Chapter 1

Introduction: Humidity and Climate Change

1.1 INTRODUCTION - RATIONALE

The climate system of the Earth is ever changing across all space and time scales. Evidence for past changes arises from "proxies" such as ice cores and geological records, and for more recent times from tree rings, coral growth, and historical documentary records. Only over the last two Centuries have we been actively measuring the atmosphere. Since the late 18th Century, measurements by thermometers and other surface instruments on land have been available along with measurements made by ships. After the Second World War, balloon-based sounding of the free atmosphere began and finally, since the 1970s satellites have also been employed to monitor the climate system.

Most of our modern measurement systems have been employed primarily for weather forecasting purposes. Little thought has been given as to whether we can compare present observations to data from a century or even a decade previously. The result has been changes in instrumentation and practice which, whilst likely improving the absolute accuracy of the measurement, also compromise the historical continuity of the record for long-term climate monitoring purposes. To create a climate data record requires the identification and removal of as many such non-climatic influences as possible (homogenisation) to yield an estimate of the true climate evolution.

To date, climate data record construction efforts have principally considered temperature and to a lesser extent pressure and precipitation. However, even taken together these are an incomplete diagnostic of the climate system and do not adequately constrain our understanding. Humidity, both relative and absolute, is potentially a very

insightful tool for climate research. To constrain the earth's near-surface energy budget the concept of moist enthalpy (Pielke *et al.*, 2004) must be understood:

$$H = C_p T + Lq$$
<div align="right">Eq. 1.1</div>

where *H* is moist static energy (or moist enthalpy) (in J kg^{-1}), C_p is the specific heat capacity of air at constant pressure, *T* is air temperature (in K), *L* is the latent heat of phase change of water vapour and *q* is specific humidity of air (in kg kg^{-1}). Hence, to warm a parcel of air when relative humidity is conserved (*q* increases with *T*, Fig. 1.1) requires considerably more energy than if the specific humidity remains constant.

Climate model interpretations of future and past climates have generally converged upon a near-constant relative humidity over time (Allen & Ingram, 2002; Ingram, 2002), thus requiring more energy per 1 K rise in global temperature than implied by the temperature change alone assuming dry processes. Whether relative humidity is conserved in reality, in addition to being essential for climate model validation, has implications for how temperature changes may occur aloft. Any increases in surface water vapour (absolute humidity) will lead to greater warming aloft due to latent heating effects upon condensation. Furthermore, any changes in surface absolute humidity have implications for upper-tropospheric water vapour content, where it plays a significant role in the global radiation budget as a greenhouse gas (Soden *et al.*, 2005).

Detection and attribution studies have previously considered temperature, and to a lesser extent precipitation and pressure changes, as diagnostics. Specific humidity too has potential use here with likely favourable signal-to-noise properties in warm, water abundant regions according to Clausius-Clapeyron theory (section 1.2). Showing consistent evidence for anthropogenic influences across a broad range of climate variables increases our confidence in the reality of human-induced global warming.

In addition, humidity has important implications for Climate Impact studies including human heat stress (Souch & Grimmond, 2004) (section 1.2). There is much potential for combining historical humidity, temperature and epidemiological records with forecast capabilities to provide improved human health warnings, hospital demand forecasts etc., over timescales from days to decades.

To date, efforts to collate records of surface water vapour to form climate records have: been limited to small regions; considered only land observations; or made no attempt to ensure station homogeneity. Therefore, this thesis aims to create a truly global homogenous humidity dataset suitable for use in climate studies. Alongside efforts underway elsewhere to create and maintain upper-air humidity datasets from radiosondes (McCarthy *et al.*, 2005) and satellites (Soden *et al.*, 2005; Jackson *et al.*, 2006; RSS (Remote Sensing Systems - http://www.remss.com/); Wagner *et al.*, 2006), this provides potential to constrain our understanding of recent changes in both temperature and humidity throughout the troposphere.

1.2 THE ROLE OF WATER VAPOUR IN THE ATMOSPHERE

Water vapour plays a key role in determining the dynamical and radiative properties of the climate system (Elliott, 1995; Allen & Ingram, 2002; Trenberth *et al.*, 2005). Water vapour and its transport around the atmosphere is a fundamental component of the hydrological cycle. It also modifies the radiative balance, being a naturally occurring greenhouse gas. These features are indicated pictorially in Fig. 1.2 (a much simplified diagram). The Clausius-Clapeyron relation yields exponential increases in the atmosphere's water holding capacity with increasing T at approximately 7 % K^{-1} (Manabe & Wetherald, 1967; Allen & Ingram, 2002; Trenberth *et al.*, 2005) (Fig. 1.1). For rising T and in the presence of unlimited water supplies (e.g. over the oceans) it can be expected that actual moisture content (i.e. specific humidity (q)) will also increase, thus maintaining a reasonably constant relative humidity (RH) (Trenberth, 1999). Where moisture is limiting (e.g. over many land areas), q should increase less thereby allowing temperatures to increase by higher amounts and RH to decrease. It is generally assumed that RH distributions remain constant in the atmosphere over long time scales and this has been an emergent constraint on which the climate models have converged at all latitudes (Allen & Ingram, 2002). However, this premise remains unproven in the observational record as to date no truly climate-quality global humidity dataset has been available.

The hydrological cycle is thought to be enhanced both in terms of weather system and precipitation intensity as higher air temperatures enable greater take up and transfer of water vapour (latent heat) from the surface to the upper atmosphere (Folland *et al.*, 2001b; Groisman *et al.*, 2004; Trenberth *et al.*, 2005). Latent heat transfer is a major

driver for atmospheric dynamics, including: the formation and propagation of mesoscale and synoptic scale weather systems; atmospheric circulation; and flooding and drought events (Elliott, 1995). Atmospheric circulation is mainly forced by latent heat release in the tropics and radiative cooling in the polar regions (Arpe, 1991; Sohn *et al.*, 2004), giving us the more predictable modes of climate (air mass formation regions, seasonal weather characteristics, ENSO (El Niño Southern Oscillation) etc.) that regionally people have learned to live with or even come to depend upon. Exactly how these climate features might be affected by changes in surface humidity is an important question. The record 2005 North Atlantic hurricane season, in terms of intensity and heavy rainfall, has been linked by some to higher sea-surface temperature (*SST)* and associated increases in water vapour where resulting latent heat release is a driver for hurricanes (Trenberth & Shea, 2006; Anthes *et al*., 2006; Santer *et al*., 2006).

