

1 **Key features of Cold-Air Pool episodes in the North-** 2 **East of the Iberian Peninsula (Cerdanya, Eastern** 3 **Pyrenees)** 4

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15

16 **ABSTRACT**

17 Located in the North-East of the Iberian Peninsula, Cerdanya experiences intense Cold-
18 Air Pool (CAP) episodes in which a decoupling between the valley atmosphere and the
19 regional circulation develops, especially in winter. A network of 40 temperature sensors
20 was deployed from 2012 to 2015 along seven elevational transects to collect hourly data
21 of temperature and humidity, enabling the measurement of CAP characteristics and
22 behaviour. Empirical Orthogonal Functions (EOFs) of minimum temperature anomalies
23 were examined to study the spatial distribution of CAP. Days were classified as CAP or
24 no-CAP using EOF analysis. The temporal variation of EOF analysis scores for the first
25 component (PC1) indicates days prone to CAP. A synoptic analysis using Principal
26 Component Analysis (factorization), cluster analysis (classification) and a Discriminant
27 Analysis (reclassification) was performed successively. Results showed CAP days to be
28 associated with high pressure and light winds, whilst no-CAP days were associated with
29 surface northerly or north-easterly flow behind frontal passages.

1 **Key words:** Cold-Air Pool, Empirical Orthogonal Function Analysis, Principal
2 Component Analysis, Cluster Analysis, Discriminant Analysis, Synoptic Types.

4 **1. Introduction**

5 During calm clear nights, especially in winter, surface temperatures in valley bottoms fall
6 and the weakening of turbulence helps to grow a layer near the surface with colder air
7 than above, producing a thermal inversion. Cold air which forms near the ground, both
8 on the valley sides and in the valley-bottom, flows down slope but can become trapped
9 by topography, a process known as Cold-Air Pooling (CAP) (Lundquist et al. 2008). The
10 extent and behaviour of CAP are challenging to determine because both involve many
11 non-linear mechanisms including temperature response to radiation exchange and the
12 transfer of heat and moisture through turbulence. Local and regional scale processes, such
13 as cold air drainage flow and/or the trapping of cold dense air masses by the relief,
14 effectively decouple the lower atmosphere from the regional signal, resulting in surface
15 temperatures which can be markedly different from those expected from simple
16 downward extrapolation of free air temperature fields (Sairouni et al., 2008; Sheridan et
17 al., 2010; Daly et al., 2010).

18 CAP is usually studied using the thermal structure of vertical temperature profiles
19 (Whiteman and McKee, 1982) coupled with studies of the thermal wind system
20 (Whiteman, 1990). Also studies have examined topographical effects such as
21 convexity/concavity. Convex surfaces (e.g. mountain ridges) tend to cool slower than
22 concave surfaces (Marvin, 1914; Neff and King, 1989; Chung et al, 2006). Furthermore,
23 valley shape along its longitudinal axis is important, due to differences in pressure
24 induced along the valley produced by differences in the cooling and heating rate

1 depending on the transversal slice shape. Such differences produce drainage on the one
2 hand or trap air on the other which weakens or strengthens CAP respectively. This effect
3 is calculated using the Topographic Amplification Factor (Whiteman, 1990).

4 The development of affordable temperature sensors (Whiteman et al., 2000; Lundquist
5 and Hugget, 2008) creates the possibility to build a dense network of measurements to
6 obtain a more realistic picture of CAP distribution/extent. Such dense networks allow the
7 spatial distribution of temperature to be modelled using Empirical Orthogonal Function
8 (EOF) analysis. This method was developed by Lundquist et al (2008) and classifies sites
9 as prone to CAP, no-CAP, or indeterminate.

10 Despite CAP mechanisms operating on a micro-scale, synoptic-scale processes are of
11 major importance in CAP formation and dissipation: decoupling between the free
12 atmosphere and valley bottom is controlled by the synoptic situation. In fact, previous
13 studies demonstrate that the synoptic scale influences the regional-scale lapse rate and the
14 vertical and horizontal extent of CAP (Daly et al. 2010, Pepin et al. 1999) while local
15 scale factors, such as turbulence, radiation and aspect influence the stratification and
16 mixing of the surface layer near the ground (Lareau, 2014; Wolyn and McKee, 1989;
17 Reeves and Stensrud 2009). Many studies have examined decoupling at a range of
18 latitudes (Gustavsson et al. 1998; McChensey et al. 1995; Zangl, 2005; Chung et al. 2006;
19 Clements et al. 2003; Daly et al. 2003; Pagès and Miró, 2010) and contrasting synoptic
20 controls have been demonstrated. The interaction between CAP and synoptic forcing (as
21 measured by an anticyclonic index) is very strong in the northern states of the United
22 States (e.g. Oregon) for example (Daly et al. 2010) but less so in the tropics and southern
23 U.S (Pepin et al. 2011). In some locations CAP can occur at low levels even when there
24 are strong winds at higher levels and thus the synoptic influence is less clear (Pepin et al,

