Data Gaps within Atmospheric Rivers over the Northeastern Pacific

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ABSTRACT: Conventional observations of atmospheric rivers (ARs) over the northeastern Pacific Ocean are sparse. Satellite radiances are affected by the presence of clouds and heavy precipitation, which impact their distribution in the lower atmosphere and in precipitating areas. The goal of this study is to document a data gap in existing observations of ARs in the northeastern Pacific, and to investigate how a targeted field campaign called AR Reconnaissance (AR Recon) can effectively fill this gap. When reconnaissance data are excluded, there is a gap in AR regions from near the surface to the middle troposphere (below 450 hPa), where most water vapor and its transport are concentrated. All-sky microwave radiances provide data within the AR object, but their quality is degraded near the AR core and its leading edge, due to the existence of thick clouds and precipitation. AR Recon samples ARs and surrounding areas to improve downstream precipitation forecasts over the western United States. This study demonstrates that despite the apparently extensive swaths of modern satellite radiances, which are critical to estimate large-scale flow, the data collected during 15 AR Recon cases in 2016, 2018, and 2019 supply about 99% of humidity, 78% of temperature, and 45% of wind observations in the critical maximum water vapor transport layer from the ocean surface to 700 hPa in ARs. The high-vertical-resolution dropsonde observations in the lower atmosphere over the northeastern Pacific Ocean can significantly improve the sampling of low-level jets transporting water vapor to high-impact precipitation events in the western United States.

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The transport of water vapor in the atmosphere from tropical/subtropical regions to higher latitudes is critical to water supply in densely populated areas, the occurrence of devastating flooding events, droughts, and the understanding of climate and hydrological systems (Benton and Estoque 1954; Koster et al. 1986; Zhu and Newell 1998; Ralph et al. 2006; Dettinger 2013; Lavers et al. 2015). Atmospheric rivers (ARs) are elongated corridors that transport water vapor from the subtropics and/or tropics to the extratropics (Zhu and Newell 1998; Ralph et al. 2004, 2005; Neiman et al. 2008; Ralph et al. 2018, 2019). They are typically associated with a pre-cold-frontal low-level jet (LLJ; Ralph et al. 2004, 2005) in the warm sector of extratropical cyclones accompanied by an upper-level jet. An AR is often characterized by the low-level transport of a moist-neutral air mass, which efficiently generates precipitation when lifted upward by the topography. Landfalling ARs over the northeastern Pacific Ocean are responsible for up to 50% of the annual precipitation over the western United States. They have large socioeconomic impacts as they contribute to both beneficial water resources and damaging extreme events (Ralph et al. 2006; Dettinger et al. 2011; Neiman et al. 2011; Ralph and Dettinger 2012; Dettinger 2013; Rutz et al. 2014; Waliser and Guan 2017; Corringham et al. 2019). Prediction of these ARs by the operational numerical weather prediction (NWP) models requires accurate initial conditions upstream, specifically east of the date line over North Pacific, which depend primarily on the available observations. Therefore, it is essential to assess the adequacy of the data sampling within these regions, such as 15°–60°N, 170°–110°W, where most landfalling ARs originate, develop, and propagate to the U.S. West Coast (Guan and Waliser 2019; Gonzales et al. 2019). The degree to which key characteristics of ARs are observed is also crucial for better understanding and modeling their dynamics. In particular, low-level moisture and winds are key parameters of water vapor transport that affect orographic precipitation and frontal systems (Ralph et al. 2004, 2005; Neiman et al. 2008; Martin et al. 2018). Upper-level winds and temperature are crucial parameters for constraining PV anomalies that influence the evolution of extratropical cyclones and their interactions with ARs (Zhang et al. 2019).

The global conventional observing system (e.g., in situ surface and land-based upper-air observations) is much sparser over the oceans, such as the northeastern Pacific, than over the continents (Kalnay et al. 1996; Rienecker et al. 2011; Dee et al. 2011; Ota et al. 2013). Observations over continents typically sample meteorological conditions using a variety of conventional observation systems (Table 1), including land surface synoptic observations (SYNOP), radiosondes, pilot balloon observations (PIBAL), meteorological terminal aviation routine (METAR) reports, rain gauges, and (commercial) aircraft. SYNOP, METAR, and radiosondes typically measure temperature (T), humidity (Q), wind (u and v) and pressure (P). Radiosondes can also provide high-vertical-resolution profiles for these variables through the troposphere. Commercial aircraft provide T , P , u , v , and sometimes Q during flight and take-off/landing, and sounding profiles are provided during the latter. Rain gauges are conventionally used to measure precipitation amount over a given time interval per unit area. The spatial and temporal resolution of these conventional observations is not evenly distributed, and the majority of the data are collected over North America and Europe (Table 1). Several

nonradiance ground-based remotely sensed observation systems also provide significant data over continents, including weather radar (i.e., NEXRAD) reflectivity and velocity–azimuth display (VAD) wind, and global positioning system meteorology (GPS-Met) integrated precipitable water vapor (IPW). Historically, marine observations largely relied on surface data (i.e., P , air/water T , and wind speed/direction) from drifting buoys (Centurioni et al. 2017) and ships, and upper-air data from commercial aircraft during flight (Table 1). Weather reconnaissance

Table 1. Summary of the nonradiance observations used in the operational GFS.

Observation type	Description	Resolution
Commercial aircraft (AIR)	Upper-air u , v , T , and Q (rare) observations from aircraft/pilot report (AI/PIREP), Aircraft Meteorological Data Delay (AMDAR), and Aircraft Communications Addressing and Reporting System (ACARS), and Meteorological Data Collection and Reporting System (MDCRS). Period of data: 1986–present (AMDAR by WMO); 1978–present (ACARS by major airlines); 1991–present (MDCRS by U.S. government and seven participating airlines) Limitations: Only sample a single upper level during flight, very few Q observations	Inhomogeneous horizontal and temporal resolution Spatial resolution (i.e., ACARS): At take-off/landing: High-vertical-resolution profiles (i.e., 30–40 levels) from ground to flight level (i.e., 200 hPa) with a vertical interval: ~10–50 hPa; during flight: Horizontal sample interval ~50–100 km at a single level, at high altitude (e.g., 11 km) Temporal resolution: Take off/landing: <1 min near surface; during flight: 3–7 min, 15–30 min, or 1 h
ASCAT-WIND (ASC)	Ocean surface u and v observations from Advanced Scatterometer (ASCAT); aboard the <i>MetOp-A(-B)</i> satellites: Radar measures backscatter to determine wind speed and directions at ocean surface Period of data: 2006–present (by EUMETSAT) Limitations: Sea ice and land contamination, gaps between swaths, only surface data	Horizontal resolution: ~25 and 50 km for ascending and descending of each satellite swath; ~550 km per swath Temporal resolution: Typically twice per day
SURFACE-LAND (LAND)	P s, u , v , T , and Q observations from land surface stations including fixed synoptic (SYNOP) stations and METAR reports (note: only surface pressure is assimilated for land stations) Limitations: Only sample land surface, lack of observations in some areas	Spatial resolution: Inhomogeneous; Average spacing is ~60 km over the continental United States, closest stations are ~15 km apart Temporal resolution: ~3 hourly for WMO synoptic stations, hourly for automated measurements, METAR reports are once per hour or per half hour
SURFACE-MARINE (SFC)	Surface wind speed/direction, air T , P s, SST, and Q (by ships) observations from ships, buoys (drifting and moored), and Coastal-Marine Automated Network (C-MAN), tide gauges. Limitations: Only sample ocean surface, sparse	Inhomogeneous spatial resolution: ~1 to 150 km. Temporal resolution: Ships: Four times per day; C-MAN buoy: Every 10 min; tide gauge near coasts: ~6 min; drifting buoys: once per hour or half an hour
VADWIND (VAD)	Upper-air u and v observations from velocity–azimuth display (VAD) wind profile from Radar Coded Message (subtype 1) and from the Next Generation Weather Radar (NEXRAD) level 2 decoder (subtype 2) Period of data: 1988–present by the U.S. NWS Limitations: Only available at land	Spatial resolution is inhomogeneous: The United States has 159 stations; about four pressure levels for one station Temporal resolution: Wind profiles typically spaced 6–10 min apart in time; assimilated data are every half-hour
RAWINSO-NDE (RADIOSONDE)	P s, u , v , T , and Q observations from radiosondes including fixed land stations and mobile stations. Period of data: 1920s–present (WMO member countries) Limitations: Inhomogeneous distribution, mainly available over land in the Northern Hemisphere	Inhomogeneous spatial resolution: For example, there are 69 fixed stations in the CONUS, 13 in Alaska, 9 in the Pacific, and 1 in Puerto Rico; raw data have high vertical resolution (~5 m), but the assimilated data are thinned to ~30 levels with a vertical resolution ~20 hPa; one profile takes ~1–2 h and drifts ~80–200 km Temporal resolution: Typically twice per day
AR Recon DROPSON-DES (DRO)	Upper-air u , v , T , and Q observations from AR Reconnaissance dropsonde profile and the flight-level report Period of data: 2016, 2018–present (Air Force, NOAA, U.S. Army Corps of Engineers, California Dept. of Water Resources, UCSD/SIO) Limitations: Nonroutine	Both spatial and temporal resolution vary with missions; Average number of deployed dropsondes per aircraft was ~25; one profile from ~300 to 1,000 hPa; dropsonde spacing is ~90 km; raw profiles have very high vertical resolution (~1–2 hPa) but assimilated data are thinned to ~30 hPa

Table 1. (Continued).