Water vapour affects the earth's energy budget in four main ways. Firstly, water vapour stores energy in the form of latent heat. This is released into the atmosphere during condensation and precipitation. Secondly, as a gas it affects the energy budget through long-wave radiation effects (Fig. 1.2). Indeed, it is by far the largest and the most significant of the greenhouse gases (Elliott, 1995; Harries, 1997; Kiehl & Trenberth, 1997), which collectively facilitate a positive feedback mechanism which at present maintains the Earth's energy budget and cycle in a habitable state. Without these greenhouse gases, our planet's equilibrium T would lie around -18 $^{\circ}$C rather than 14 $^{\circ}$C (global mean surface T) (Ahrens, 2000; Jones *et al.*, 1999). Thirdly, water vapour is the source for clouds which have significant and complex radiative properties depending on their height, optical properties and latitude (Zhang *et al.*, 1995; Kiehl & Trenberth, 1997; Philipona & Dürr, 2004). Finally, as discussed earlier, the amount of moisture in the air determines the energy required to change the T of that air (moist enthalpy - Pielke *et al*., 2004).

Water vapour as a greenhouse gas is part of a major positive feedback loop (Cess, 1989; Elliott, 1995; Zhang *et al.*, 1995), increasing climate sensitivity by a factor of two (Manabe & Wetherald, 1967; Sohn & Schmetz, 2004; Stephens *et al.*, 2004; Bony *et al*., 2006). Notably, this long-wave radiation trapping is at its maximum in the mid- to upper-troposphere, despite the vertical water vapour profile which is greatest at the surface reducing rapidly with height (Held & Soden, 2000). As water vapour can be transported vertically through convection and subsidence, and horizontally by

atmospheric circulation, changes in surface absolute moisture can effect changes in moisture aloft (McCarthy & Toumi, 2004).

An increase in atmospheric moisture provides more condensate for cloud formation. However, this and cloud development depends on many other factors such as atmospheric *T*, *RH*, stability, circulation and availability of condensation nuclei. Observed changes have been found in cloud amount, height and optical properties such as depth, liquid water content and opacity (Cess *et al.*, 2003; Trenberth *et al.*, 2005; Bony *et al.*, 2006) which will in turn affect radiation and thus impact on climate. These can effect a net cooling or a net warming through interaction with both short-wave and long-wave radiation (Fig. 1.2). This depends on latitude, altitude and optical properties (Stephens and Greenwald 1991; Zhang *et al.* 1995; Philipona & Dürr, 2004; Trenberth *et al.*, 2005). Additionally, the quantity of atmospheric water vapour directly interacts with radiation prior to cloud interaction thus further complicating cloud feedbacks (Groisman *et al.*, 2000; Sun *et al.*, 2000). The presentday net radiative effect of clouds is thought to be close to zero. However, cloud feedback depends on so many factors that it is uncertain as to whether climate change may impact short-wave and long-wave radiation differentially (Bony *et al.*, 2006). As such, cloud feedbacks are the key source of uncertainty in climate models (Trenberth *et al*., 2005; Webb *et al*., 2006).

Of more direct societal interest, surface humidity has a compound effect on human comfort in terms of heat stress (Levzey & Tinker, 1996). High humidity in terms of *RH*, inhibits evaporation, making cooling by perspiration less effective (Souch & Grimmond, 2004) contributing to higher heat-stress and potential mortality than would otherwise be expected (Davis *et al.*, 2002; Changnon *et al*., 2003). However, low *RH* too can be a source of heat stress, particularly through dryness enhancing the effect of air pollution (Diaz *et al*., 2002a, 2002b). Generally, temperatures and humidities outside of the usually accustomed range pose a human health threat (Souch & Grimmond, 2004; McGregor, G. *pers. comm.*). A change in amount or distribution of surface water vapour can thus be linked to direct human health impacts.

Surface humidity may be affected by factors other than rising temperatures. These include: changes in atmospheric circulation (possibly brought about by changes in climate); changes in land-use including irrigation and reservoirs; and increasing air-traffic although this is essentially an upper-tropospheric effect (Lee, 1991; Elliott, 1995;

Schwartzman *et al*., 1998; Gaffen & Ross, 1999; Changnon *et al.*, 2003; Marquart *et al.*, 2003).

Clearly, water vapour has played and will continue to play a key role in our changing climate as: a much affected variable; a major agent of change; and a human health issue. However, more research is urgently needed to quantify and understand recent changes, their causes, and their impacts fully.

1.3 MEASURING SURFACE HUMIDITY

Station observed humidity is commonly measured as one of: wet-bulb temperature (T_w); dewpoint temperature (T_{dw}); or *RH*. Other humidity variables can then be calculated through empirically based conversions from any of these observed parameters with the inclusion of pressure (*P*) and air *T* (dry-bulb temperatures) where necessary (Chapter 2). There are a wide variety of instruments, collectively called hygrometers, available to measure each of the above variables. The following discussion is by no means exhaustive.

The most commonly reported surface measure, T_w, is usually obtained using a psychrometer which contains both a dry-bulb and wet-bulb thermometer. Under suitably aspirated conditions, the contact of a hydrated wick (by means of a reservoir) around the wet-bulb thermometer causes evaporative cooling of the wet-bulb relative to the dry-bulb. The quantity of this depression relative to the dry-bulb temperature is directly related to the level of saturation of the air. Aspiration of the thermometer may be done: manually, by whirling the psychrometer through the air (Sling Psychrometer); mechanically, by means of a fan (Assman Psychrometer); or naturally, by situating the psychrometer in a ventilated box (often a Stevenson Screen) with adequate exposure to allow air-flow though.

Instruments to measure *RH* most commonly use either capacitance or resistance of an electrical current. For example, the Dewcel calculates *RH* from changes in the conductivity of lithium chloride as it absorbs/evaporates moisture from/to the surrounding air, requiring adequate ventilation. It can also measure T_{dw}. Chilled mirror hygrometers measure T_{dw} directly by cooling the mirror to the temperature at which moisture forms.