1 2009). In others regional scale upslope/downslope flows can discourage/encourage CAP
2 through modification of cloud patterns and stability. In British Columbia for example
3 strong south-west and west upslope flow was associated with widespread cloud and
4 precipitation and therefore absence of CAP (Stahl et al. 2005).

5 More recent studies have shown how meso-scale phenomena induced under certain
6 synoptic situations can influence CAP formation. A strong example is mountain wave
7 development over the Pyrenees during strong northerly winds which can prevent or erode
8 CAP formation in Cerdanya (Pagès et al, 2017).

9 The aim of this paper is to detect CAP and no-CAP days and identify the synoptic
10 situations which encourage the decoupling between the free air temperature regime and
11 bottom valley temperatures in the Cerdanya basin (~15 km wide and ~30 km long). The
12 study area and field data collection methods are described in section 2. Section 3 outlines
13 the application of EOF analysis to detect the spatial and temporal occurrence of CAP
14 (Lundquist et al, 2008). Synoptic situations associated with CAP and no-CAP days are
15 then characterised using a combination of Principal Component Analysis (PCA), Cluster
16 Analysis (CA) and Discriminant Analysis (DA) (Aran et al, 2011; Peña et al., 2011).
17 Section 4 presents the results both spatially in terms of CAP distribution, and temporally
18 in terms of appropriate synoptic conditions. The consequences of our findings are
19 discussed in section 5.

20

21 **2. Study Area and data**

22 **2.1. Study area**

23 Cerdanya (Figure 1) is in the upper reaches of the catchment of the river Segre. Unlike
24 most other Pyrenean valleys which run from north to south, it has an unusual orientation

1 running from east-northeast to west-southwest. Within the broad main study area (marked
2 by a box on Figure 1) Cerdanya valley itself is about 15 km wide and flat bottomed. The
3 surrounding peaks are higher than 2500 m asl so, although wide, the valley has
4 considerable elevation range, with the valley floor at around 1000 m above sea-level
5 (1095 m at Das). Our study area is particularly prone to CAP. A constriction located 15
6 km down river to the west of Das (C on Figure 1) encourages CAP upstream because
7 valley narrowing makes it difficult for down-valley flow to escape fast enough. Even
8 further upstream, the upper part of Cerdanya includes a high elevation plateau near Mont
9 Louis (ML) where cold air can originate. The plateau is breached at its lowest point at the
10 Col de Perche (CP ~1.500 m asl). Upper Cerdanya has been studied in terms of its
11 inversion climatology in past papers (Pepin & Kidd, 2006, Pages et al. 2017).

12 **2.2. Field data collection**

13 Spread along Cerdanya in several elevational transects, 40 HOBO U23-001 sensors
14 (temperature/relative humidity) were installed (see Figure 1). Data from these sensors
15 was recorded every 30 minutes for a 3 year period from July 2012 until July 2015, but the
16 data used in this study only covers the winter months: December, January and February
17 (DJF) which are the months when CAP events are strong. The accuracy of the temperature
18 sensor is +/-0.21 °C and the operating range from -40 °C to 70 °C, adequate for local scale
19 temperature monitoring (Whiteman, 2000). The sensor network includes slopes with
20 differential aspects and land-use since at mid-latitudes there are large contrasts in
21 radiation receipt between north and south facing slopes. Seven main transects were
22 installed, three each on the north and south side of Cerdanya, and another one in Conflent.
23 Sensors were installed at approximately equal elevational intervals (every 200-250 m),
24 extending to include a difference of around 1000 m on all transects. An additional transect

1 along the bottom valley made sure that longitudinal differences in temperature along the
2 Segre river were measured. Because Conflent is known to be less prone to CAP than
3 Cerdanya (Pepin and Kidd, 2006, Pages et al. 2017) an additional transect was installed
4 on the north-facing valley side in Conflent to more closely approximate the free
5 atmosphere. In all cases, the sites extended from the valley floor (~1000 m asl) up to
6 around tree line (~2.100-2.400 m asl). At each site, local scale aspect was representative
7 of a larger area (e.g. south facing on the Malniu transect) and we had a preference for
8 sites on slopes from which air would freely drain, which would avoid microclimates as
9 far as possible.