Observation type	Description	Resolution
GPS RO (GPS)	<p>Bending angle from GPS radio occultation sensitive to the gradient of the refractive index which is a function of temperature, moisture, and pressure</p> <p>Period of data: 1995–present [Global Navigation Satellite System (GNSS)]</p> <p>Limitations: Degraded quality and quantity in the lower troposphere</p>	<p>Global sampling with inhomogeneous horizontal and temporal resolution for an average of approximately seven soundings per day in each $5^\circ \times 5^\circ$ lat–lon box; above 20 km, the vertical sampling is ~20 m increasing to ~30 m near the surface; Superobs-ed to ~100 m during assimilation in GFS; sampling frequency at 0000, 0600, 1200, and 1800 UTC is not uniform</p>
SATWND (AMV)	<p>Atmospheric motion vectors (u and v) from satellite images, JMA <i>Himawari-8</i> satellites, EUMETSAT <i>Meteosat-8/11</i>, NESDIS <i>GOES-15/16</i>, and polar winds from MODIS <i>Aqua/Terra</i>, VIIRS <i>SNPP</i>, and AVHRR <i>MetOp-A</i></p> <p>Period of data: 1970s–present (EUMETSAT, JMA, NESDIS)</p> <p>Limitations: Difficulty in height assignment, only sample a few levels (i.e., geostationary images)</p>	<p>Horizontal and temporal resolutions vary with different satellites and instruments: for example, NESDIS <i>GOES-15/16</i> product: pixel resolution for longwave IR and water vapor channels are 4 km for <i>GOES-15</i> and 2 km for <i>GOES-16</i>; wind resolution is ~10 km for longwave IR and cloud-top drifted winds, and ~25 km for deep-layer winds; thinning box for EUMETSAT and JMA is 200 km $\times$ 200 km $\times$ 100 hPa in GFS</p> <p>Temporal resolution: <i>GOES-15</i> is every 30 min; <i>GOES-16</i> is every 15 min; Assimilated winds are hourly</p>

dropsonde profiles, which are typically considered as the airborne counterpart to the conventional radiosondes, provide supplemental observations over oceans when available. Since the 1990s, satellite-based scatterometer wind estimates, such as those from the Advanced Scatterometer (ASCAT), have been providing a significant amount of ocean surface wind data.

Atmospheric motion vectors (AMVs) are an important source for horizontal wind data produced by tracking cloud features or water vapor features in clear-sky conditions through consecutive satellite images. The height of an AMV datum is derived using satellite radiance measurements and temperature profiles from numerical models. Considerable uncertainty in AMVs arises from the height assignment (i.e., Salonen et al. 2015; Santek et al. 2019a). AMVs became operational at the National Centers for Environmental Prediction (NCEP; Nieman et al. 1997) in early 1996 and are still providing the majority of upper-level wind observations (Key et al. 2003; Velden et al. 2005; Santek 2010; Santek et al. 2019a,b) in the troposphere over oceans. While they are grouped into cloud top, deep layer, and infrared longwave depending on the satellite instruments (Table 1), data at a single location usually only have one vertical level. Ma et al. (2017) demonstrated that AMVs have improved the short- to medium-range forecasts of global upper-tropospheric water vapor. The GPS radio occultation (RO) technique, based on measurements from a rising or setting low-Earth-orbit (LEO) satellite receiving signals from GPS satellites, samples the atmosphere with nearly horizontal ray paths to provide high-vertical-resolution information on the atmosphere state (Kuo et al. 2004). GPS RO measurements can also be made from reconnaissance aircraft (Xie et al. 2012; Haase et al. 2014; Chen et al. 2018). While ray paths sample successively lower layers of the atmosphere, the rays are refracted due to the variations in refractive index of the atmosphere, which depends on T , Q , and P . The refractive bending angle profile is the preferred variable to be assimilated directly into NWP models to avoid additional retrieval errors. These high-quality thermodynamic profiles have contributed significantly to the enhancement of upper-air observing system, particularly over oceans. The data quality is sometimes degraded by low signal-to-noise ratio in the lower troposphere compared to aloft (Kuo et al. 2004). While AMVs have good coverage over oceans and RO data provide high-quality measurements of the upper atmosphere, Ralph et al. (2014) pointed out that there is still a sparsity of accurate high-vertical-resolution profiles of T , Q , u , and v over the oceans.

Satellite data, including radiance and retrieved temperature and moisture (Rodgers 1976;

Susskind et al. 2003) with near-global or global coverage at temporal resolution from hourly to daily (Table 2), have significantly increased observational coverage and improved forecast skill on a global scale, particularly after the development of variational data assimilation techniques for radiance (e.g., Simmons and Hollingsworth 2002; Collard and McNally 2009). With the increase in the number of satellite missions and the improvement of assimilation techniques, satellite radiance has become a major source of information about the atmosphere and oceans (Liu et al. 2012; Zupanski 2013; Zhu et al. 2014; Geer et al. 2018, 2019). The Global Forecast System (GFS)/Global Data Assimilation System (GDAS) operated by the National Oceanic and Atmospheric Administration (NOAA)/NCEP has been assimilating radiances directly since 1995, instead of retrieved temperature. Until recently, the radiances were assimilated only in cloud-free conditions and cloudy radiance data were discarded. To date, some operational weather centers have developed “clear-sky” approaches to assimilate infrared (IR) radiances above clouds, and “all-sky” approaches in order to make use of cloud- and precipitation-affected microwave radiances. Microwave humidity and temperature sounder

Table 2. Summary of the satellite radiance observations used in the operational GFS. Most of the information from this table can be found from the Observing Systems Capability Analysis and Review Tool (OSCAR) website (www.wmo-sat.info/oscar/spacecapabilities; accessed 15 July 2020), developed by WMO.

Observation type	Description	Operating period	Horizontal resolution and coverage	Swath width
AMSU-A	<p>Advanced Microwave Sounding Unit-A</p> <p>Radiance type: Microwave sounder radiances</p> <p>Aboard European Organisation for the Exploitation of Meteorological Satellites' (EUMETSAT's) <i>Meteorological Operation (MetOp)-A/B</i>, National Aeronautics and Space Administration (NASA) <i>Aqua</i>, <i>National Oceanic and Atmospheric Administration (NOAA)-15</i>, <i>NOAA-18</i>, and <i>NOAA-19</i></p> <p>Orbit: Sun synchronous</p> <p>Scan techniques: Cross track: 30 steps of 48-km sub-satellite point (s.s.p.); along track: One 48-km line every 8 s</p> <p>Channels: 15 channels from 23 to 90 GHz; channel 14 is not assimilated by the GFS</p> <p>Note: All-sky approach is applied for the assimilation in GFS</p>	1998–present	48 km at nadir; near-global coverage twice per day	2,250 km
ATMS	<p>Advanced Technology Microwave Sounder</p> <p>Radiance type: Microwave sounder radiances</p> <p>Aboard the U.S. NASA/NOAA/Department of Defense (DoD) <i>Suomi National Polar-Orbiting Partnership (Suomi NPP)</i> and <i>NOAA-20</i></p> <p>Orbit: Sun synchronous</p> <p>Scan techniques: Cross track: 96 steps of 16-km s.s.p.; along track: One 16-km line every 8/3 s</p> <p>Channels: 22 channels from 23.8 to 183.3 GHz</p> <p>Note: All-sky approach is applied for the assimilation</p>	2011–present	16–75 km at nadir; near-global coverage twice per day	2,200 km
AIRS-Aqua	<p>Atmospheric Infrared Sounder</p> <p>Radiance type: Hyperspectral infrared sounder</p> <p>Aboard NASA's <i>Aqua</i> satellite; the first hyperspectral sounder</p> <p>Orbit: Sun synchronous</p> <p>Scan techniques: Cross track: 90 ground footprints per scan; along track: one 13.5 km every 8/3 s</p> <p>Channels: 2,378 at 3.7–15.4 μm spectral coverage in frequency; 1–2-km vertical resolution; 281 (117) channels are selected (assimilated) in GFS</p> <p>Note: Clear-sky approach is applied for the assimilation</p>	2002–present	13.5 km; global coverage once per day	1,650 km

Table 2 (Continued).