All instruments have potential for error. Wet-bulb thermometers can be affected by: both under- and over-ventilation depending on the Screen location; the presence of the observer which can cause positive errors in both T and T_w; and by heat conduction from dry parts of the thermometer depending on the stem length (Folland, 1977). In sub-zero temperatures where an ice-bulb calculation is used to convert to other humidity variables (section 2.1), the wick around the bulb may not actually be frozen and so small positive errors may occur (Simidchiev, 1986). Furthermore, the Stevenson Screen or wick around the wet-bulb may freeze preventing ventilation of the wet-bulb (icing) (Makkonnen & Laakso, 2005; van Wijngaarden & Vincent, 2005). The wet-bulb reservoir may freeze or in warm conditions evaporate completely, causing the wick around the wet-bulb thermometer to dry out. Icing and reservoir freezing were found to be particular problems for automatic stations in Canada, if instruments were not checked regularly (Déry & Stieglitz, 2002). By implication this is likely a problem at other high latitude stations. Reservoir evaporation is a common problem even in temperate conditions. The 2003-2004 Global Climate Observing System (GCOS) plastic screen trial at three British stations had to discount 13 % of psychrometer measurements because the wet-bulb had dried out (Elms & Hatton, 2005). All of these problems, in effect, inhibit evaporation, and thus inhibit depression of T_w relative to T giving erroneously high (frequently 100%) *RH* recordings and a moist bias to the data. Automated stations, which are increasingly common (http://www.faa.gov/asos/hist-aos.htm), are especially prone to such problems where stations are unmanned for long periods.

Retarded response of *RH* sensors, which increases as T decreases (Elms & Hatton, 2005; Simidchiev, 1986) is also a problem, as is potential dripping of condensation down the sensor probe. The latter can be avoided by situating the *RH* sensor with the probe pointing skywards, as recommended by the manufacturer. However, to keep the sensor close to the dry-bulb thermometer and avoid the effect of any temperature gradient within the Screen, it is common practice to place the sensor technically upside down.

Further sources of error occur when the humidity record is physically observed as one variable but converted to and reported as another. The algorithms chosen for such conversions are not standardised and vary often between stations and even within one

station over time. The error introduced from such conversions is discussed further in section 2.6.

Over land there is little in the way of metadata (data providing information about the station, instrument and observing practices) and so statistical methods must be utilised to detect and adjust for artificial discontinuities in individual station records (homogenisation). However, where available this metadata can prove useful. For example, the change over from psychrometer to Dewcel, widespread in Canadian stations, produced a negative step in RH at a number of stations (van Wijngaarden & Vincent, 2005). Outside of the US and north-west Europe, available metadata for land stations is sparse to non-existent. Even for these regions there are no comprehensive, easily accessible, repositories of high quality, electronically available (necessary for use with very large datasets) metadata at the time of undertaking this thesis. Therefore, there is a large degree of ambiguity in how to assign and adjust for breakpoints leading to differences in results depending upon the exact methodology applied (structural uncertainty - Thorne *et al*. (2005a)). For marine data there exists an electronic record of metadata from 1955 for observing ships (http://icoads.noaa.gov/metadata/) which lists information about instrument type and exposure (including height) for each year. While this aids identification of inhomogeneities and adjustment quantification, some structural uncertainty may still exist due to inevitable subjectivity of decision making regarding error adjustments and bias corrections.

1.4 THE PHYSICAL RELATIONSHIPS BETWEEN HUMIDITY VARIABLES OF INTEREST

Atmospheric water vapour is a complex meteorological element. For atmospheric studies at the surface it can be described in numerous ways, the most common of these being: RH; e; saturated vapour pressure (e_s); q; T_{dw}; and T_w (WMO, 1996; McIlveen, 1998) (Table 1.1). All except q can be measured directly.

The chosen humidity variables for this project are e, q and RH. These are selected because: they represent an absolute, proportional and a relative (respectively) measure of humidity; they are highly suitable for climate studies; they are represented in climate models (q and RH); and because they are comparable with other studies both at the

surface (New *et al.*, 2000; Gaffen & Ross, 1999; van Wijngaarden & Vincent, 2005; Dai, 2006) and in the upper air (McCarthy & Toumi, 2004).

Vapour pressure is the partial pressure of water vapour as an atmospheric gas. It is measured in mb or hPa. Within the earth's atmosphere, water vapour behaves as an ideal gas, satisfying the following conditions:

$$P \propto 1/V \text{ at constant } T \qquad\qquad \text{Eq. 1.2}$$
$$V \propto T \text{ at constant } P \qquad\qquad \text{Eq. 1.3}$$
$$P \propto T \text{ at constant V} \qquad\qquad \text{Eq. 1.4}$$

where V is volume in m^3. It can thus be described by water vapour density (ρ_v) in kg m^{-3} using the equation of state:

$$e = \rho_v R_v T \qquad\qquad \text{Eq. 1.5}$$

where R_v is the specific gas constant for water vapour (462 J K^{-1} kg^{-1}) (McIlveen, 1998).

Specific humidity is the proportion of the mass of water vapour to the total mass of moist air. It is measured in g kg^{-1} or kg kg^{-1} and can be described thus:

$$q = \frac{m_v}{m_v + m_d} \qquad\qquad \text{Eq. 1.6}$$

where m_v is the mass of water vapour in kg and m_d is the mass of dry air in kg. It can also be described in terms of density because the water vapour and the moist air occupy the same total volume:

$$q = \frac{\rho_v}{\rho} \qquad\qquad \text{Eq. 1.7}$$

where ρ is the density of the moist air (kg m^{-3}). If each density is then replaced by the appropriate equation of state this gives:

$$q = \frac{eR}{PR_v} \qquad\qquad \text{Eq. 1.8}$$

where R is the specific gas constant for moist air (which can be substituted with the dry air value 287 J K^{-1} kg^{-1} without causing serious error). The ratio of the gas constants R/R_v is the inverse ratio of the molecular weights of each and can be substituted with 0.622 (known as ε). Thus q can be derived from e as follows:

$$q = \frac{\varepsilon e}{P}$$ Eq. 1.9

where e and P are both either in mb or hPa, and q is output in kg kg^{-1} (McIlveen, 1998).