10 Sensors were placed into white PVC pipes 30-40 cm long and 15 cm wide (see Pagès et
11 al., 2017) to protect from direct radiation, yet still allow ventilation (Figure 2). Trees (36
12 cases) or other permanent fixtures (4 cases) were used and the sensor installed at 1.5 m
13 above the ground. The top end was orientated north at an angle of 45° to stop sunlight
14 from directly entering the tube. Most trees were evergreen, either pine (*Pinus halepensis*
15 and *Pinus sylvestris*) or juniper (*Juniperus phoenicea*). Although trees can create their
16 own microclimate, large parts of the study area are forested so trees have a strong
17 influence on the broader climate (see Pagès et al, 2017).

18 Sensors range in elevation from 739 m asl (Val1) to 2484 m asl (Mas1). The screen height
19 (1.5 m) meant that snow build up around sensors was rare. This did occur at two locations
20 (Les1 and Cad1) and so a limited amount of data (4 months) at these sites was deleted.
21 Despite some limited data loss and one stolen sensor (Eyn5) we have a fairly
22 comprehensive dataset over the 3 years at 39 locations.

1 **2.3. Large scale model data**

2 ERA-Interim analysis provided by the ECMWF (European Centre of Medium Range
3 Weather Forecast) at 1° resolution (Dee et al, 2011) was used to classify the synoptic
4 situation for each day (see section 3). Variables used to discriminate every case included
5 sea level pressure (SLP), relative humidity at 700 hPa (H700), temperature at 850 hPa
6 (T850) and 700 hPa (T700), and geopotential height at 700 hPa (Z700) and 500 hPa
7 (Z500). The grid area covered 30 °N to 70 °N and 30 °W to 30 °E.

8 **3. Methodology**

9 **3.1. Spatial and temporal CAP features**

10 Minimum temperatures were calculated at each location for each day using the period
11 midnight to midnight UTC. A methodology using EOF analysis was applied to minimum
12 temperature anomalies from the HOBO sensors in order to discriminate between locations
13 more and less prone to CAP (Lundquist et al, 2008). According to this methodology the
14 spatial structure of CAP is represented by loadings of each site (EOF). Days more or less
15 likely to develop CAP can be identified using the PC time series.

16 Daily minimum temperatures (0000 UTC to 0000 UTC) $T(\vec{x}, t)$, are decomposed into
17 various components as in equation 1 in order to remove variability caused by different
18 sensor elevations and synoptic effects:

$$19 \quad T(\vec{x}, t) = \bar{T}(\vec{x}) + \bar{T}'(t) + \tilde{T}(\vec{x}, t) + \varepsilon \quad (1)$$

20 where $\bar{T}(\vec{x})$ is the long-term mean minimum temperature at each site (variability due to
21 different elevations), $\bar{T}'(t)$ is the temporal deviations in the mean (area-averaged)
22 minimum temperature across the domain (synoptic and seasonal effects), and $\tilde{T}(\vec{x}, t)$ are
23 the local spatial deviations that change through time and are contrasting between sites.

1 Finally ε represents remaining error which can be related to the instrument accuracy.
 2 Subtracting $\bar{T}(\bar{x})$ and $\bar{T}(t)$ from the original minimum temperatures, $T(\bar{x}, t)$, creates a
 3 new detrended time series of anomalies which avoids elevational and seasonal/synoptic
 4 effects.
 5 The EOF analysis is very efficient at decomposing a time series into the main components
 6 of variability, including in this case variability associated with CAP (Lundquist and
 7 Cayan, 2007). The eigenvectors (EOF) obtained for each component represent spatial
 8 variability across the domain related to that component and the eigenvalues (PC) are
 9 related to temporal variability of that component. Varimax rotation of components
 10 (Richman, 1986) was applied to help interpretation and to improve physical reality.
 11 The relationships between minimum temperature anomalies with both PC scores and EOF
 12 loadings can be deduced using this decomposition:

$$13 \quad \tilde{T}(x, y, t) + \varepsilon = \sum_{k=1}^N PC(t).EOF(x, y) \quad (2)$$