Observation type	Description	Operating period	Horizontal resolution and coverage	Swath width
AVHRR	Advanced Very High Resolution Radiometer Radiance type: Infrared radiances aboard EUMETSAT's <i>MetOp-A</i> and <i>NOAA-18</i> Orbit: Sun synchronous Scan techniques: Cross track: 2,048 pixel of 800-m s.s.p.; along track: One 1.1-km line every 1/6 s Channels: 5, channels 3–5 are used by the GFS Note: Clear-sky approach is applied for the assimilation	2005–present	1.1 km at nadir; global coverage twice per day	2,900 km
CRIS	Cross-Track Infrared Sounder Radiance type: Hyperspectral infrared sounder Aboard the <i>Suomi NPP</i> and <i>NOAA-20</i> Orbit: Sun synchronous Scan techniques: Cross track: 32 steps of 48-km s.s.p.; along track: One 48-km line every 8 s Channel: 1,305 spectral channels from 3.92 to 15.38 μm , 1–2-km vertical resolution, 84 channels are used by the GFS model Note: Clear-sky approach is applied for the assimilation	2011–present	~20 km; near-global coverage twice per day	2,200 km
IASI	Infrared Atmospheric Sounding Interferometer Radiance type: Hyperspectral infrared sounder radiances Aboard EUMETSAT's <i>MetOp-A</i> and <i>MetOp-B</i> Orbit: Sun synchronous Scan techniques: Cross track: 30 steps of 48-km s.s.p.; along track: One 48-km line every 8 s Channels: 8,461 channels from 3.62 to 15.5 μm , ~1-km vertical resolution, 174 channels are assimilated in the GFS Note: Clear-sky approach is applied for the assimilation	2006–present	~25 km; near-global coverage twice per day	2,200 km
MHS	Microwave Humidity Sounder Radiance type: Microwave sounder radiances Aboard <i>MetOp-A</i> , <i>MetOp-B</i> , and <i>NOAA-19</i> Orbit: Sun synchronous Scan techniques: Cross track: 90 steps of 16-km s.s.p., covering ~49.4° on each side of the s.s.p. with an antenna beamwidth of ~1.1° at half power point; along track: One 16-km line every 8/3 s; channels: 5 channels from 89 to 190 GHz Note: Clear-sky approach is applied for the assimilation	2006–present	17 km at nadir; near global coverage twice per day	2,180 km
SAPHIR	Sounder for Atmospheric Profiling of Humidity in the Intertropics by Radiometry Radiance type: Microwave sounder radiance Aboard <i>Megha-Tropiques (meghat)</i> by Indian Space Research Organization and the Centre National d'Etudes Spatiales, France; orbit: Drifting orbit, circular, a 20° inclination at the equator Scan strategy: A cross-track scan of $\pm 43^\circ$, 130 steps of 10-km s.s.p.; along-track: One 10-km line every 1.6 s Channels: 6 channels located close to the 183.31 GHz Note: Clear-sky approach is applied for the assimilation	2011–present	10 km at nadir; intertropical (i.e., $\pm 30^\circ$ latitude) coverage 2–5 times per day, depending on latitude; 14 orbits per day	1,705 km

Table 2 (Continued).

Observation type	Description	Operating period	Horizontal resolution and coverage	Swath width
SEVIRI	Spinning Enhanced Visible and Infrared Imager Radiance type: Clear-sky radiances Aboard EUMETSAT's geostationary meteorological satellites <i>Meteosat-8 (M8)</i> , <i>M10</i> , and <i>M11</i> Orbit: Geostationary Scanning technique: Mechanical, E–W continuous, S–N stepping, rapid scanning Channels: 12 channels in the visible, IR, and water vapor Note: Clear-sky approach is applied for the assimilation	2002–present (Note: <i>M8</i> ended in 2016)	1 km (channel 12); 3 km (channels 1–11); full disk every 15 min (Note: not sampling the investigated domain)	Equatorial s.s.p. is along 3.5°E (<i>M8</i>), 9.5°E (<i>M10</i>), and 0° (<i>M11</i>).
SNDRD-g15	Geostationary Operational Environmental Satellite (GOES) infrared sounder radiances Radiance type: Infrared sounder radiances Aboard <i>GOES-15</i> Orbit: Geostationary Scan technique: Step angle 280- μ rad E–W with step and dwell time of 0.1, 0.2, 0.4 s adjustable Channels: 18 IR thermal bands Note: Clear-sky approach is applied for the assimilation	2010–20	~10-km diameter for each circular pixel; 60°S–60°N scan full disk every 3 h (at 0000, 0300, 0600 UTC, etc.)	Equatorial s.s.p. is along 135°W
SSMIS	Special Sensor Microwave Imager Sounder Radiance type: Microwave imager and sounder radiances Aboard the U.S. Air Force Defense Meteorological Satellite Program (DMSP) <i>F16</i> and <i>F17</i> Orbit: Sun synchronous Scan technique: Conical scan 53.1°zenith angle; scan rate: 31.9 scans per minute or 12.5 km per scan Channels: 24 channels from 19 to 183 GHz; assimilated: 1, 5–7, 24 Note: Clear-sky approach is applied for the assimilation	2003–present; <i>F16</i> ended in 2019	12–55 km; global coverage once per day	

data under all-sky conditions are currently assimilated by both NCEP and the European Centre for Medium-Range Weather Forecasts (ECMWF) (Geer et al. 2018; Zhu et al. 2016, 2019). Other operational centers such as the Met Office are also developing all-sky assimilation techniques for these soundings (Migliorini and Candy 2019). Significant errors in assimilating radiances are typically due to 1) approximations in the radiative transfer observation operators, 2) inaccuracies in the forecast models used in the radiative transfer calculation, and 3) simplifications in implementing the interface between the model simulation and the observation operator (Zhu et al. 2014; Geer et al. 2018). Radiance assimilation often requires references from nearly unbiased observations (Healy et al. 2005; Zhu et al. 2014). The sparsity of these observations over marine areas can bias the analysis toward the first guess (Cucurull et al. 2014). The nature of remaining gaps in the observing system has not been explicitly documented following the recent advances in radiance assimilation. Specifically, any remaining data gap over the northeastern Pacific in observing the dynamic and thermodynamic structures of ARs in current NWP systems has not been quantitatively assessed. The latter is the scope of this paper.

Several studies illustrate the need for sufficiently dense observations to characterize multiscale rapidly evolving systems and to capture strong temperature and moisture gradients in order to reduce landfall errors of ARs. Zhang et al. (2019) showed that ~80% of landfalling ARs in the western United States are dynamically related to extratropical cyclones in North

Pacific. ARs enhance cyclone deepening through the feedback of latent heating. Three-dimensional observations at multiple temporal and spatial scales are needed to capture the evolution of both ARs and cyclones and their interactions. Other studies (Wick et al. 2013; Lavers et al. 2018) indicated that upstream observations and their assimilation in NWP systems are key to improving the downstream forecasts of heavy precipitation events associated with landfalling ARs. Schindler et al. (2020) found that the assimilation of additional dropsondes and radiosondes, collected during the international North Atlantic Waveguide and Downstream Impact Experiment (NAWDEX; Schäfler et al. 2018) and other concurrent field campaigns, can reduce the root-mean-square error (RMSE) of 500-hPa geopotential by 1%–3% on day 2–3 over Europe and the southwestern Atlantic region based on a 1-month cycled experiment with ECMWF global system. NAWDEX explored the diabatic process of extratropical cyclones and warm conveyor belts in North Atlantic. The AR landfall forecast errors, including errors in location, timing, intensity, duration, orientation, and snow level, or altitude in the atmosphere at which snow melts to rain (Leung and Qian 2009; Wick et al. 2013; Ralph et al. 2019), significantly project onto errors in precipitation and streamflow. These errors have several sources, with the mesoscale frontal wave error being an important one for short-range forecasts (i.e., day 1–3; Martin et al. 2018, 2019; Demirdjian et al. 2020). The errors and uncertainties in the structure and propagation of synoptic-scale baroclinic waves along North Pacific upper-level jet could be an important factor leading to errors in the strength and position of landfalling ARs for longer lead time (i.e., >day 5). Initial errors and uncertainties can be amplified through the downstream development process of upper-level Rossby wave packets (Baumgart et al. 2018; Zheng et al. 2013).

Recent adjoint sensitivity experiments assessing heavy precipitation events over the U.S. West Coast identified forecast error development to be most sensitive to initial-condition errors in and near ARs in the short-range forecasts (Doyle et al. 2014; Reynolds et al. 2019; Stone et al. 2020; Demirdjian et al. 2020). As summarized in Demirdjian et al. (2020), initial positive moisture perturbations near the warm side of an AR often slowly feed into the moisture convergence region (i.e., developing frontal zone). Once they reach the frontal zone (i.e., after 24 h), substantial latent heat release will generate strong PV anomaly and further enhance the existing moisture transport and thereby amplify the transverse circulation. The amplified transverse circulation increases ascent and enhances precipitation.