Importantly, e recorded at T is by definition the same as e_s at the simultaneous T_{dw} ($e_s(T_{dw})$). The saturation vapour pressure is the partial pressure of water vapour on a parcel of air should that parcel become saturated at its current T (e_s (T)), essentially a measure of the water holding capacity of the air. The saturation specific humidity (q_s) is the equivalent for q. From this knowledge of both the actual moisture content of the air and potential moisture content of the air (at saturation), the relative humidity, which refers to the extent of saturation of the air as a percentage, can be calculated (McIlveen, 1998):

$$RH = 100 \left(\frac{e_s \left(T_{dw} \right)}{e_s \left(T \right)} \right)$$ Eq. 1.10

which can be rewritten:

$$RH = 100 \left(\frac{e}{e_s} \right)$$ Eq. 1.11

1.5 RECENTLY OBSERVED CLIMATE CHANGES

1.5.1 Recent Changes in Atmospheric Humidity at the Surface

To date there have been few observational surface humidity studies. Those of note are described in detail in Table 1.2 along with abbreviations which will be used henceforth. All but DAI, ISSM and WOR are regionally focussed and most end before 2000. None are truly global (land and marine) homogenised humidity datasets. Without such testing and adjustment (where necessary) a dataset is arguably not suitable for climate research as the possibility that any apparent trends in the data result from non-climatic origin cannot be ignored. Homogenisation (see section 3.3.1 for a full discussion), while unlikely to remove all non-climatic discontinuities in the data, produces a dataset that as a reflection of actual climate changes, is far more robust. While six out of the ten datasets described make efforts to detect inhomogeneities, most simply remove any suspect stations and only one (WG) makes any attempt to adjust the data.

The range of quality control varies widely between datasets. GR, ROB, VWV and SSR require stations with a certain length of record or minimum missing data requirements. Only DAI and GR document checking the physical plausibility of each variable (e.g. T_{dw} >-80 $^{\circ}$, <60 $^{\circ}$C and ≤ T), although this may have been undertaken by the institutions that collect and provide the data originally. Six datasets incorporate an outlier test of some form. No dataset makes any attempt to remove humidity specific errors such as wick drying or icing (section 1.3).

The primary data sources are not entirely independent between each dataset as can be seen in Table 1.2. However, differences in quality control tests, period of record, station coverage, trend fitting method and dataset construction approach, the latter of which is referred to as structural uncertainty (Thorne *et al*., 2005a), can be expected to lead to discrepancies between datasets.

Given the lack of homogenisation, and ad-hoc quality control applied, it can be argued that none of the datasets discussed here are truly climate quality. HadCRUH will incorporate all the above quality control tests, undergo homogenisation, have near-global coverage and at some point in the future be updateable, thus improving on any humidity dataset available to the climate community to date.

According to these studies, over the US, there was an overall picture of moistening both annually (since 1951 - ROB, since 1961- GR and since 1975 - NEW and DAI) with significant positive trends found in q, T_{dw} and e over most regions except Hawaii (GR). DAI showed statistically significant positive trends in regionally averaged q (0.1 g kg^{-1} 10yr^{-1}). Similarly, GR (1961-1995) showed significant moistening (q and T_{dw}) in all seasons except Autumn, but the longer, earlier record period of ROB (1951-1990) while concordant with positive trends in Spring, showed drying trends in Winter (not significance tested). For *RH*, DAI found mostly positive and significant (0-2 % 10yr^{-1}) trends in *RH* whereas although GR found some evidence of increases, especially at night and during Winter (Alaska and High Plains) and Spring (south-west and south-central), trends were not generally statistically significant nor spatially consistent. DAI found little of significance over much of Alaska but the earlier analysis of GR found large positive trends (significant at the 0.01 confidence level) in all seasons except Autumn. Clearly there are some discrepancies between the datasets, likely due to the reasons discussed above. GR investigated sources of potential inhomogeneity but did

not make any adjustments. They also looked into sources of the water vapour increase and discounted changes in instrumentation and fossil fuel burning emission of water vapour (too small). They cited irrigation as a potential local contributing factor in some regions.

Trends in q and e over Canada from 1975 were predominantly positive and significant (NEW; DAI). After improving the trend fitting model to account for a negative trend bias caused by countrywide changes in procedure and instruments (VWV), significant trends in RH of either sign were found (DAI; VWV). Converse to the stated trends for the US, RH trends were most negative in Spring (VWV).

Significant positive trends in q and e were found over most of Europe (DAI; NEW; SSR). These were largest over northern Europe in DAI (1975-2005) and conversely, over southern Europe in SSR (1961-1990). Trends were more commonly significant in DAI and NEW (1975-1995) than SSR. DAI found a statistically significant positive regionally averaged q trend over western Europe (0.13 g kg^{-1} 10yr^{-1}), larger than over the US, and mostly negative and significant RH trends over the same region.

Trends over China were overwhelmingly positive for q (~0.04 g kg^{-1} 10yr^{-1}, WG (1951-1994)), e (0.07 hPa 10yr^{-1}, KAI (1954-1996)) and T_{dw}, (~0.15 ^{o}C 10yr^{-1}, WG). Trends in RH were significantly decreasing in the northeast region, especially in Spring (KAI; WG), although not in DAI, and significantly increasing in many northwest stations, especially in Summer (KAI; WG; DAI).

Over the oceans the DAI data showed significant but small positive q trends over the Atlantic, Indian and western Pacific oceans concordant with the global warming signal reported by ISSM in T_{dw}. Non-significant negative trends were found over most of the southern oceans and eastern Pacific (DAI). For RH, marine trends were mostly small and negative. Regionally averaged trends for the globe, Northern and Southern Hemisphere were all significant at -0.16, -0.11 and -0.22 % 10yr^{-1} respectively (DAI).

At the global scale (land and oceans) (DAI), regionally averaged trends were significant for Global and Northern Hemisphere q (0.06 and 0.08 g kg^{-1} 10yr^{-1} respectively). Seasonal trends for the Globe and Northern Hemisphere in DJF (December, January and February) (0.06 and 0.07 g kg^{-1} 10yr^{-1} respectively) and JJA (June, July and August)

(0.07 and 0.10 g kg^{-1} 10yr^{-1} respectively) were also significant. Over large spatial scales at least, *RH* appeared to remain near constant although small significant negative trends were found for the Globe and Southern Hemisphere means (-0.09 and -0.20 % 10yr^{-1}).