14 where PC(t) is the score matrix and EOF(x,y) is the loading matrix of the EOF analysis.
 15 Lundquist et al (2008) suggest that the first component PC1 is related to synoptic
 16 situations related to CAP (clear skies, high pressures and weak winds). Bearing in mind
 17 that the first component retains the main variability; the equation (2) could be simplified
 18 as:

$$19 \quad \tilde{T}(x, y, t) + \varepsilon \approx PC1(t).EOF1(x, y) \quad (3)$$

20 where PC1 represents the first PC and EOF1 the first EOF.
 21 Depending on the sign of the EOF1, sites will be classified as prone (negative loading) or
 22 not (positive loading) to experience CAP. Negative/positive anomalies of minimum
 23 temperature ($\tilde{T}(\bar{x}, t)$) at high mountain/valley sites respectively indicate that mountain

1 temperatures are relatively colder than valley-bottom ones, expected for no-CAP
2 situations; Conversely, positive/negative anomalies of minimum temperature at high
3 mountain/valley sites indicate relatively cold temperatures in valley-bottoms, typical of a
4 CAP situation.

5
6 The temporal evolution of the first component PC1 identifies situations experiencing
7 CAP and no-CAP. To classify days as CAP/no-CAP, we choose the 60th and the 40th
8 percentiles of PC1 respectively. This gives a wide representation of events and not solely
9 extreme cases.

10 **3.2. Synoptic analysis**

11 A multivariate analysis for all days classified previously as CAP (top 40%) or no-CAP
12 (bottom 40%) days was applied to obtain a synoptic classification related to these events.
13 The multivariate analysis was carried out using gridded data at 1° resolution from ERA-
14 Interim analysis (see section 2.3). The methodology is based on three steps: PCA (for
15 reducing the data dimension), cluster analysis (to classify the different synoptic
16 situations) and discriminant analysis (to validate the model) (Figure 3).

17 **3.2.1. Factorization: Principal component analysis (PCA)**

18 PCA can be used in synoptic classification in different ways (Huth et al., 2008), either as
19 a tool prior to Cluster Analysis (CA) in S-mode, or as a classification tool in T-mode
20 (Cattell, 1952). We apply PCA only as an intermediate tool for data dimension reduction
21 using S-mode. Variables are grid points and days are observations. The scree-test is
22 employed to determine the number of components involved, based on a detectable change
23 in the slope on the scree plot (Cattell, 1966). Orthogonal Varimax rotation is used to

1 minimise the number of variables with high factorial EOF (Richman, 1986; Huth, 1996).
2 The method was applied twice, one for days with CAP and another for days with no-CAP.

3

4 **3.2.2. Classification: Cluster analysis (CA)**

5 CA is applied to the matrix which is formed by the individual PCA scores retained with
6 the previous principal component analysis. The resultant clusters correspond to the main
7 atmospheric circulation patterns associated with CAP or no-CAP. The clustering
8 algorithm used is the non-hierarchical K-means method (McQueen, 1967).

9 The number of groups to be obtained in cluster analysis is user-defined (see Tibshirani et
10 al, 2001; Jain, 2010; Debatty et al., 2014). To determine the initial number of clusters the
11 elbow method (Thorndike, 1953; Ketchen and Shook, 1996; Omrani et al, 2016) is
12 applied to hierarchical Ward clusters which gives the number of initial groups (Aran et
13 al, 2011; Peña et al., 2011).

14 **3.2.3. Reclassification: Discriminant analysis (DA)**

15 Finally DA is applied in order to reclassify any borderline cases if necessary (Michailidou
16 et al., 2009; Fernández, 2002). Since DA needs predefined classes (Sioutas and Flocas,
17 2003) the previous classification obtained from CA is used in this step. PCA scores are
18 used as predictors in DA. Then, a stepwise selection criterion, the Wilks' lambda criterion,
19 is applied to obtain the discriminant functions (Diab et al., 1991).

20 **4. Results**

21 **4.1 Spatial and temporal CAP features**

22 The first component PC1 represents 59% of the variance of minimum temperature
23 anomalies and is representative of CAP. The subsequent PCs identified other more subtle

1 topographical and geographical contrasts but the detailed discussion of their loadings is
2 beyond the scope of this paper.