Given the insight provided by these sensitivity studies and the characteristics of the current operational observing system, a field program called AR Reconnaissance (AR Recon; Ralph et al. 2020) was initiated in February 2016 to better understand and reduce forecast errors of landfalling ARs at 1–5-day lead times. The program developed as a multiyear research and operation partnership among the Center for Western Weather and Water Extremes (CW3E) of the Scripps Institution of Oceanography, at the University of California San Diego, NOAA NCEP, the U.S. Air Force, and other major stakeholders in water management. During these field experiments, dropsondes are deployed from research aircraft operated by the U.S. Air Force Reserves 53rd Weather Reconnaissance Squadron and NOAA Aircraft Operations Center. In 2016, three intensive observation periods (IOPs) were conducted in coordination with the El Niño Rapid Response campaign (Dole et al. 2018). In 2018 and 2019, 6 IOPs were conducted each year in 2018 with NOAA G-IV and two Air Force C-130s, and in 2019 with two Air Force C-130s. As of June 2019, AR Recon was officially called for in the National Winter Season Operations Plan [NWSOP; Office of the Federal Coordinator for Meteorology (OFCM); OFCM 2019].¹ About 25 dropsondes were released from each C-130 flight and 30 dropsondes were released from each G-IV flight at 75–100-km spacing during the 0000 UTC data assimilation window (Ralph et al. 2020). These dropsondes gather high temporal and vertical resolution observations of T , P , Q , u , and v within the AR core region and nearby dynamically active regions (i.e., upper-level jet, PV streamer, and

¹ In 2020, 17 IOPs were conducted, but analysis of those missions is not included in this study.

parent cyclone). Flight-level meteorology data are also collected on board. Other instruments on the NOAA G-IV include airborne GPS RO and tail Doppler radar. At the ocean surface, since 2019 AR Recon has been partnering with the Global Drifter Program to increase the density of drifting buoys with surface pressure over crucial areas of the northeastern Pacific (Centurioni et al. 2017; Ralph et al. 2020). The dropsonde data are first quality controlled on board and normally thinned to mandatory and significant levels, then transmitted to Chief Aerial Reconnaissance Coordination All Hurricanes (CARCAH), which performs a second quality-control step and then transmits data to the Global Telecommunications System (GTS). Global operational forecast centers such as ECMWF, the U.S. Naval Research Laboratory (NRL), and NCEP retrieve the data from the GTS for their assimilation systems. Each model often has its unique procedures to further quality control the data (i.e., remove data if the departure from model first guess is 3 times greater than the observation error in NCEP GFS) and assimilate them in the model depending on the data assimilation system and model first guess. For the GFS model, typically 1%–5% of the raw data are finally assimilated.

This study quantitatively assesses the data availability within and around ARs in the northeastern Pacific Ocean during 15 AR Recon IOPs in 2016, 2018, and 2019 (Table 3) using as a basis the subset of observations that were assimilated into the NCEP operational GFS model. This work is a fundamental step to inform future AR Recon targeting plans and data denial experiments by assessing where the available data are and how AR Recon data are augmenting the existing observational network. The domain of interest is 15°–60°N, 170°–110°W over the northeastern Pacific and the U.S. West Coast, where the highest track densities are found for landfalling ARs (Gonzales et al. 2019). This work is motivated by the following questions:

- How are routine observations, including both conventional observations and satellite radiances, distributed relative to ARs during the 15 AR Recon IOPs?
- Are satellite radiance data and other satellite products sufficient to sample ARs and the dynamically important surrounding areas?
- Can AR Recon fill existing observation gaps?

To quantify data density, we consider only those observations that passed the quality-control step of the data assimilation procedure of the NCEP operational GFS. This provides a more realistic evaluation of the density of AR Recon data relative to that of usable observations. The second section describes the GFS system and data used in this study. The third section assesses the nonradiance observation coverage relative to an AR, while the fourth section discusses the distributions of the clear- and all-sky radiance data. The fifth section examines how the AR Recon observations fill the data gap that currently exists within ARs. The sixth section presents conclusions and discusses future work.

Data and methodology

NCEP operational GFS. The NOAA's Next Generation Global Prediction System, with the new finite-volume cubed-sphere (FV3) dynamical core and Geophysical Fluid Dynamics Laboratory (GFDL) single-moment six-category cloud microphysics scheme, was implemented in operations on 12 June 2019 (GFSv15.1; NCEP 2019). The model's horizontal resolution is C768

Table 3. List of AR Recon IOPs and the targeted analysis dates. All the model analyses are at 0000 UTC.

IOPs	Dates	IOPs	Dates
2016IOP1	14 Feb 2016	2018IOP6	28 Feb 2018
2016IOP2	16 Feb 2016	2019IOP1	2 Feb 2019
2016IOP3	22 Feb 2016	2019IOP2	11 Feb 2019
2018IOP1	27 Jan 2018	2019IOP3	13 Feb 2019
2018IOP2	29 Jan 2018	2019IOP4	24 Feb 2019
2018IOP3	1 Feb 2018	2019IOP5	26 Feb 2019
2018IOP4	3 Feb 2018	2019IOP6	1 Mar 2019
2018IOP5	26 Feb 2018		

(~13-km grid resolution), and there are 64 sigma–pressure hybrid layers in the vertical with the model top at 0.2 hPa. The GDAS consists of a four-dimensional hybrid ensemble Kalman filter (EnKF) and variational algorithm (Hybrid 4D-EnVar) with 80-member ensemble forecasts that are run with a horizontal resolution of C384 (~25-km grid resolution).

Data. Detailed information regarding the assimilated nonradiance observations, including the nonroutine AR Recon data, is summarized in Table 1. Satellite radiance types and observational platforms are summarized in Table 2. NCEP GDAS applies the all-sky method (Zhu et al. 2016, 2019) to the radiances not affected by precipitating clouds from the Advanced Microwave Sounding Unit-A (AMSU-A) and the Advanced Technology Microwave Sounder (ATMS), therefore we label these two types of radiance as all-sky radiance and the rest of the sensors, which are primarily IRs, as clear-sky radiance. To make observations available for the 6-h assimilation window centered at 0000 UTC, as required in the NWSOP (OFCM 2019), the AR Recon dropsonde releases are planned to span ± 3 h of 0000 UTC. For the data comparisons, we are showing the observation density of all observational systems available within the same 6-h time window centered at 0000 UTC for each IOP date (Table 3).

The analyzed integrated water vapor transport (IVT) data are based on the wind and humidity data from GFS final analysis (FNL) at $1^\circ \times 1^\circ$ latitude–longitude horizontal resolution. IVT is calculated by multiplying specific humidity and wind at each layer and integrating the product from 1,000 to 200 hPa. The Global Precipitation Measurement (GPM) 6-h accumulated precipitation (Huffman et al. 2015) centered at 0000 UTC for each IOP are used to show the precipitating areas within the investigated domain.

Coverage of nonradiance observations

This section summarizes the coverage of conventional observations along with the nonradiance remotely sensed data (e.g., AMVs and GPS RO) over the northeastern Pacific Ocean and the western United States. AR Recon data are excluded in order to represent the quality-controlled data available from the routinely assimilated observations in the operational GFS.

Surface to 700 hPa (lower troposphere). Over 80% of the IVT in a typical AR is concentrated in the lower troposphere, or roughly below 700 hPa (Ralph et al. 2005; Guan et al. 2018). Observations in the lower troposphere reveal both the horizontal thermal and moisture gradients and the vertical structure of the low-level jet.