Despite structural differences, where comparisons can be made, there is gross consensus between these studies at the largest scales on recent changes in surface humidity. However, given the lack of homogenisation and robust data quality control efforts to date, this does not preclude the possibility that they all contain biases, and as such, the more intricate findings of each dataset should be used with caution.

There has been little quantification of uncertainty in surface humidity datasets. This is principally because there are fewer data and more problems associated with observing humidity than *T*. These are chiefly linked to: icing and wick drying affecting the wet-bulb measurement (section 1.3); conversion algorithms; the quality of other non-humidity input variables (*T*, *P*); the numerous different humidity variables; widely varying observing instruments; and observing practices (Elliott & Gaffen, 1993; Kent *et al.*, 1993; Kent & Taylor, 1996; Gaffen & Ross, 1999; Kent *et al*., 1999; Robinson, 2000; Elms & Hatton, 2005; Kent & Berry, 2005; Makkonen & Laakso, 2005; van Wijngaarden & Vincent, 2005; McCarthy & Willett, 2006). Furthermore, in very low temperatures, *e* and *q* can be very low and thus small absolute errors (~0.1 hPa/g kg^{-1}) become considerable in relative terms providing large uncertainty in any conversions (New *et al.*, 2002).

1.5.2 Recent Changes in Atmospheric Humidity Aloft

Tropospheric humidity measurements come from radiosonde and satellite observations. As with surface humidity, these are riddled with potential sources of inhomogeneity. Radiosondes are single-use instruments. They have experienced many changes in instrument type and considerable improvements have been made in response time and accuracy. There are humidity specific problems: accuracy at very low air temperatures (Wang *et al.*, 2000): data cutoffs below -40 ^{o}C in the US pre-1993 (Elliott, 1995; Ross & Elliott, 1996 - section 3.2.1); and data sparsity particularly in the Southern Hemisphere and oceans (Wang *et al.*, 2000). The satellite record is hindered by: satellite drift over time; deterioration of instruments with age; conversions from brightness temperatures to geophysical variables; short temporal coverage of individual

platforms; and instrument changes over the record period coupled with a lack of an *in situ* standard suitable for absolute calibration (McCarthy & Toumi, 2004; Trenberth *et al.*, 2005; Wagner *et al.*, 2006).

Reanalyses (NCEP-1 Kalnay *et al.*, 1996; NCEP-2 Kanamitsu *et al.*, 2002; ERA-40 Uppala *et al.*, 2005) provide global coverage of various humidity variables for a range of atmospheric levels and temporal resolutions. They incorporate surface observations (stations, ships), satellite, radiosonde, pibal and aircraft data with a state-of-the-art data assimilation system. However, these have largely been found unsatisfactory for accurate trend analyses of humidity related products, especially over the oceans largely due to the lack of constraint by radiosondes there (Trenberth *et al.*, 2005).

The radiosonde is the only operational instrument to measure atmospheric humidity from the surface to the stratosphere (with high vertical resolution) under all weather conditions (Wang *et al.*, 2003). In terms of large spatial climate analyses of humidity, they have been operating usefully since 1958, although often only reliably to 850 hPa until 1973 due to hygristor biases at cold dry temperatures above this level (Ross & Elliott, 2001). Major changes in radiosonde types have impeded updates beyond 1995 (Elliott *et al.*, 2002). The IGRA (International Global Radiosonde Archive, Durre *et al.*, 2006) dataset, continuing up to present, is now available. However the most comprehensive radiosonde humidity studies to date are Ross & Elliott (2001) who look at un-homogenised humidity data from 1973 to 1995, and McCarthy & Willett (2006) who look at the homogenised humidity dataset HadTH (work in progress at the Hadley Centre, Met Office – McCarthy *et al.*, 2005) from 1973 to 2003. Both studies focus on the Northern Hemisphere land only. Ross & Elliot found widespread positive trends of similar distribution in total precipitable water (*PW*), q (850 hPa), T_{dw} (850 hPa) and T (850 hPa). These were significant over China (consistent with Zhai & Eskridge, 1997), the central Pacific and the US. This was largely in agreement with trends from HadTH. However, over Europe and north Asia, negative *PW*, q and T_{dw} (but not T) trends shown by Ross & Elliott (of sporadic significance) were found to be positive in the homogenised q from HadTH. McCarthy & Willett found absolute moistening aloft but drying relative to the surface in q. However, they suggested an underestimation of T and q in the upper-troposphere. This was thought to be likely due to instrument improvement over time and thus disproportional rejection of cold-condition

observations in the earlier record. This bias was thought not to affect *RH* which remained approximately constant over the period from the surface to 400 hPa.

There are three satellite records of note, these are: Bates & Jackson, (2001) (analysed by McCarthy & Toumi, (2004)); Trenberth *et al*., (2005); and Wagner *et al.*, (2006), henceforth referred to as MT, TREN and WAG respectively. MT discuss upper-tropospheric relative humidity (*UTRH* – between 500-200 hPa) calculated from HIRS (High-resolution Infrared Radiation Sounder) brightness temperatures. The available data spans 1979 to 1998. It is global (land and marine), but required cloud clearing, giving it a largely unknown systematic dry bias estimated at 5-10 % in convective regions. TREN looks at *PW* from the SSM/I (Special Sensor Microwave Imager) over the period 1988 to 2003. This is effective even in cloudy conditions but only useful over oceans (ice free). However, much work has been done by RSS (Remote Sensing Systems) to cross calibrate over the different satellite instruments reporting over the record making it purportedly suitable for decadal trend studies (Trenberth *et al*., 2005). WAG use GOME (Global Ozone Monitoring Experiment) spectrometers to measure global (land and marine) total column *PW* from 1996 to 2003. As the analysis is performed in the visible spectral range it was very sensitive to the water vapour profile close to the surface (where the majority of water vapour lies) unlike HIRS. The GOME data are: less accurate than SSM/I data, particularly in cloudy skies; of coarser resolution; and of very short longevity. However, like SSM/I and HIRS, the data has potential for future updates.