3 Observing the relationship between PC1 and different meteorological variables given by
4 the ERA-Interim analysis for the nearest point to Das, shows: a positive correlation of
5 PC1 with 850 hPa temperature (which indicates warm advection during CAP) and surface
6 pressure (which indicates anticyclonic situations with CAP events) and a negative
7 correlation with 700 hPa relative humidity (which is related to dry air and cloudless skies
8 during CAP events) and 10 m wind speed (which means calm winds) (Table 1). Thus,
9 high values of PC1 representative of CAP are associated with the presence of anticyclonic
10 weather, warm advection above, clear skies and no wind (typical synoptic conditions
11 related to CAP).

12 The EOF1 loadings at each site show that both high elevation and valley-bottom sensors
13 tend to be strongly correlated with PC1, but intermediate stations located on slopes tend
14 to be indeterminate (Table 2 and Figure 4). Mountain summits show positive loadings
15 and for days with positive/negative PC1 will have positive/negative minimum
16 temperature anomalies, typical of sites not prone to CAP. On the other hand, sites located
17 in valley-bottoms have negative loadings and for days with positive/negative PC1 there
18 will be negative/positive anomalies, typical of a site prone to CAP.

19 The exception is the Fontpedrouse transect, located in Conflent, which is universally
20 positively correlated with PC1 except in the bottom of the valley where there is a very
21 weak negative loading. These results suggest that Conflent is much less prone to CAP
22 and often shows indeterminate behaviour even in its lower reaches. This is expected since
23 the valley is steep and narrow with a considerable longitudinal (downstream) terrain
24 gradient meaning that cold air can freely drain out to lower elevations.

1 The overall correlation between EOF1 and elevation is strong with an r^2 of 0.76 (Figure
2 5a) but without the Fontpedrouse transect r^2 rises to 0.83 (Figure 5b). Ignoring the outliers
3 in Fontpedrouse, all stations above 1500 m have similar high positive EOF1 and stations
4 below 1500 m tend to have negative loadings. 1500 m appears to be the dividing line
5 which separates stations prone to CAP or not. ~~Interestingly however, this line increases~~
6 ~~as the valley bottom elevation increases up valley and is located approximately at 300 m~~
7 ~~above ground level, rising from 1500 to 1700 m.~~

8 The temporal evolution of PC1 shows the evolution of CAP over the three winters (Figure
9 6). Strong CAP days occur in all three years but are concentrated in the months of
10 December and January. Although most periods of CAP are fairly short-lived, there are
11 some extended periods of strong CAP, for example in January 2015. The magnitude of
12 the score represents the strength of CAP on that particular day. Using the 40th and 60th
13 percentiles of PC1 to separate no-CAP/CAP days from the remainder respectively
14 generates 114 CAP days and 156 no-CAP days for further analysis.

15

16 **4.2. Overview of synoptic patterns associated with CAP/no-CAP conditions.**

17 Four synoptic patterns have been extracted relating to CAP and five to no-CAP days (as
18 defined in the previous section). Patterns prone to CAP are in general defined by an
19 anticyclonic ridge over the Iberian Peninsula and absence of surface wind in Cerdanya,
20 particularly in December and January (Figures 7a and 8). In contrast synoptic patterns
21 related to no-CAP are generally characterized by a trough over western Europe and strong
22 northerly winds promoting the formation of mountain waves and air-mass mixing over
23 Cerdanya, and are more frequent during February (Figures 7b and 9).

24 **4.2.1. Synoptic patterns related to CAP conditions**

1 We describe the patterns in order of frequency. The first pattern (Figure 8a: 68% of cases)
2 consists of a warm anticyclonic ridge at 500 hPa with indistinct surface pressure in the
3 Iberian Peninsula characterized by the absence of a definite circulation at low levels and
4 light winds at the surface. At 700 hPa a north-westerly flux can be observed that could
5 interact with the mountains and influence CAP formation. In general, positive
6 temperature anomalies together with negative relative humidity anomalies characterize
7 this atmospheric configuration. The second pattern (Figure 8b: 18% of cases) is also
8 defined by a warm anticyclonic ridge at 500 hPa with high pressure at the surface over
9 the Iberian Peninsula. There are positive temperature anomalies at 850 hPa and negative
10 RH anomalies at 700 hPa (dry air) similar to the first pattern. Unlike subsequent patterns
11 there is an absence of strong southerly advection since the ridge is centred over the region.
12 The third pattern (Figure 8c: 11% of cases) is defined by a warm anticyclonic ridge at
13 500 hPa with high pressure at the surface over the Iberian Peninsula but weak southerly
14 advection over the region. Positive temperature anomalies at 850 hPa and negative RH
15 anomalies at 700 hPa (dry air) characterise this pattern. The final and fourth pattern
16 (Figure 8d: 4% of cases) is characterized by a warm anticyclonic ridge at 500 hPa with
17 moderate southerly winds at the surface, positive temperature anomalies at 850 hPa and
18 negative humidity anomalies (dry air) at 700 hPa.