Figures 1 and 2 show the analyzed IVT and the assimilated nonradiance observations from the surface to 700-hPa pressure level at analysis times for all 15 IOPs. The surface data over the western United States are distributed densely. Surface observations are much less dense over the ocean than over land across all the cases. In general, surface observations are even more sparse within an AR object, defined in this study as $\text{IVT} \geq 250 \text{ kg m}^{-1} \text{ s}^{-1}$ and contiguous grid cell (i.e., $1^\circ \times 1^\circ$ latitude–longitude) number within the object > 25 . The $250 \text{ kg m}^{-1} \text{ s}^{-1}$ threshold is used because it typically corresponds well with the 85th-percentile IVT climatology over the northeastern Pacific (Guan and Waliser 2015). Moreover, areas with $\text{IVT} \geq 250 \text{ kg m}^{-1} \text{ s}^{-1}$ on a landfalling AR often match the spatial extent of heavy precipitation (Rutz et al. 2014). During AR Recon operations, the flight plans were designed based on downstream forecasts of extreme precipitation events with 1–3-day lead time. These are usually but not always associated with ARs. The $250 \text{ kg m}^{-1} \text{ s}^{-1}$ for IVT threshold is provided on each plot to guide the reader in identifying the regions of maximum water vapor transport. Some cases such as 2019IOP6 (Fig. 2g) have no conventional observations over the region with IVT greater than $500 \text{ kg m}^{-1} \text{ s}^{-1}$ while this moderate AR made landfall at 0000 UTC 2 March 2019, and brought about 50 mm of precipitation to coastal southern California and over 100 mm of precipitation

In the lower troposphere the land-based radiosondes and the radar network provide good-quality profiles over the continent; however, neither of these networks is available over the

Fig. 2. As in Fig. 1, but for the seven IOPs from (a) 2018IOP6 to (g) 2019IOP6.

marine regions (Figs. 1 and 2). The AMVs are the most copious observation type over the northeastern Pacific Ocean. Although the observation technique typically requires the presence of clouds for motion tracking between images, the presence of high clouds that are frequent in AR conditions prevents retrieval of AMVs from clouds at middle/lower levels. The AMV observations are therefore much more numerous in the upper levels and quite sparse in low levels over the marine AR regions. This is illustrated with Fig. ES1 in the online supplemental material (<https://doi.org/10.1175/BAMS-D-19-0287.2>), which shows higher AMV density in the upper troposphere over AR objects than in the lower levels, and with Fig. ES2 showing 6-times-denser cloud-top and infrared AMVs over AR objects at upper levels than over the non-AR region. AMVs are often single-level observations, and therefore provide minimal vertical structure information for a given location. The lack of middle- and lower-level AMV

data over the ARs is not improving despite the increase in satellite data volume with time. Additional AMVs derived from visible or shortwave infrared imagery of the *Geostationary Operational Environmental Satellite-15/-16 (GOES-15/-16)*, which are not currently assimilated, will also not improve this coverage (Fig. ES3).

Fig. 3. Observation density (boxplot) defined by the counts of observations per $1^\circ \times 1^\circ$ lat-lon grid cell for the assimilated observations over (a),(c),(e),(g) the marine AR object and (b),(d),(f),(h) the marine non-AR areas. (a),(b) The surface, (c),(d) the lower-troposphere (pressure ≥ 700 hPa), (e),(f) the middle-troposphere (450–699 hPa), and (g),(h) the upper-troposphere (200–449 hPa) observations. Colors represent the seven observed variables: temperature (T), humidity (q), zonal wind (u), meridional wind (v), GPS RO bending angle (GPS), surface pressure (P_s), and sea surface temperature (SST). The characteristics of observation types on the x axis can be found in Table 1. The boxplot graphically depicts the range of values for the 15 IOPs as follows: the top and bottom edges of the box indicate the top and bottom quartiles, the centerline in the box denotes the median, and the whiskers at the top and bottom extend to the most extreme data points, which are no more than 1.5 times the interquartile range from the box.

GPS RO bending angle data are assimilated in GFS, but not all profiles reach the surface, often because of strong temperature and moisture gradients near the top of the boundary layer. Horizontal gradients also contribute to retrieval error, so observation errors that increase to large values near the surface are assigned to these data and reduce their impact in constraining the model analysis at the lowest levels (Kuo et al. 2004; Healy and Thepaut 2006; Cucurull et al. 2014; Xie et al. 2012). There are already negligibly few humidity profiles available over the marine areas, and the humidity information contained in GPS RO bending angle observations is down weighted.

To summarize, observations measuring the lower troposphere are greatly reduced over marine areas when compared with the continental regions downstream of ARs. The deficit of observations under cloudy AR conditions is even worse, with the result being that the AR Recon data contribute to ~50% of the total conventional observations (see “Coverage of AR Recon data” section) for the cases sampled.

Middle troposphere (450–700 hPa). The middle troposphere, from around 450 to 700 hPa, contains one-third of the total mass of the troposphere. Monitoring the dynamical and thermodynamical properties of this region is critical to understanding the development and evolution of synoptic and mesoscale features, such as warm/cold advection, degree of static instability, baroclinic waves, and convective clouds.

The radiosondes, radars, and commercial aircraft again provide a good observing network over land for the middle troposphere (Figs. 4 and 5). Over the ocean, only two observation types, the AMVs and GPS RO, are available, and observations of the latter are quite sparse. When compared with lower levels, the density of AMVs is far lower mainly due to the large bias and errors arising from cloud-height uncertainty. For the three 2016 IOPs (Figs. 4a–c), AR Recon data are all that is available to provide direct wind, temperature, and humidity observations in the entire marine area within the investigated domain. With the enhancement of AMV assimilation techniques (Lim et al. 2019), the quantity of assimilated AMVs increased in the 2018 and 2019 cases (Figs. 4d–h and 5). Nevertheless, very few AMVs are used within the AR object. For example, no AMVs are assimilated over the region with IVT greater than $400 \text{ kg m}^{-1} \text{ s}^{-1}$ for 2019IOP6 (Fig. 5g); AR Recon dropsonde data are the sole direct observations available there (see “Coverage of AR Recon data” section). The data density for AMVs is less with higher IVT (i.e., areas with $\text{IVT} \geq 500 \text{ kg m}^{-1} \text{ s}^{-1}$, Figs. ES2d,e). The average density of AMVs within AR objects is ~75% lower than in the non-AR region (Figs. 3e,f). Beyond forecasting impacts, this lack of dense high-vertical-resolution temperature and humidity observations may hinder the understanding of midlevel cloud physics in mixed-phase clouds that are poorly represented in both weather and climate models (Sassen and Wang 2012).

Upper troposphere and lower stratosphere (UT–LS). The upper troposphere, from approximately 200 to 450 hPa, includes the upper-level jet stream and waveguide and plays a critical role in the genesis, development, and propagation of midlatitude baroclinic Rossby waves. Recent studies (e.g., Baumgart et al. 2018, 2019) have shown that initial-condition errors and uncertainties tend to grow upscale such as from mesoscale at short range (i.e., day 2) to synoptic scale at medium to long range (i.e., day 3–14). Therefore, observing this layer, particularly the baroclinic waves along the North Pacific jet stream, is important for understanding and forecasting an AR and its interactions with large-scale dynamics.

The quantity of observations is greater in the upper troposphere compared to the middle and lower troposphere due to an increase of AMVs, commercial aircraft observations, and GPS RO data (Figs. 6, 7, 3g,h, and Fig. ES1), as discussed previously. GPS RO figures more prominently because of its high accuracy and the greater weight applied in data assimilation schemes in

Fig. 4. As in Fig. 1, but for middle troposphere with the observed pressure from 450 to 699 hPa.

the UT-LS. In this layer, the spatial data gap is no longer apparent over AR objects compared to regions without ARs. However, AMVs and commercial aircraft preferentially sample only a few discrete heights at cloud top and flight level. The same sparsity of nonradiance observations over marine compared to continental regions is present as was seen at other levels, due to fewer radiosonde, radar, and commercial aircraft ascent/descent observations (Figs. 6 and 7).

Coverage of satellite radiance

Radiance data from modern satellites have become the major source of information about the atmosphere over oceans for most NWP systems (e.g., Geer et al. 2018). Initial imbalance introduced by the data assimilation process can degrade the forecast skill of a numerical model. In NCEP GFS, a tangent-linear normal-mode constraint was implemented

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Fig. 6. As in Fig. 4, but for upper troposphere with the observed pressure from 200 to 449 hPa.

assimilated radiances during AR Recon IOPs within our investigation domain, grouped into clear- and all-sky radiances.

Coverage of radiance assimilated using the clear-sky approach. By overall quantity, most of the radiance data (Table 2) are assimilated by a clear-sky approach, that includes radiances under clear-sky conditions or affected by optically thin clouds. Figure 8 presents the spatial distribution of clear-sky radiance for 2016IOP1 and 2019IOP3, the latter illustrating the typical coverage using the most recent observations. In these plots, the radiances are assigned to different altitudes based on the pressure value at the peak absorption layer of the specific channel in the atmosphere. In the lower troposphere

² Since only clear-sky radiances are supposed to be assimilated for these two radiance types, these data might be erroneously leaked into the system.

Fig. 8. Satellite radiance assimilated using clear-sky approach for (a),(c),(e) 2016IOP1 and (b),(d),(f) 2019IOP3 for peak pressure value (a),(b) greater than and equal to 700 hPa, (c),(d) between 450 and 699 hPa, and (e),(f) less than 450 hPa. Different colors denote different radiance types (see Table 2 for the short names in the legend). Gray shaded areas are the IVT values starting from $250 \text{ kg m}^{-1} \text{ s}^{-1}$. Blue contours represent the AR objects. Black dots are the locations of AR Recon dropsondes.

$500 \text{ kg m}^{-1} \text{ s}^{-1}$. Since 2019IOP3 has no SSMIS data in this layer, the radiance distribution over the AR object is even sparser east of 135°W .