As with the surface and radiosonde record, there was an overall picture of moistening with a global ocean mean trend in *PW* of 1.3 % 10yr^{-1} for the 1988 to 2003 period (TREN) and global land and ocean increase in *PW* of 2.8 % from 1996 to 2002 (WAG – excluding the ENSO period). The SSM/I and GOME data were found to correlate highly (WAG), giving support to GOME trends despite its associated caveats (discussed above). SSM/I trends of *PW* were strongly positive in the equatorial western Pacific, especially the South China Sea, and markedly negative in the subtropical eastern Pacific (TREN). These were found to correlate strongly with *SST* both in distribution and temporal variability close to the 7 % K^{-1} increase expected from the Clausius-Clapeyron relation consistent with constant *RH* (Trenberth *et al.*, 2005). *UTRH* was found to be increasing significantly in the deep tropics at 0.8 % 10yr^{-1} (MT), especially over parts of the Amazon and western Indian Ocean / central eastern Africa. In the subtropics and

mid-latitudes *UTRH* trends were significantly negative in the Southern Hemisphere at -1 % $10yr^{-1}$ but of mixed sign in the Northern Hemisphere. However, it was thought that these trends were likely an artefact of the dataset length and uncertainty relating to the inter-satellite calibration such that the hypothesis of constant *RH* could not be confidently rejected (MT).

In summary, there is general agreement that atmospheric moisture both at the surface and aloft has increased over the latter part of the 20th century. There are regions of significant trends in *RH* but these are generally small and not coherent on the large spatial scale, unlike the 'absolute' humidity variables such as *PW*, *q*, T_{dw} and *e*. It is difficult to compare changes aloft to changes at the surface due to the differing record periods, variables and units of measurement studied. Although some inferences can be drawn, further study is required both on vertical and horizontal trends to improve the temporal and spatial coverage and further address known remaining issues of underlying data quality.

1.5.3 Recent Changes in Atmospheric Temperature at the Surface

Similar to the humidity, observed *T* has its problems for climate analyses in terms of: instrument moves; instrumental and recording errors; and changes to instrument type and practices. However, a vast amount of time and intellectual effort has been spent investigating and attempting to mitigate such issues and provide a reliable *T* record. While no current *T* record can claim to be perfect, the global *T* record is in relatively good shape and widely agreed upon, at least for the instrumental period (1850 to present) (Folland *et al.*, 2001b; Hansen *et al.*, 2001; Jones & Moberg, 2003; Brohan *et al.*, 2006; Karl *et al.*, 2006). Urbanisation throughout the record may have had some warming effect (Jones *et al.*, 1990; Englehart & Douglas, 2003) and some datasets attempt to account for this by expanding error ranges (e.g. Folland *et al.*, 2001a; Brohan *et al.*, 2006). However, such effects are believed to be very small (Parker, 2004; Peterson, 2004). Most commonly, the marine surface *T* record comes from *SST* as sampling errors are generally smaller than for marine air *T* (*MAT*) which suffers from diurnal heating effects (Brohan *et al.*, 2006).

Rapidly increasing temperatures for the period 1976 to 2000 (close to the HadCRUH period of record) are a global phenomena across all datasets (Table 1.3). Small regions of negative trends are present but these differ slightly in location and extent between datasets. Seasonally, warming is largest and most widespread (mostly in the Northern Hemisphere) in DJF (Folland *et al.*, 2001b; Jones and Moberg, 2003). Regionally averaged trends are summarised in Table 1.3 and generally concur in sign and magnitude across datasets. Notably, trends are strongest in the Northern Hemisphere and all trends in the Tropics lack statistical significance.

Following the Clausius-Clapeyron relation, a global mean trend in T of ~ 0.15 $^{\circ}$C $10yr^{-1}$ (mean of values in Table 1.3) at a base global mean T of 14 $^{\circ}$C (Jones *et al.*, 1999) and assuming an RH of 70 % would be expected to bring about a global mean trend in q of 0.07 g kg^{-1} $10yr^{-1}$. Although exactly comparable humidity records are not available the global q trend from Dai (2006) of 0.06 g kg^{-1} $10yr^{-1}$ over the period 1975 to 2005 is broadly consistent with this expectation.

The global mean T timeseries land and marine components are mutually consistent until ~ 1980 when the land appears to warm faster than the oceans (Folland *et al.*, 2001b; Brohan *et al.*, 2006). This could be due to a number of reasons: a real effect in response to increasing greenhouse gas concentrations; a result of possible changes in atmospheric circulation; an uncorrected bias in one or both data sources; or a combination of the above.

The most complete and recent global temperature dataset to date is HadCRUT3 (Brohan *et al.*, 2006), a product of the Hadley Centre and Climatic Research Unit. It is a near globally complete, regularly updated 5 $^{\circ}$ by 5 $^{\circ}$ monthly mean gridded dataset available from 1850 (Fig. 1.3) (www.hadobs.org). Great effort has been made to provide accompanying uncertainty estimates to account for: estimates of measurement and sampling error; temperature bias effects; and sampling density.

1.5.4 Recent Changes in Atmospheric Temperature Aloft

There is currently much debate over upper-atmosphere T trends (Seidel *et al.*, 2004; Thorne *et al.*, 2005a and 2005b; Karl *et al.*, 2006). As described for the humidity record, changes in instrumentation and procedure have been much more pervasive than the

surface record and dataset builders have many more choices to make, leading to much greater dataset structural uncertainty (Thorne *et al.*, 2005a).

Current climate models suggest cooling in the stratosphere. Within the troposphere, they predict warming with a maximum in the tropical upper-troposphere relative to the surface (Karl *et al.*, 2006). This 'amplification' is an expected physical consequence of latent heat release during condensation processes aloft. Stratospheric cooling is widely agreed upon in the observations (Folland *et al.*, 2001b; Seidel *et al.*, 2004; Thorne *et al.*, 2005b). However, depending on timescale and dataset used, tropospheric trend estimates disagree considerably such that it cannot be concluded whether globally the troposphere is cooling or warming relative to the surface (Thorne *et al.*, 2005a), reflecting the ambiguity in the historical observations. For the tropospheric global average most observed changes over the period 1958 to 2004 demonstrate amplification or at least equivalent warming relative to the surface. In contrast, most upper-tropospheric observed trends for the period 1979 onwards are smaller than at the surface (Parker *et al.*, 1997 (global radiosonde temperature dataset - HadRT); Thorne *et al.*, 2005b (global radiosonde temperature dataset – HadAT (supersedes HadRT)); Karl *et al.*, 2006). The largest discrepancy occurs in the Tropics where the majority of climate models converge on amplification but the majority of observations do not, especially for 1979 onwards (Santer *et al.*, 2005). The Climate Change Science Program (CCSP) report (Karl *et al.*, 2006) concluded that the discrepancy in the Tropics was likely to be real, and that its most likely cause (but this is not conclusive) was due to residual non-climatic influences (errors) in the observations. Critically, the recommendations to resolve this issue included a requirement for a multi-variate monitoring capability and efforts to create climate datasets for other variables including humidity.