19 Although there are similarities between all four patterns, there is a distinction between
20 the most common anticyclonic patterns (patterns a, b) and the latter two which also have
21 southerly advection (patterns c, d). The former account for most of the CAP days (Figure
22 7a) and are especially dominant in December when the night-time cooling mechanism is
23 most efficient (longest nights).

24 **4.2.2. Synoptic patterns related to no-CAP conditions**

1 The five patterns associated with no-CAP are dominated by frontal progression in
2 different stages. The first pattern (Figure 9a: 47% of cases) is dominated by northerly
3 advection at the surface and negative temperature anomalies. Clouds and precipitation
4 will be widespread along the western Mediterranean. Instability promotes no-CAP
5 conditions in Cerdanya. The second pattern (Figure 9b: 30% of cases) is dominated by
6 westerly advection at the surface and negative temperature anomalies along the western
7 part of the Mediterranean. An upper trough at 500 hPa over Catalonia implies clouds and
8 precipitation would be widespread across Western Europe. Together these two patterns
9 account for the vast majority (87%) of cases.

10 The third pattern (Figure 9c: 10% of cases) is defined by westerly surface flow over the
11 study area associated with a trough at 500 hPa. Precipitation is located over the west of
12 the Iberian Peninsula. The 850 hPa temperature shows positive temperature anomalies
13 over the Pyrenees. Strong winds at all levels lead to air-mass mixing and a lack of CAP.

14 The fourth pattern (Figure 9d: 10% of cases) is dominated by a north-easterly advection
15 at the surface and negative temperature anomalies along the flanks of the Mediterranean.

16 Clouds cover almost all of the north east of the Iberian Peninsula but not the
17 Mediterranean. This unstable situation again promotes no-CAP conditions in Cerdanya

18 A frontal system located over southwestern Europe dominates the synoptic configuration
19 in the final synoptic pattern related to no-CAP conditions (Figure 9e: 3% of cases). Strong
20 winds and cloud cover could promote no-CAP conditions. There are positive temperature
21 anomalies at 850 hPa.

22

1 **5. Discussion**

2 In this paper, a methodology for classifying days prone to CAP or no-CAP was inspired
3 from previous work (Lundquist et al. 2008). In general synoptic patterns associated with
4 high or low PC1 values are mostly in line with expected theories.

5 Cerdanya is a small closed basin with marked continental character and despite the
6 strongest inversions usually taking place in surface anticyclonic synoptic situations, these
7 are not the only conditions in which CAP formation can occur. Synoptic situations which
8 generate surface southerly winds can also experience CAP formation due to the
9 decoupling of the free atmosphere from a stable layer located immediately above the
10 ground, which cools quicker than that above forming a thermal inversion. Strong
11 inversions which form under anticyclonic conditions tend to disappear during daytime
12 under solar heating, even in mid-winter and only in a few cases are they persistent (Pages
13 et al. 2017). When the synoptic situations are favourable however an inversion can
14 strengthen over several days until a change in air mass changes this behaviour. This often
15 happens as warm southerly advection overrides a surface cold layer developed in a
16 previous anticyclone. The typical synoptic progression in the Pyrenean region in winter
17 means that planetary waves pass across the Iberian Peninsula. Prior to the passage of a
18 trough, south and south-west winds blow over the Pyrenees. Following the passage of the
19 trough the winds change abruptly to north and north-west and introduce cold advection.
20 The period with strong inversions begins when a travelling surface anticyclone traps cold
21 air near the surface at night. The CAP remains and reinforces as another shortwave trough
22 approaches with upper-level southerly and south-westerly winds. The oncoming warm
23 advection typically reaches the mountaintops first and the bottom of the valley can remain
24 decoupled from the increasing upper-level circulation aloft. Despite southerly winds