From the upper troposphere to the model top (Figs. 8e,f), more clear-sky radiance data are assimilated over the whole domain because they are less affected by clouds than at lower levels. However, even in the upper levels, the radiance data that are rejected are systematically located over the ARs. For example, the infrared sounder radiances from *GOES-15* (SNDRD-g15)

data show a clear gap from 165° to 150°W over the AR object (Fig. 8e). More detailed stratifications (see Figs. 9 and 10) show that except for Infrared Atmospheric Sounding Interferometer (IASI), radiances above the 100-hPa pressure level do not show fewer observations over the ARs, and that the severe decrease in observations is most obvious in the lower levels where the AR moisture is concentrated.

In general, the observation density of clear-sky radiances over an AR is much lower than over non-AR marine regions (Fig. 9). The number of radiance observations rejected largely depends on the height of the highest clouds. For the top three clear-sky radiance types Atmospheric Infrared Sounder (AIRS), Cross-Track Infrared Sounder (CRIS), and SNDRD, the observation density over AR objects is reduced at all levels in the troposphere (Figs. 9a–c). For example, the median observation density based on all 15 IOPs is reduced from 4.8 to 2.0 per $1^\circ \times 1^\circ$ grid cell for AIRS in the lower troposphere and from 2.3 to 1.1 in the middle troposphere (Figs. 9a,b). The median observation density is reduced from 1.1 to near 0 for IASI in the lower troposphere (Fig. 9a). The observation density for clear-sky radiance is slightly lower in upper levels ($p < 200$ hPa) over ARs except for CRIS (Figs. 9d,e). Figure 10 shows that clear-sky radiance density in the lower–middle troposphere is typically lower by 50%–75% within ARs for AIRS, AVHRR, IASI, SSMIS, and Sondeur Atmospherique du Profil d’Humidite Intertropicale par Radiometrie (SAPHIR), and by 25%–75% for CRIS, Microwave Humidity Sounding (MHS) and SNDRD.

These results provide a quantitative measure of the gap in the quantity of assimilated clear-sky radiances in the lower to middle troposphere within an AR. This biased spatial sampling is a direct result of the fact that ARs are closely associated with clouds and precipitation (Cannon et al. 2020), and the clear-sky approach discards the radiances within these cloud- and precipitation-affected areas. Note that the extensive spatial coverage of radiance data and the high-resolution profiles provided by hyperspectral IRs render them still one important data category utilized in GFS (Le Marshall et al. 2006; Ota et al. 2013). In the next subsection we examine whether, or the extent to which, the all-sky radiance approach can mitigate the gap within an AR.

Coverage of radiance assimilated using the all-sky approach. The all-sky approach considers cloud information during the data assimilation process, and includes the

Fig. 9. Observation density (boxplot) of the radiance data with the peak pressure in the (a) lower troposphere, (b) middle troposphere, (c) upper troposphere, (d) 100–199 hPa, and (e) top layer from 99 hPa to model top. The red is for the marine AR object and the blue is for the non-AR region based on clear-sky radiance. The magenta and green are for the marine AR object and non-AR region, respectively, based on all-sky radiance. The boxplot graphically depicts the range of values for the 15 IOPs as follows: the top and bottom edges of the box indicate the top and bottom quartiles, the centerline in the box denotes the median, and the whiskers at the top and bottom extend to the most extreme data points, which are no more than 1.5 times the interquartile range from the box. The cyan dot denotes the mean value for the 15 IOPs.

effects of liquid water and cloud ice in the radiative transfer calculation. Currently, clear-sky and nonprecipitating AMSU-A and ATMS radiances are assimilated in the all-sky approach. Testing of using precipitation-affected radiances has been underway (Liu et al. 2019; Tong et al. 2020). Radiances affected by clouds and precipitation are often associated with large departures from the model first guess or observation minus first guess (OmF). Therefore, the observation errors are inflated to make use of these potentially useful radiances while minimizing the initial model shocks. Symmetric observation error (Geer and Bauer 2011) and the situation-dependent observation error inflation (Zhu et al. 2016) are combined to form the “final error” for the optimization. The normalized OmF, defined by the OmF divided by the final observation errors, is a key indicator of the potential contribution of a radiance observation.

Figure 11 shows the assimilated AMSU-A radiances from channel 15 and their normalized OmF amplitude along with the GPM 6-h accumulated precipitation. Channel 15 is a window channel at 89 GHz with the peak of the weighting function at the surface and directly responds to the emission from liquid droplets and the scattering from ice particles, rendering it a good representation of cloud-affected radiances. More radiances are assimilated over the AR objects (Fig. 11) using the all-sky approach for all IOPs when compared with the clear-sky distribution (Fig. 8). The all-sky approach rejects any radiances within precipitating areas. For example, data are rejected near 25°N, 128°W in Fig. 11h, where the 6-h precipitation is greater than 12 mm. Regarding the remaining radiances, the normalized OmF amplitudes are typically less than 0.5 over an AR object, particularly near the AR core (i.e., $IVT > 750 \text{ kg m}^{-1} \text{ s}^{-1}$) or around precipitating areas. For example, all the normalized OmF amplitudes are less than 0.25 south of 30°N over the AR object in 2018IOP4 (Fig. 11d). Large final errors, which often increase with increasing IVT amplitude (Fig. ES4), could be one important factor contributing to these small OmFs. The assigned errors near the core of the ARs are typically greater than 30 K, and often far more than typical model first-guess departure for brightness temperature (Zhang et al. 2013; Zhu et al. 2016).

The radiance data distribution and normalized OmF amplitude for channel 4, which is targeted at the lower-troposphere temperature sounding with the peak pressure around 950 hPa and is also sensitive to hydrometeors, show that the OmF amplitude is slightly smaller than that for channel 15 (Fig. 12) over northeast Pacific. Typical observation errors

Fig. 10. Percentage (boxplot) of observation density within an AR object relative to that in the non-AR regions based on assimilated radiance data with the peak pressure value in the (a) lower troposphere, (b) middle troposphere, (c) upper troposphere, (d) 100–199 hPa, and (e) top layer from 99 hPa to model top. The short names for radiance types are similar with those on Fig. 9. “ALL” summarizes all the radiances. The blue (orange) are for clear-sky (all-sky) radiances. The interpretation for the boxplot is similar to that in Fig. 9. Red dashed line (100%) in each panel represents that the observation density on an AR object and non-AR marine regions are equal.

Fig. 11. AMSU-A radiance data distribution based on assimilated data from channel 15 (dots, peak $p > 700$ hPa) and the normalized OmF amplitudes (colors on dots) from (a),(b) 2016IOP1-IOP2, (c)–(e) 2018IOP1-IOP3, and (f)–(h) 2019IOP1-IOP3. Gray shaded areas are the IVT at 0000 UTC for each IOP. Black dots are the locations of AR Recon dropsondes. Blue contour represents an AR object. The green-to-magenta shaded areas are for the 6-hourly accumulated GPM precipitation from 2100 UTC on the prior day to 0300 UTC.

for the non-AR marine domain are usually less than 2 K, while errors for some areas within an AR object increase to over 10 K (Fig. ES5). The heaviest precipitation is often located over the northeastern leading edge, northern boundary, or near the core of an AR object, and here either the all-sky radiances are rejected because of the presence of precipitation and/or extremely large OmF (Figs. 12f,h), or the assimilated radiances have relatively small normalized OmF amplitudes (i.e., < 0.25 , Figs. 12a,b,d,e). Similar results are found in the other

all-sky ATMS radiance data (Fig. ES6). One can easily identify the data gap near the AR core and its northern boundary because of the rejection of these radiances from channels 2–3 and 16–17 (Tong et al. 2020). The error assigned to the assimilated radiance within the AR object is often double or more than the typical first-guess departure in brightness temperature (Zhu et al. 2019) such as near 20°N, 132°W in Figs. ES6a and ES6b.

To summarize, the all-sky radiance approach augments the quantity of data within an AR in the lower–middle troposphere. The observation density of AMSU-A (ATMS) radiance over an AR object is ~15% (~25%) less than that over the non-AR regions below 450 hPa (Figs. 9a,b and 10a,b). In the upper troposphere (Figs. 9c and 10c), AMSU-A radiance is

Fig. 12. As in Fig. 11, but based on channel 4 for (a),(b) 2016IOP1 and IOP2, (c)–(e) 2018IOP1 to IOP3, and (f)–(h) 2019IOP1 to IOP3.

sparser by ~10% over the AR object. No clear gaps are found above 200 hPa over AR objects (Figs. 9d,e and 10d,e) for both AMSU-A and ATMS. However, the normalized OmFs of the assimilated data are typically small (<0.25), particularly in or near the AR core and precipitating regions, indicating that the assimilated data near the AR core or its northern boundary might have a limited capability for modifying the model analysis.³ Nevertheless, the availability of multiple radiance channels plays an important role in the magnitude of the analysis increment. For example, although each radiance may have a small contribution to analysis increment, collectively, they may make the proper magnitude of contribution to a grid analysis increment if the OmFs from different channels do not cancel or offset each other. ARs involve multiscale processes that are guided by large-scale forcing, particularly Rossby wave dynamics. So, it is useful in addition to including radiances that densely capture the large-scale systems outside the core of the ARs, to have crucial observations that capture the critical small-scale to mesoscale features of the AR core. While future expansion of the all-sky approach to the full complement of radiance channels in GFS may modify these results somewhat, the assimilation of these additional channels is more challenging. The developments of assimilating precipitation affected radiances have shown promising results over the Southern Hemisphere (Liu et al. 2019; Tong et al. 2020). The impact of including these radiances on forecasts over the Northern Hemisphere is overall neutral (Tong et al. 2020).