1.6 HUMIDITY IN CLIMATE MODELS

General circulation models (GCMs) or climate models have become increasingly important in climate analyses and will continue to do so for the foreseeable future. The most sophisticated incorporate a wide range of forcings including greenhouse gases, land use change, volcanoes, solar output changes and fully interactive natural and anthropogenic aerosol modelling. A comprehensive list can be found at http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php (International Panel for Climate Change (IPCC)

Archive). While GCMs are widely thought of as useful tools in climate research, their limitations should be noted. Necessarily, many sub-grid-box scale physical processes must be parameterised, especially in cases where these processes occur on scales smaller than the grid-box resolution of the model (Held & Soden, 2000). There is considerable uncertainty in these parameterisations (Murphy *et al.,* 2004). Notably, cloud feedbacks and many of the critical process controlling water vapour are parameterised and are consequently areas of large uncertainty.

At least for *T*, coupled (atmosphere and ocean) models can now provide credible climate simulation down to sub-continental and seasonal scales (McAvaney *et al*., 2001; Stott *et al.*, 2006). However, little work has been done to date to validate humidity in the models, with virtually no mention within the Third Assessment Report of the IPCC (McAvaney *et al*., 2001). This is most likely due to a lack of suitable observations with which to compare the models.

The majority of the literature relating climate models to observed or theoretical humidity changes refers to the positive feedback mechanism of water vapour, and *RH* in the free troposphere. The water vapour feedback occurs in models because increasing temperatures lead to increases in atmospheric water vapour content which as a greenhouse gas leads to further warming. Huang *et al*. (2005) compared tropical mid- and upper-tropospheric humidity model output of GFDL (Geophysical Fluid Dynamics Laboratory) AM2 with HIRS radiance measurements and found good agreement. Constant *RH* over large spatial and temporal scales is a feature exhibited in most climate models. It originates from physical processes within the model as opposed to initial assumptions. This is even the case in low latitudes where this was not thought so plausible (Allen & Ingram, 2002; Held & Soden, 2000; Cess, 2005). These findings support near constant *RH* as a robust constraint on atmospheric humidity such that *q* could be expected to increase exponentially with *T* following Clausius-Clapeyron theory. Indeed, model projections have shown a possible doubling of atmospheric water vapour by 2100 resulting from increasing greenhouse gas forcings on climate (Soden *et al.*, 2005), with the increasing water vapour, through radiation, leading to further increases in temperature.

Observed trends in surface *q* (1976 to 1999) were found broadly comparable to those from the coupled Parallel Climate Model (PCM) (Washington *et al*., 2000) as were *q-T*

correlations. In the model, the correlations were slightly higher and inter-annual variability underestimated (Dai, 2006). It should be noted, however, that a good ability to simulate past climates does not necessarily mean that responses to future perturbations remain plausible (McAvaney *et al.*, 2001).

1.7 CONCLUSIONS AND PROJECT OUTLINE

The evidence for an anthropogenic effect upon climate is growing. Time is of the essence for greater knowledge and understanding. The aim of this project is to provide a high quality data source for the climate community with which to address issues related to surface humidity. This thesis outlines the construction of HadCRUH - a quality-controlled, globally homogenised land and marine monthly mean 5 ^{o} by 5 ^{o} gridded surface humidity product from 1973 to 2003 in *q* and *RH*. HadCRUH provides:

- An improved understanding of changes in global surface humidity over the past 30 years;
- A new and potentially favourable diagnostic for detection and attribution studies;
- The missing component (alongside *T*) for constraining our knowledge of near-surface heat content and thus the global energy budget with near-globally complete coverage;
- An historical and near-global product with which to broaden our knowledge of human heat stress with global forecasting potential of use by health services, governments and operations (outdoor workers, military);
- Validation for climate models;
- An improved understanding of observational issues surrounding humidity;
- An improved understanding of suitable quality control methods and homogenisation of observed humidity.

HadCRUH is built from raw hourly data. Suitably high accuracy conversion algorithms are identified and discussed (Chapter 2). To improve on the quality of previous humidity datasets, necessary steps are taken to devise appropriate quality control procedures for the land (Chapter 3) and marine (Chapter 4) components and undertake homogenisation. The blended product is then analysed (Chapter 5) in the context of

recent climate change. Conclusions are drawn along with further avenues for exploration (Chapter 6).

1.8 TABLES AND FIGURES FOR CHAPTER 1

Variable	What does it measure?	Units	Uses	How is it measured?
RH (relative humidity)	- closeness of the air to saturation (RELATIVE)	%	- measure of human comfort - parameter in climate models	- directly by hygrometers or electronic RH sensors - derived from e and e_s
e (vapour pressure)	- the partial pressure of water vapour in the atmosphere (ABSOLUTE)	hPa	- climate studies - synoptic analyses	- directly by a tensimeter (rare at weather observations) - derived from T_{dw} and pressure
e_s (saturated vapour pressure)	- the partial pressure of water vapour in the atmosphere if conditions are saturated	hPa	- synoptic analyses	- derived from T using standard formulae
q (specific humidity)	- ratio of mass of water vapour to the total mass of the moist atmosphere (PROPORTIONAL)	g kg^{-1}	- climate studies - necessary for calculating surface flux (evaporation) - parameter for climate models	- derived from e and pressure
T_{dw} (dewpoint temperature)	- the atmospheric temperature lowered to the point of saturation	°C	- climate studies - synoptic analyses	- directly from Dewcel sensors and dewpoint hygrometers - derived from psychrometric tables or combinations of other variables
T_w (wet-bulb temperature)	- the temperature at which the measured air is saturated by evaporating water into it from the wet-bulb	°C	- synoptic analyses	- directly from wet-bulb thermometers - derived from psychrometric tables or combinations of other variables

Table 1.1: Common humidity variables and their properties. Information is based on Folland (1977), Elliott (1995), WMO (1996), McIlveen (1998) and van Wijngaarden & Vincent (2005).

