/10.1371/journal.pone.0010036`.

[3] Centers for Disease Control and Prevention. Overview of Influenza Surveillance in the United States; 2013. [Online; accessed 29-August-2014]. Available from: `http://www.cdc.gov/flu/weekly/overview.htm`.