1 being perpendicular to the Pyrenees range they usually don't produce strong mountain
2 waves which potentially could transfer energy downwards and erode the CAP (Lareau,
3 2014). Understanding why this does not happen will require a more detailed investigation
4 of mesoscale mechanisms including the wind speed over the mountains coupled with
5 regional atmospheric stability and the possible presence of upper level subsidence
6 inversions acting as a lid in the atmosphere. One particularly strong hypothesis is that the
7 top of the CAP acts as a "pseudo-surface" which inhibits the penetration of the wind aloft
8 into Cerdanya through the reduction of the effective mountain height.

9 Perhaps surprisingly situations related to southerly winds produce a stronger gradient of
10 the minimum temperature anomalies across height than pure situations of high surface
11 pressure (Figure 9 right hand side). Although the latter two "anticyclonic" patterns are
12 the most frequent for CAP conditions, some of the strongest inversions are therefore
13 recorded under the two southerly advection patterns. Southerly winds induce mountaintop
14 warming while in the bottom valley temperatures can continue to drop becoming
15 decoupled from the temperature aloft. The absence of mountain waves avoids mixing of
16 the valley air mass with that aloft and also the absence of any synoptic-scale wind inside
17 the valley contributes to efficient ~~radiation~~ cooling during the night. In a pure anticyclonic
18 case, the temperature inversions in Cerdanya are usually destroyed in the morning as the
19 sun heats the valley as have been seen in previous works (Lareau et al, 2013). On the
20 other hand, southerly advective situations associated with warm advection aloft can
21 strengthen further the inversion and maintain it throughout the day, like in January 2015.
22 Thus, minimum temperature anomalies have a steeper gradient with elevation, despite
23 absolute minimum temperatures not being as low as during a pure anticyclonic example.

1 After the passage of a trough the wind turns to the north or north-west, normally with an
2 increase in speed. This can favour mountain wave formation which can aid CAP
3 destruction. Previous work has shown that in favourable conditions, mountain waves
4 break up CAP through displacing the cold air (Lee et al., 1989). Indeed this mechanism
5 is more efficient than the turbulent erosion of the cold air layer by means of turbulence
6 produced by the mountain waves (Whiteman et al., 2001; Lareau and Horel, 2015).

7 87% of cases related to no-CAP were dominated by northerly or north-westerly winds
8 with cold advection aloft (patterns a, b) indicative of instability. The remaining cases
9 include warmer north-westerly, westerly and north-easterly advection (Figure 7b).

10 Differences between classification types mainly depend on differences in the
11 temperatures of the air mass aloft: in situations with relatively warm advection aloft the
12 minimum temperature anomalies tend to be homogenous between the mountaintops and
13 the valley bottom, whereas in situations of cold advection aloft the elevational gradient
14 in minimum temperature anomalies are steeper (Figure 9).

15 Most days with no-CAP correspond with the passage of Atlantic fronts over the Iberian
16 Peninsula which usually produce overcast skies and precipitation on the northern side of
17 the Pyrenees and often strong northerly winds perpendicular to the range. Such winds,
18 unlike in southerly wind situations, are prone to form mountain waves, which often
19 penetrate down into the valley, mixing the boundary layer and preventing the formation
20 of temperature inversions (Sun et al, 2015; Pagès et al, 2017). Typically mountain waves
21 produced by northerly flow are amplified as the air mass stabilizes following the frontal
22 passage and as winds turn north-easterly they are channelled into Cerdanya through the
23 Col de la Perche due to the valley axis running from SSW to NNE (Udina et al, 2016)
24 thus preventing any CAP.

1 **6. Conclusions**

2 The aim of this research was to detect Cold-Air Pooling (CAP) days during winter (DJF)
3 and quantify the synoptic situations which produce decoupling between free air and
4 bottom valley minimum temperatures in the Cerdanya basin in the Eastern Pyrenees. 40
5 HOBO U23-001 sensors (temperature/relative humidity) across the valley allowed
6 identification of air temperature patterns. EOF analysis applied to the minimum
7 temperature anomalies detected the spatial and temporal features of CAP through the first
8 component (59% of variance). The temporal variation of PC1 identifies days more/less
9 likely to develop CAP and thus in turn to identify relevant synoptic situations using a
10 multivariate analysis approach. The spatial loadings on EOF1 clearly separate stations at
11 high elevation (positive values) from valley sites (negative values) and differentiate
12 Cerdanya (prone to CAP) from Conflent (not prone to CAP).