³ These small normalized OmFs worked well in the preimplementation tests and parallel experiments. The weights given to each observation type are typically tuned based on the GFS model performance over at least a month or longer. Retuning is suggested to be done periodically as the system evolves.

Coverage of AR Recon data

AR Recon missions considered in this study include 15 IOPs during 2016, 2018, and 2019. This section investigates how well the AR Recon data fill the observation gap by assessing the added coverage from these unique observations.

Added data coverage from AR Recon observations. An attractive feature of dropsondes is that they provide exceptionally high-resolution profiles of all prognostic variables of the atmospheric state (i.e., T , Q , P , u , and v) with high accuracy over the marine areas. In the lower troposphere (Figs. 1, 2, 3c,d), AR Recon dropsondes are the major source of observations within these ARs over oceans with very good cross-sectional sampling. They are the sole direct observation type over regions with IVT greater than $500 \text{ kg m}^{-1} \text{ s}^{-1}$ in 11 out of the 15 IOPs (Figs. 1, 2). Moreover, there are negligibly few direct measurements of humidity profiles available over the marine areas except for those provided by AR Recon. The microwave all-sky radiance data provide the only other comprehensive sampling of moisture indirectly through brightness temperature, but their vertical resolution is very low and completely absent in heavy precipitation regions within or near the AR core. AR Recon dropsonde data account for over 99% of the humidity observations and ~46% of the wind observations within the AR object (Figs. 3c,d, Table 4). In the middle troposphere (Figs. 3e,f, 4, 5 and Table 4), AR Recon

Table 4. Contribution (%) of AR Recon dropsonde observations for temperature, humidity, and horizontal winds to the total observations in the lower/middle troposphere over the AR objects. The calculations are based on all 15 IOPs listed in Table 3.

Atmospheric layers	Temperature	Humidity	Horizontal winds
From near the surface to 700 hPa	78.7%	99.9%	45.5%
From near the surface to 450 hPa	76.8%	99.9%	48.0%
450–700 hPa	74.1%	99.8%	56.9%

dropsondes provide most of the direct observations within ARs and their surrounding areas, and largely alleviate the most severe data gap left from other data types. In the upper troposphere (Figs. 6, 7, 3g,h), the dropsonde data provide critical vertical resolution of winds that sample the upper-level jet (Figs. ES2 and ES3), even though they are horizontally sparse compared to AMVs and commercial aircraft data. Figures 3g and 3h highlight that these data provide the only direct humidity observations in the upper troposphere over oceans.

In the analysis so far, we have focused predominantly on the horizontal observational gaps divided into three vertical categories. When the vertical distributions of observations are being examined, the advantages become much more apparent. Figures 13a and 13b compare the three-dimensional nonradiance data distributions in a typical AR event during 2016IOP1 with and without AR Recon data assimilated. The nonradiance data distribution is much denser in the critical atmospheric layers that contain the low-level jet and is typically below 700 hPa (Fig. 13b). Dropsondes add the required level of details about the vertical properties of stability and saturation in this region that often impact cyclogenesis (Eiras-Barca et al. 2018).

The cross section (Figs. 13c,d) perpendicular to the AR along a flight path shows that the height distribution of radiances (assigned to the pressure value at the peak absorption layer of the specific channels) grossly undersamples the vertical structure between 400 and 900 hPa, and misses the maximum IVT in and above the core of the AR that peaks at 850 hPa. Although the microwave radiances have broad weighting functions, that make them sensitive to the integrated effect of the layer, their coarse vertical resolution does not distinguish the vertical details of the AR structure. Therefore, the dropsonde data are not only denser along the flight track but also more accurate than the radiance data at the lower levels. One caveat is that the horizontal resolutions of these radiances usually do not reflect the original spacing of the raw radiance data. Traditionally, dropsondes are assimilated at mandatory and significant levels, which are not adapted to the vertical structure of ARs, as seen in Fig. 13d. The raw AR Recon dropsonde profiles are fully sufficient to fill the gaps from near the surface to the middle troposphere (Fig. 13d). One important conclusion of this work is that there may be much to be gained in the existing data assimilation methods for dropsonde data in ARs, simply by increasing the number of vertical levels for the aircraft data transmission and assimilation, to take full advantage of the unique vertical resolution, especially wind and humidity data.

To summarize their sampling characteristics, AR Recon data can largely fill the observation gap from near the surface to the middle troposphere, where they contribute 76.8% of the direct temperature, 99.9% of the humidity, and 48.0% of the wind observations in an AR object (Table 4, Fig. ES1). The variables measured by dropsondes are readily assimilated as prognostic model state variables and therefore are very complementary to observations that require the use of complicated forward observation operators.

Comparison between AR Recon dropsondes and GFS analysis. To investigate the potential for AR Recon dropsondes to improve the model analysis, we have calculated the differences between the dropsonde observations and the GFS analysis (data denial experiment withholding AR Recon dropsonde observations in the data assimilation) by interpolating model-analyzed variables to measured dropsonde locations. The model analyses are found to have a small but consistent cold bias in temperature and a moist bias in humidity from 600 to 900 hPa (Figs. ES7a,b). The horizontal winds do not show a clear bias (Figs. ES7c,d). The RMSEs for temperature are 10%–50% larger than the assigned observation errors from 300 to 950 hPa (Fig. ES7a). The RMSEs for zonal wind are 30%–50% larger than the observation errors from 200 to 950 hPa, and for meridional wind are 20%–65% larger than the observations errors from 200 to 1,000 hPa. The RMSEs for specific humidity are 5%–35% larger

Fig. 13. (top) Three-dimensional illustration of observation distributions for nonradiance data (a) without and (b) with AR Recon flight-level and dropsonde data (black filled circles); (bottom) the radiance locations (colored markers) and their final errors (colors on each marker) along a flight path A–B (c) without and (d) with AR Recon dropsondes. The cyan dots in (d) are the raw dropsonde observations. The black dots are the AR Recon flight-level and dropsonde data used in the operational GFS. The coordinates for A are 49.9°N, 144°W and for B are 39.2°N, 141.4°W. This figure is based on the observations for 2016IOP1. The gray and pink shaded areas in (a) and (b) are the isosurface for 50th ($25 \text{ kg m}^{-1} \text{ s}^{-1}$)- and 95th ($80 \text{ kg m}^{-1} \text{ s}^{-1}$)-layer IVT values, respectively. The surface shades with black contours are for the total IVT value starting from $250 \text{ kg m}^{-1} \text{ s}^{-1}$ with an increment of 250.

than the observation errors from 500 to 800 hPa, and they are smaller than the observation errors from near the surface to 800 hPa. The specific humidity differences are significantly larger from 700 to 850 hPa, which corresponds to the vertical level with the poorest vertical resolution and sampling in the radiances (Figs. 13c,d). It is worth noting that the assigned

observation errors are typically 4 (i.e., for temperature) to 10 (i.e., humidity) times larger than the measurement accuracy (Fig. ES7).

Relationship to initial-condition sensitivity. In the context of NWP models and forecast error sensitivity (e.g., Rabier et al. 1996), the value of targeted observations largely depends on whether they sample the variables and regions in the initial state that have the greatest impact on the forecasts of high-impact events during the verification period over the verification regions (Majumdar et al. 2011; Majumdar 2016). Adjoint and/or ensemble-based sensitivities are often employed to determine the targeted areas for these events (Langland et al. 1999; Majumdar et al. 2002; Ancell and Hakim 2007; Torn and Hakim 2008; Chang et al. 2013; Zheng et al. 2013). Doyle et al. (2014) first applied the adjoint sensitivity technique to an AR-related extratropical cyclone event over the North Atlantic and found that predictions of low-level kinetic energy (KE) of the cyclone are highly sensitive to small filaments of moisture within an AR. Reynolds et al. (2019) employed the NRL moist adjoint modeling system to evaluate the sensitivity of AR forecasts for January and February 2017 and found that the forecasts for both the accumulated precipitation and the low-level KE respond predominantly to initial conditions in and around the AR. Furthermore, they confirmed the case study result from Doyle et al. (2014) that the largest forecast sensitivities are from the AR moisture content, followed by temperature and winds. Finally, they demonstrated that the forecast errors are closely associated with the strength of the initial-condition sensitivities, suggesting that the moist adjoint sensitivity is appropriate for the targeted observation applications such as AR Recon.