**Table 1.2 page 1
(1Table1_2.pdf)**

**Table 1.2 page 2
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Dataset and Period of Record	Global	Northern Hemisphere	Southern Hemisphere	Tropics
CRU *LSAT* + UKMO *SST* Folland *et al*., 2001a 1976-2000	**0.17**	**0.24**	**0.11**	---
HadCRUT2v Jones & Moberg, 2003 1977-2001	**0.16**	**0.22**	**0.11**	---
UKMO *LSAT* + UKMO *SST* Jones *et al*., 2001in IPCC (Folland *et al*., 2001b) 1979-2000	**0.16**	---	---	0.10
GISS *LSAT* + NCEP *SST* Hansen *et al*., 1999 and Rayner *et al*., 2000 in IPCC (Folland *et al*., 2001b) 1979-2000	**0.13**	---	---	0.09
NCDC *LSAT* + NCEP *SST* Quayle *et al*., 1999 and Reynolds & Smith, 1994 in IPCC (Folland *et al*., 2001b) 1979-2000	**0.14**	---	---	0.10

Table 1.3: Trends for regionally averaged land surface air *T* and sea surface *T*. Units are $^{\circ}$C 10yr^{-1}. Significance at the 5 % level (according to statistical tests described in references for each dataset) is shown by bold type. LSAT stands for land surface air temperature and acronyms refer to dataset names.
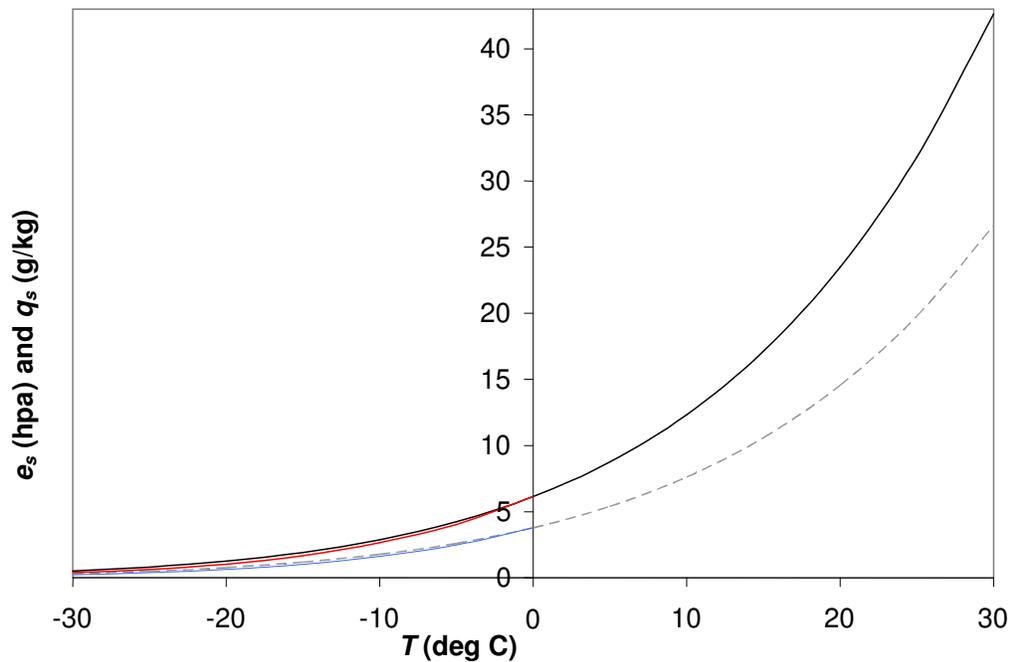

Figure 1.1: The Clausius-Clapeyron curve for saturated vapour pressure (e_s) and saturated specific humidity (q_s). The solid black line shows e_s with respect to water and the red line with respect to ice. The dashed grey line shows q_s with respect to water and the blue line with respect to ice. Each line represents *e* or *q* at 100 % *RH*.

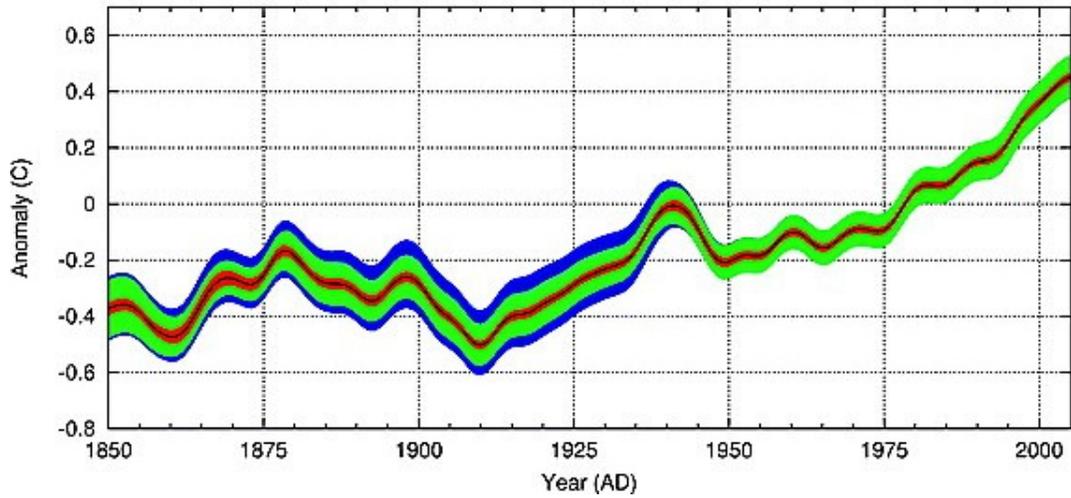**Figure 1.2**
(1Figure 1_2.pdf)

Figure 1.3: Global mean *T* anomalies and uncertainty estimates from HadCRUT3. The solid black line is the best estimate value, the red band gives the 95 % uncertainty range caused by station, sampling and measurement errors; the green band adds the 95 % error range due to limited coverage; and the blue band adds the 95 % error range due to bias errors (Brohan *et al*., 2006).