13 Multivariate analysis on gridded data of six atmospheric variables during winter extracts
14 four synoptic patterns related to CAP and five to no-CAP conditions. Patterns prone to
15 CAP are defined by an anticyclonic ridge over the Iberian Peninsula and absence of
16 surface wind in Cerdanya, especially in December and January. However, warm air
17 advection from the south is also commonly associated with persistent CAP and further
18 research is required to understand the mesoscale mechanisms taking part. Patterns related
19 to no-CAP are characterized by a trough over Western Europe with strong winds in the
20 study area which promote the mixing of the air-mass and typically northerly advection.

21

22 **7. Acknowledgements**

23 This study was conducted by the Meteorological Service of Catalonia, the PaleoRisk
24 Research Group (2014 SGR 507) of the University of Barcelona and the Geography

1 Department of the University of Portsmouth. We wish to thank the Meteorological
2 Service of Catalonia and the University of Portsmouth for providing the HOBO U23-001
3 temperature/relative humidity series. The authors would also like to thank the European
4 Centre for Medium-Range Weather Forecasts (ECMWF) for supplying the grid data from
5 ERA-Interim analysis.

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14 **FIGURE CAPTIONS**

15 Fig. 1: Topographic map of Cerdanya valley with sensor locations (white dots). The
16 position of the valley in the wider context of the Pyrenees is also shown. Letters
17 represent features mentioned in the main text: C=constriction, ML=Mont Louis,
18 CP=Col de Perche.

19 Fig. 2: Sensor installation at Cad3. Nearly all sensors were attached to trees at a height of
20 1.5 m above ground level shielded by white PVc tubing as shown (open at both ends).

21 Fig. 3: Steps of multivariate analysis to determine synoptic patterns prone to CAP or no-
22 CAP conditions.

23 Fig. 4: Spatial variation in EOF1 values representing CAP/no-CAP features. The first
24 component represents 59% of the variability of the minimum temperature anomalies.

1 Fig. 5: a) Relationship between EOF1 and the height above sea level for all stations. b)
2 The same as in the left panel but without the outlying Conflent stations Font5 and
3 Font4.

4 Fig. 6: The temporal variation of PC1. The thresholds to separate CAP (top black line)
5 and no-CAP days (bottom black line) are specified by the 60th and 40th percentiles
6 respectively.

7 Fig. 7: Monthly distribution of synoptic patterns for CAP (a) and no-CAP (b) days.

8 Fig. 8: The rows represents the four synoptic patterns (a, b, c and d) prone to CAP
9 conditions in the Cerdanya Valley (first three columns) and interpolated minimum
10 temperature anomalies across Cerdanya (last column). From left to right the weather
11 charts represent: The first column mean sea level pressure in hPa (contour lines) and
12 850 hPa temperature anomalies in °C (shaded contours), the second column is the
13 geopotential height in meters (lines) and RH anomalies in % (shaded contours) at 700
14 hPa, in the third column there is 500 hPa geopotential height in meters (lines) and
15 temperature anomalies at the same level in °C (shadow contours).

16 Fig. 9: The same as Fig. 8 but for the five synoptic patterns (a,b, c, d and e) prone to no-
17 CAP conditions.

18 Table Captions

19 Table 1: Correlation coefficients of PC1 with the variables 850 hPa temperature (T850),
20 Surface pressure (PSFC), 700 hPa Relative Humidity (700RH) and 10 m Wind Speed
21 (10WS), for a central point in La Cerdanya given by the ECMWF-Interim model.

22

23 Table 2: Loadings of the first EOF (EOF1): Most high and low elevation sensors are
24 strongly correlated with EOF1 but intermediate slope stations have low correlations

1 and become indeterminate. Positive/negative values indicate CAP/no-CAP formation.
2 ND: no-data or not enough data (due to snow cover or stolen sensor). The TOP, INT
3 and BOT words in brackets after the sensor name refer to transect position. BOT: from
4 0 to 300 m above valley floor elevation, INT: from 300 to 900 m above valley floor
5 elevation and TOP: over 900 m above valley floor elevation. The numbers below the
6 sensor name indicate the height in m asl. and height above valley floor elevation
7 respectively.