A schematic summary (Fig. 14) shows the relation of AR Recon data and the adjoint-based initial-condition sensitivities for landfalling ARs from Reynolds et al. (2019). A typical AR over the northeastern Pacific (Ralph et al. 2017), includes a parent cyclone to its northwest, a cold front near its core and the northern flank, and a warm front crossing its leading edge (Fig. 14a). A cross section is made across the AR to show key meteorological features and the vertical structure of the AR (Fig. 14b), which includes the cold side, AR sector, and the warm side, further separated to show the lower, middle, and upper levels. The top left is the upper-tropospheric jet, where the strongest winds and minimal water vapor are often present. The jet streak aloft provides large-scale forcing for the development of synoptic features such as the fronts and ARs, and thereby are often associated with scattered postfrontal convective and/or stratiform clouds and precipitation below. The AR sector is concentrated below the 700-hPa pressure level at the bottom center of the figure, which carries the vast majority of the horizontal water vapor transport, even though the winds are not as strong as in the upper-level jet. Just above the AR sector and its northern flank, the overcast low- and midlevel clouds and/or convective clouds and precipitation typically exist (see Fig. 12 from Cannon et al. 2020). Meanwhile, the overcast upper-level clouds are often above the AR sector and the narrow frontal zone.

Figure 14c consolidates some of the major results from Reynolds et al. (2019) on sensitivity of 1–2-day forecasts of landfalling ARs along the U.S. West Coast to initial-condition errors of wind and moisture (see Figs. 7 and 8 in Reynolds et al. 2019). The highest sensitivity of AR-related precipitation forecasts to both winds and humidity are located within the AR sector and above middle levels. Moderate sensitivities for winds are found in the upper level above the AR and in the lower to middle levels on the cold side. Figure 14d overlays the AR Recon data categories with the same 3×3 subregions denoting the front–jet–AR system. Clouds and precipitation in and/or above an AR often block AMV measurements and degrade the quality of radiance data. GPS RO data quality is also degraded within the AR due to the strong moisture gradients (Sokolovskiy et al. 2007). The AR Recon data, including the flight-level and airborne RO (ARO) in the upper level, the dropsonde profiles through the troposphere, and supplemental drifting buoys at the surface (Ralph et al. 2020) provide high-quality wind

Fig. 14. A schematic summary of the AR Recon observations relative to key meteorological features and structure of an AR over the northeastern Pacific Ocean, and the adjoint sensitivity of West Coast landfalling ARs to initial-condition winds and moisture 1–2 days ahead. (a) A plan-view representation of the AR and the surrounding meteorological features, including the parent low pressure system and associated cold (bold black with triangles), warm (bold black with semicircles), and occluded surface fronts (thick black with both triangles and semicircles). IVT amplitude is shown by color fill ($\text{kg m}^{-1} \text{s}^{-1}$), with IVT exceeding $250 \text{ kg m}^{-1} \text{s}^{-1}$ in gray indicating the AR boundaries. A representative length scale is shown. The position of the cross section shown in the other panels is denoted by the dashed line A–A'. (b) Vertical cross section of key meteorological features in and near an AR over the northeastern Pacific Ocean, including the core of the water vapor transport in the AR (orange contours and color fill) and the cloud distribution, in the context of the upper-level jet (blue contour), frontal zone (light gray filled), and tropopause (bold black line). (a),(b) Adapted from Ralph et al. (2017). © American Meteorological Society. Used with permission. (c) Adjoint sensitivity of forecasts of West Coast landfalling ARs at 1–2-day lead time to initial-condition errors in wind and moisture offshore summarized from Reynolds et al. (2019). The background is as in (b). (d) The distributions of AR Recon observations over the northeastern Pacific Ocean during AR conditions. The supplemental buoys and ARO data so far have not been assimilated by GFS/GDAS.

and moisture data over the most wind- and moisture-sensitive regions, where the initial errors will presumably trigger forecast errors in landfalling ARs and the associated precipitation over the western United States.

Summary and future work

The atmospheric science community has been aware of the data gap over the northeastern Pacific, although satellite radiances and other satellite products such as atmospheric motion

vectors (AMVs) are believed to provide extensive coverage in general. This work shows that to date, nonradiance observations available for studying and modeling atmospheric rivers (ARs) are insufficient from near the surface to middle troposphere, and that satellite radiances are not able to adequately fill this gap.

The only nonradiance observations available in the troposphere within an AR are AMVs, commercial aircraft, global positioning system (GPS) radio occultation (RO), and AR Reconnaissance (Recon) data during field campaigns. GPS RO and commercial aircraft data have limited capability to sample the lower troposphere, although GPS RO will improve in performance significantly with the launch of new COSMIC-2 satellites (Ho et al. 2020). AMVs have limited sampling between 450 and 750 hPa and often cannot provide the vertical distribution for a given location. During the 15 IOPs in 2016, 2018, and 2019 considered in this work, dropsonde observations contribute ~99% of the direct observations of humidity, 77% of temperature, and 48% of the wind within an AR object from near the surface to the middle troposphere (Table 4). The gap in data becomes even more severe for stronger ARs, which could be related to the decreasing quality of AMVs below high or multilevel clouds, and with increasing precipitation rates.

The quantities of radiance data assimilated by clear-sky approaches are typically 40%–60% lower within an AR when compared with non-AR marine regions in the lower–middle troposphere. All-sky approaches often provide ~10%–30% fewer observations within an AR object than over non-AR regions. The heaviest precipitation is often located at the northeastern leading edge, northern flank, and/or the core of an AR. Most of the radiances in these parts of the AR are either rejected, leaving a data gap, or prescribed extremely large errors for assimilation in the operational Global Forecast System (GFS). This may decrease the potential impact of these observations on model analysis and forecasts for ARs. Nevertheless, ARs involve multiscale processes and often interact with extratropical baroclinic waves. Satellite radiances and their products are important to monitor the environment, the background baroclinic waves, and the interactions between ARs and extratropical cyclones.

The schematic (Fig. 14) highlights that the AR Recon dropsondes and the supplemental drifting buoys and airborne RO data are not only filling the observation gap in the lower to middle levels within and above an AR, but also provide high-quality wind and moisture data over the highest wind- and moisture-sensitive regions where initial errors will most likely trigger forecast errors in the landfalling ARs and the associated precipitation over the western United States. The dropsonde data used by NCEP GFS (Fig. 13d) compose only a small portion (1%–5%; subsampled mainly at the mandatory and significant meteorological levels) of the raw dropsonde profiles. Even this small fraction of data can largely alleviate the data gap in the lower part of the atmosphere.

To summarize, a clear gap in nonradiance and clear-sky radiance data available for studying and modeling ARs exists from near the surface to the middle troposphere. All-sky microwave radiance data cannot fully fill the gap mainly due to the removal of precipitation-affected data and the small weights of the data under AR conditions. Zhu et al. (2016) found that the forecast impact of adding all-sky radiances are overall neutral in the Northern Hemisphere, while they do augment the assimilated data and reduce the analysis biases in the tropics. With the application of the all-sky approach to precipitation-affected data (Tong et al. 2020), it is expected that the impact of all-sky radiance will improve. Furthermore, all observational systems, including the all-sky radiance data, grossly undersample the vertical structure of the oceanic AR, particularly in the critical layer with the maximum IVT roughly below the 700-hPa pressure level (Fig. 13). The high-vertical-resolution dropsondes that include winds, can provide significantly improved sampling adapted to ARs, specifically in the leading edge of high-impact events where clouds and precipitation adversely affect all satellite radiances. This work also recommends an increase in the number of vertical levels for assimilation in GFS, to take full advantage of the unique vertical resolution, and of wind and humidity data specifically.

This work underscores the importance of AR Recon dropsondes to fill the data gap for high-impact AR events that make landfall at the U.S. West Coast. This is particularly relevant as the upstream initial conditions are directly linked to predicting heavy precipitation events over the whole western United States at multiple time scales from nowcast to several days prior to the events. This study is a fundamental step to inform future AR Recon targeting plans and data denial experiments by assessing where the available data are and how AR Recon data are augmenting existing observational networks. Additionally, the dropsondes provide valuable data to study the physical processes associated with ARs and heavy precipitation events upon their landfall as analogous to how the dropsonde data provide great value for studying hurricanes (Majumdar 2016). They can also provide validation data for new satellite missions such as *GOES-16/-17* products and anchoring data for radiance assimilation in the lower atmosphere over the oceans (Poli et al. 2010; Cucurull et al. 2014; Zhu et al. 2014). Future efforts could focus on data denial experiments to thoroughly assess the usefulness and effectiveness of different observational datasets in improving initial conditions and predictions generated with numerical models.

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